AI-Driven Occupational Structural Transformation and Service-Oriented Manufacturing

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Abstract: *Occupational structural transformation is a common pattern during the steady growth of GDP per capita in major economies worldwide. In recent years, there has been a decline in the employment share of goods occupation and an increase in service occupation within the Chinese manufacturing industry, presenting a trend of occupational structural transformation and rapid development of service-oriented manufacturing. It is an important driving force and typical performance of the high-end, intelligent, and green development of the manufacturing industry. As a strategic general technology which leads the new round of technological revolution and industrial transformation, artificial intelligence (AI) has become a new fundamental force to accelerate the occupational structural transformation and service-oriented manufacturing development in China. Thus, this paper establishes a dynamic general equilibrium model with AI technology and occupational heterogeneity, showing the endogenous mechanism of occupational structural transformation. We find that when AI technology is biased towards goods occupation, and the elasticity of substitution between goods occupation and service occupation is less than 1, then AI will drive the transformation of occupational structure from goods to service within the manufacturing sector, increase the proportion of service-oriented manufacturing, improve labor productivity of manufacturing relative to service and stabilize the real output share of manufacturing. Promoting deeper integration of different occupations, intensifying R&D in AI technology and reducing labor mobility barriers between occupations can effectively accelerate the occupational structural transformation and industrial structural upgrading. We use theoretical analysis and numerical simulation method to show the theoretical mechanism by which AI affects occupational structural transformation and industrial structural transformation from a macroeconomic perspective, and put forward policy implications on how to promote the service-oriented manufacturing development and accelerate the construction of modern industrial system through AI innovation.*

Keywords: *Artificial intelligence; occupational structural transformation; service-oriented manufacturing; industrial structural transformation*

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1. Introduction

The Report to the 20th National Congress of the Communist Party of China (CPC) outlines a vision that "In pursuing economic growth, we must continue to focus on the real economy. We will advance new industrialization and move faster to boost China's strength in manufacturing, product quality, aerospace, transportation, cyberspace, and digital development". China's manufacturing sector, as the bedrock of the real economy and the stabilizing "ballast stone" of a major nation's economic system, drives the new development stage through its transformation and upgrading from sheer scale to global strength. This shift underpins the construction of a modern industrial system and the pursuit of high-quality development. The *Outline of the 14th Five-Year Plan for National Economic and Social Development and Long-Range Objectives Through 2035* explicitly mandates that "We will further implement intelligent manufacturing and green manufacturing projects, develop new service-oriented manufacturing models, and promote high-end, intelligent, and green manufacturing". Amid the rapid emergence of next-generation artificial intelligence (AI) technologies, this paper examines how China can harness the dynamics of technological revolution and industrial transformation to promote service-oriented manufacturing, thereby facilitating industrial structure upgrading and the development of a modern industrial ecosystem.

China's manufacturing sector boasts the world's most comprehensive industrial categories and complete industrial system. Yet, despite its vast scale, it remains "large but not strong", long anchored in the low-to-mid tiers of the global value chain, with an urgent need to ascend toward the high-value ends of the "smile curve". Service-oriented manufacturing, an innovative paradigm blending production and service functions, emerges as a critical pathway for the sector's transformation and upgrading. Within a typical manufacturing enterprise, operational activities extend beyond conventional production tasks—such as processing and assembly—to encompass service-oriented functions, including research and development, design, logistics, distribution, installation, and after-sales support. Thus, manufacturing inherently incorporates service dimensions. Viewed through the lens of employee occupational structure, which reflects a firm's diverse production and operational activities, these shifts mirror changes in production models and business formats. Cross-country data reveal that, alongside economic growth, numerous economies—including China—have experienced notable transformations, marked by a declining share of production roles and a rising proportion of service roles, especially within manufacturing. This transition from production- to service-dominated patterns constitutes both a hallmark and a key driver of service-oriented manufacturing. What underlying forces propel this change? How does it influence industrial structure upgrading and the broader enhancement of manufacturing? These questions delineate the scope and focus of our investigation.

Over the past decade, artificial intelligence (AI) technology has advanced rapidly, fundamentally reshaping traditional production paradigms. Its widespread adoption across manufacturing and service sectors positions it as a strategic catalyst for a new wave of technological revolution and industrial transformation, poised to propel China's occupational structure transformation and the rise of service-oriented manufacturing. Notably, the integration of industrial robots into China's industrial production surged between 2011 and 2017, achieving an average annual growth rate of 30%. Scholarly perspectives on AI's impact on employment remain divided. Some contend that AI-driven automation substitutes labor, precipitating unemployment (Frey & Osborne, 2017; Wang & Dong, 2020). Others argue that AI's influence is structural, exhibiting significant heterogeneity and asymmetric effects across workforce segments, rather than uniform job loss (Acemoglu & Autor, 2011; Sun & Hou, 2019; Yu et al., 2021; Wang et al., 2023; Chen et al., 2023; He & Liu, 2023; Yin et al., 2023). As a productivity-enhancing tool, AI often reconfigures rather than eliminates labor, prompting job transitions rather than outright displacement (McKinsey, 2017[1]).

[1] McKinsey. Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation, 2017.

Data from Chinese listed companies over the past decade reveal a marked shift in occupational structure. At the macro-industry level, the employment share of production roles has declined across both general enterprises and manufacturing firms, while service roles have proportionally increased. At the micro-enterprise level, empirical analysis of both the full enterprise sample and the manufacturing sub-sample demonstrates that AI technology significantly reduces the share of production occupation[2]. Yet, among surviving manufacturing firms[3], total employment has not diminished; instead, it has grown at an average annual rate of 4%. Within these firms, the proportion of production workers has decreased, while service job roles have expanded. This suggests that AI does not wholly supplant labor but preferentially enhances production processes, boosting labor productivity in production roles and facilitating a labor shift toward service functions. This dynamic underpins both occupational structure transformation and the advancement of service-oriented manufacturing.

Building on these insights, this paper develops a multi-sector dynamic general equilibrium model that incorporates AI and job heterogeneity to explore how AI drives changes in occupational structure and industrial upgrading. Within this model, production and service labor inputs are combined through a constant elasticity of substitution (CES) function to form sectoral labor contributions. AI technology grows endogenously via R&D investment, impacting labor-augmenting technologies differently across job types. Unlike prior models, this study emphasizes AI's externality and bias effects: its externalities boost labor productivity across all occupation and industries, while its bias disproportionately enhances the productivity of production roles relative to others.

The analysis shows that, under certain conditions, AI advancements trigger a shift in occupational structure—reducing the share of production occupation while increasing the share of service roles—while also promoting service-oriented manufacturing. At the same time, AI raises the manufacturing sector's relative labor productivity, stabilizes its real output share, and accelerates its transformation and upgrading. Through theoretical modeling and numerical simulations, this paper clarifies the economic mechanisms by which AI reshapes job dynamics and advances manufacturing. Based on these findings, it provides targeted policy recommendations to support China's growth in service-oriented manufacturing and hasten its rise as a manufacturing powerhouse.

This paper advances research in artificial intelligence, a field where extensive literature examines AI's heterogeneous effects on employment at the micro-individual level, alongside its macroeconomic impacts, including industrial structure upgrading, income distribution, skill premiums, and productivity (Acemoglu & Restrepo, 2018; Aghion et al., 2019; Guo, 2019; Chen et al., 2019; Guo & Wang, 2022; Guo et al., 2023). Li (2021) demonstrated that next-generation digital technologies, such as AI and the industrial internet, markedly enhance manufacturing capabilities in processing and production, dismantling barriers to service-oriented manufacturing development. Yet, existing studies have largely overlooked the economic mechanisms driving AI's influence on this domain. This paper constructs a macro-level theoretical model incorporating AI and job heterogeneity, analyzing the impact of AI on occupational structure transformation and industrial upgrading, thus enriching the socio-economic perspective within AI studies.

This paper expands on prior research related to industrial structure transformations. Traditional theories link these shifts to supply-side factors, such as technological progress and capital deepening, as well as demand-side preferences (Kongsamut et al., 2001; Ngai & Pissarides, 2007; Acemoglu & Guerrieri, 2008). Other studies emphasize the roles of international trade, government policies, and investment (Uy et al., 2013; Guo et al., 2021; Herrendorf et al., 2018; Sposi, 2019; Dekle &

[2] Detailed empirical evidence can be found in the attachments on the China Industrial Economics website (http://ciejournal.ajcass.org).

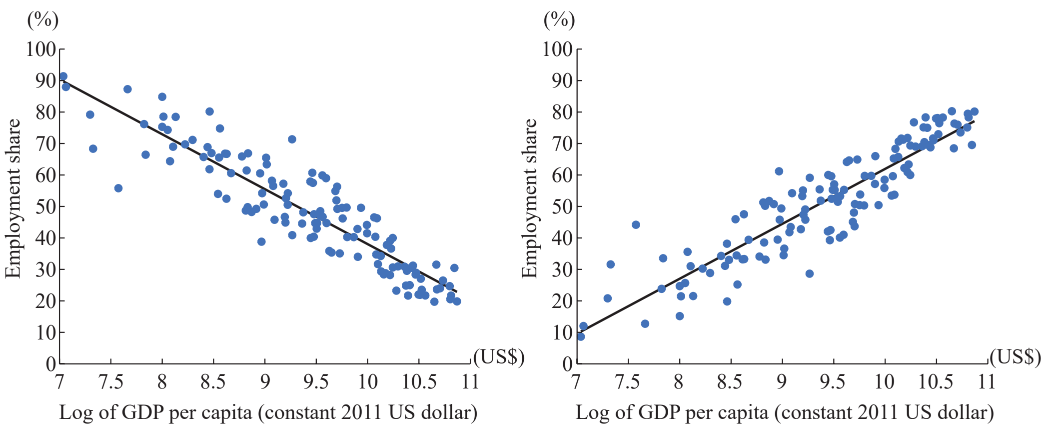
[3] The number of surviving manufacturing enterprises among Chinese listed companies is 1,082, and the total number of employees increased from 5,217,581 in 2012 to 7,755,941.

Vandenbrouke, 2012). However, these analyses focus on the industry level, neglecting job heterogeneity within sectors. Recently, researchers have shifted attention to occupational structure changes, pinpointing job-specific technological advances as a key driver (Duernecker & Herrendorf, 2022; Aum et al., 2018; Bárány & Siegel, 2020). Yet, these studies neither address AI technology nor provide detailed quantitative analysis using Chinese data. This study explores AI's impact on the transformation of occupational structure and manufacturing upgrading from an AI-focused perspective. It also conducts a quantitative analysis incorporating China's economic characteristics, thereby providing a theoretical foundation for advancing service-oriented manufacturing development in China.

2. Characteristic Facts

The shift in occupational structure refers to the movement of labor from production to service roles within enterprises, reflected in a declining employment share of production occupation and a growing share of service occupation. This pattern manifests not only in the economy-wide reconfiguration of production and service employment but also in sectoral shifts within enterprises across diverse industries.

Data on occupational structure are sourced from the Integrated Public Use Microdata Series (IPUMS) International, which offers detailed sector and occupation information for individual employment. IPUMS standardizes and harmonizes original data for consistency across years and countries. Following Duernecker & Herrendorf (2022), this paper classifies individual employment into production and service sectors, as well as production and service occupation[4]. A scatter plot (see Figure 1) displays the employment shares of these job types against logarithmic per capita GDP across 30 global economies, including China. The aggregated data reveal a clear pattern: as per capita GDP increases, the share of production occupation drops significantly, while the share of service occupation rises steadily, highlighting the dynamics of occupational structure shifts.



(a) Employment share of production occupation
(b) Employment share of service occupation

Figure 1: Global Occupational Structure and GDP Per Capita

Sources: Occupational structure data are sourced from the IPUMS, while GDP per capita data are derived from the Maddison Project Database (2020). Figure 2 and 3 are the same.

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[4] Detailed data processing procedures and the list of countries can be found in the attachments on the *China Industrial Economics* website (http://ciejournal.ajcass.org).

Figure 2 illustrates the link between occupational structure and logarithmic per capita GDP within the production and service sectors, respectively. On average, economic growth spurs a labor shift from production to service roles in both sectors, with the production sector showing a more pronounced change. Across economies at different development stages, the composition of occupation in the production sector varies widely: in less developed countries, the workforce is mostly engaged in production roles, while in advanced economies, only about 50% of the sector's labor remains in such positions.

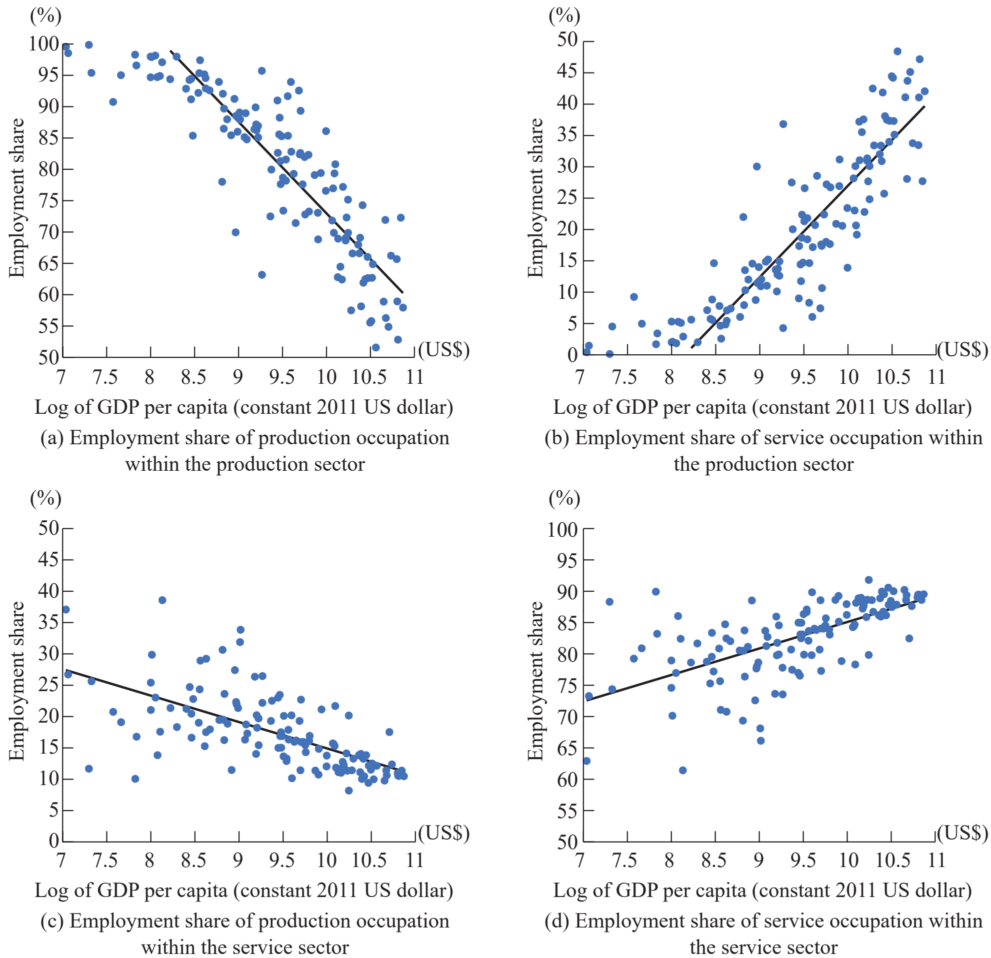


Figure 2: Global Occupational Structure and GDP Per Capita within Production and Service Sectors

Figure 3 shows the evolution of occupational structure over time in selected nations. Initial employment shares of production occupation vary widely, reflecting different stages of economic development, yet a clear pattern of such shifts emerges. The proportion of production occupation has dropped by 20%-40% across these countries, with developed nations like the United States, France, and Canada now having roughly 20% of their workforce in production roles.

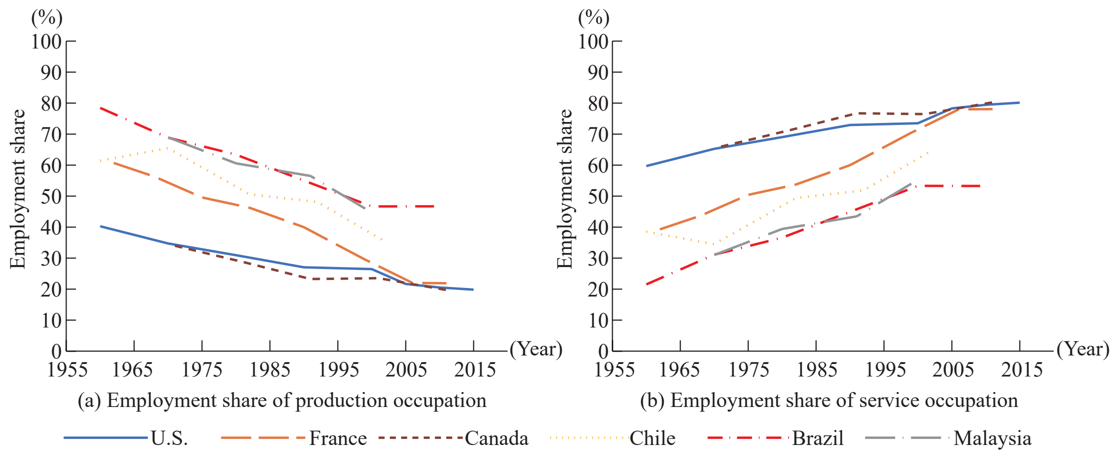


Figure 3: Evolutionary Trend of Occupational Structure in Selected Countries

China exhibits a parallel trend of occupational structure transformation. Given the scarcity of continuous and detailed national census data on employment positions, and the availability of occupational structure disclosures from Chinese A-share listed companies since 2011, this study utilizes a sample of A-share listed company data from 2011 to 2022, subjected to selective processing[5]. Figure 4 depicts the evolving employment shares of various job types in China over this period. Within a decade, the proportion of production occupation among these firms steadily declined from 52.5% to 45.4%, while the share of service occupation rose from 47.5% to 54.6%, surpassing production occupation by 2012. Notably, since 2016, this transformation has markedly slowed or plateaued, a phenomenon warranting further exploration later in this paper.

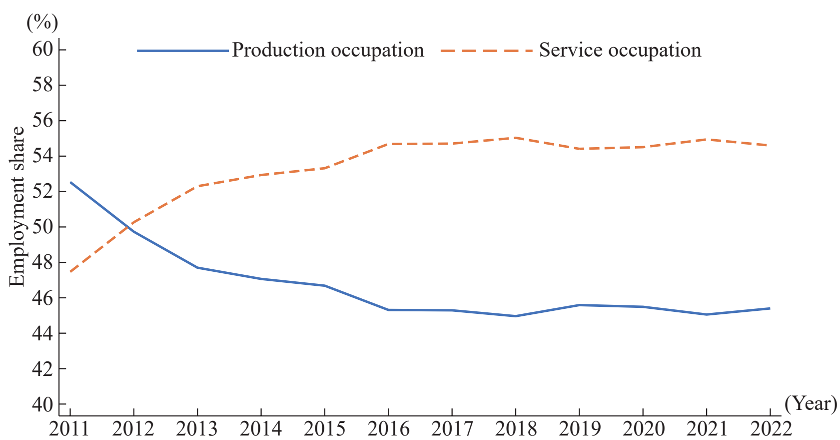
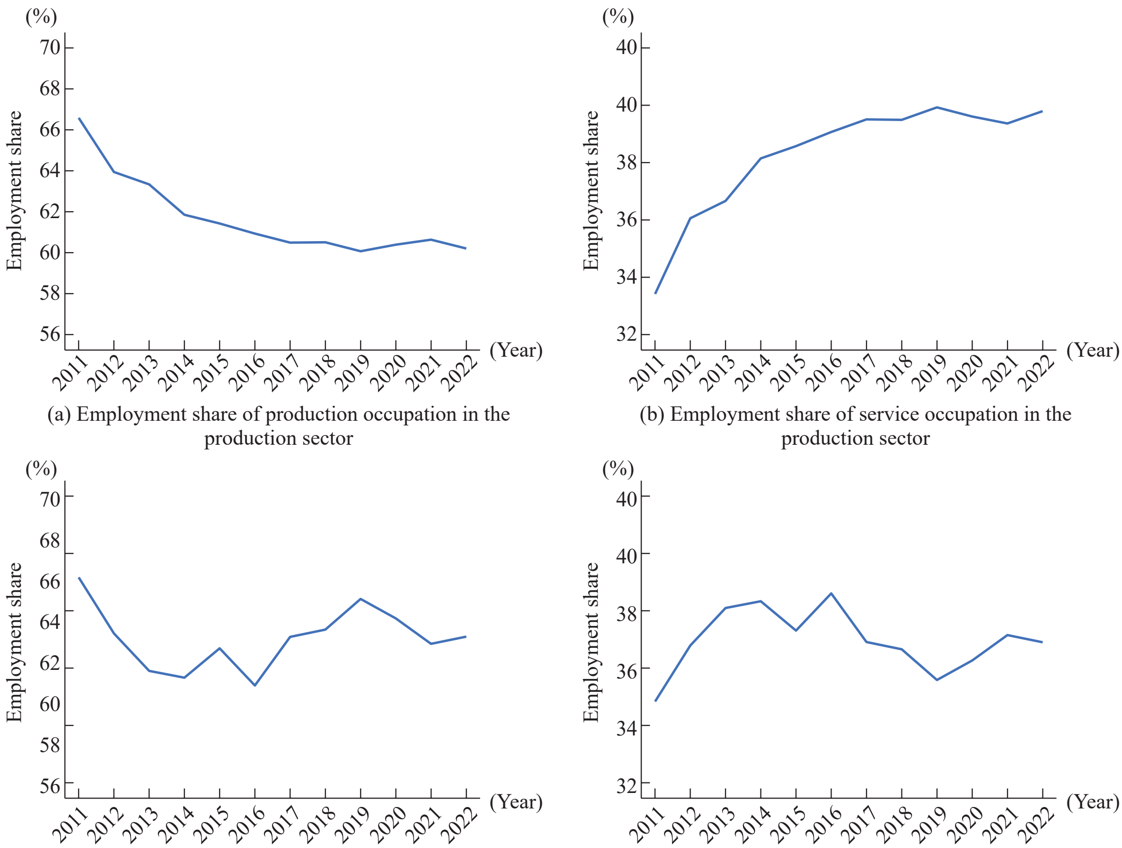


Figure 4: Evolution of Occupational Structure in Chinese A-Share Listed Companies

Source: Occupational structure data derived from Chinese A-share listed company records. Figures 5 and 6 are the same.

[5] Detailed processing procedures can be found in the attachments on the *China Industrial Economics* website (http://ciejournal.ajcass.org). production occupation in the service industry mainly refer to enterprises or subsidiaries that have a portion of production operations.

Figure 5 shows the changing occupational structure within China's manufacturing and service sectors. The manufacturing sector reveals a clearer shift: the employment share of production occupation fell from 66.6% to 60.2%, while the share of service occupation increased from 33.4% to 39.8%, marking an early move toward "service-oriented manufacturing". In contrast, the service sector's production job share has also declined, but its overall job composition shows greater volatility and a less consistent trend than manufacturing.



(a) Employment share of production occupation in the production sector

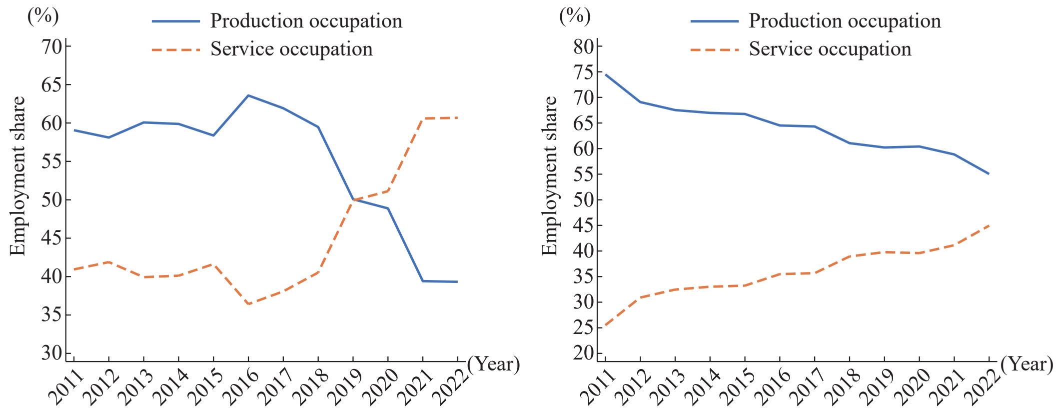
(b) Employment share of service occupation in the production sector

(c) Employment share of production occupation in the service sector

(d) Employment share of service occupation in the service sector

Figure 5: Evolution of Occupational Structure within China's Manufacturing and Service Sectors

The findings of this study further underscore that substantial shifts in occupational structure are most evident within large manufacturing firms characterized by extensive and advanced AI integration. Figure 6 displays occupational structure trends over the past decade for two example firms, Sany Heavy Industry and Weichai Power. Both companies have actively pursued digital transformation during the latest technological wave, using deep AI integration to enable intelligent production processes. At Sany Heavy Industry, the employment share of production occupation dropped from 59.1% to 39.3% between 2011 and 2022, while the share of service occupation grew from 40.9% to 60.7%. Similarly, at Weichai Power, production job employment fell from 74.5% to 55.1%, with service job employment rising from 25.5% to 44.9%.



(a) Trend of occupational structural change in SANY heavy industry

(b) Trend of occupational structural change in Weichai Power

Figure 6: Evolution of Occupational Structure in Leading Listed Manufacturing Firms

In conclusion, cross-country survey data reveal significant disparities in occupational structures across nations at varying stages of economic development. As per capita GDP rises, economies around the world exhibit a consistent pattern of occupational transformation, marked by shifts from production to service roles in both manufacturing and service sectors. Over the past decade, China has likewise witnessed a shift of labor from production-oriented positions to service-oriented positions, which has been even more significant within manufacturing enterprises. The extent of this transformation is greater in economies and enterprises that combine strong economic performance with deeper integration of AI technologies, suggesting a link between technological advancement and evolving job composition.

3. Model Framework

This section extends the model framework of Duernecker & Herrendorf (2022) by incorporating artificial intelligence (AI) technology, developing a multi-sector dynamic general equilibrium model that captures both AI integration and changes in occupational structure. On the supply side, the model considers heterogeneous labor inputs, with AI influencing the structure of labor across occupation and industries through its effect on job-augmenting technological progress. On the demand side, the model distinguishes between the industrial origins of consumption, investment, and R&D expenditures.

Let the subscript $t \in \{0,1,2,...\}$ denote discrete time periods. The production sector is bifurcated into manufacturing and services, each produced by a representative firm that rents capital and employs labor within a perfectly competitive market. Hereafter, $J \in \{G,S\}$ designates the manufacturing and service sectors, respectively, while $j \in \{g,s\}$ corresponds to production and service occupation, respectively.

Both industrial sectors adopt the Cobb-Douglas production function form:

$$Y_{Jt} = K_{Jt}^{\theta} L_{Jt}^{1-\theta} \tag{1}$$

In equation (1), $\theta \in (0,1)$ represents the capital income share of industry J[6]. L_{Jt} is the composite labor from production occupation and service occupation, using the constant elasticity of substitution function form:

[6] To emphasize the impact of occupational structure transformation on labor while mitigating the heterogeneous effects of capital deepening across sectors, the baseline model assumes uniform capital income shares for the manufacturing and service industries. Empirical data confirm that the capital income shares of China's manufacturing and service sectors are nearly identical.

$$L_{Jt}=[(\alpha_J)^{1/\sigma_J}\left(A_{gt}N_{Jgt}\right)^{(\sigma_J-1)/\sigma_J}+(1-\alpha_J)^{1/\sigma_J}\left(A_{st}N_{Jst}\right)^{(\sigma_J-1)/\sigma_J}]^{\sigma_J/(\sigma_J-1)} \tag{2}$$

In equation (2), N_{Jjt} represents the labor of job j hired by industry J, the parameter $\alpha_J\in(0,1)$ is a constant, measuring the weight of production occupation in the composite labor of industry J, $\sigma_J>0$ represents the elasticity of substitution between production occupation and service occupation. A_{jt} is the labor-augmenting technology of job j, and it is further assumed that:

$$A_{gt}=B_gM_t^{\gamma_g},\quad A_{st}=B_sM_t^{\gamma_s} \tag{3}$$

In equation (3), the parameter $B_j>0$ measures traditional technological progress related to the job, M_t represent general-purpose AI technology, $\gamma_j>0$ is a constant, measuring the degree of influence of AI technology on the two types of occupation. If $\gamma_g\neq\gamma_s$, then the impact of AI technology on different occupation is biased. Note that the subscripts of parameters B_j and γ_j are both j, indicating that the job-augmenting technology A_{jt} here is job-related, not industry-related.

Let P_{Jt}, r_t and w_{Jjt} represent the output price, capital rent, and labor wage, respectively. The first-order optimality condition for the firm's profit maximization problem is:

$$r_t=\theta P_{Jt}Y_{Jt}/K_{Jt} \tag{4}$$

$$w_{Jgt}=(1-\theta)P_{Jt}K_{Jt}^{\theta}L_{Jt}^{-\theta}L_{Jt}^{1/\sigma_J}\alpha_J^{1/\sigma_J}A_{gt}^{(\sigma_J-1)/\sigma_J}N_{Jgt}^{-1/\sigma_J} \tag{5}$$

$$w_{Jst}=(1-\theta)P_{Jt}K_{Jt}^{\theta}L_{Jt}^{-\theta}L_{Jt}^{1/\sigma_J}(1-\alpha_J)^{1/\sigma_J}A_{st}^{(\sigma_J-1)/\sigma_J}N_{Jst}^{-1/\sigma_J} \tag{6}$$

The investment goods sector uses the outputs of the manufacturing and service industries as intermediate goods to produce investment goods in a perfectly competitive market, with its production technology adopting the constant elasticity of substitution function form:

$$I_t=\left[\omega_I^{1/\varepsilon_I}I_{Gt}^{(\varepsilon_I-1)/\varepsilon_I}+(1-\omega_I)^{1/\varepsilon_I}I_{St}^{(\varepsilon_I-1)/\varepsilon_I}\right]^{\varepsilon_I/(\varepsilon_I-1)} \tag{7}$$

In equation (7), I_t represents investment goods, I_{Jt} represents the output from industry J used in the production of investment goods, $\omega_I\in(0,1)$ is a constant parameter, and $\varepsilon_I\in(0,1)$ is also a constant parameter, which represents the elasticity of substitution of the outputs of the two industries in the production of investment goods. Solving the investment goods production firm's profit maximization problem yields:

$$\frac{P_{Gt}I_{Gt}}{P_{St}I_{St}}=\frac{\omega_I}{1-\omega_I}\left(\frac{P_{Gt}}{P_{St}}\right)^{1-\varepsilon_I} \tag{8}$$

The price of investment goods I_t satisfies: $P_{It}=\left[\omega_IP_{Gt}^{1-\varepsilon_I}+(1-\omega_I)P_{St}^{1-\varepsilon_I}\right]^{1/(1-\varepsilon_I)}$.

The household sector is described by a representative household with a lifetime utility function of the form:

$$\sum_{t=0}^{\infty}\beta^t\log(C_t)$$

where $\beta\in(0,1)$ is a constant parameter representing the discount factor, C_t is the instantaneous utility, which is composed of consumption in the two industry products, satisfying:

$$C_t=\left[\omega_C^{1/\varepsilon_C}C_{Gt}^{(\varepsilon_C-1)/\varepsilon_C}+(1-\omega_C)^{1/\varepsilon_C}C_{St}^{(\varepsilon_C-1)/\varepsilon_C}\right]^{\varepsilon_C/(\varepsilon_C-1)} \tag{9}$$

In Equation (9), C_{Jt} represents the output of the two industries used for consumption, $\omega_C\in(0,1)$ is a constant parameter, and $\varepsilon_C\in(0,1)$ is also a constant parameter, which represents the elasticity of substitution of the outputs of the two industries in consumption.

The demand sector is described by a representative household. The household holds capital K_t and one unit of labor N_t in each period, earning capital rent r_tK_t and labor income w_t. The household uses part of its income for AI technology research and development T_t, and the rest for consumption and investment. Investment increases the amount of capital held by the household. Thus, the household budget constraint satisfies:

$$P_{Gt}C_{Gt}+P_{St}C_{St}+P_{It}I_t=r_tK_t+w_t-T_t \tag{10}$$

$$K_{t+1}=\left(1-\delta_k\right)K_t+I_t \tag{11}$$

In Equation (11), $\delta_k\in\left(0,1\right)$ represents the capital depreciation rate. Solving the household utility maximization problem yields the consumption structure satisfying:

$$\frac{P_{Gt}C_{Gt}}{P_{St}C_{St}}=\frac{\omega_C}{1-\omega_C}\left(\frac{P_{Gt}}{P_{St}}\right)^{1-\varepsilon_C} \tag{12}$$

The price of composite consumption goods C_t satisfies: $P_{Ct}=\left[\omega_C P_{Gt}^{1-\varepsilon_C}+\left(1-\omega_C\right)P_{St}^{1-\varepsilon_C}\right]^{1/\left(1-\varepsilon_C\right)}$, and the Euler equation:

$$\frac{C_{t+1}}{\beta C_t}=\frac{P_{Ct}}{P_{Ct+1}}\frac{r_{t+1}+P_{It+1}\left(1-\delta_K\right)}{P_{It}} \tag{13}$$

AI technology R&D investment T_t is used for expenditure on the outputs of the two industries H_{Jt}, namely:

$$T_t=P_{Gt}H_{Gt}+P_{St}H_{St} \tag{14}$$

Expenditure on the outputs of the two industries can form new AI technology H_t, which satisfies in form:

$$H_t=\left[\omega_H^{1/\varepsilon_H}H_{Gt}^{\left(\varepsilon_H-1\right)/\varepsilon_H}+\left(1-\omega_H\right)^{1/\varepsilon_H}H_{St}^{\left(\varepsilon_H-1\right)/\varepsilon_H}\right]^{\varepsilon_H/\left(\varepsilon_H-1\right)} \tag{15}$$

In Equation (15), $\omega_H\in\left(0,1\right)$ is a constant parameter, and $\varepsilon_H\in\left(0,1\right)$ is also a constant parameter, which represents the elasticity of substitution of the outputs of the two industries in AI technology R&D. Solving its cost minimization problem yields:

$$\frac{P_{Gt}H_{Gt}}{P_{St}H_{St}}=\frac{\omega_H}{1-\omega_H}\left(\frac{P_{Gt}}{P_{St}}\right)^{1-\varepsilon_H} \tag{16}$$

The price of new AI technology H_t satisfies: $P_{Ht}=\left[\omega_H P_{Gt}^{1-\varepsilon_H}+\left(1-\omega_H\right)P_{St}^{1-\varepsilon_H}\right]^{1/\left(1-\varepsilon_H\right)}$.

New AI technology improves the level of AI technology in the next period, that is:

$$M_{t+1}=\left(1-\delta_M\right)M_t+H_t \tag{17}$$

In equation (17), the parameter $\delta_M\in\left(0,1\right)$ represents the rate of AI technology iteration. The level of AI technology M_t will in turn have a biased impact on the labor force of different occupation, as shown in Equation (3).

The market clearing conditions for product and factor markets satisfy:

$$Y_{Jt}=C_{Jt}+I_{Jt}+H_{Jt} \tag{18}$$

$$K_t=K_{Gt}+K_{St} \tag{19}$$

$$N_{Jt}=N_{Jgt}+N_{Jst},\quad N_{jt}=N_{Gjt}+N_{Sjt} \tag{20}$$

$$N_{Gt}+N_{St}=N_{gt}+N_{st}=N_t=1 \tag{21}$$

4. Theoretical Analysis

This section rigorously examines the impact of AI technology on occupational and industrial structures. Initially, the employment shares of the manufacturing and service sectors are defined as follows:

$$X_t = \frac{N_{Gt}}{N_t}, \quad 1 - X_t = \frac{N_{St}}{N_t} \tag{22}$$

The employment shares of total production occupation and total service occupation are defined as follows:

$$x_t = \frac{N_{gt}}{N_t}, \quad 1 - x_t = \frac{N_{st}}{N_t} \tag{23}$$

The employment shares of production and service occupation within the manufacturing and service sectors are defined as follows:

$$x_{Jt} = \frac{N_{Jgt}}{N_{Jt}}, \quad 1 - x_{Jt} = \frac{N_{Jst}}{N_{Jt}}, \quad J \in \{G, S\} \tag{24}$$

Assuming frictionless labor mobility across occupation and sectors, combining the aforementioned equations (5) and (6) yields:

$$\frac{x_{Jt}}{1 - x_{Jt}} = \frac{\alpha_J}{1 - \alpha_J} \left(\frac{B_g}{B_s} M_t^{\gamma_g - \gamma_s} \right)^{\sigma_J - 1} \tag{25}$$

Given a fixed level of AI technology M_t, Equation (25) establishes the occupational structure for industry J under static equilibrium. Conducting a comparative static analysis on M_t, we obtain:

$$\frac{d \log x_{Jt}}{d \log M_t} = (1 - x_{Jt})(\sigma_J - 1)(\gamma_g - \gamma_s) \tag{26}$$

The influence of AI on occupational structure hinges on the elasticity of substitution between job types and the bias inherent in AI technology. Despite ongoing debate surrounding AI's overall impact on employment, scholarly consensus converges on the biased nature of AI-driven technological progress, which predominantly enhances the efficiency of procedural, repetitive tasks (Ge et al. 2021; Duernecker & Herrendorf, 2022; Wang et al., 2022; Chen et al., 2023). Consequently, in the early stages of AI adoption, its impact on production occupation surpasses that on service occupation, expressed as $\gamma_g > \gamma_s$. Moreover, if the complementary synergy between job types outweighs their substitution effect—that is, if the elasticity of substitution between occupation is $\sigma_J < 1$—then AI advancements will reduce the share of production occupation while increasing the share of service occupation within industries. The converse holds when substitution dominates.

Proposition 1: When AI technology exhibits a bias toward production occupation and the elasticity of substitution between production and service occupation is low, AI advancements trigger occupational structure transformation in both manufacturing and service sectors. Specifically, the employment share of production occupation declines while that of service occupation rises. At the aggregate economy level, the overall share of production occupation similarly decreases, with a corresponding increase in the share of service occupation[7].

The economic mechanism underlying Proposition 1 aligns with insights from Ngai & Pissarides (2007). When the elasticity of substitution between production and service occupation within an industry is less than 1, labor shifts toward job types where growth is slower. Given AI's bias toward production

[7] All conclusion derivations in this paper can be found in the attachments on the *China Industrial Economics* website (http://ciejournal.ajcass.org).

occupation, it accelerates labor-augmenting technological progress in these roles, boosting their output. This, in turn, drives labor reallocation from production to service occupation within industries. As this transformation occurs concurrently across manufacturing and service sectors, the aggregate economy reflects a diminished share of total production occupation and an increased share of service occupation. According to Equation (26), a smaller elasticity of substitution σ_J and a greater AI technology bias $(\gamma_g - \gamma_s)$ amplify AI's impact on occupational structure, intensifying labor reallocation across job types.

The economic mechanism of Conclusion 1 is similar to Ngai and Pissarides (2007). If the elasticity of substitution between production occupation and service occupation within the industry is less than 1, then labor will shift to slower-growing occupation. Since AI technology is more biased toward production occupation, it leads to faster growth of labor-augmenting technology in production occupation and higher output in production occupation, which leads to the transfer of labor from production occupation to service occupation within the industry. Since occupational structure transformation occurs simultaneously in the manufacturing and service industries, in aggregate, the proportion of total production occupation will decrease, and the proportion of service occupation will increase. According to Equation (26), the smaller the elasticity of substitution σ_J between production occupation and service occupation, and the greater the bias difference of AI technology $(\gamma_g - \gamma_s)$, the greater the impact of AI on the occupational structure, and the greater the transfer of labor between different occupation.

In order to intuitively show the impact of AI technology on the labor structure at the industry level, the demand side and the supply side are further simplified[8]. To this end, Assumption 1 is made: $\omega_C=\omega_I=\omega_H=\omega$, $\varepsilon_C=\varepsilon_I=\varepsilon_H=\varepsilon$, that is, on the demand side, the weights of the manufacturing industry are equal, and the elasticity of substitution is also equal. Therefore, from equations (8), (12) and (16), no matter how much proportion of output is used for consumption, investment, and AI R&D, it will not affect the relative proportion of the manufacturing and service industries. At this time, there is:

$$\frac{P_{Gt}Y_{Gt}}{P_{St}Y_{St}} = \frac{\omega}{1-\omega}\left(\frac{P_{Gt}}{P_{st}}\right)^{1-\varepsilon} \tag{27}$$

Assumption 2 is further made $\sigma_G=\sigma_S=\sigma$, that is, on the supply side, disparities in the elasticity of substitution between occupation across industries are disregarded. Following derivation and simplification, this yields:

$$\frac{X}{1-X} = \frac{\omega}{1-\omega}\left(\frac{1-\alpha_G+\alpha_G\left(B_g/B_sM_t^{\gamma_g-\gamma_s}\right)^{\sigma-1}}{1-\alpha_S+\alpha_S\left(B_g/B_sM_t^{\gamma_g-\gamma_s}\right)^{\sigma-1}}\right)^{(\varepsilon-1)(1-\theta)/(\sigma-1)} \tag{28}$$

Taking the natural logarithm and total differential of both sides of equation (28) yields: $\frac{d\log X_t}{d\log M_t} \propto (\gamma_g-\gamma_s)(\alpha_G-\alpha_S)(\varepsilon-1)$. Existing literature consistently finds that the elasticity of substitution between industries in consumption and investment is near zero (Herrendorf et al., 2018; Guo et al., 2021), indicating that the manufacturing and service sectors are largely complementary, i.e., $\varepsilon<1$. If the share of production occupation in the composite labor of the manufacturing sector exceeds that in the service sector, i.e., $\alpha_G>\alpha_S$, then AI technology advancements will reduce the employment share of the manufacturing sector while increasing that of the service sector, resulting in industrial structure transformation. The reverse holds true otherwise.

Proposition 2: When AI technology exhibits a bias toward production occupation, the elasticity

[8] The qualitative conclusions of the model remain robust regardless of parameter simplification, as can be demonstrated analytically. To clearly illustrate the theoretical mechanisms and derive explicit qualitative insights, this study employs a series of parameter simplifications. Notably, the subsequent numerical simulations diverge from these simplified parameter assumptions.

of substitution between the manufacturing and service sectors is low, and the share of production occupation in manufacturing surpasses that in services, AI advancements drive industrial structure transformation—specifically, a decline in the employment share of the manufacturing sector and a rise in that of the service sector.

Proposition 2 highlights that, at the industry level, a higher weight of production occupation in manufacturing amplifies the sector's overall productivity gains due to AI's bias toward production roles. Given the complementarity between manufacturing and services, alongside occupational structure transformation, the manufacturing sector's aggregate employment share diminishes. Thus, within a model incorporating occupational structure shifts, the industrial-level structural transformation persists, with labor reallocating from manufacturing to services.

Further calculations of the relative labor productivity and real output of the manufacturing and service sectors yield:

$$\frac{Y_{Gt}/N_{Gt}}{Y_{St}/N_{St}} = \left(\frac{1-\alpha_G + \alpha_G \left(B_g / B_s M_t^{\gamma_g - \gamma_s} \right)^{\sigma-1}}{1-\alpha_S + \alpha_S \left(B_g / B_s M_t^{\gamma_g - \gamma_s} \right)^{\sigma-1}} \right)^{(1-\theta)/(\sigma-1)} \tag{29}$$

Applying natural logarithms and total differentiation to both sides of the preceding equation yields: $\frac{d\log(\frac{Y_{Gt}/N_{Gt}}{Y_{St}/N_{St}})}{d\log M_t} \propto \left(\gamma_g - \gamma_s\right)\left(\alpha_G - \alpha_S\right)$. If AI technology exhibits a bias toward production occupation and production occupation carry a greater weight in the manufacturing sector compared to the service sector, then the relative labor productivity of manufacturing over services rises with AI technology accumulation. Conversely, the opposite holds true. Concerning the real output ratio between the manufacturing and service sectors:

$$\frac{Y_{Gt}}{Y_{St}} = \left(\frac{\omega}{1-\omega} \right)^{1/(1-\varepsilon)} \left(\frac{X}{1-X} \right)^{-\varepsilon/(1-\varepsilon)} \tag{30}$$

According to Proposition 2, if the elasticity of substitution between the manufacturing and service sectors is low and the share of production occupation in manufacturing exceeds that in services, then AI's job bias will increase the real output share of the manufacturing sector. The converse also applies.

Proposition 3: When AI technology disproportionately biases toward production occupation and the share of production occupation in manufacturing surpasses that in services, AI advancements enhance the relative labor productivity of manufacturing compared to services. Moreover, if the elasticity of substitution between these sectors is small, the real output share of manufacturing rises, thereby facilitating its transformation and upgrading.

This effect stems from AI's enhancement of production job efficiency, coupled with the higher weight of such occupation in manufacturing, which accelerates the sector's overall labor productivity growth. Despite a declining employment share in manufacturing due to industrial structure transformation, the low elasticity of substitution amplifies productivity gains in manufacturing relative to services. Consequently, the real output share of manufacturing increases with AI technology accumulation. Proposition 3 underscores that AI's job bias not only boosts manufacturing labor productivity but also sustains the sector's real output share, driving its transformation and upgrading in the AI era.

5. Numerical Simulation

5.1 Parameter Calibration

This section employs numerical simulation to quantitatively assess AI technology's impact on occupational structure and industrial structure transformations over a 30-year horizon, with each model period representing one year (2011 as the initial period). Given that Chinese listed companies began disclosing occupational structure data in 2011, parameters are calibrated to align the model's first-period results with the 2011 occupational structure characteristics of these firms. On the supply side, the capital income share θ for both manufacturing and service sectors is set at 0.5, total labor supply is normalized to 1, and initial capital and AI levels are set to 1. Capital depreciation is fixed at 0.1, while AI depreciation is 0, reflecting standard values in the literature. Without loss of generality, in the baseline model, parameters are set to γ_g=1 and γ_s=0.75 to capture AI's initial bias toward production occupation, with subsequent sensitivity analysis increasing the value of γ_s to explore AI's growing influence on service occupation. The weights of production occupation in the composite labor of manufacturing and service sectors α_G, α_S are calibrated using Equation (25), yielding α_G=0.666 and α_S=0.207 based on 2011 employment shares from Chinese listed companies. The elasticity of substitution between occupation σ is calibrated via regression. According to the derivation in the theoretical part, if the elasticity of substitution σ between occupation in different industries is equal, then:

$$\frac{1-x_{Gt}}{1-x_{St}}=\frac{1-\alpha_G}{1-\alpha_S}\left(\frac{Y_{Gt}/N_{Gt}}{Y_{St}/N_{St}}\right)^{\frac{1-\sigma}{1-\theta}} \tag{31}$$

Taking the natural logarithm of Equation (31), we performed an OLS regression. The dependent variable was the service job share within the manufacturing sector, while the independent variable was labor productivity, represented by actual operating income per employee from 2011-2022 listed company data. This regression yielded a coefficient of 0.58. Hence, σ=0.71<1. This elasticity, below 1, aligns with the assumptions of Propositions 1-3. Finally, parameters B_g and B_s are calibrated to ensure the model's 12th period (2022) closely matches the 2022 occupational structure data of Chinese listed companies.

On the demand side, studies by Herrendorf et al. (2018) and Guo et al. (2020) indicate that the elasticity of substitution for value-added across industries in consumption and investment is near zero, reflecting the complementarity of manufacturing and services. Thus, the baseline model sets the elasticity of substitution for these sectors in consumption, investment, and AI R&D to $\varepsilon_C=\varepsilon_I=\varepsilon_H=0.01$. The weights of industries in consumption and AI R&D are set to $\omega_C=\omega_H=0.5$, while the manufacturing sector's weight in investment is higher, with ω_I calibrated as ω_I=0.9 to align employment shares with Chinese data. To isolate AI's effects on occupational and industrial structures, the model controls for capital deepening by fixing the investment rate exogenously, avoiding endogenization via the Euler equation. The aggregate investment rate $s=s_I+s_H=\left(P_I I+P_H H\right)/\left(P_G Y_G+P_S Y_S\right)$ is set at 0.4, with AI R&D investment $s_H=\left(P_G H_G+P_S H_S\right)/\left(P_G Y_G+P_S Y_S\right)$ at 0.01.

5.2 Baseline Results

Figure 7 presents the numerical simulation results of the baseline model. As AI technology progresses, the simulation reveals distinct trends: from an industrial structure perspective, the employment share of the manufacturing sector experiences a modest decline. From an occupational structure viewpoint, the aggregate share of production occupation decreases substantially, with a sustained reduction in production occupation within manufacturing. Meanwhile, the labor productivity ratio of manufacturing to services rises steadily, and manufacturing's real output share increases incrementally. These patterns corroborate Propositions 1-3, demonstrating that AI induces structural shifts at both industry and job levels—driving labor reallocation from production to service occupation and from manufacturing to service sectors. This occupational structure transformation accelerates labor productivity gains in manufacturing, sustains its real output share, and facilitates the sector's transformation and upgrading in the AI era.

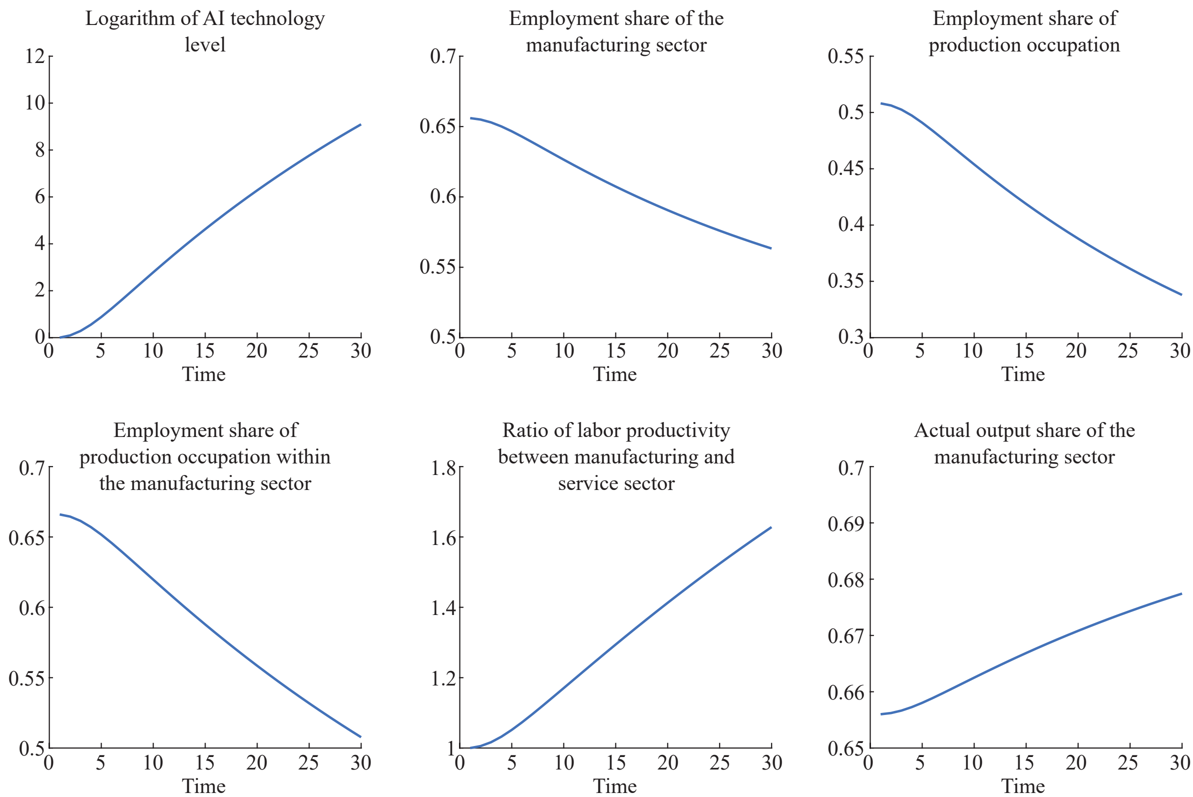


Figure 7: Simulation Results of the Baseline Model

Table 1 compares the model's simulated values for key variables in 2011 (first period) and 2022 (12^{th} period) against actual data[9]. Overall, the model closely aligns with real data, particularly in replicating occupational structure shifts within manufacturing and service sectors. At the aggregate level, while simulated industrial and occupational structures show minor deviations from actual data, the downward trends and magnitudes remain consistent.

Table 1: Comparison of Simulated and Actual Data for Key Variables (2011 vs. 2022)

Main variables	Model		Actual data	
	2011	2022	2011	2022
Employment share of production occupation within the manufacturing sector x_G	0.666	0.607	0.666	0.602
Employment share of production occupation within the service sector x_S	0.207	0.168	0.207	0.176
Employment share of the manufacturing sector X	0.656	0.619	0.638	0.591
Employment share of production occupation x	0.508	0.439	0.525	0.454

[9] The actual data primarily consist of aggregated statistics from manufacturing and service enterprises listed on China's A-share market. The employment share of production occupation in the manufacturing sector is defined as the ratio of production job employees to the total workforce in all manufacturing enterprises, while the employment share of the manufacturing sector is calculated as the number of employees in manufacturing enterprises divided by the combined total of employees in both manufacturing and service enterprises.

Table 2 details the evolution of key variables from the first to the 30th period. In the baseline model, a 9.095 increase in the logarithm of AI technology leads to several key outcomes: a 0.158 fall (23.7% reduction) in the manufacturing sector's production job share, and a 0.093 drop (14.2% reduction) in its overall employment share. Concurrently, the total production job share across the economy experiences a 0.170 decrease (33.5% reduction). Conversely, the model shows a 0.628 increase (62.8% growth) in the manufacturing-to-service labor productivity ratio, and a 0.021 growth (3.2% increase) in manufacturing's real output share. Notably, AI-driven occupational structure transformation outpaces industrial structure shifts, with production job shares in manufacturing steadily declining. Manufacturing labor productivity surges by 62.8% relative to services, while its real output share remains largely stable, underscoring significant transformation and upgrading.

Table 2: Changes in Key Variables Across Periods (1st to 30th)

	Change in the logarithm of AI technology level	Employment share of production occupation within the manufacturing sector	Employment share of the manufacturing sector	Overall employment share of production occupation	Ratio of labor productivity between manufacturing and service sector	Actual output share of the manufacturing sector
Baseline model	9.095	-0.158	-0.093	-0.170	0.628	0.021
Sensitivity analysis I: Changes in the elasticity of substitution between occupation						
$\sigma_G(\sigma_S)$=0.6	9.031	-0.219	-0.089	-0.213	0.594	0.020
$\sigma_G(\sigma_S)$=0.55	9.003	-0.246	-0.087	-0.232	0.578	0.020
Sensitivity analysis II: Changes in the degree of AI bias						
γ_s=0.9	10.726	-0.072	-0.045	-0.083	0.271	0.010
γ_s=1	12.088	0	0	0	0	0
Sensitivity analysis III: Changes in the investment rate						
s_H=0.02	11.541	-0.203	-0.116	-0.211	0.826	0.027
s_H=0.05	14.866	-0.262	-0.146	-0.260	1.105	0.033

Note: Variable changes reflect shifts from the first to the 30th period.

5.3 Sensitivity Analysis

This subsection conducts sensitivity analysis on key parameters, beginning with the elasticity of substitution σ between different occupation[10]. Duernecker & Herrendorf (2022) calibrate this elasticity in the U.S. economy at 0.56. Here, σ is adjusted from 0.71 to 0.60 and 0.55 to simulate increasing job specialization and stronger complementarity. Figure 8 and Table 2 present the simulation results. Overall, varying σ does not alter the directional trends of key variables, preserving the qualitative conclusions. According to Equation (25), a lower σ amplifies AI's impact on occupational structure, intensifying the transformation. Figure 8 confirms that as σ decreases, production job shares decline significantly, both in total and within manufacturing. Specifically, as σ drops to 0.60 and 0.55, the aggregate production job share falls by 0.213 and 0.232, respectively, while production job shares in manufacturing decrease by 0.219 and 0.246. This indicates that greater complementarity between roles within an industry amplifies the magnitude of changes in occupational structure. However, the elasticity of substitution between roles has minimal impact on industrial structure, as variations in σ exert little influence on manufacturing

[10] When σ's values for the two sectors differ, the analysis in the theoretical section no longer holds. For numerical simulation results, please refer to the appendix on the China Industrial Economics website (http://ciejournal.ajcass.org).

employment share, relative labor productivity in manufacturing, or the proportion of manufacturing's real output.

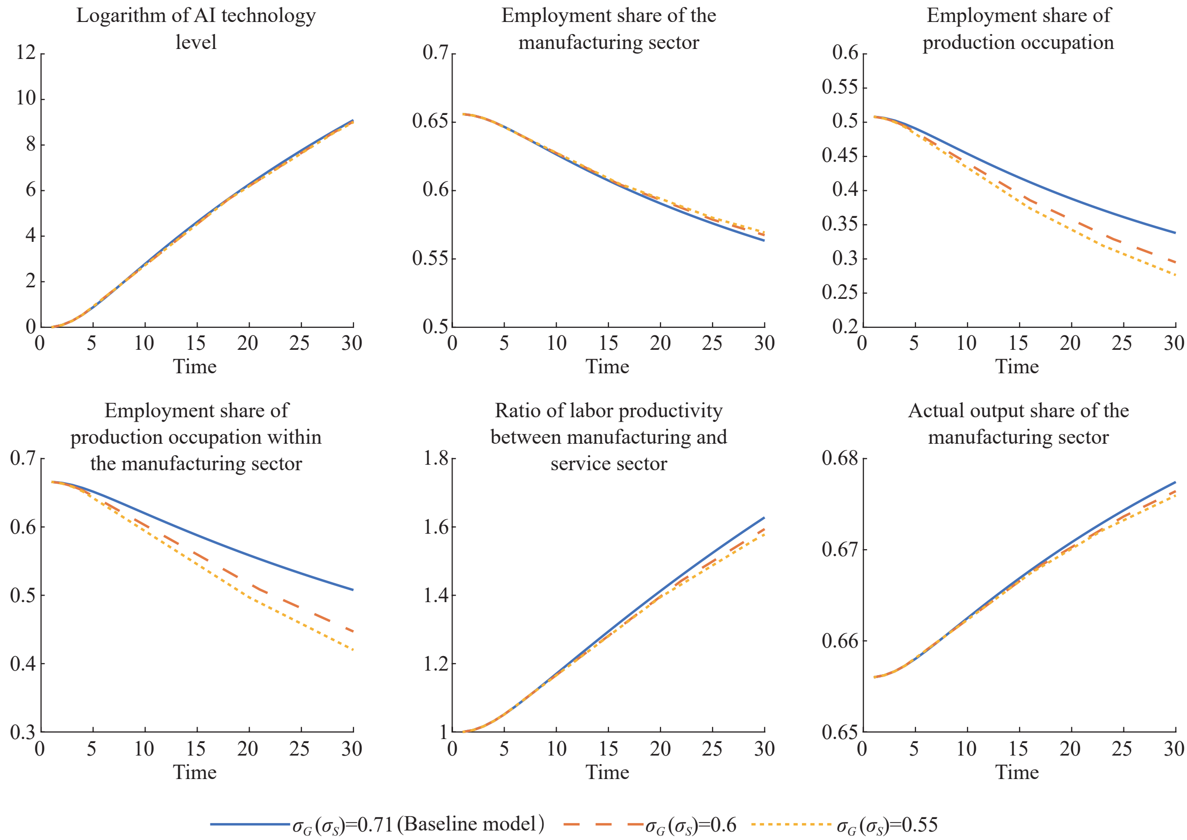


Figure 8: Simulation Results for Varying Values of the Elasticity of Substitution Parameter between Occupation

Next, we adjust the job-bias parameter γ_s of artificial intelligence (AI). In the baseline model, this parameter γ_s is set at 0.75. Here, we incrementally increase γ_s to 0.9 and 1.0 to simulate a scenario where AI technology increasingly biases toward service occupation. As outlined in the theoretical section, a reduced bias differential ($\gamma_g-\gamma_s$) between AI's impact on the two job types diminishes the magnitude of changes in occupational and industrial structures. Figure 9 and Table 2 detail the corresponding simulation results. When γ_s is assigned the value of 0.9, the proportion of production job employment within manufacturing falls by 0.072, the manufacturing employment share decreases by 0.045, and the overall production job employment share drops by 0.083. These changes in occupational and industrial structures are markedly smaller than those in the baseline model. When γ_s is assigned the value of 1.0, $\gamma_g=\gamma_s$, that is, despite continued improvements in AI technology, its unbiased effect across job types prevents any alteration to the job or industrial structure.

In recent years, with the application of technologies such as big data, cloud computing, and large language models (LLMs), the application areas of artificial intelligence have increasingly penetrated service occupation—including white-collar workers, researchers, and roles in the emerging platform economy—reducing the technology bias gap with production occupation. As shown in Figure 9, this narrowing of the job bias gap in artificial intelligence enhances the relative labor productivity of the service industry. Consequently, as artificial intelligence technology advances, the labor productivity gap between manufacturing and the

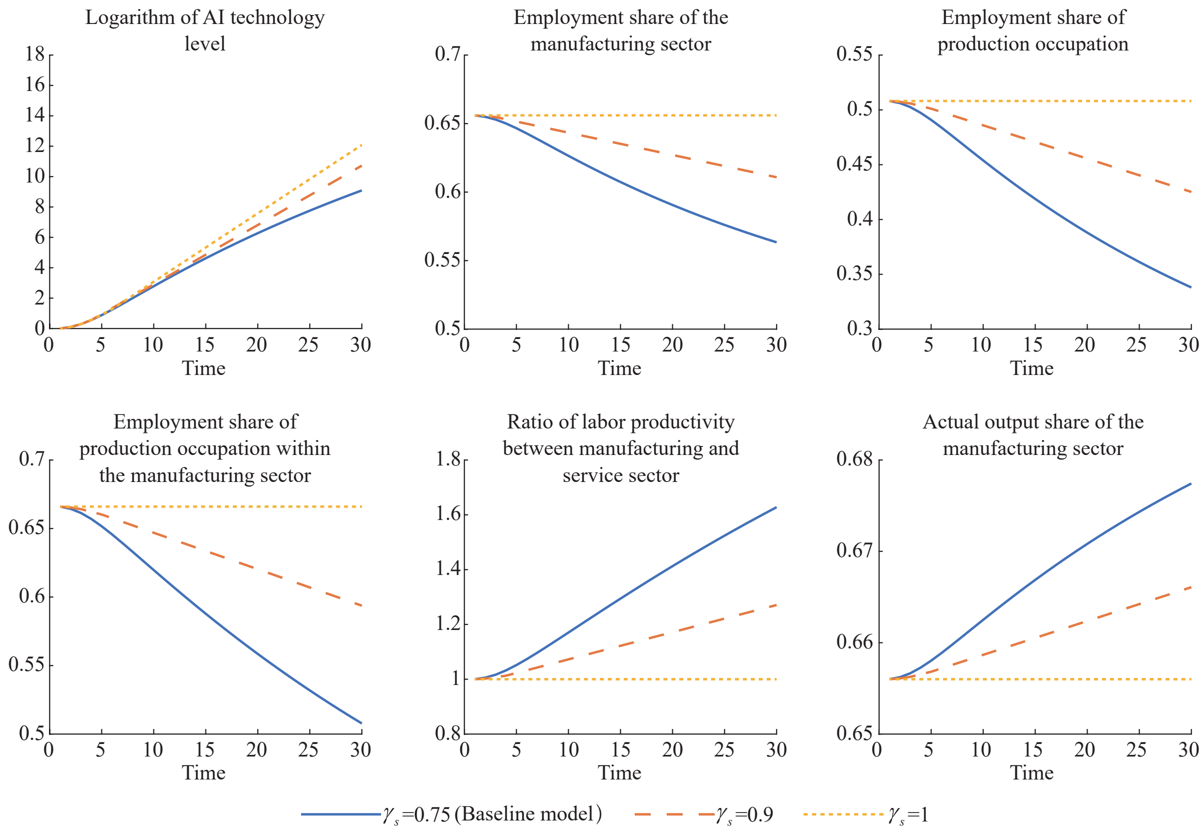


Figure 9: Simulation Results Under Different Values of the AI Job Bias Parameter

service industry continues to shrink, partially mitigating Baumol's cost disease.

Finally, we adjust the investment rate S_H in AI technology R&D. Increasing this rate directly accelerates the accumulation of AI technology, amplifying changes in occupational and industrial structures. As depicted in Figure 10 and Table 2, when the AI technology R&D investment rate S_H rises from 0.01 to 0.02 and 0.05, the magnitude of changes in key variables intensifies. Specifically, the employment share of production occupation within manufacturing declines by 0.203 and 0.262, while manufacturing's overall employment share drops by 0.211 and 0.260. The share of production occupation across all sectors decreases by 0.116 and 0.146. In contrast, the labor productivity ratio between manufacturing and services increases by 0.826 and 1.105. These results suggest that increasing investment in AI R&D can lead to significant shifts in occupational and industrial structure, while substantially enhancing the relative labor productivity of the manufacturing sector.

6. Further Discussions

In the baseline model, labor can flow freely between different occupation and sectors. In this section, we introduce wage friction factors for occupation or sectors to characterize labor mobility cost, in order to examine the quantitative impact of labor market frictions.

6.1 Labor Mobility Cost Exists between Different Occupation

Due to varying skill requirements, labor transfer between different occupation incurs training costs,

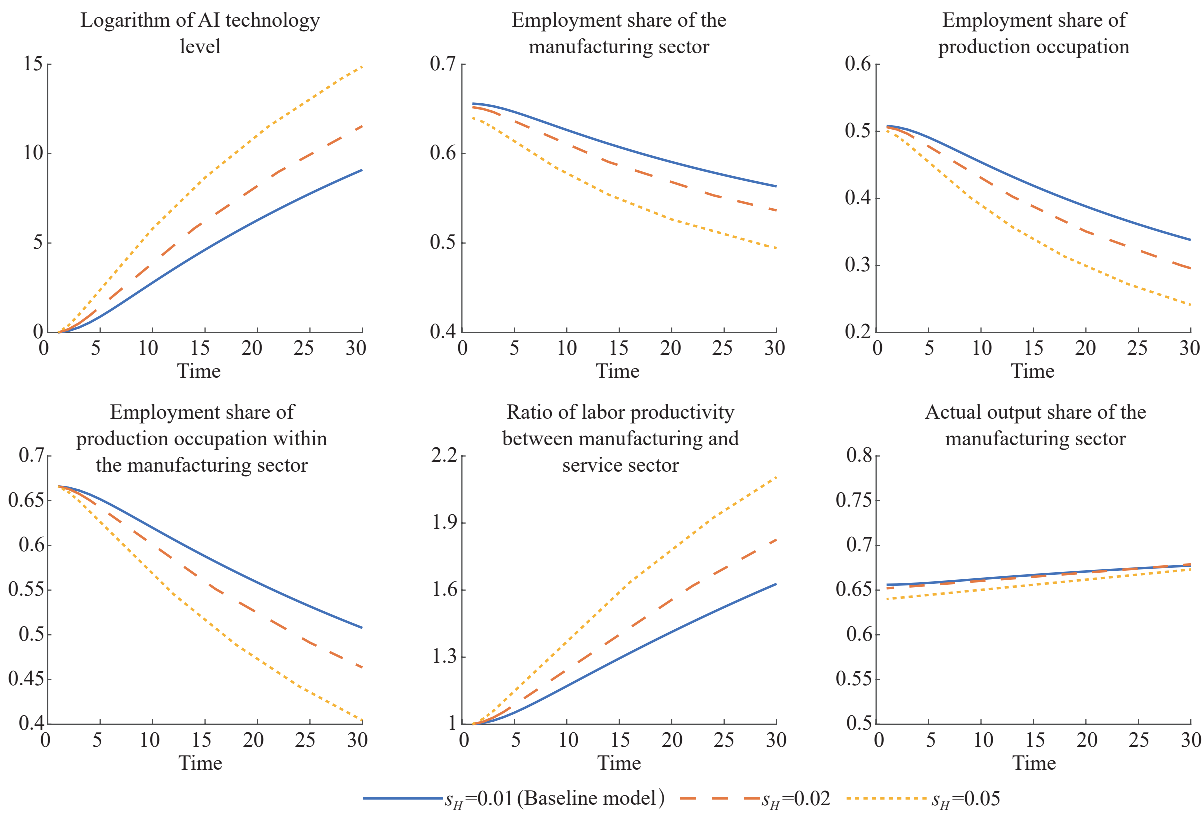


Figure 10: Simulation Results Under Different Values of the AI R&D Investment Rate Parameter

thus creating a labor mobility cost. In recent years, the National Bureau of Statistics (NBS) has published the average wages of employees in five types of positions in large enterprises across the country. Among them, the wages of production, manufacturing, and related personnel are 77% of the overall average wage level. Here, we assume that the wage of service occupation is λ times that of production occupation[11], i.e., $w_{st}=\lambda w_{gt}$, $\lambda \geq 1$. Here, λ measures the labor mobility cost between different occupation. Then, equation (25), which determines the occupational structure, becomes:

$$\frac{x_{Jt}}{1-x_{Jt}} = \lambda^{\sigma} \frac{\alpha_J}{1-\alpha_J} \left(\frac{B_g}{B_s} M_t^{\gamma_g - \gamma_s} \right)^{\sigma_J - 1} \tag{32}$$

Define $\tilde{N}_{Jt} = N_{Jgt} + \lambda N_{Jst}$, $J \in \{G, S\}$, then Equation (28), which determines the labor force structure of the sector, becomes-

$$\frac{\tilde{N}_{Gt}}{\tilde{N}_{St}} = \frac{\omega}{1-\omega} \left(\frac{1-\alpha_G + \lambda^{\sigma-1} \alpha_G \left(B_g / B_s M_t^{\gamma_g - \gamma_s} \right)^{\sigma-1}}{1-\alpha_S + \lambda^{\sigma-1} \alpha_S \left(B_g / B_s M_t^{\gamma_g - \gamma_s} \right)^{\sigma-1}} \right)^{(\varepsilon-1)(1-\theta)/(\sigma-1)} \tag{33}$$

$$= \frac{X_t x_{Gt} + \lambda X_t (1 - x_{Gt})}{(1 - X_t) x_{St} + \lambda (1 - X_t)(1 - x_{St})}$$

[11] Data from Chinese listed companies does not include wage details for specific job roles. In contrast, IPUMS data from the US reveals that average wages for production occupation are lower than those for service occupation across both the production and service sectors.

From Equation (32), it is evident that higher labor mobility cost (λ) between occupation increases the difficulty of shifting labor from production to service roles, thereby slowing changes in employment patterns. Equation (33) further reveals that λ influences the labor composition across industrial sectors. Naturally, the level of artificial intelligence technology (M_t), a key driver of occupational structure shifts, must also be considered holistically. The following analysis uses numerical simulations to quantitatively assess the effects of labor mobility cost (λ) on employment structure, industrial structure, and relative labor productivity.

Figure 11 presents simulation results for λ values of 1, 1.3, and 1.5, representing scenarios of increasing labor mobility costs between occupation. These results show that, for any given λ value, the job bias of AI technology continues to drive occupational structure transformation and broader industrial shifts, with Propositions 1-3 remaining valid. However, holding other factors constant, higher λ values correlate with elevated employment shares of production occupation—both overall and within the manufacturing sector—and a slightly higher manufacturing sector employment share. This indicates a slower pace of occupational structure transformation and industrial restructuring, with λ exerting a more significant impact on the occupational composition within manufacturing.

Thus, while restricted labor mobility between occupation does not alter the overall direction of occupational and industrial structure transformation, a higher labor mobility cost significantly slows these processes. Conversely, government initiatives that facilitate labor transitions from production to service roles, such as enhanced skills training, can accelerate workforce shifts and drive manufacturing transformation and upgrading by increasing job mobility. Quantitatively, reducing λ by one-third could lower the employment share of production occupation within manufacturing by 0.06-0.07 per timeframe and the overall production job employment share by 0.05-0.07. This magnitude aligns with labor market changes observed in China over the past decade. Therefore, lowering mobility barriers and enhancing workforce flexibility can effectively advance employment structure evolution and manufacturing upgrades.

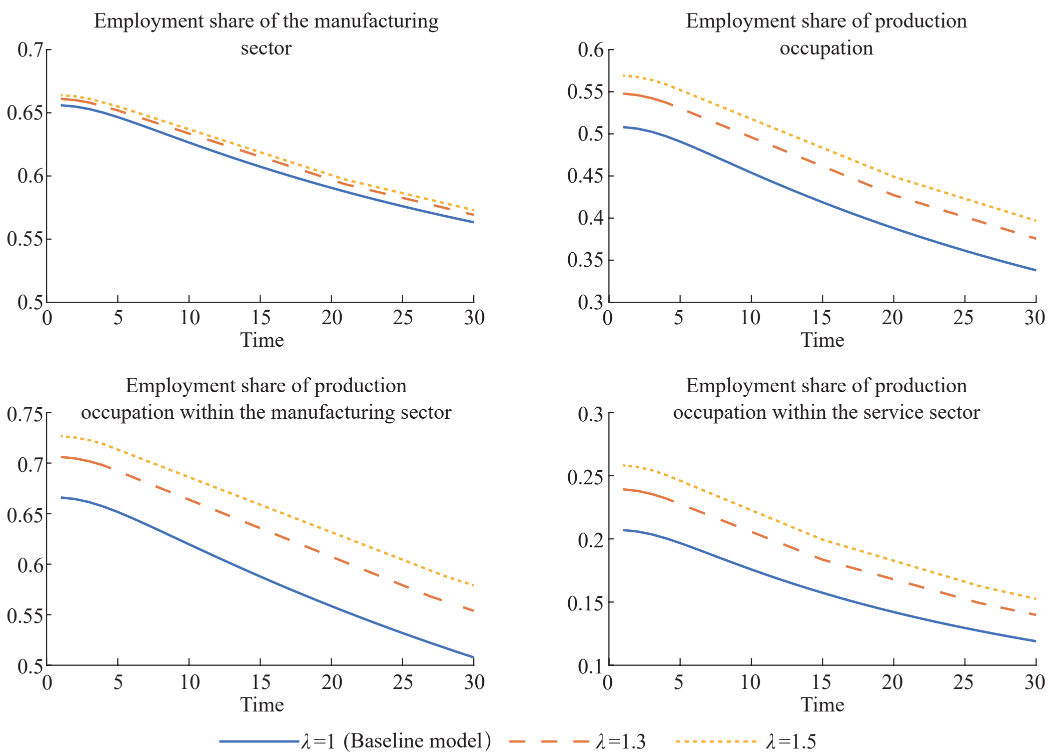


Figure 11: Simulation Results for Varying Labor Mobility Cost Between Occupation

6.2 Labor Mobility Cost between Sectors

When labor cannot flow freely between sectors, a labor mobility cost arises across sectoral boundaries. Data from Chinese listed companies indicate that, over the past decade, average salaries in the service sector have ranged from 1.2 to 1.8 times those in the manufacturing sector. Let the service sector wage be η times the manufacturing sector wage, defined as $w_{St}=\eta w_{Gt}$, where $\eta \geq 1$. Here, η quantifies the labor mobility cost between sectors. While η does not alter the occupational structure within a sector—leaving equation (25) in the baseline model unchanged—it modifies equation (28), which governs the sectoral labor structure, as follows:

$$\frac{X_t}{1-X_t}=\eta^{\varepsilon}\frac{\omega}{1-\omega}\left(\frac{1-\alpha_G+\alpha_G\left(B_g/B_sM_t^{\gamma_g-\gamma_s}\right)^{\sigma-1}}{1-\alpha_S+\alpha_S\left(B_g/B_sM_t^{\gamma_g-\gamma_s}\right)^{\sigma-1}}\right)^{(\varepsilon-1)(1-\theta)/(\sigma-1)} \tag{34}$$

Based on the above equation, labor mobility cost η between sectors affects the distribution of labor across industries. Figure 12 presents simulation results where the inter-sector mobility cost η is increased to 1.5 and 2, respectively. While these changes in η do not alter the overall trajectory of employment and industrial transformation, higher values of η make it more difficult for workers in manufacturing to shift to the service sector. This leads to a greater employment share in manufacturing and a slower pace of industrial restructuring. However, the employment composition across occupations remains nearly identical across different η values. Thus, while higher inter-sector mobility costs significantly hinder industrial transformation, their impact on occupational distribution appears minimal.

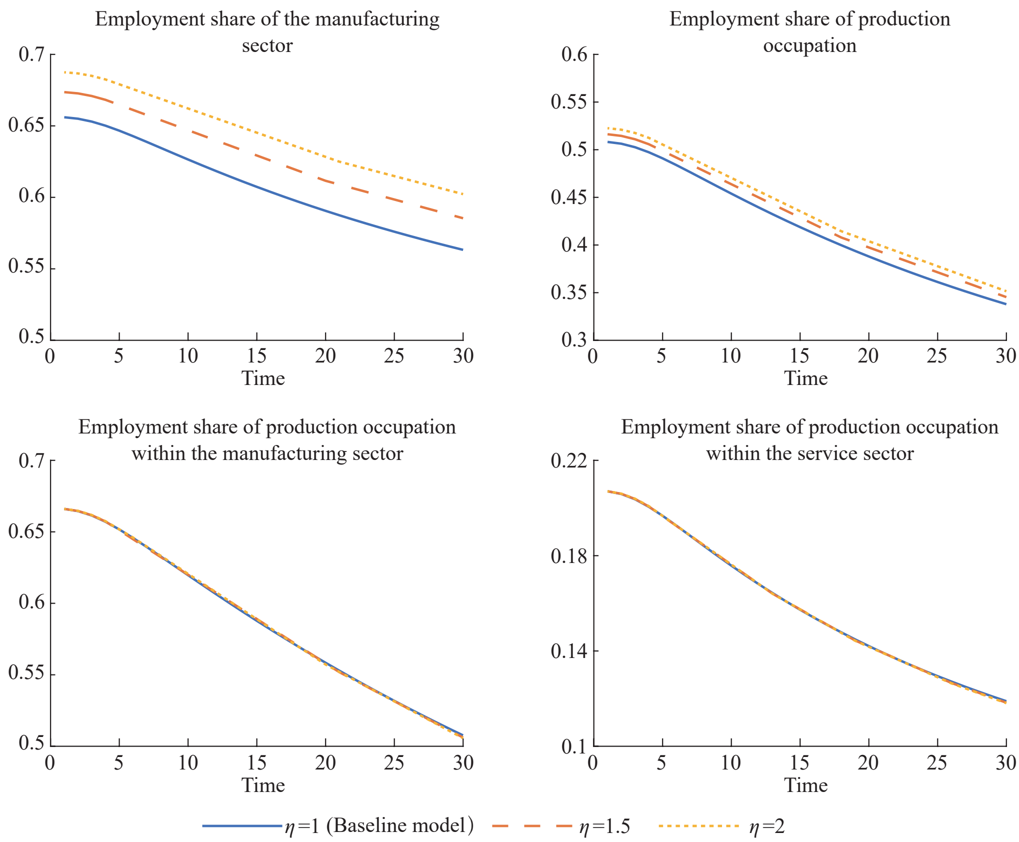


Figure 12: Simulation Results for Varying Labor Mobility Cost Values between Sectors

In summary, while labor market barriers do not alter the overall direction or trend of employment shifts and industrial transformation, they do influence the pace of these changes, and the propositions of the baseline model remain valid. However, the effects of different types of barriers vary. Job-level mobility constraints hinder both occupational reallocation and broader industrial upgrading. The higher the labor mobility cost between roles, the greater the share of production occupation—both overall and within sectors—and the slower the pace of workforce restructuring. Quantitatively, sector-level mobility barriers have a noticeable effect on industrial structure transformation, but only a limited influence on occupational dynamics.

7. Conclusions and Implications

With the rise of artificial intelligence (AI), China's manufacturing sector has experienced a significant shift in its employment composition, with labor increasingly moving from production to service-oriented roles. Drawing on characteristic facts, this paper develops a general equilibrium model that incorporates AI and job heterogeneity to analyze how these forces shape labor market evolution and support manufacturing transformation and upgrading. The key findings are outlined below.

First, when artificial intelligence technology biases toward production occupation and the elasticity of substitution between production and service occupation is low, advancements in AI drive labor shifts from production to service roles, fostering occupational structure changes both within sectors and across the broader economy. Additionally, if the elasticity of substitution between manufacturing and service industries is low, and production occupation hold a greater weight in manufacturing than in services, AI's job bias reduces the manufacturing employment share while increasing that of the service industry, thereby catalyzing industrial structure transformation.

Second, if artificial intelligence technology demonstrates a stronger bias toward production occupation—and such occupation comprise a larger share of manufacturing than of the service industry—then advancements in AI will enhance labor productivity in manufacturing relative to services. Although the share of employment in manufacturing may decline, substantial productivity gains driven by occupational structure shifts help maintain the sector's real output share, thereby supporting its transformation and upgrading.

Third, robustness analysis shows that encouraging deeper integration of diverse job types within industries and increasing AI R&D investment can further promote shifts in occupational structure and accelerate industrial transformation, all while preserving the stability of manufacturing's real output share. Conversely, as AI increasingly affects service-sector occupation, the gap in job bias narrows, slowing changes in occupational structure and the pace of transformation. This, in turn, raises labor productivity in services relative to manufacturing, partially alleviating the effects of Baumol's cost disease.

Fourth, labor market barriers do not change the overall direction or trend of occupational structure shifts and industrial transformation. However, reducing barriers to mobility between occupations can speed up the development of service-oriented manufacturing and accelerate the upgrading of the manufacturing sector, whereas barriers between sectors have a limited impact on these structural changes.

China's service-oriented manufacturing sector is growing rapidly, with significant potential for further evolution in occupational structure. This serves as a vital pathway to expand the profit margins of the manufacturing sector and forge new competitive advantages. It will reinforce China's position in global industrial chains, facilitate smooth economic circulation, and help build a modern industrial system. This paper provides a theoretical foundation for promoting occupational structure change and industrial transformation in the AI era and offers following policy recommendations to support the ongoing upgrading of manufacturing.

(1) Policymakers should provide greater support for generic AI technology R&D and strengthen digital infrastructure development. General-purpose AI technologies, such as large language models

(LLMs), represent a key frontier in AI innovation, offering versatile applications across diverse sectors. The AI technology examined in this paper is versatile and can be adopted by various industries, which is a typical characteristic of general AI. To this end, we propose two key recommendations. First, China should leverage its national institutional strengths to sustain and expand R&D investment in generic LLM AI models, fostering a comprehensive and self-reliant technological ecosystem. Second, it is also important to strategically and incrementally advance digital infrastructure by proactively deploying critical assets like 5G networks, data centers, and cloud computing hubs, laying a strong foundation for future deep integration and application.

(2) Market-oriented labor market reforms should be deepened to effectively address structural employment challenges. This study reveals that mobility barriers between occupation and sectors hinder occupational structure shifts and industrial transformation. To overcome these obstacles, we propose two key strategies. First, the government must advance labor market reforms by accelerating changes to the household registration system, dismantling labor market segmentation and regional barriers, breaking industry monopolies, and fostering an integrated labor market. Second, efforts should be made to enhance vocational skills training by supporting on-the-job and transitional training programs, improving workers' adaptability to new roles, and cultivating versatile "all-rounders" who can succeed across diverse occupation, thereby alleviating structural employment tensions.

(3) Enterprises should accelerate their adoption of "cloud, data, and intelligence" initiatives to drive job integration through digital transformation. This study finds that stronger integration of production and service occupation significantly advances occupational structure evolution and the development of service-oriented manufacturing. However, unclear job delineations hinder effective complementarity, reducing human capital efficiency. To address this, we propose two key suggestions. First, the government must promote accessible "cloud adoption, data utilization, and intelligence" services by incentivizing platforms—through targeted funding and financial support—to equip small and medium-sized enterprises with technologies like cloud computing, big data, and AI. This will enable digital upgrades in critical areas such as R&D, operations, production, logistics, and after-sales. Second, enterprises should reform human resource management by leveraging digital tools and systems to define clear role boundaries, ensure precise labor-position alignment, and foster deep integration across job types.

(4) Policy support should be strengthened for service-oriented manufacturing enterprises to foster deep integration between the digital and real economies. This study highlights artificial intelligence as a powerful catalyst for advancing service-oriented manufacturing. Harnessing AI and related technologies offers a powerful avenue for the seamless integration of the digital and real economies. To achieve this, we propose two key measures. First, the government should encourage leading manufacturing firms within industrial clusters to transition toward service-oriented manufacturing by strengthening collaboration with upstream and downstream partners in the industrial chain and supply chain stakeholders. This would support the establishment of customized, service-oriented manufacturing networks, aligned with the needs of individual industries and their industrial chains. Second, targeted funding should be introduced through industrial guidance policies to provide financial support for enterprises shifting toward service-oriented manufacturing, complemented by temporary tax exemptions or incentives to accelerate their transformation and growth.

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