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RESEARCH ARTICLE

Artificial Intelligence, Industrial Integration, and Industrial Restructuring and Upgrading in China*

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Abstract

Boosting the intelligent, green, and integrated development of industries is fundamental to building a modern industrial system. Among them, promoting industrial integration serves as the industrial bedrock for advancing the construction of this system and accelerating the emergence of new quality productive forces. Producer services' inherent integrative specialty positions them as a key direction for China' s industrial restructuring and upgrading. Analysis based on cross-national data reveals that the share of producer services remains relatively low in China, indicating untapped potential for driving economic growth. As a strategic general-purpose technology driving the new wave of technological revolution and industrial transformation, artificial intelligence (AI) shifts industrial development from stronger specialization to mutual integration, becoming a critical tool for accelerating industrial integration and promoting the development of producer services. This paper develops a multi-sector dynamic general equilibrium model that incorporates AI and industrial integration. The findings suggest that when AI is biased toward manufacturing and the elasticity of substitution between manufacturing and producer services is low, AI promotes the integration of manufacturing and producer services, thereby increasing the share of producer services through intensive marginal effects. Simulation results demonstrate that AI can effectively promote industrial integration and industrial restructuring and upgrading. Furthermore, raising new infrastructure investment rates and reducing labor mobility costs across service sectors can further promote industrial integration and accelerate the development of producer services. This paper presents the theoretical mechanism through which AI affects industrial integration and industrial restructuring and upgrading from a macroeconomic structure perspective and provides policy recommendations on how AI can promote industrial integration and develop producer services.

Keywords artificial intelligence (AI); industrial integration; producer services; industrial restructuring and upgrading

1 Introduction

Industrial integration represents a key trend and a leading direction for industrial restructuring and upgrading. Accompanying a new wave of general-purpose technological revolution,

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industrial development is progressively shifting from stronger specialization toward mutual integration. Traditional boundaries between industries are becoming increasingly blurred, and industrial integration has emerged as a new trend in industrial development. As industrial integration continues to deepen, economic growth increasingly relies not on the rapid expansion of individual sector but on cross-sector synergistic collaboration and deep integration, which injects new momentum into economic development. The first meeting of the Central Commission for Financial and Economic Affairs, a key body of the 20th Central Committee of the Communist Party of China (CPC), called for boosting the intelligent, green, and integrated development of industries to build a modern industrial system that is holistic, advanced, and secure, thereby defining the essential requirements for establishing such a system. The third plenary session of the 20th CPC Central Committee further highlighted the imperative to promote the integrated development of producer services. Therefore, accelerating industrial integration constitutes an essential requirement for adapting to new industrial development trends and establishing a modern industrial system.

The integration between manufacturing and producer services exemplifies the most prominent form of industrial integration. As China's manufacturing sector faces the "low-end lock-in" problem, fostering the integrated development between it and producer services is pivotal for enhancing the resilience of industrial and supply chains and moving toward the high end of the global industrial value chain (Huang, 2016). Producer services act as a catalyst for deep integration and coordinated development between manufacturing and services. Spanning the entire production process, they provide platform-based services across the industrial chain for manufacturing, serving as a vital engine for manufacturing transformation and upgrading. The stronger a nation's manufacturing, the greater the contribution of producer services, such as R&D, design, trade, and after-sales, to its value addition. These producer services empower manufacturing significantly by boosting efficiency and competitiveness.

Figure 1 illustrates the relationship between the share of producer services and per capita GDP across major economies in the world.[1] It reveals a consistent rise in both the employment share and output share of producer services alongside per capita GDP growth, underscoring their escalating importance in economic development. However, the share of producer services in China has remained persistently low, showing a significant gap compared to advanced economies. As Table 1 shows, in 2018, China's employment share and output share in producer services stood at 11% and 27%, respectively, below the corresponding shares in

[1] According to the industry classification of the Groningen Growth and Development Centre (GGDC), producer services primarily encompass transport, warehousing & postal services, finance, real estate, and business services. Figure 1 utilizes data from 45 economies, including the United States, the United Kingdom, Germany, Denmark, Spain, France, Italy, Sweden, Netherlands, China's mainland, China's Hong Kong, China's Taiwan, Japan, the Republic of Korea, Singapore, Israel, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, India, Malaysia, Bangladesh, Pakistan, Philippines, Sri Lanka, Burkina Faso, Cameroon, Kenya, Malawi, Mauritius, Morocco, Mozambique, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Tunisia, Türkiye, and Zambia.

Japan and the Republic of Korea during the same year. By contrast, the United States had already achieved a 22% employment share and 44% output share in this sector by 2010. This comparison reveals that compared with advanced economies, China still lags significantly in the share of producer services, particularly in employment share and output share, holding substantial potential for future expansion.

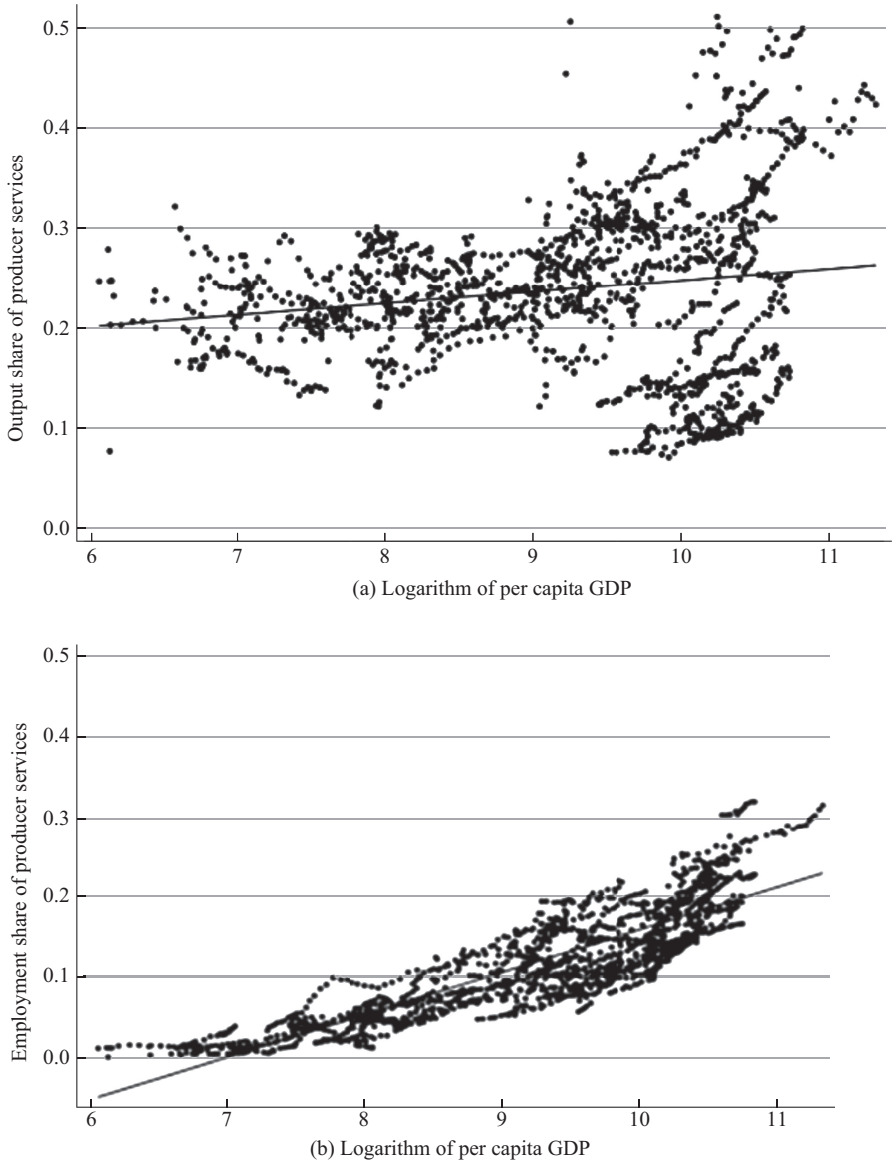

Figure 1 The Relationship between the Share of Producer Services and Per Capita GDP across Major Economies in the World

Source: Per capita GDP from Penn World Table 10.01, and producer services' shares from the GGDC 10-Sector Database 2014. The source of Table 1 is identical.

Table 1 Comparison of the Share of Producer Services between China and Selected Developed Economies

Economy	Per capita GDP (Constant USD, 10,000)	Employment share of producer services (%)	Output share of producer services (%)
China (2018)	1.390	11.255	26.918
The United States (2010)	5.437	22.483	44.013
Japan (2018)	3.982	22.607	33.912
The Republic of Korea (2018)	4.200	22.439	31.113
The United Kingdom (2011)	4.069	22.419	28.450

Artificial intelligence (AI), as a strategic general-purpose technology, plays a pivotal role in driving the new wave of scientific and technological revolution and industrial transformation. Over the past decade, AI has transitioned from laboratory to industrial-scale applications, reshaping traditional industrial models and contributing significantly to the global economic and social activities (Cai & Chen, 2019). AI technology was initially introduced into the production activities of the manufacturing sector in the form of industrial robots. In China, the industrial robotics sector has expanded continuously. Since 2013, China has surpassed Japan as the world's largest industrial robotics market, accounting for 33% of the global market by 2021. AI exhibits infrastructural spillover effects, which can enhance labor productivity across diverse industries (Graetz & Michaels, 2018; Zhong et al., 2024). High-efficiency production modes conserve resources and reduce costs, facilitating not only industrial restructuring (Guo, 2019) but also a shift in manufacturing employment from low-end processing toward high-end services (Pan & Guo, 2024). Concurrently, the share of producer services can be effectively elevated (Wang et al., 2020). As industrial integration emerges as a new trend of industrial restructuring and the world enters the era of AI, what implications will the constantly advancing AI hold for industrial integration and the development of producer services? How can we develop a comprehensive understanding of AI's impact mechanism through the lens of industrial integration to better leverage AI in driving industrial restructuring and upgrading?

Based on these considerations, this paper establishes a multi-sector general equilibrium model incorporating AI and industrial integration. According to the characteristics of industrial integration, services are divided into producer services and consumer services, where manufacturing and producer services integrate to produce industrial goods, and consumer services and producer services integrate to produce service goods. Theoretical analysis shows that when AI is biased toward manufacturing and the elasticity of substitution between manufacturing and producer services is low, AI promotes the integration of

manufacturing and producer services, increasing the share of producer services through intensive margin effects. Calibrating the model's core parameters using the data from the Groningen Growth and Development Centre (GGDC) (2021), the paper achieves a robust fit for China's industrial structural changes from 1990 to 2018. Numerical simulation results show that AI continues to promote industrial integration and increase the share of producer services. Raising new infrastructure investment rates and reducing labor mobility costs across service industries can further accelerate the development of producer services.

This paper has enriched research on AI. Many studies have explored the heterogeneous impacts of AI on employment from a micro perspective (Acemoglu & Autor, 2011; Sun & Hou, 2019; Wang et al., 2022; Yin et al., 2023). Some other studies have examined AI's impacts on macro-level aspects such as economic growth, income distribution, aging, and industrial structure from a macro perspective (Acemoglu & Restrepo, 2018; Aghion et al., 2019; Chen et al., 2019; Graetz & Michaels, 2018; Guo, 2019). However, these studies mostly establish theoretical models based on the traditional three-sector structure, discussing sectoral shifts. Regarding the relationship between AI and industrial integration, some studies have used enterprise data and case studies to preliminarily verify conclusions about AI driving industrial integration (Gao et al., 2022; Wan et al., 2021). This paper approaches from the perspective of industrial integration, constructs a theoretical model to characterize the integrative features of producer services, and systematically elaborates on the impact mechanism of AI on industrial integration and the share of producer services.

This paper has expanded theoretical research on industrial integration. Regarding the integrated development of manufacturing and services, Vandermerwe and Rada (1988) first systematically expound the path of integrated development where traditional manufacturing enterprises sharpen their market competitiveness by integrating product and service resources. In quantitative research on the degree of industrial integration, numerous studies have focused on the degree of integration between manufacturing and services, namely the phenomenon of servitization in manufacturing. From the production relationship dimension, industrial integration can be further subdivided into input servitization and output servitization. The former form uses consumption coefficients in input-output tables to calculate the proportion of service inputs in total manufacturing inputs (Liu et al., 2016; Liu & Zhao, 2020); and the latter form focuses on analyzing the business formats and contents provided by enterprises, measured by the ratio of manufacturing enterprises' service business revenue to their total revenue (Chen & Zhang, 2016; Zhang et al., 2019). This paper adopts a similar metric for the industrial integration degree, assessing it through the lens of input servitization within production relationships, specifically measured by the proportion of producer services' input value in total inputs. Additionally, some studies have focused on factors affecting industrial integration, such as institutional differences (Yao et al., 2019), the "replacing business tax with value-added tax" policy (Sun et al., 2020), and labor productivity (Guo & Huang, 2020). These studies have provided useful insights for analyzing the driving factors of industrial integration. However, the role of AI as a new driving force for industrial integration has

been overlooked. This paper examines the impact of AI on industrial integration and the development of producer services from a macrostructural transformation perspective, incorporating quantitative validation tailored to China's economic characteristics, thereby enriching research in the field of industrial integration.

Compared to extant literature, this paper has three marginal contributions. (1) From the research perspective, this paper breaks through traditional industry classification standards, dividing service sectors into producer services and consumer services based on their integrative attributes and emphasizing the integration role of producer services in goods and service production. Furthermore, this paper focuses on AI's role in industrial integration and the development of producer services, expanding research perspectives in the AI field. (2) From the research methodology, this paper characterizes the industrial integration process within the traditional structural transformation framework, introduces the biased impacts of AI, and explores the relationships between AI, industrial integration, and industrial restructuring and upgrading both qualitatively and quantitatively based on China's industrial structure characteristics. (3) From the research findings, this paper theoretically elaborates on the mechanism by which AI affects producer services through intensive margin effects and extensive margin effects, finding that raising new infrastructure investment rates and reducing labor mobility costs across service sectors can further accelerate industrial integration and industrial restructuring and upgrading. This paper's findings provide a theoretical foundation for promoting industrial integration and the development of producer services in the era of AI.

2 Benchmark Model

This section introduces AI technology within the structural transformation framework, constructing a multi-sector general equilibrium model that characterizes industrial integration. On the supply side, the model assumes producer services integrate with manufacturing and consumer services, respectively, to produce final goods, with AI technology changing industrial structure and consumption structure through biased impacts on different industries' total factor productivity.

The production sector consists of intermediate goods sectors and final goods sectors. The intermediate goods sector comprises manufacturing, producer services, and consumer services, represented by subscripts $j \in \{m, x, s\}$, respectively. Each intermediate goods sector has a representative firm producing under perfect competition by inputting capital and labor, using the following production function form:

$$Y_j = A_j K_j^{\beta_j} L_j^{1-\beta_j},\ j \in \{m, x, s\}, \tag{1}$$

where Y_j, K_j, and L_j represent the output, capital, and labor inputs of the intermediate goods sector j, respectively. β_j denotes the capital income share. A_j represents productivity, determined by the AI technology level:

$$A_j = B_j M^{\gamma_j}, \tag{2}$$

where the parameter $B_j > 0$ represents the traditional technology level of the sector j. M denotes the AI technology level. $\gamma_j > 0$ is a constant representing the degree of AI technology's impact on different industries. Compared to traditional technological progress, the model in this paper sets productivity into two parts: one that captures the conventional technology level B_j of each sector and another that reflects the heterogeneous impact of AI. AI cannot only improve all intermediate goods sectors' total factor productivity, but also if $\gamma_j \neq \gamma_{j'}$, AI's impact on different intermediate goods sectors is biased; as the AI technology level improves, the biased impact on different industries is also amplified.

Let p_j, R, and W_j denote the product price, capital price, and wage level of the intermediate goods sector j, respectively. The first-order condition for maximizing the profit of the intermediate goods sector is

$$p_j \beta_j A_j K_j^{\beta_j - 1} L_j^{1-\beta_j} = R,\ p_j (1-\beta_j) A_j K_j^{\beta_j} L_j^{-\beta_j} = W_j. \tag{3}$$

Suppose that labor cannot freely flow between different intermediate goods sectors. Then $\xi_j = W_x / W_j$ represents the wage ratio between producer services and the sector j, measuring the degree of labor market friction.

Final goods sectors produce industrial goods and service goods, represented by the subscript $J \in \{M, S\}$. Part of the output of the producer services sector Y_{xM} combines with the output of the manufacturing sector Y_m to produce industrial goods M, while another part of the output of the producer services sector Y_{xS} combines with the output of the consumer services sector Y_s to produce service goods S. Therefore, the total output of the producer services sector is

$$Y_{xM} + Y_{xS} = Y_x. \tag{4}$$

The final goods production sector has a representative firm purchasing intermediate goods as inputs for production under perfect competition, with each firm's production function satisfying the constant elasticity of substitution function form:

$$Q_M = \left[\alpha_M^{1/\sigma_M} Y_m^{(\sigma_M - 1)/\sigma_M} + (1-\alpha_M)^{1/\sigma_M} Y_{xM}^{(\sigma_M - 1)/\sigma_M}\right]^{\sigma_M/(\sigma_M - 1)}, \tag{5}$$

$$Q_S = \left[\alpha_S^{1/\sigma_S} Y_s^{(\sigma_S - 1)/\sigma_S} + (1-\alpha_S)^{1/\sigma_S} Y_{xS}^{(\sigma_S - 1)/\sigma_S}\right]^{\sigma_S/(\sigma_S - 1)}, \tag{6}$$

where Q_J represents the output of the final goods sector J. Parameter $\alpha_J \in (0, 1)$ is a constant representing the weights of different intermediate goods. $\sigma_J > 0$ is the elasticity of substitution between different intermediate goods. Producer services integrate with manufacturing and consumer services, respectively, at certain substitution-complementarity relationships to produce industrial goods and service goods, reflecting the industrial integration process.

Let the variable P_J denote the output price of the final goods sector J. Solving for profit maximization in the sector yields:

$$p_m = P_M \left[\alpha_M^{1/\sigma_M} Y_m^{(\sigma_M - 1)/\sigma_A} + (1-\alpha_M)^{1/\sigma_M} Y_{xM}^{(\sigma_M - 1)/\sigma_M}\right]^{1/(\sigma_M - 1)} \alpha_M^{1/\sigma_M} Y_m^{-1/\sigma_M}, \tag{7}$$

$$p_s = P_S \left[\alpha_S^{1/\sigma_S} Y_s^{(\sigma_S - 1)/\sigma_S} + (1-\alpha_S)^{1/\sigma_S} Y_{xS}^{(\sigma_S - 1)/\sigma_S}\right]^{1/(\sigma_S - 1)} \alpha_S^{1/\sigma_S} Y_s^{-1/\sigma_S}, \tag{8}$$

$$\begin{aligned} p_x &= P_M \left[\alpha_M^{1/\sigma_M} Y_m^{(\sigma_M - 1)/\sigma_M} + (1-\alpha_M)^{1/\sigma_M} Y_{xM}^{(\sigma_M - 1)/\sigma_M}\right]^{1/(\sigma_M - 1)} (1-\alpha_M)^{1/\sigma_M} Y_{xM}^{-1/\sigma_M} \\ &= P_S \left[\alpha_S^{1/\sigma_S} Y_s^{(\sigma_S - 1)/\sigma_S} + (1-\alpha_S)^{1/\sigma_S} Y_{xS}^{(\sigma_S - 1)/\sigma_S}\right]^{1/(\sigma_S - 1)} (1-\alpha_S)^{1/\sigma_S} Y_{xS}^{-1/\sigma_S}. \end{aligned} \tag{9}$$

The final goods price is the composite of intermediate goods prices, satisfying the following condition:

$$P_M = \left[\alpha_M p_m^{1-\sigma_M} + (1-\alpha_M) p_x^{1-\sigma_M}\right]^{1/(1-\sigma_M)}, \tag{10}$$

$$P_S = \left[\alpha_S p_s^{1-\sigma_S} + (1-\alpha_S) p_x^{1-\sigma_S}\right]^{1/(1-\sigma_S)}. \tag{11}$$

The following uses relative share changes in employment and output value of different intermediate goods sectors to characterize industrial restructuring. From equation (7) to equation (9), we get:

$$\frac{p_m Y_m}{p_x Y_{xM}} = \frac{\alpha_M}{1-\alpha_M}\left(\frac{p_m}{p_x}\right)^{1-\sigma_M} \triangleq \theta_M, \tag{12}$$

$$\frac{p_s Y_s}{p_x Y_{xS}} = \frac{\alpha_S}{1-\alpha_S}\left(\frac{p_s}{p_x}\right)^{1-\sigma_S} \triangleq \theta_S. \tag{13}$$

The above θ_J represents the relative output value of two intermediate goods sectors in final goods production. The smaller θ_J, the greater the proportion of producer services in the production process of the final goods sector J, and the higher the degree of industrial integration. Therefore, $1/\theta_J$ measures the degree of industrial integration.

On the demand side, a representative household is used, with composite consumption goods satisfying[2]:

$$C = \left[\omega_C^{1/\varepsilon_C} C_M^{(\varepsilon_C-1)/\varepsilon_C} + (1-\omega_C)^{1/\varepsilon_C} C_S^{(\varepsilon_C-1)/\varepsilon_C}\right]^{\varepsilon_C/(\varepsilon_C-1)}. \tag{14}$$

C_J represents household consumption in the final goods sector J. Parameter $\omega_C \in (0, 1)$ is a constant representing the weight of industrial goods in composite consumption goods. Parameter $\varepsilon_C \in (0, 1)$ is a constant representing the elasticity of substitution between two types of final goods in consumption.

Each period, the household holds capital and labor to participate in the intermediate goods sector's production. The government collects a lump-sum tax T, and the household uses capital rental income and wage income minus the tax for consumption. Therefore, the household sector's budget constraint is

$$P_M C_M + P_S C_S = \sum_j R K_j + \sum_j W_j L_j - T, \tag{15}$$

$$K' = (1 - \delta_K)K + I, \tag{16}$$

where K' represents the next period's capital stock and $\delta_K \in (0, 1)$ denotes the capital depreciation rate. Solving for the utility maximization problem for the representative household yields:

$$\frac{P_M C_M}{P_S C_S} = \frac{\omega_C}{1-\omega_C}\left(\frac{P_M}{P_S}\right)^{1-\varepsilon_C} \triangleq \eta, \tag{17}$$

where η is defined as the ratio of total consumption of industrial goods to service goods, representing the consumption structure.

The investment goods sector has a representative firm producing under perfect competition

[2] To intuitively show the mechanism by which AI changes industrial structure and consumption structure through industrial integration, income effects are ignored here, so homothetic preferences are adopted.

by inputting industrial goods and service goods, with the production function adopting the constant elasticity of substitution function form:

$$I = \left[\omega_I^{1/\varepsilon_I} I_M^{(\varepsilon_I - 1)/\varepsilon_I} + (1-\omega_I)^{1/\varepsilon_I} I_S^{(\varepsilon_I - 1)/\varepsilon_I}\right]^{\varepsilon_I/(\varepsilon_I - 1)}, \tag{18}$$

where I represents investment goods and I_J denotes the output from the final goods sector J used as input in investment goods production. $\omega_I \in (0, 1)$ represents the weight of industrial goods in investment. ε_I is a constant representing the elasticity of substitution of the output from the final goods sector in investment, satisfying:

$$\frac{P_M I_M}{P_S I_S} = \frac{\omega_I}{1-\omega_I}\left(\frac{P_M}{P_S}\right)^{1-\varepsilon_I}. \tag{19}$$

The government uses the taxes collected T to purchase the output H_J from the final goods sector to invest in new infrastructure construction, i.e.,

$$T = P_M H_M + P_S H_S. \tag{20}$$

The output H_J from both sectors can form new infrastructure H, following the constant elasticity of substitution function form:

$$H = \left[\omega_H^{1/\varepsilon_H} H_M^{(\varepsilon_H - 1)/\varepsilon_H} + (1-\omega_H)^{1/\varepsilon_H} H_S^{(\varepsilon_H - 1)/\varepsilon_H}\right]^{\varepsilon_H/(\varepsilon_H - 1)}, \tag{21}$$

where $\omega_H \in (0, 1)$ is a constant representing the weight of industrial goods in new infrastructure production and ε_H is a constant representing the elasticity of substitution between the output from the final goods sector in new infrastructure construction. Similarly:

$$\frac{P_M H_M}{P_S H_S} = \frac{\omega_H}{1-\omega_H}\left(\frac{P_M}{P_S}\right)^{1-\varepsilon_H}. \tag{22}$$

New infrastructure H promotes the development of AI and contributes to its technological accumulation, i.e.,

$$M' = (1-\delta_M)M + H, \tag{23}$$

where M' represents the next period's AI technology level, and parameter $\delta_M \in (0, 1)$ denotes the depreciation rate of AI technology. The AI technology level M' has biased effects on different intermediate goods sectors, as shown in the equation (2).

The general equilibrium condition requires that each final goods sector's output equals consumption, capital investment, and new infrastructure investment, i.e.,

$$Q_J = C_J + I_J + H_J, J \in \{M, S\}. \tag{24}$$

The factor market clearing condition is

$$K_m + K_s + K_x = K, L_m + L_s + L_x = 1. \tag{25}$$

When the total labor supply per period is assumed to be normalized to 1, then L_j also represents the employment share of the intermediate goods sector j. We define y_j as the output share of the intermediate goods sector j, where the sector j's nominal output share in the total output is:

$$y_j = \frac{P_j Y_j}{\sum_j P_j Y_j} = \frac{L_j/(1-\beta_j)\xi_j}{\sum_j L_j/(1-\beta_j)\xi_j}. \tag{26}$$

This paper uses the employment share L_j and output share y_j of the intermediate goods sector to measure industrial restructuring.

3 Theoretical Analysis

To theoretically elucidate the impact mechanism of AI on industrial integration and the development of producer services, this section simplifies the demand-side modeling by assuming $\omega_C = \omega_I = \omega_H = \omega$, $\varepsilon_C = \varepsilon_I = \varepsilon_H = \varepsilon$. Consequently, according to equations (17), (19), and (22), the input share of the two final goods in consumption, investment, and new infrastructure investment is equal, expressed as:

$$\frac{P_M Q_M}{P_S Q_S} = \frac{\omega}{1-\omega}\left(\frac{P_M}{P_S}\right)^{1-\varepsilon} = \eta. \tag{27}$$

Solving the model yields the employment shares of the three intermediate goods sectors:[3]

$$L_m = \frac{(1-\beta_m)\xi_m\eta(1+\theta_S)\theta_M}{(1-\beta_m)\xi_m\eta(1+\theta_S)\theta_M + (1-\beta_s)\xi_s(1+\theta_M)\theta_S + (1-\beta_x)[\eta(1+\theta_S)+(1+\theta_M)]}, \tag{28}$$

$$L_x = \frac{(1-\beta_x)[\eta(1+\theta_S)+(1+\theta_M)]}{(1-\beta_m)\xi_m\eta(1+\theta_S)\theta_M + (1-\beta_s)\xi_s(1+\theta_M)\theta_S + (1-\beta_x)[\eta(1+\theta_S)+(1+\theta_M)]}, \tag{29}$$

$$L_s = \frac{(1-\beta_s)\xi_s(1+\theta_M)\theta_S}{(1-\beta_m)\xi_m\eta(1+\theta_S)\theta_M + (1-\beta_s)\xi_s(1+\theta_M)\theta_S + (1-\beta_x)[\eta(1+\theta_S)+(1+\theta_M)]}. \tag{30}$$

In the following theoretical analysis, we temporarily ignore labor market frictions and differences in capital income shares across intermediate goods sectors (i.e., assuming $\beta_j = \beta_{j'}$, $\xi_j = 1$).[4] This simplifies the expression for the employment share of producer services to:

$$L_x = \frac{\eta}{1+\eta}\frac{1}{1+\theta_M} + \frac{1}{1+\eta}\frac{1}{1+\theta_S}. \tag{31}$$

Equation (27) shows the output shares of industrial goods and service goods in the final goods sector as $\frac{\eta}{1+\eta}$ and $\frac{1}{1+\eta}$, respectively. Equations (12) and (13) indicate the input shares of producer services in producing industrial goods and service goods as $\frac{1}{1+\theta_M}$ and $\frac{1}{1+\theta_S}$, respectively. Therefore, equation (31) economically implies that the employment share of producer services is the weighted sum of its input shares in final goods production, with the weights determined by the output shares of final goods. Then the impact of AI on this employment share can be decomposed into its effect on the share of the final goods sector (extensive margin effect), and its effect on the input share of producer services in final goods production (intensive margin effect).[5]

[3] For detailed derivation procedures, please refer to the supplementary materials on the journal website of *China Industrial Economics*.

[4] This section employs simplified parameters to provide an intuitive demonstration of the theoretical analysis conclusions; however, the subsequent numerical simulations utilize the non-simplified parameter configurations.

[5] Extensive margin effects primarily focus on the scale or breadth of production factor inputs, manifesting in adjustments to the overall structure; intensive margin effects emphasize the intensity or depth of production factor inputs.

3.1 The Intensive Margin Effect of AI on Producer Services

The intensive margin effect manifests in changes to the industrial integration degree $1/\theta_J$. So we get the equation (3),

$$\frac{p_j}{p_x} = \frac{A_x}{A_j} = \frac{B_x}{\xi_j B_j} M^{\gamma_x - \gamma_j}. \tag{32}$$

Substituting this into equations (12) and (13), we get:

$$\theta_M = \frac{\alpha_M}{1-\alpha_M}\left(\frac{B_x}{\xi_m B_m} M^{\gamma_x - \gamma_m}\right)^{1-\sigma_M},\ \theta_S = \frac{\alpha_S}{1-\alpha_S}\left(\frac{B_x}{\xi_s B_s} M^{\gamma_x - \gamma_s}\right)^{1-\sigma_s}. \tag{33}$$

Taking logarithms and total differentials of them, we get:

$$\mathrm{d}\theta_M/\mathrm{d}M < 0 \Leftrightarrow (1-\sigma_M)(\gamma_x - \gamma_m) < 0, \tag{34}$$

$$\mathrm{d}\theta_S/\mathrm{d}M < 0 \Leftrightarrow (1-\sigma_S)(\gamma_x - \gamma_s) < 0. \tag{35}$$

Thus, AI's impact on the industrial integration degree θ_J depends on the elasticity of substitution between intermediate goods sectors in final goods production and AI's bias. In industrial goods production, if the elasticity of substitution between manufacturing and producer services is low and AI is biased toward manufacturing, then AI technology advancements can help reduce θ_M, increase the output share of producer services in industrial goods production, and enhance the industrial integration degree. The reverse is also true. Similarly, in service goods production, AI's impact on the industrial integration degree also depends on AI's bias direction and the elasticity of substitution between producer services and consumer services. Therefore, we put forward:

Proposition 1: In industrial goods production, if the elasticity of substitution between manufacturing and producer services is low and AI is biased toward manufacturing, AI technology advancements can help enhance the degree of industrial integration between the two sectors.

AI's impact on the industrial integration degree aligns with the price effects of structural change (Ngai & Pissarides, 2007). The equation (32) shows AI's bias alters relative prices across intermediate goods sectors. If AI has a greater impact on manufacturing, then as AI technology accumulates, it drives up the relative productivity of manufacturing versus producer services while bringing down the relative price, leading industrial goods production to use more of the relatively cheaper manufacturing inputs. If the elasticity of substitution between manufacturing and producer services is low, the decline in manufacturing's relative price is greater, causing the output value share of manufacturing in industrial goods production to fall and the share of producer services to rise, thereby enhancing the degree of integration between manufacturing and producer services in industrial goods production. The reverse is also true. Similarly, AI's impact on the degree of integration between producer services and consumer services depends on the elasticity of substitution between these service sectors and AI's degree of bias.

Compared to traditional technological progress, even if industry-specific technological progress remains unchanged, as long as AI has biased impacts across industries, the industrial

integration degree changes as AI technology accumulates. Therefore, in the early stages of AI development, AI rapidly enhances manufacturing productivity. When manufacturing and producer services exhibit high complementarity and synergy, AI can promote the integration between manufacturing and producer services, increasing producer services' input share in industrial goods and then raising producer services' share through intensive margin effects.

3.2 The Extensive Margin Effect of AI on Producer Services

The extensive margin effect manifests in changes to the final goods output share η. From equations (10), (11), and (27):

$$\eta = \frac{\omega}{1-\omega} \frac{\left\{ \alpha_M \left(\frac{B_x}{\xi_m B_m} M^{\gamma_x-\gamma_m} \right)^{1-\sigma_M} + (1-\alpha_M) \right\}^{(1-\varepsilon)/(1-\sigma_M)}}{\left\{ \alpha_S \left(\frac{B_x}{\xi_s B_s} M^{\gamma_x-\gamma_s} \right)^{1-\sigma_s} + (1-\alpha_S) \right\}^{(1-\varepsilon)/(1-\sigma_S)}}. \tag{36}$$

Taking logarithms and total differentials of them, we get:

$$\frac{\mathrm{d}\log\eta}{\mathrm{d}\log M} = (1-\varepsilon)\left[\frac{(\gamma_x-\gamma_m)\theta_M}{1+\theta_M} - \frac{(\gamma_x-\gamma_s)\theta_S}{1+\theta_S} \right], \tag{37}$$

$$\mathrm{d}\eta/\mathrm{d}M < 0 \Leftrightarrow (1-\varepsilon)[(\gamma_x-\gamma_m)\theta_M(1+\theta_S) - (\gamma_x-\gamma_s)\theta_S(1+\theta_M)] < 0. \tag{38}$$

As shown above, AI's impact on final goods output share η depends on the elasticity of substitution between final goods, AI's bias, and the industrial integration degree. If AI's impact on producer services and consumer services is similar (i.e., $(\gamma_x - \gamma_s) \approx 0$), then AI's extensive margin effects depend on $(1 - \varepsilon)(\gamma_x - \gamma_m)$, namely the elasticity of substitution between final goods and AI's bias degree. If AI has a greater impact on manufacturing, it can drive faster relative productivity growth in manufacturing and cause the relative price of the sector's output to fall, thereby reducing the entire industrial goods sector's production costs. Consequently, households choose to substitute industrial goods at a lower relative price for service goods in consumption. If the elasticity of substitution between industrial goods and service goods is less than 1, the increase in the relative quantity of industrial goods consumed by households is smaller than the decrease in their relative price, resulting in a decline in the relative output share η of industrial goods to service goods. The reverse is also true. Therefore, we put forward:

Proposition 2: When the impact of AI on different service sectors is relatively similar, if the elasticity of substitution between industrial goods and service goods is low and AI is more biased toward manufacturing, then as AI technology advances, the output share of industrial goods declines while that of service goods increases.

As *Proposition 2* indicates, AI can drive consumption restructuring even when income effects are disregarded. Specifically, as AI technology accumulates, the share of industrial goods declines while that of service goods increases. This occurs primarily because AI's biased impact on manufacturing exceeds that on services, leading to lower prices for industrial goods. When the elasticity of substitution between industrial goods and service goods is low,

the output share of service goods rises. Therefore, AI serves as one of the driving forces for consumption restructuring and upgrading.

In summary, the impact of AI on producer services hinges on its intensive margin effect on the industrial integration degree θ_j and extensive margin effects on the final goods output share η. If the elasticity of substitution between manufacturing and producer services is low and AI is more biased toward manufacturing, AI advancements can promote the integration between these sectors and amplify the intensive margin effects. Furthermore, when the impact of AI on producer services and consumer services is comparable, its effect on the degree of industrial integration between the two sectors θ_S becomes negligible, and a low elasticity of substitution between final goods outputs drives AI to elevate the output share of service goods, thereby influencing the extensive margin effects. Consequently, how AI impacts the share of producer services hinges on the trade-off between intensive and extensive margin effects. This paper subsequently employs the numerical simulation method to quantitatively validate the impact of AI on industrial integration and producer services.

4 Numerical Simulations

4.1 Parameter Calibration

This paper compiles China's sectoral data from 1990 to 2018 using the Economic Transformation Database provided by the GGDC. In the model, each period corresponds to one year in the empirical data, with the initial period set to 1990. The remaining 11 sectors from the GGDC's sectoral database (2021), after excluding agriculture, are mapped to the three intermediate goods sectors in the model: manufacturing (mining, manufacturing, utilities, construction), producer services (transport services, business services, financial services, real estate), and consumer services (remaining sectors). By aggregating the nominal value-added, real value-added, and employment figures from the GGDC's sectoral database across sectors into manufacturing, producer services, and consumer services, we obtain the nominal output, real output, and employment for these three intermediate goods sectors. Their sectoral prices p_j are calculated as nominal output divided by real output. Regarding sectoral capital income shares, this study utilizes 14 input-output tables in China from 1990 to 2020 provided by the China Industrial Productivity (CIP) database to calculate aggregated capital income shares for the three industrial sectors. Sectoral capital income and value-added data from the CIP are aggregated into these three sectors to derive their capital income shares. Taking the annual averages as the parameter values for β_j, we calculate the capital income shares for manufacturing, producer services, and consumer services as 0.614, 0.658, and 0.439, respectively. From the equations (1) and (3), we get:

$$\xi_j = \frac{W_x}{W_j} = \frac{(1-\beta_x)p_x Y_x / L_x}{(1-\beta_j)\, p_j Y_j / L_j}. \tag{39}$$

Using the constructed nominal output, employment data, and capital income shares of the three intermediate goods sectors, the labor market friction factors $\{\xi_j\}$ from Period 1 to

Period 29 are calculated. To estimate the preference parameter, the demand-side structure is simplified by assuming $\omega_C = \omega_I = \omega_H = \omega$ and $\varepsilon_C = \varepsilon_I = \varepsilon_H = \varepsilon$. Based on the derivation equation for employment shares in manufacturing and producer services in the theoretical part, the left side of the equation represents the employment shares of manufacturing and producer services, respectively, while the right side not only includes the friction factor ξ_j and the capital income share β_j, but also contains θ_M, θ_S, η, three variables that are all functions of the price p_j. Since the employment share and the price p_j have been constructed using empirical data, these two equations become expressions in terms of the parameters to be estimated: σ_M, σ_S, α_M, α_S, ω, ε. This involves selecting these parameters to achieve the highest goodness of fit between the predicted employment shares for manufacturing and producer services and the empirical data. This paper employs the feasible generalized nonlinear least squares method following Herrendorf et al. (2013). Table 2 presents the parameter estimation results. As Table 2 indicates, the elasticity of substitution between manufacturing and producer services is 0.587, demonstrating a certain level of complementarity between these sectors in China. Meanwhile, the elasticity of substitution between producer services and consumer services registers at 1.057, suggesting a certain level of substitutability within these service sectors. For final consumption, the near-zero and statistically insignificant elasticity of substitution between industrial goods and service goods confirms strong complementarity between them—a finding consistent with estimates from numerous studies (Herrendorf et al., 2013; Herrendorf et al., 2021).

Table 2 Parameter Estimation Results

Parameter	σ_M	σ_S	α_M	α_S	ω	ε
Estimate	0.587***	1.057***	0.959***	0.676***	0.673***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(–)

Note. Values in parentheses represent p values; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

To control for the impact of capital deepening caused by investment rate changes, the simulation employs an exogenous investment rate approach.[6] The aggregate investment rate s is set at 40%, consistent with empirical data. In recent years, China's broad infrastructure investment has accounted for approximately 25% of total investment, while new infrastructure investment represents roughly 10% of total infrastructure investment, yielding a new infrastructure investment rate of $s_H = 1\%$. Regarding AI's impact parameter, without loss of generality, the benchmark model sets $\gamma_m = 1$, $\gamma_x = \gamma_s = 0.5$ to simulate scenarios where AI exhibits a bias toward manufacturing while demonstrating similar impacts on both

[6] The investment rate is held exogenously fixed to control for the impact of capital deepening caused by investment rate changes, thereby isolating the impact mechanism of AI. A sensitivity analysis of the aggregate investment rate is further conducted in the appendix, and the results show that the quantitative impact from aggregate investment rate fluctuations is quite limited. For details, please refer to the supplementary materials on the journal website of *China Industrial Economics*.

service sectors. In subsequent sensitivity analyses, we further increase the values of γ_x and γ_s to simulate scenarios where AI exerts progressively stronger impacts on service sectors. The initial capital is set at 1, AI level to 1, capital depreciation rate to 0.1, and AI depreciation rate to 0. The parameter B_j is calibrated to ensure the employment shares of the three intermediate goods sectors in Period 1 of the model optimally approximate China's actual data in 1990.

4.2 Benchmark Results

This section employs numerical simulations to demonstrate AI's impact on industrial integration and industrial restructuring. Setting each model period to one year, we simulate the economic structural transformation process over 60 periods. The labor market friction factors for the 29 periods from 1990 to 2018 have been constructed, and assuming the labor market friction factor remains constant after 2018, we obtain the complete exogenous variable sequence $\{\xi_j\}$. AI was initially deployed in production in the form of industrial robots and had a biased impact on productivity across the three industrial sectors. Moreover, industrial robots began large-scale deployment in China in 2010. Therefore, this paper assumes no AI-driven impact on sectoral productivity (i.e., $\gamma_j = 0$) during the first 20 periods from 1990 to 2010. From Period 21 onward, AI's biased impact gradually increases over the following decade to reach the parameter values of γ_j in the benchmark model, thereafter stabilizing. By substituting each period's exogenous friction factor and parameter values into the benchmark model, we can simulate the dynamic process of industrial restructuring. Figure 2 below presents a comparison between the industrial structure of the three intermediate goods sectors under the benchmark model and the empirical data.

Empirical data reveal that from 1990 to 2018, China's manufacturing experienced continuous declines in both the employment share and the output share, while services witnessed sustained increases in the above two dimensions. Notably, consumer services demonstrated greater growth than producer services. A significant observation is that since 2010, producer services have shown considerable increases in both the employment share and the output share, coinciding with the large-scale introduction of industrial robots and rapid advancements in AI. The numerical simulation results demonstrate that the benchmark model effectively captures China's industrial structural shifts, whether measured by the employment share or the output share.

Figure 3 presents the benchmark model's numerical simulation results over 60 periods, with the horizontal axis representing simulation periods.[7] Figure 3 reveals that as AI advances, the degree of integration between manufacturing and producer services intensifies, while that between producer services and consumer services remains essentially unchanged.

[7] The source of significant fluctuations in all variables during the first 30 periods of the numerical simulation results is the labor market friction parameter. Based on empirical data, the labor market friction parameters across industries vary annually. In the subsequent 30 periods, the labor market friction parameter is held constant, resulting in relatively smooth simulation outcomes.

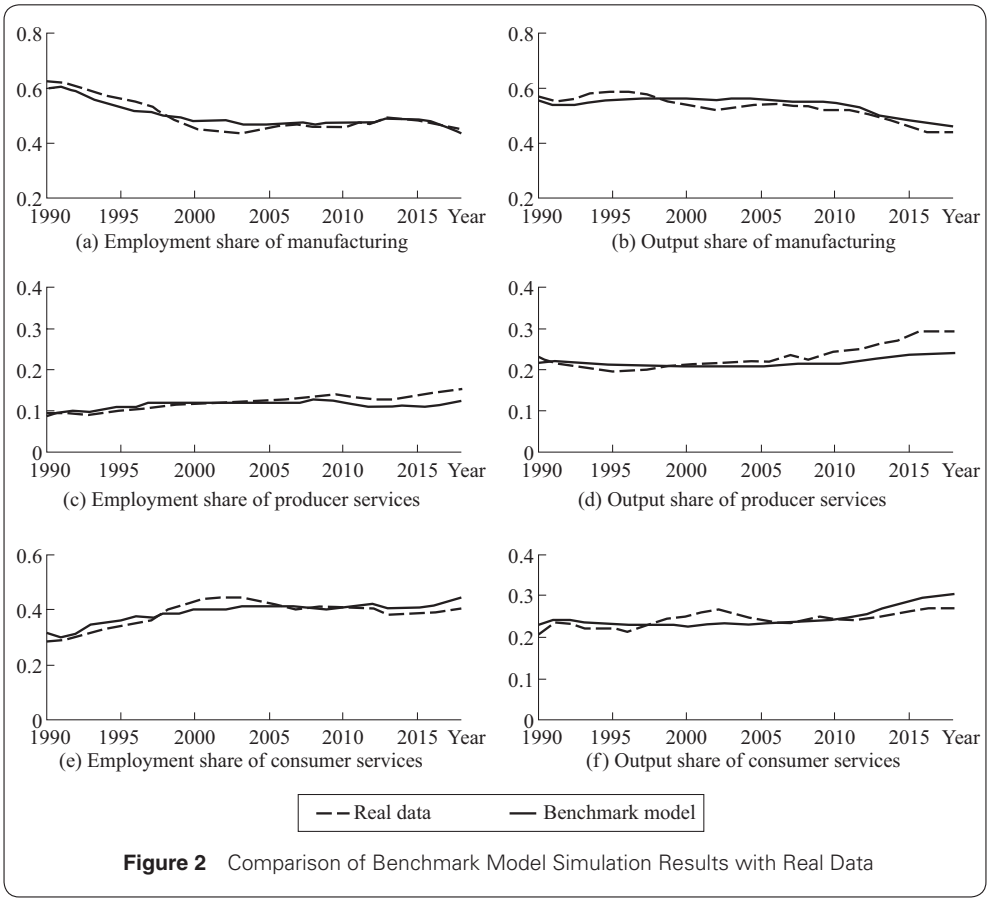

Figure 2 Comparison of Benchmark Model Simulation Results with Real Data

Overall, the intensive margin effects progressively strengthen. In terms of the consumption structure, the consumption expenditure ratio of industrial goods to service goods declines steadily after an initial period of fluctuation, indicating a decreasing share of industrial goods and an increasing share of service goods, accompanied by diminishing extensive margin effects. From an industrial structure perspective, manufacturing's employment share has continuously declined, while productive services' employment share has experienced modest growth, and consumer services' employment share has achieved more rapid expansion. Table 3 provides the quantitative numerical simulation results. In terms of the employment share, manufacturing declines from 0.597 to 0.182, producer services increase from 0.088 to 0.150, and consumer services rise from 0.315 to 0.668. Regarding the output share, the trends across these sectors mirror those of employment shares, with manufacturing's output share declining from 0.551 to 0.200, producer services rising from 0.219 to 0.310, and consumer services increasing from 0.231 to 0.490. Therefore, AI advancements can facilitate the integration between manufacturing and producer services, drive increases in producer services' employment share and output share, promote a continuous industrial structural transformation from manufacturing toward services, and simultaneously shift the consumption structure from industrial goods toward service goods.

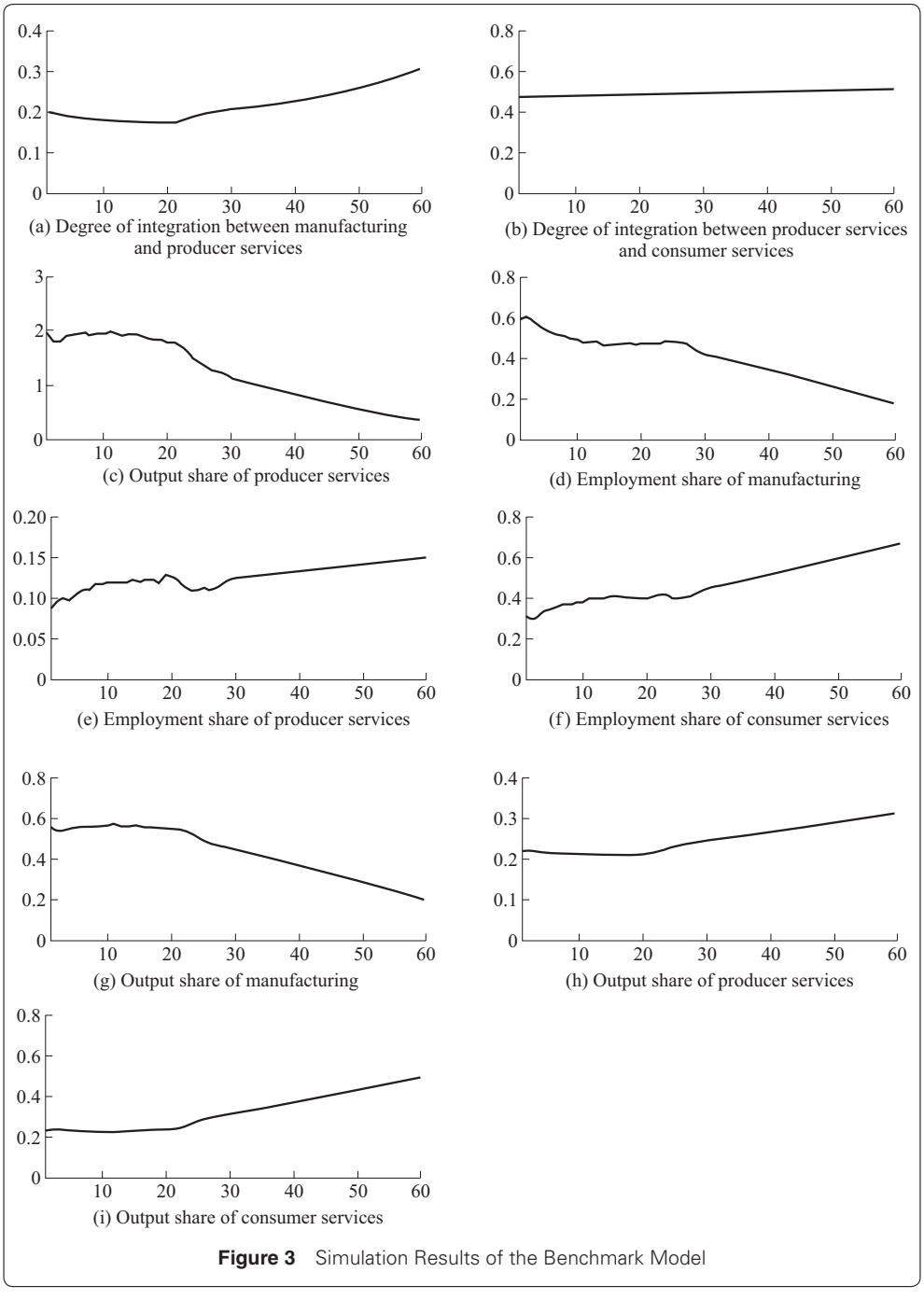

Figure 3 Simulation Results of the Benchmark Model

Table 3 Changes in the Numerical Simulation of Variables under Different Simulation Environments

	Degree of industrial integration		Employment share			Output share		
	Between manufacturing and producer services	Between producer services and consumer services	Manufacturing	Producer services	Consumer services	Manufacturing	Producer services	Consumer services
Benchmark model	0.104	0.037	−0.415	0.062	0.353	−0.351	0.091	0.259
Sensitivity analysis 1: Changes in AI's bias degree								
$\gamma_x = 0.6$	0.090	0.041	−0.414	0.061	0.353	−0.349	0.091	0.259
$\gamma_x = 0.7$	0.074	0.048	−0.416	0.061	0.355	−0.352	0.091	0.261
Sensitivity analysis 2: Changes in the new infrastructure investment rate								
$s_H = 0.02$	0.296	0.052	−0.539	0.072	0.467	−0.486	0.124	0.362
$s_H = 0.05$	1.080	0.080	−0.590	0.078	0.513	−0.544	0.140	0.403
Sensitivity analysis 3: Changes in the elasticity of substitution								
$\sigma_M = 0.8$	0.042	0.037	−0.413	0.058	0.355	−0.349	0.086	0.263
$\sigma_M = 0.3$	0.223	0.037	−0.419	0.069	0.351	−0.355	0.102	0.253
Sensitivity analysis 4: Changes in the labor market friction								
$\xi_M \to 1$	0.080	0.037	−0.459	0.072	0.387	−0.321	0.084	0.238
$\xi_S \to 1$	0.106	0.044	−0.374	0.125	0.248	−0.375	0.097	0.278

Note. The values in the table refer to the variation in each variable from Period 1 to Period 60.

4.3 Sensitivity Analysis

This section conducts sensitivity analyses of four key parameters. First, we alter AI's sectoral bias parameter. In the benchmark model, $\gamma_m = 1$ and $\gamma_x = \gamma_s = 0.5$, simulates scenarios where AI exhibits a greater bias toward manufacturing than services. In recent years, with the application of technologies such as 5G, big data, cloud computing, and large language models (LLMs), AI has gradually penetrated both traditional and emerging service sectors, including warehousing and logistics, wholesale and retail, scientific research, and government and public sectors. Here, we progressively raise γ_x and γ_s to 0.6 and 0.7 to simulate scenarios where AI technology upgrades amplify the impact on services. Figure 4 and Table 3 report the simulation results under these conditions. Specifically, altered values of γ_x and γ_s do not change the trend patterns of the variables: The degree of integration between manufacturing and producer services still increases, the consumption expenditure share of industrial goods declines, the employment share and output share of manufacturing decrease, while the shares of producer services and consumer services rise. From the quantitative results in Table 3, compared to the benchmark model, when AI's bias difference between manufacturing and services gradually narrows, its quantitative impact on industrial integration and industrial structure remains quite limited, with curves under different values of the parameters nearly overlapping. This result demonstrates the high robustness of the parameters γ_x and γ_s and also indicates that the intensifying impact of AI on services does not impede industrial integration and industrial restructuring and upgrading. As long as AI's biased impact on manufacturing exceeds that on services, AI will continue to drive industrial integration and the development of producer services. Therefore, the role of AI in facilitating industrial integration remains resilient to future trends of AI development, with the degree of integration between manufacturing and producer services continuing to deepen and the share of producer services further expanding.

Second, we vary the new infrastructure investment rate. Here, s_H is increased to 0.02 and 0.05, respectively, while the aggregate investment rate s is held constant to simulate scenarios where the new infrastructure investment rate continuously goes up. When the new infrastructure investment rate increases, AI technology accumulates at a faster pace, thereby strengthening AI's impact on industrial integration and industrial restructuring. As shown in Figure 5 and Table 3, as s_H increases, the trend patterns of all variables remain unchanged. AI continues to drive industrial integration and industrial restructuring, with faster growth in the degree of integration between manufacturing and producer services and greater progress in industrial restructuring. Specifically, when s_H increases from 0.01 to 0.02 and 0.05, the degree of integration between manufacturing and producer services improves by 0.296 and 1.080 respectively, while the consumption expenditure ratio of industrial goods to service goods declines at a faster pace, deepening the transition of the consumption structure from industrial goods toward service goods. Under these conditions, manufacturing's employment share decreases by 0.539 and 0.590, producer services' employment share increases by 0.072 and 0.078, and consumer services' employment share rises by 0.467 and 0.513. Manufacturing's

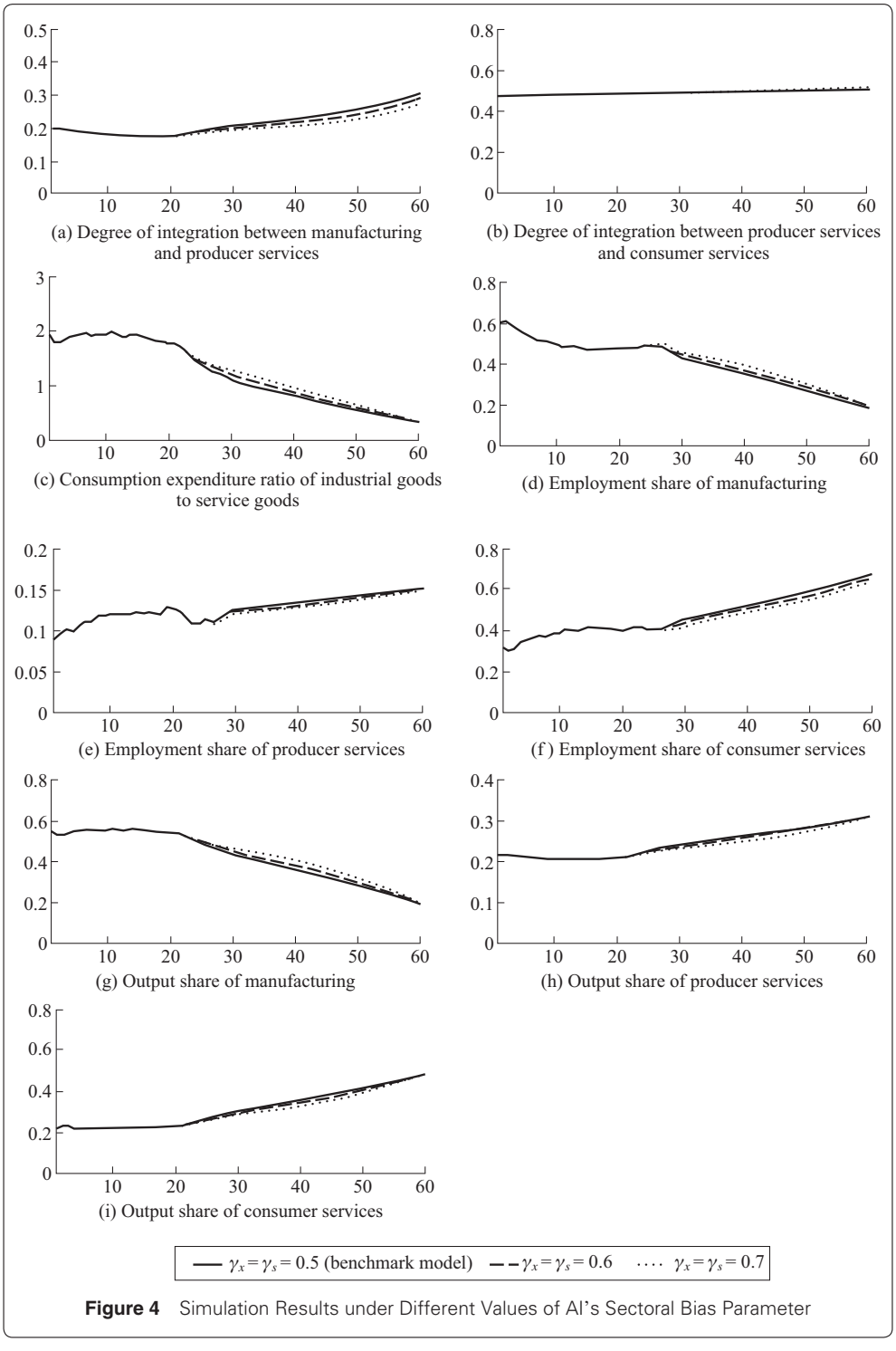

Figure 4 Simulation Results under Different Values of AI's Sectoral Bias Parameter

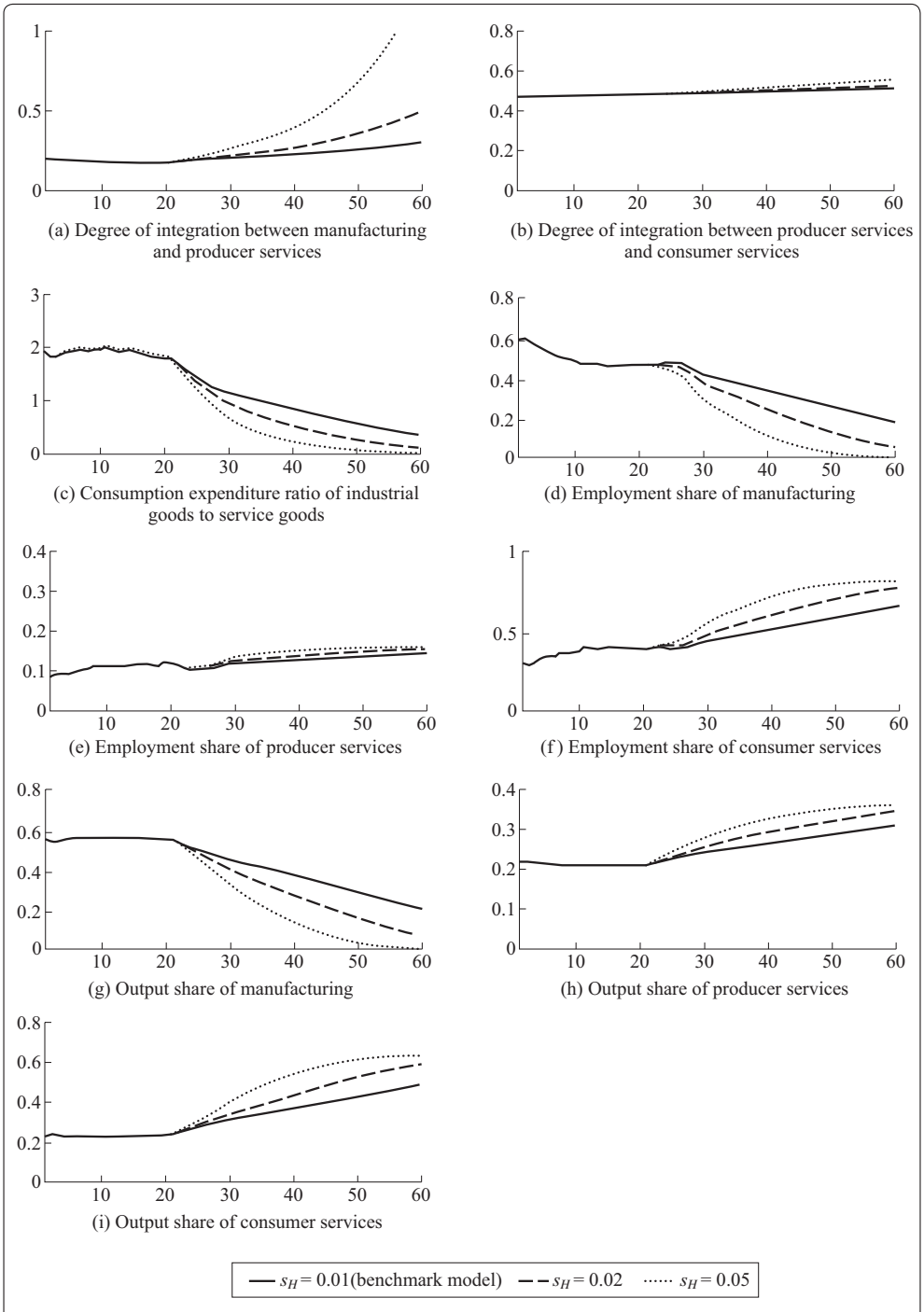

Figure 5 Simulation Results under Different Values of the New Infrastructure Investment Rate

output share declines by 0.486 and 0.544, producer services' output share increases by 0.124 and 0.140, and consumer services' output share rises by 0.362 and 0.403, with quantitative results for industrial structural change significantly exceeding those of the benchmark model. This demonstrates that AI, distinct from conventional capital, plays a crucial role in industrial integration and industrial restructuring through its characteristics of generality and bias. Even at constant aggregate investment rates, adjusting investment structure to raise the new infrastructure investment rate can further accelerate AI technology accumulation, strengthen AI's impact mechanism, effectively promote the integration between manufacturing and producer services, and expedite industrial restructuring and upgrading.

Next, we change the elasticity of substitution between manufacturing and producer services. In the benchmark model, σ_M is calibrated to 0.587. Here, we set $\sigma_M = 0.8$ and $\sigma_M = 0.3$ respectively to test the sensitivity of the elasticity of substitution. According to the equation (33) in the theoretical analysis, varying the values of the elasticity of substitution between manufacturing and producer services has a certain impact on the degree of integration between manufacturing and producer services. When the elasticity of substitution σ_M is smaller, θ_M becomes larger, indicating a higher degree of integration between manufacturing and producer services. That is, when the complementarity between the two sectors is higher, industrial integration becomes more intensive. According to equation (31), the elasticity of substitution σ_M has no impact on the extensive margin effects. Therefore, the elasticity of substitution θ_M between manufacturing and producer services indirectly affects the industrial structure by influencing the industrial integration degree θ_M. The quantitative results of this effect are presented in Figure 6 and Table 3. The results show that the lower the value of the elasticity of substitution σ_M, the higher the degree of integration between manufacturing and producer services. In addition, the changes in the employment share and output share of manufacturing, producer services, and consumer services remain almost identical to those in the benchmark model. This indicates that the magnitude of the elasticity of substitution between manufacturing and producer services only changes the degree of integration between the two sectors, while having a very limited impact on industrial restructuring. The simulation results under different values of σ_M are highly robust.

Finally, we modify the labor market friction factor. In the benchmark model, we suppose that the labor market friction factor remains constant after Period 29. Here, we assume progressive labor market reforms to reduce the wage gap ξ_j across different intermediate goods sectors to test the impact of the labor market friction factor on industrial integration and industrial restructuring. Specifically, we assume that both ξ_m (the wage gap between producer services and manufacturing) and ξ_s (the wage gap between producer services and consumer services) decline uniformly to 1 from Period 30 to simulate the trend of decreasing labor market friction factors. As shown in Figure 7 and Table 3, compared to the benchmark model, the decline in the labor market friction factor has a relatively small impact on the industrial integration and output share, but exerts quite some impact on the employment share across different intermediate goods sectors: When ξ_m approaches 1, the employment shares of

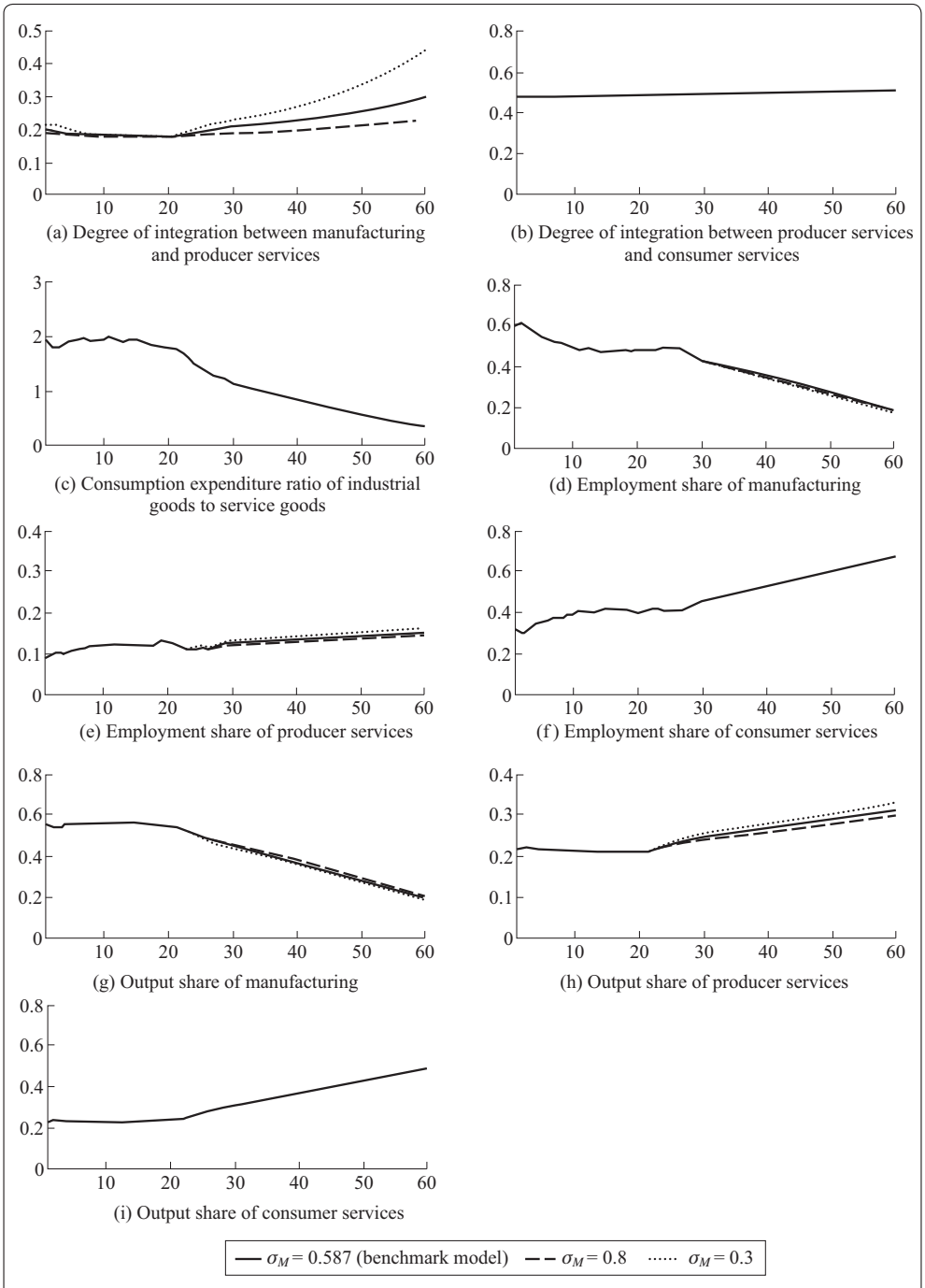

Figure 6 Simulation Results under Different Values of the Elasticity of Substitution

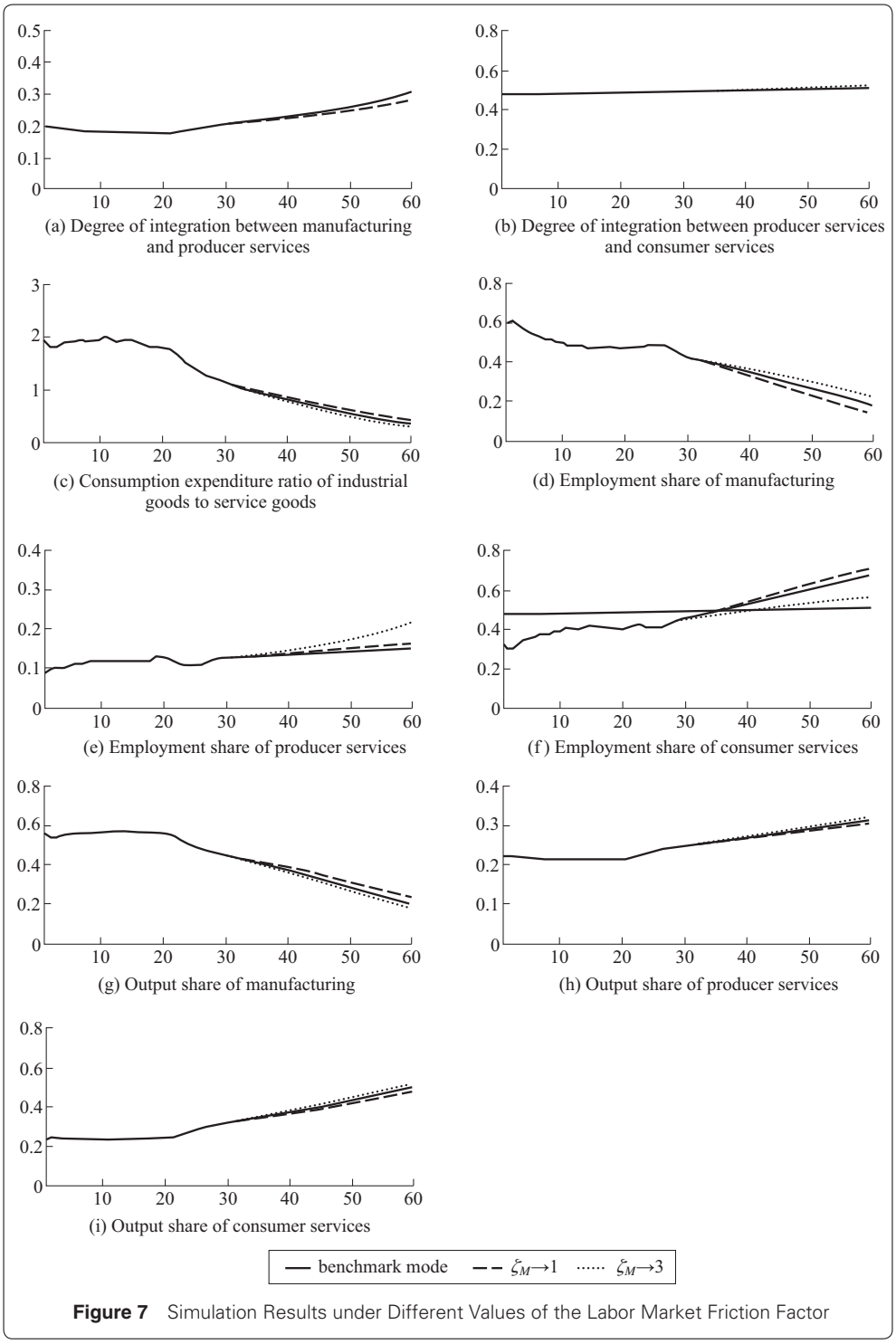

Figure 7 Simulation Results under Different Values of the Labor Market Friction Factor

manufacturing, producer services, and consumer services decrease by 0.459, increase by 0.072, and go up by 0.387, respectively; when ξ_s approaches 1, the employment shares of these sectors decrease by 0.374, increase by 0.125, and go up by 0.248, respectively. Therefore, compared to the benchmark model, when ξ_s declines, the employment share of producer services experiences a more substantial increase. To accelerate the development of producer services, labor market reforms should more effectively focus on reducing labor mobility barriers between producer services and consumer services, thereby narrowing the wage gaps between different service sectors to maximize the advantages of AI.

Additionally, this study varies the values of the demand-side weight parameter ω, aggregate investment rate s, and elasticity of substitution ε in the final goods sector, and further examines scenarios involving international trade.[8] However, quantitatively, the demand-side mechanism exerts a limited impact on industrial integration and industrial restructuring, with numerical simulation results showing minimal deviation from the benchmark model.

In summary, the numerical simulation results validate the theoretical model's conclusions. Within certain ranges, altering parameter values does not affect the qualitative trends of the model's key variables. As AI advances, the degree of integration between manufacturing and producer services continues to increase, driving growth in both the employment share and output share of producer services. Sensitivity analyses reveal that the narrowing difference in AI's bias in recent years does not decelerate industrial integration and industrial restructuring. Raising new infrastructure investment rates and reducing labor mobility costs across different service sectors can further promote industrial integration, drive industrial restructuring, and foster the development of producer services.

5 Conclusions and Policy Implications

In the AI era, how can AI technologies be leveraged to advance the integrated development of the manufacturing and service sectors, thereby facilitating industrial restructuring and upgrading in China? This study investigates the impact of AI on industrial integration and producer services within a structural transformation framework that incorporates both AI technological progress and industrial convergence. There are four findings as follows. First, when the elasticity of substitution between manufacturing and producer services is low and AI exhibits a bias toward the manufacturing sector, advances in AI technology can enhance the degree of integration between these two sectors. Second, if AI is biased toward manufacturing and its impact across various service sectors is relatively uniform, a low elasticity of substitution between industrial goods and service goods implies that AI advancement can drive consumption restructuring—specifically, the output share of industrial goods declines while that of service goods increases. Third, theoretically, the influence of AI on producer services operates through both intensive and extensive margins. Numerical simulations based

[8] For details, please refer to the supplementary materials on the journal website of *China Industrial Economics*.

on the model suggest that, in the long run, AI can promote integration between manufacturing and producer services, increase the employment and output shares of producer services, and thereby accelerate industrial restructuring and upgrading. Fourth, sensitivity analysis shows that as AI's impact on the service sector strengthens, it continues to facilitate industrial integration and the growth of producer services. Increasing investment in new infrastructure and reducing barriers to labor mobility within services can further accelerate integration and promote the development of producer services.

At present, the global digital economy is developing rapidly, with emerging producer services demonstrating counter-cyclical growth. Cross-country data reveal that China's producer services still lag behind those of developed economies, indicating significant potential for future industrial restructuring and upgrading, as well as untapped opportunities for industrial integration. This paper provides a theoretical foundation for promoting industrial integration and structural transformation in the AI era. To further advance integrated development and the growth of producer services, the following four policy recommendations are proposed.

Strengthening top-level design for AI to enhance drivers of industrial integration. As a general-purpose technology, AI possesses broad application potential across sectors and scenarios, serving as a critical engine for industrial transformation and integrated development. This study confirms that AI can significantly boost productivity in manufacturing and foster deeper integration with producer services. Therefore, it is essential to improve the top-level design of AI development, formulate comprehensive strategic plans, and establish a policy system aimed at promoting industrial integration. AI's pivotal role in the integrated development of manufacturing and producer services should be clearly emphasized. Meanwhile, policy guidance and financial support should be leveraged to reduce barriers to AI adoption and accelerate its deployment in traditional industries. This will enhance collaboration and deep integration along the industrial chain, injecting strong momentum into China's industrial upgrading.

Increasing investment in new infrastructure to solidify the foundation for industrial integration. Compared to traditional infrastructure, new infrastructure relies more heavily on producer services such as R&D, digital technologies, and financial services, highlighting the cross-sectoral integration characteristic of the AI era. This study finds that raising investment in new infrastructure can effectively promote industrial integration and increase the proportion of producer services. Accordingly, it is critical to expand investment in new infrastructure—particularly digital infrastructure such as 5G networks, the industrial internet, and big data centers—to facilitate the application of informatization, digitalization, and intelligent technologies in producer services. Medium- and long-term plans should define goals and priorities for digital infrastructure construction, promote synergistic development between traditional and new infrastructure, and establish a solid foundation for the in-depth application of AI and integrated industrial development.

Deepening labor market reforms to strengthen institutional support for industrial

integration. The results indicate that reducing labor mobility barriers across service sectors can further promote the development of producer services. Therefore, it is imperative to deepen labor market reforms, eliminate obstacles such as labor market segmentation, regional barriers, and industry monopolies, and establish an open and efficient integrated labor market. Concurrently, skills training systems should be enhanced by providing targeted cross-sectoral training programs and continuing education opportunities to improve the digital literacy and technical proficiency of the workforce. By lowering knowledge and skill thresholds for cross-sector mobility and strengthening both general and professional competencies, high-quality labor supply for producer services can be ensured, providing solid support for industrial restructuring and upgrading.

Accelerating the development of producer services to reinforce momentum for industrial integration. Cross-national data illustrate the stylized fact that the share of producer services increases with economic development. Currently, China's producer services remain underdeveloped, suggesting substantial potential for future industrial upgrading. Thus, it is crucial to strengthen the strategic positioning of producer services and introduce targeted supportive policies to encourage the growth of emerging sectors such as big data services, cloud computing, and AI application services. In addition, tax incentives and financial support should be enhanced to cultivate internationally competitive firms in emerging producer services, further increase the sector's proportion in the industrial chain, and provide sustained momentum for building a modern industrial system.

This paper elucidates the macro-structural relationship among AI, industrial integration, and the development of producer services. Future research should focus on refining the measurement of industrial integration and AI development levels, as well as validating these findings through micro-empirical methods.

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