Interindustry Factor Allocation and Trade Network Status

Xiaosong Wang, Yuding Zhou*

Against the backdrop of production and sales globalization, a country can utilize its trade network position to secure greater benefits from international trade and gradually enhance its economic and trade influence. This process is inseparable from the rational allocation of production factors. As a crucial cornerstone of China's economic growth, the industrialization system represented by the manufacturing sector has achieved significant development over an extended period. However, in recent years, influenced by multiple factors, the level of factor allocation within the industrial system has shown a rapid decline. Based on theoretical and empirical analyses, this study demonstrated that a rapid decline in the efficiency of production factor allocation has significantly lowered the position of Chinese industries in the global trade network, which is especially evident in the export trade network. A mechanism analysis revealed that an excessive decline in factor allocation efficiency exacerbates resource misallocation, increases production costs, and dampens regional entrepreneurial activity, thereby undermining industries' positions in the global trade network. However, abundant human capital, the advancement of new industrialization, well-functioning market mechanisms, and proactive industrial policies significantly mitigate these adverse effects.

Keywords: factor allocation, trade network, economic transformation, new industrialization, digital economy

1. Introduction

As a crucial foundation for advancing new industrialization and cultivating new quality productive forces, the sound and healthy development of the manufacturing sector is inseparable from sustained high-quality factor inputs. However, since the new millennium, China's industrial growth has slowed significantly, with the secondary sector gradually yielding its core role in economic growth and employment provision to the tertiary sector. Particularly after 2012, the industrial structure dominated by manufacturing has shown marked contraction. In terms of production factor allocation, the proportion of factor inputs in the secondary sector has exhibited a clear downward

* Xiaosong Wang, China Economic Reform and Development Research Institute, Renmin University of China, School of Economics, Email: wangxiaosong@ruc.edu.cn. Yuding Zhou (corresponding author), School of International Trade and Economics, University of International Business and Economics, Email: zhou_zyd@uibe.edu.cn.

Open Access. © 2025 The Author(s), published by De Gruyter.
This work is licensed under the Creative Commons Attribution 4.0 License.

trend since 2012, with the share of manufacturing labor continuing to decline. This phenomenon has already drawn widespread attention and concern from multiple stakeholders. Against this backdrop, the Third Plenary Session of the 20th Central Committee of the Communist Party of China emphasized the critical role of “developing new quality productive forces according to local conditions” and “establishing mechanisms to maintain appropriate investment proportions in manufacturing” for achieving high-quality economic development. These developments demonstrate that, against the significant reality of China’s declining manufacturing dominance in recent years, quantifying interindustry production factor allocation changes, analyzing their economic effects, and mitigating corresponding adverse impacts hold profound theoretical and practical significance for improving industrial policies, strengthening emerging industries, and realizing high-quality industrial development in China’s future.

A nation’s position in global trade networks serves as an international manifestation of its manufacturing sector’s development quality. In the context of production and sales globalization, a country can utilize its status and role in trade networks to secure greater benefits from international trade, enhance its influence across industrial and value chains in the global production system, and elevate its economic and trade discourse power. This aligns perfectly with key medium- to long-term strategies outlined in the *14th Five-Year Plan for High-Quality Foreign Trade Development*, which emphasizes “deepening participation in international economic and trade cooperation centered on industrial and value chains.” By utilizing its comparative advantages to participate in the international division of labor and deeply integrate into global value chains, China has gradually obtained a central position in global trade networks since its WTO accession. The comprehensive industrialization system rapidly established since the reform and opening up undoubtedly constitutes one of the most crucial driving forces behind these achievements. From an economic activity perspective, the organization and allocation of production factors play fundamental supporting roles in product manufacturing and operational decision-making for foreign trade enterprises throughout trade activities and the deepening of trade networks. However, as emphasized by the guiding principle of “maintaining fundamental stability in the manufacturing sector’s proportion and consolidating the foundation of the real economy,” the dual contraction of manufacturing production scale and factor inputs—against the backdrop of China’s incomplete industrialization process and remaining industrial system deficiencies—will undoubtedly exert profound impacts on the nation’s transition from a “manufacturing and trading giant” to a “manufacturing and trading power” and on its competitiveness and influence within global trade networks.

In reality, the shift in production factor resources from the secondary to the tertiary sector represents a general trend in global industrial development (Cai, 2021).

However, the level and pace of factor allocation constitute more critical issues worthy of in-depth investigation. Specifically, has the decline in factor allocation efficiency in China's manufacturing sector been too rapid? What are its underlying causes and economic effects? While existing studies have predominantly examined the impact of factor allocation changes on economic growth from qualitative perspectives, relatively few have quantitatively assessed their trade effects—particularly the long-term consequences for trade competitiveness. This paper aims to make breakthroughs in this research direction.

2. Theoretical Model and Research Hypotheses

From an industrial adjustment perspective, this study incorporates the fundamental framework of enterprises' economic behaviors in trade networks established by Dhyne *et al*. (2021) and Huang *et al*. (2023) while characterizing the economic implications of trade network topological features. Building upon this foundation, we examine how changes in factor allocation efficiency affect industries' positions in global trade networks and analyze the underlying mechanisms.

2.1. Consumer Preferences

Assume that the representative consumer has a homogeneous CES utility function U_H for product consumption, as shown in the following equation:

$$U_H = \left(\sum_{k \in \Omega_H} \left(\lambda_{kH} q_{kH} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where the subscripts H and F represent domestic and foreign, respectively, Ω is the feasible consumption set for consumers, k represents the corresponding product, λ is the consumption preference parameter, and σ is the elasticity of substitution between products, satisfying $\sigma > 1$. Under the assumption of utility maximization, given the product price p_{kH}, the consumption level of the product q_{kH} can be obtained as follows:

$$q_{kH} = \lambda_{kH}^{\sigma-1} \frac{p_{kH}^{-\sigma}}{P_H^{1-\sigma}} E_H. \tag{2}$$

P_H is the domestic consumer price index, as shown in Equation (3). Here, p_{kH} is the market price of the product k locally. E_H represents the expenditure level of domestic consumers.

$$P_H = \left(\sum_{k\in\Omega_H} \lambda_{kH}^{\sigma-1} p_{kH}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{3}$$

Similarly, under the assumption of homogenous preferences of foreign consumers, the consumption level of foreign consumers for domestic product *k* can be obtained from the following equation, where $p_{kF} = \tau_{kF} p_{kH}$, $\tau_{kF} = \tau_{Fk} > 1$, representing the bilateral trade cost between the domestic and foreign markets:

$$q_{kF} = \lambda_{kF}^{\sigma-1} \frac{p_{kF}^{-\sigma}}{P_F^{1-\sigma}} E_F. \tag{4}$$

2.2. Enterprise Production and Network Structure

For product *k*, suppose that the enterprise uses both labor and intermediate input products (from domestic or foreign sources) during the production process and that the production function is in the form of Cobb–Douglas, as shown in the following equation:

$$q_k = \Gamma_k z_k \left(\prod_{f\in\Omega_{Fk}} M_{fk}^{\gamma_{fk}} \prod_{h\in\Omega_{Hk}} M_{hk}^{\gamma_{hk}}\right)^{1-\eta} \left(L_k\right)^{\eta}, \tag{5}$$

where Γ_k is a constant and z_k is the total factor productivity. M_{fk} and M_{hk} represent the quantities of intermediate inputs from abroad and domestically (with corresponding prices p_{fk} and p_{hk}), respectively. Ω_{Fk} and Ω_{Hk} are sets of intermediate inputs from abroad and domestically, respectively, and γ_{fk} and γ_{hk} are the corresponding shares of the intermediate inputs, satisfying $\sum_{f\in\Omega_{Fk}} \gamma_{fk} + \sum_{h\in\Omega_{Hk}} \gamma_{hk} = 1$. The wage level *w* in the manufacturing sector is determined by the following equation under equilibrium, where N_k represents the number of enterprises producing product *k* and L_{kH} represents the total labor force in industry *k*:

$$N_k L_k = L_{kH}. \tag{6}$$

Then, the marginal cost c_k of product *k* can be expressed as follows:

$$c_k = \frac{\chi_k w^{\eta}}{z_k}, \tag{7}$$

where $\chi_k = \left(\prod_{f\in\Omega_{Fk}} p_{fk}^{\gamma_{fk}} \prod_{h\in\Omega_{Hk}} p_{hk}^{\gamma_{hk}}\right)^{1-\eta}$, under the assumption of cost minimization:

$$L_k = \frac{\eta q_k}{w^{1-\eta}} \frac{\chi_k}{z_k}. \tag{8}$$

Drawing on the representative research approaches of Ballester *et al*. (2006) and Liu *et al*. (2021), this paper defines the characteristics of the most central node in a trade network as follows: Compared to the initial equilibrium, its participation or drop out generates the largest variation in overall profit levels, indicating that this node possesses maximum influence and control over the network. Regarding the global trade network, for the original directed weighted trade network $\boldsymbol{G}\langle \boldsymbol{V}, \boldsymbol{E}\rangle$, the removal of the most central node J (resulting in the transformed network $\boldsymbol{G'}\langle \boldsymbol{V}^{(-J)}, \boldsymbol{E}^{(-J)}\rangle$) would cause the greatest welfare loss, where V represents the set of nodes (countries or regions) and E denotes the set of edges (trade flows), as follows:

$$J = \arg\max_{J\in V}\left\{\sum\nolimits_{i\in V}\boldsymbol{\Pi}_{iF} - \sum\nolimits_{i\in V^{-J}}\bar{\boldsymbol{\Pi}}_{iF}\right\} = \arg\max_{J\in V}\left\{\boldsymbol{\Pi}_{JF} + \sum\nolimits_{i\in V^{-J}}\left(\boldsymbol{\Pi}_{iF} - \bar{\boldsymbol{\Pi}}_{iF}\right)\right\}, \tag{9}$$

where $\bar{\boldsymbol{\Pi}}_{iF}$ represents the profit level of other nodes in the new equilibrium of $\boldsymbol{G'}\langle \boldsymbol{V}^{(-J)}, \boldsymbol{E}^{(-J)}\rangle$. Furthermore, this paper introduces the position index Net_{JF} of node J in the global trade network, as shown in Equation (10). In combination with Equation (9), it can be seen that Net_{JF} is positively correlated with the network position of node J; the higher the position and influence of node J in the trade network, the larger the Net_{JF}:

$$e^{Net_{JF}} = \left(\sum\nolimits_{i\in V}\boldsymbol{\Pi}_{iF} - \sum\nolimits_{i\in V^{-J}}\bar{\boldsymbol{\Pi}}_{iF}\right) = \boldsymbol{\Pi}_{JF} + \sum\nolimits_{i\in V^{-J}}\left(\boldsymbol{\Pi}_{iF} - \bar{\boldsymbol{\Pi}}_{iF}\right). \tag{10}$$

For product k:

$$e^{Net_{kF}} = N_k\left[\boldsymbol{\Pi}_{kF} + \sum\nolimits_{i\in V^{-k}}\left(\boldsymbol{\Pi}_{iF} - \bar{\boldsymbol{\Pi}}_{iF}\right)\right], \tag{11}$$

where $\boldsymbol{\Pi}_{kF}$ represents the export profits of representative enterprises. At this time, the market clearing condition for the product is as follows:

$$q_k = q_{kH} + q_{kF} + \sum\nolimits_{h^d\in\Phi_{kh}} M_{kh^d} + \sum\nolimits_{f^d\in\Phi_{kf}} M_{kf^d}, \tag{12}$$

where q_{kH} and q_{kF} represent the final consumption of product k in the domestic and international markets, respectively. M_{kh^d} and M_{kf^d} are the quantities of domestic and foreign demand that require product k as an intermediate input, while Φ_{kh}

and Φ_{kf} represent the domestic and foreign demand sets that require product k as an intermediate input. Furthermore, this paper introduces the assumption from studies by Dhyne *et al*. (2021) and Huang *et al*. (2023) that domestic companies offer intermediate inputs at a marginal cost. For products k used for other demands, companies price them at a ratio of $\sigma/(\sigma-1)$ based on marginal cost, and the profit level $\mathbf{\Pi}_k$ of the enterprise is shown in Equation (13). Here, $\mathbf{\Pi}_{kH}$ and $\mathbf{\Pi}_{kF}$ represent the profits earned by the enterprise from domestic and foreign markets, $\aleph_k = \aleph_{kH} + \aleph_{kF} = \left[\frac{\lambda_{kH}^{\sigma-1}\chi_k^{1-\sigma}E_H}{\sigma P_H^{1-\sigma}}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} + \boldsymbol{I}_{kF}\frac{\lambda_{kF}^{\sigma-1}\chi_k^{1-\sigma}\tau_{kF}^{1-\sigma}E_F}{\sigma P_F^{1-\sigma}}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\right] > 0$. When product k is exported to foreign countries, $\boldsymbol{I}_{kF} = 1$; otherwise $\boldsymbol{I}_{kF} = 0$.

$$\mathbf{\Pi}_k = \underbrace{\frac{\lambda_{kH}^{\sigma-1}\chi_k^{1-\sigma}w^{\eta(1-\sigma)}z_k^{\sigma-1}E_H}{\sigma P_H^{1-\sigma}}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}}_{\mathbf{\Pi}_{kH}} + \underbrace{\boldsymbol{I}_{kF}\frac{\lambda_{kF}^{\sigma-1}\chi_k^{1-\sigma}w^{\eta(1-\sigma)}z_k^{\sigma-1}\tau_{kF}^{1-\sigma}E_F}{\sigma P_F^{1-\sigma}}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}}_{\mathbf{\Pi}_{kF}}$$
$$= w^{\eta(1-\sigma)}z_k^{\sigma-1}\aleph_k. \tag{13}$$

2.3. Fator Allocation and Trade Network

Taking the labor factor as an example, assuming that the shock effect is ΔL_{kH}, the actual labor employment scale L_{kH} in the manufacturing sector's labor market is lower than the initial optimal allocation L_{kH}^*; that is,

$$L_{kH} = L_{kH}^* - \Delta L_{kH}, \tag{14}$$

where $\Delta L_{kH} > 0$. At this time, the change level of the production factor allocation is noted as $fap_k = \frac{\zeta \Delta L_{kH}}{\rho_k \varrho_k} > 0$. The higher its value, the greater the degree of decline in factor allocation. In this definition, this paper incorporates market efficiency (ρ_k) and industrial support policy level (ϱ_k) into the investigation. Their increase can effectively adjust the magnitude of the impact, thereby reducing the actual degree of change in factor allocation. ζ is a corresponding constant. Under the condition of the given initial optimal allocation L_{kH}^*, taking the total differential of Equation (14) yields the following:

$$\mathrm{d}L_{kH} = -\frac{\rho_k \varrho_k}{\zeta}\mathrm{d}fap_k. \tag{15}$$

Given that whether an enterprise enters industry k depends on the profit level of that industry, the higher the profit level, the more motivated an enterprise is to enter that industry. For simplification, assume $\frac{\partial N_k}{\partial \mathbf{\Pi}_k} = \frac{1}{\tilde{\Pi}} > 0$, where $\tilde{\Pi}$ represents the average profit level of other industries in society. Considering that during the outflow of production factors in the manufacturing industry, the labor scale of production enterprises, which is an important support for industrial development, will shrink. In response, this paper describes this process using the following equation:

$$\frac{\partial L_k}{\partial fap_k} = s_1 fap_k = -\frac{\varphi fap_k}{\varpi_k \vartheta_k} < 0 . \tag{16}$$

Here, ϖ_k and ϑ_k represent human capital and new industrialization levels, respectively, with $s_1 = -\varphi / \left(\varpi_k \vartheta_k\right) < 0$. Based on Equation (16), the rise in human capital and the development of industrial digitization mitigate the decline in actual effective labor during the reduction in factor allocation efficiency, where φ is the corresponding constant. Integrating the above analysis, the partial derivative of the node's position index Net_{kF} in the global trade network with respect to fap_k yields the following:

$$\frac{\partial Net_{kF}}{\partial fap_k} = \mathcal{A}\left[\underbrace{\frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_k s_1 fap_k}{N_k \tilde{\Pi}}}_{①} + \underbrace{\frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_{kF} s_1 fap_k}{\mathbf{\Pi}_{total}}}_{②}\right] + \underbrace{\left[\left(\frac{\aleph_k}{N_k \tilde{\Pi}} + \frac{\aleph_{kF}}{\mathbf{\Pi}_{total}}\right)\vartheta_k\right]\frac{\partial z_k}{\partial fap_k}}_{③} , \tag{17}$$

where $\mathcal{A} = \frac{\eta^2 (\sigma-1) w^{\eta-1} q_k \chi_k}{(1-\eta) L_k^2} > 0$, $\mathbf{\Pi}_{total} = \mathbf{\Pi}_{kF} + \sum_{i \in V^{-k}} \sum_{f^d \in \Phi_{kf}} \left(\mathbf{\Pi}_{if^d F} - \bar{\mathbf{\Pi}}_{if^d F}\right) > 0$, and $\vartheta_k = \left[\frac{\eta^2 (\sigma-1) w^{\eta(2-\sigma)-1} z_k^{\sigma-3} q_k \chi_k}{(1-\eta) L_k} + (\sigma-1) w^{\eta(1-\sigma)} z_k^{\sigma-2}\right] > 0$. Equation (17) shows that the impact of factor allocation changes on the trade network can be decomposed into: ① the enterprise entry–exit effect, ② the production cost effect, and ③ the productivity effect. Since $s_1 < 0$, we have $① < 0$ and $② < 0$, meaning that a decline in factor allocation efficiency negatively affects the trade network position by crowding out enterprises within the industry and raising production costs. As for ③, its sign is uncertain: when the productivity effect is negative, $\frac{\partial Net_{kF}}{\partial fap_k} < 0$, whereas when the productivity effect is positive and exceeds the absolute sum of the enterprise entry–exit and production cost effects, $\frac{\partial Net_{kF}}{\partial fap_k} > 0$. Based on the above theoretical analysis, and considering the uncertainty of the productivity effect, this paper proposes the following competing hypotheses at the aggregate level for empirical testing:

Hypothesis 1a: A rapid decline in factor allocation efficiency in the manufacturing sector raises production costs and dampens entrepreneurial incentives, thereby exerting a negative impact on trade network position. Conversely, an improvement in factor allocation generates a significantly positive effect.

Hypothesis 1b: A rapid decline in factor allocation efficiency in the manufacturing sector eliminates outdated production capacity, releases surplus factors, enhances enterprise productivity, and consequently has a positive impact on the trade network position.

Building on Equation (17), this study further incorporates the contemporary context of factor allocation dynamics to analyze the roles of labor quality improvement and new industrialization in shaping the trade network effects of factor allocation. Specifically, by taking partial derivatives of Equation (17) with respect to ϖ_k and ϑ_k, we obtain the following:

$$\frac{\partial^2 Net_{kF}}{\partial fap_k \partial \varpi_k} = \frac{\mathcal{A}\varphi}{\varpi_k^2 \vartheta_k}\left[\frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_k fap_k}{(1-\eta) N_k \tilde{\Pi}} + \frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_{kF} fap_k}{(1-\eta) \mathbf{\Pi}_{total}}\right] > 0, \tag{18}$$

$$\frac{\partial^2 Net_{kF}}{\partial fap_k \partial \vartheta_k} = \frac{\mathcal{A}\varphi}{\varpi_k \vartheta_k^2}\left[\frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_k fap_k}{(1-\eta) N_k \tilde{\Pi}} + \frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_{kF} fap_k}{(1-\eta) \mathbf{\Pi}_{total}}\right] > 0. \tag{19}$$

The above Equation (18) and (19) demonstrate that improvements in labor quality and advancements in new industrialization can effectively moderate the trade network effects of factor allocation. Based on this analysis, this paper proposes the following testable theoretical hypothesis:

Hypothesis 2: The rise of factor quality, represented by human capital, and new industrialization characterized by digital empowerment will mitigate the corresponding effects induced by changes in factor allocation.

Building upon the preceding analysis of the mechanisms underlying factor allocation dynamics, this study further examines how two key economic characteristics—effective markets and industrial policies—shape the trade network effects of factor allocation changes. Specifically, by deriving partial derivatives from Equation (17), we obtain the following:

$$\frac{\partial^2 Net_{kF}}{\partial fap_k \partial \rho_k} = -\frac{s_1 \zeta \Delta L_{kH} \mathcal{A}}{\rho_k^2 \varrho_k}\left[\frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_k}{(1-\eta) N_k \tilde{\Pi}} + \frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_{kF}}{(1-\eta) \mathbf{\Pi}_{total}}\right] > 0, \tag{20}$$

$$\frac{\partial^2 Net_{kF}}{\partial fap_k \partial \varrho_k} = -\frac{s_1 \zeta \Delta L_{kH} \mathcal{A}}{\rho_k \varrho_k^2} \left[\frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_k}{(1-\eta) N_k \tilde{\Pi}} + \frac{w^{\eta-\sigma\eta} z_k^{\sigma-2} \aleph_{kF}}{(1-\eta) \mathbf{\Pi}_{total}} \right] > 0 . \tag{21}$$

The above Equation (20) and (21) indicate that well-functioning markets and proactive industrial policies can effectively moderate the trade network effects of factor allocation. In economic terms, as efficient mechanisms for resource allocation optimization, effective market systems and industrial policies play a pivotal role in promoting stable economic performance. Based on this analysis, this paper proposes the following testable theoretical hypothesis:

Hypothesis 3: Through price and signaling mechanisms, effective markets and industrial policies can moderate the impact of factor allocation changes on trade network position.

3. Indicator Calculation and Explanation

3.1. Measurement of Trade Network Position

3.1.1. HITS Algorithm

The Hyperlink-Induced Topic Search (HITS) algorithm categorizes network pages into two types based on node attributes: authority pages and hub pages. Translating this algorithmic concept to the global trade network reflects that countries with a more central position as importers (high authority value) will be pointed to by multiple key exporting countries, while countries with a more central position as exporters (high hub value) will point to core importers in multiple trade networks. Consider the directed weighted trade network $\boldsymbol{G}\langle \boldsymbol{V}, \boldsymbol{E} \rangle$, where u and v represent country nodes in the trade network, totaling N nodes. All nodes collectively form the node set $\boldsymbol{V}$ of the trade network. A directed edge (u, v) indicates the existence of exports from country u to country v, and the set of all directed edges (u, v) constitutes the edge set $\boldsymbol{E}$ of the trade network. According to the HITS algorithm, the authority and hub values are calculated as follows:

$$\boldsymbol{A}_d = \boldsymbol{M}^T \cdot \boldsymbol{H}_{d-1} , \tag{22}$$

$$\boldsymbol{H}_d = \boldsymbol{M} \cdot \boldsymbol{A}_d , \tag{23}$$

where d represents the number of iterations and $\boldsymbol{A}$ and $\boldsymbol{H}$ represent the $N \times 1$ dimensional column vectors of authority values and hub values, respectively. Under the initial iteration condition ($d = 0$), the authority values and hub values of all nodes are $1/N$. $\boldsymbol{M}$ is the $N \times N$ dimensional adjacency matrix used to describe the connection relationships in the trade network, and $\boldsymbol{M}^T$ is its transpose. The calculation method for the element m_{uv} in matrix $\boldsymbol{M}$ is as follows:

$$m_{uv} = \begin{cases} 1 & \text{If country } u \text{ exports to country } v \\ 0 & \text{If country } u \text{ does not exporte to country } v \end{cases}. \tag{24}$$

After each iteration, the obtained column vectors $\boldsymbol{A}_k$ and $\boldsymbol{H}_k$ are normalized to unit vectors to ensure the convergence of the iterative calculation process. Furthermore, this paper adjusts m_{uv} with trade volume weighting to differentiate the heterogeneous impacts of trade partners of different sizes on node trade network characteristics, making the calculated trade network characteristics more realistic and accurate, as follows:

$$m_{uv} = \frac{export_{uv}}{\sum_v export_{uv}} \text{ ,if country } u \text{ exports to country } v, \tag{25}$$

where $export_{uv}$ refers to the export scale from country *u* to country *v*.

3.1.2. PageRank Algorithm

Similar to the HITS algorithm, the PageRank algorithm assumes that the quality of a network node is determined by both the quantity and quality of its neighboring nodes. To prevent divergence in the iterative computation caused by the existence of zero outbound links, this study utilizes the following modified PageRank algorithm:

$$PR(u) = \frac{(1-\beta)}{N} + \beta \sum_{(v,u)\in E} \frac{PR(v)}{outdegree(v)}, \tag{26}$$

$$\boldsymbol{PR}_d = \boldsymbol{P}^{\mathrm{T}} \cdot \boldsymbol{PR}_{d-1}, \tag{27}$$

$$\boldsymbol{P} = \beta \boldsymbol{M} + \frac{1-\beta}{N} \boldsymbol{e}\boldsymbol{e}^{\mathrm{T}}, \tag{28}$$

where $\boldsymbol{PR}$ is the $N \times 1$ dimensional column vector representing the PageRank value of the nodes, $\boldsymbol{P}$ is the modified $N \times N$ adjacency matrix, $\boldsymbol{e}=[1,1,1\cdots,1]^{\mathrm{T}}$, β is the corresponding damping factor, which is set to 0.85 according to existing research, and the meanings of other symbols are the same as above.

3.2. Measurement of Changes in the Allocation of Production Factors

Drawing on the measurement approach of Rodrik (2016), this paper constructs the manufacturing factor allocation index (fap) as shown in Equations (29) and (30). A higher value of this index indicates a greater outflow of production factors from manufacturing, while a lower value reflects a net inflow of factors into the sector.

$$fap1_{i,c,t}=-\left[\sigma_K\left(\frac{\frac{K^m_{i,c,t}}{K_{i,t}}-\frac{K^m_{i,c,t-1}}{K_{i,t-1}}}{\frac{K^m_{i,c,t-1}}{K_{i,t-1}}}\right)+\sigma_L\left(\frac{\frac{L^m_{i,c,t}}{L_{i,t}}-\frac{L^m_{i,c,t-1}}{L_{i,t-1}}}{\frac{L^m_{i,c,t-1}}{L_{i,t-1}}}\right)\right], \tag{29}$$

$$fap2_{i,c,t}=-\left[\sigma_K\left(\frac{\frac{K^m_{i,c,t}}{K_{i,t}}-\frac{K^m_{i,c,t-1}}{K_{i,t-1}}}{\frac{K^m_{i,c,t-1}}{K_{i,t-1}}}\right)+\sigma_L\left(\frac{\frac{L^m_{i,c,t}}{L_{i,t}}-\frac{L^m_{i,c,t-1}}{L_{i,t-1}}}{\frac{L^m_{i,c,t-1}}{L_{i,t-1}}}\right)\right]-\left(\frac{A^m_{i,c,t}-A^m_{i,c,t-1}}{A^m_{i,c,t-1}}\right), \tag{30}$$

where $K^m_{i,c,t}$ and $L^m_{i,c,t}$ represent the fixed asset investment and labor level of sub-industry c in the manufacturing sector m of province i at time t, respectively. $K_{i,t}$ and $L_{i,t}$ represent the total fixed asset investment and total labor in all industries of province i at time t. $A^m_{i,c,t}$ is the total factor productivity of industry c in province i calculated based on the algorithm of Lee and Schmidt (1993). σ_K and σ_L represent the elasticity of output with respect to capital and labor, respectively. Under the assumption of constant returns to scale, this paper takes the values of σ_K and σ_L to be 0.6 and 0.4, respectively. Furthermore, in reference to the approach taken by Brandt *et al*. (2017), the national economic industry classification is aligned with the HS2002 six-digit level, thus obtaining the measurement indicators for the level of factor allocation changes in industry h under HS6, denoted as $fap1_{i,h,t}$ and $fap2_{i,h,t}$.[1]

4. Empirical Design and Data Selection

Based on the HS6 subindustry data of 30 provinces (autonomous regions/municipalities directly under the central government) in China from 2002 to 2021,[2] this paper specifically constructs the empirical equation, as shown in the following equation:

[1] In addition to the combination of 0.6/0.4, this paper also selects a series of weight combinations such as 0.3/0.7, 0.4/0.6, 0.5/0.5, and 0.7/0.3 to reconstruct indicators and conduct empirical analysis, and the conclusions do not change significantly.

[2] Due to the serious lack of some data from the Xizang Autonomous Region, the corresponding samples are not included in the empirical analysis.

$$Y_{i,h,t} = \alpha_0 + \alpha_1 fap_{i,h,t} + \sum_l \beta_l x^l_{i,(h),t} + \eta_i + \eta_h + \eta_t + \eta_{h,t} + \varepsilon_{i,h,t}, \quad (31)$$

where $Y_{i,h,t}$ is the explained variable, which represents the global trade network status of h industry in the period t of province i under the six-digit level of HS2002, which reflects the pivot degree and guiding ability of the industry in the global trade network. The higher the value, the closer the connection between the industry and other trade subjects in the global trade network, the greater the impact on trade flow, and the stronger the ability to control and obtain resources. This paper further takes the logarithm of it. $fap_{i,h,t}$ is the core explanatory variable, representing the level of factor allocation change in industry h of province i during period t, and $x^l_{i,(h),t}$ is the set of other control variables. η_h and η_t represent the fixed effects of industry and year, respectively. Considering that there are relatively few data on trade characteristics at the industry level, this paper further controls for the fixed effect $\eta_{h,t}$, which represents the fixed effect of the HS4 digit industry × years. $\varepsilon_{i,h,t}$ is the error term. The raw data used to calculate the specific indicators were selected from the UN Comtrade database, the customs database, the *China Industrial Statistical Yearbook*, the *China Fixed Asset Investment Statistical Yearbook*, the *China Statistical Yearbook*, and provincial statistical yearbooks.

In addition to the core explanatory variables, this paper includes the following control variables in the empirical equation:① GDP scale of each province in the current year (natural logarithm, *lngdp*), ② industrial added value of each province in the current year (natural logarithm, *lnindvalue*), ③ general budget revenue of local finance in each province in the current year (natural logarithm, *lnbudget*), ④ number of large-scale industrial enterprises in each province in the current year (natural logarithm, *lnenterprise*), ⑤ employment in railway transportation in each province in the current year (natural logarithm, *lnrailway*), ⑥ patent application status in each province in the current year (natural logarithm, *lnpatent*). Descriptive statistics of variables can be found in the Appendix on the Journal's website.

5. Empirical Results and Analysis

5.1. Benchmark Regression and Robustness Test

5.1.1. Benchmark Regression

Based on empirical Equation (31), Table 1 reports the corresponding benchmark regression results. In columns (1)–(6), the regression coefficients of the core explanatory variables $fap1$ and $fap2$ are all significantly negative.[1] Notably, the

[1] In the subsequent regression analysis, except for the analysis of the explained variable at the province × industry level, all others control for the fixed effects of province × year to identify the characteristics of the control variables.

benchmark regression significantly observes the negative effect of declining factor allocation efficiency on the import trade network position.

Table 1. Benchmark Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	lnpagerank	*lnhub*	*lnauth*	*lnpagerank*	*lnhub*	*lnauth*
*fap*1	–0.367***	–0.369***	–0.259***			
	(0.026)	(0.027)	(0.028)			
*fap*2				–0.353***	–0.353***	–0.242***
				(0.026)	(0.027)	(0.028)
Sample size	1575898	1575898	1575898	1575898	1575898	1575898
Adjusted R^2	0.469	0.486	0.364	0.469	0.486	0.364
Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively, with the numbers in parentheses representing the standard errors clustered at the province-industry level, and the same applies below.

5.1.2. Instrumental Variable Regression

To address potential endogeneity issues in the core explanatory variables $fap1$ and $fap2$, this study employed an instrumental variable approach. For the selection of instruments, drawing on the research strategy of Wang *et al*. (2023), we used the topographic ruggedness index of each province (municipality) as the instrumental variable. Since this topographic ruggedness index is time invariant, we further incorporated regional environmental protection intensity (lagged by one period) as a time-varying factor, based on existing studies analyzing the causes of declining factor allocation. The product of these two variables serves as the instrumental variable (*IV*). Regarding the construction of the regional environmental protection intensity indicator, this study followed the methodology of Chen and Chen (2018) by measuring the frequency of keywords such as environmental protection, pollution, energy consumption, emission reduction, sewage discharge, ecology, green development, low carbon, air quality, chemical oxygen demand (COD), sulfur dioxide, carbon dioxide, PM10, and PM2.5 in local government work reports. Using the aforementioned instrumental variables in a two-stage least squares regression, the results show that the coefficients of the core explanatory variables remain significantly negative. This confirms that even after addressing endogeneity concerns, the adverse impact of declining factor allocation efficiency on trade network position remains statistically significant.

It should be noted that in the regression results, the coefficient for *lnauth* is no longer significant, indicating that, after addressing endogeneity, the decline in factor allocation does not have a statistically significant impact on the import trade network. A potential explanation is that, in addition to the negative channels identified in the benchmark regression, there exists a mutually reinforcing positive interaction between factor allocation changes and the import trade network. On the one hand, a declining factor allocation may prompt downstream enterprises to import more raw materials and intermediate goods to compensate for domestic factor shortages. On the other hand, developing countries often lack a comparative advantage in certain industries, and trade liberalization may expose their manufacturing sectors to external shocks, turning them into net importers in those industries, thereby exacerbating factor allocation distortions (Rodrik, 2016). The instrumental variable regression results are shown in the Appendix online.

5.2. Heterogeneity Analysis

5.2.1. Group Regression by Geographic Location

Given the pronounced regional heterogeneity in China's industrial development stages, this study conducted a heterogeneity analysis from a geographical perspective. Grouped regressions based on eastern, central, and western regions show that the coefficients of the core explanatory variables $fap1$ and $fap2$ are significantly negative across all regions, with relatively consistent magnitudes observed from east to west. However, it is noteworthy that unlike the eastern region, which has entered the postindustrialization stage, the central and western regions have yet to reach this phase and still need to advance their industrialization processes. Nevertheless, the observed decline in manufacturing factor allocation—accompanied by weakening industrial advantages and the outflow of labor and capital—has already exerted adverse effects on long-term industrial development. In the next development stage, targeted industrial policies should be prioritized to address these challenges. Group regression results by geographic location are shown in the online Appendix.

5.2.2. Group Regression by Product Contract Density

Drawing on Nunn's (2007) measurement approach, this study conducted grouped regressions by distinguishing the contract density levels of trade products. The regression results show that the coefficients of the core explanatory variables $fap1$ and $fap2$ are significantly negative in all groups but relatively larger in the high-contract-density group. This finding provides supplementary validation for the reliability of the benchmark regression results. It also indicates that stronger contract protection reduces uncertainty in expectations about future production activities, thereby mitigating the impact of factor allocation changes on high-contract-density products. Group regression results by product contract density are shown in the online Appendix.

5.2.3. Group Regression Based on the Level of Changes in Factor Allocation

To further examine whether the impact of varying degrees of factor allocation changes on trade networks exhibits heterogeneity, this study divided the extent of factor allocation changes into four groups—low, medium-low, medium-high, and high—using quartile intervals (25% increments) and conducted additional empirical tests. The regression results reveal that, the natural and gentle outflow of these factors, will facilitate the upgrade and transformation of the industry, thereby enhancing its position in the global trade network. The regression coefficients in columns (3) and (4) are also significantly negative, reflecting severe declines in factor allocation with premature and excessive characteristics. Notably, compared to column (3), the adverse impact on trade network position is somewhat mitigated in column (4), where factor allocation declines more rapidly. Further analysis of the sample in column (4) reveals that the sample includes industries which have long suffered from backward and excess capacity. This suggests that during new industrialization, advancing structural reforms to eliminate overcapacity and optimize industrial structure can improve interindustry resource allocation and enhance these industries' positions in the global trade network.

Table 2. Regression Results of the Changes of Key Factor Allocation

	(1) *lnpagerank* Low	(2) *lnpagerank* Medium–low	(3) *lnpagerank* Medium–high	(4) *lnpagerank* High
*fap*2	0.911***	–0.120	–1.000***	–0.244***
	(0.138)	(0.289)	(0.293)	(0.063)
Sample size	392779	392975	393156	392417
Adjusted R^2	0.514	0.492	0.468	0.483
Industry × Year	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes

6. Mechanism Examination and Further Analysis

6.1. Examination of the Impact Channels of Factor Allocation in Production

6.1.1. Resource Mismatch and Manufacturing Production Costs

The theoretical model analysis reveals that inter-industry factor allocation may exacerbate factor misallocation in the manufacturing sector, raising production costs and undermining global competitiveness. Drawing on the measurement approaches of Hsieh and Klenow (2009) and Bai and Liu (2018), this study introduced a resource misallocation index for the secondary sector across regions. By taking the absolute values of the derived misallocation indices, we obtained the misallocation levels for labor (*abstaul*) and capital (*abstauk*). Higher values of these indices indicate more severe resource misallocation in the regional secondary sector.

The empirical results show that the coefficients of the core explanatory variables *abstaul* and *abstauk* are both significantly positive, indicating that an excessively rapid decline in manufacturing factor allocation leads to the misallocation of both labor and capital. Resource mismatch regression results are shown in the online Appendix.

6.1.2. Regional Entrepreneurial Enthusiasm

In addition to the aforementioned channels affecting the production costs of manufacturing entities, the large-scale outflow of production factors from the industry leads to a relative contraction in manufacturing output. As a long-cycle, high-investment entrepreneurial activity, manufacturing inherently carries significant uncertainty in returns. Against this backdrop, a decline in factor allocation will dampen entrepreneurs' profit expectations and reduce their willingness to start businesses. Based on the above logic and empirical evidence, this paper examined the mechanism through which changes in production factor allocation affect regional entrepreneurial activity. Specifically, we measured the level of regional industry entrepreneurship using the number of newly established manufacturing enterprises (natural logarithm, *lnnumber*) in each province from annual business registration data. Building on this foundation, Table 3 reports the corresponding empirical results. As shown, the regression coefficients of the core explanatory variables are all significantly negative at the 1% level, indicating that a decline in factor allocation levels leads to a contraction in local entrepreneurial enthusiasm to some extent, thereby weakening the supportive role of relevant market entities in industrial trade development.

Table 3. Mechanism Examination of Regional Entrepreneurial Enthusiasm

	(1)	(2)	(3)	(4)
	lnnumber	*lnnumber*	*lnnumber*	*lnnumber*
*fap*1	–0.508***	–0.614***		
	(0.007)	(0.008)		
*fap*2			–0.477***	–0.595***
			(0.008)	(0.008)
Sample size	1569120	1569120	1569120	1569120
Adjusted R^2	0.848	0.890	0.848	0.890
Industry × Year	Yes	Yes	Yes	Yes
Province × Year	No	Yes	No	Yes
Control variable	Yes	No	Yes	No

6.2. Further Analysis of Production Factor Allocation

6.2.1. The Moderating Effect of Human Capital

Based on the conclusions derived from the theoretical model, this paper further examined whether improvement in labor quality moderates the trade network effects of factor allocation changes manifested as labor quantity reduction. Specifically, it investigated whether a steady rise in labor "quality" can mitigate the adverse impacts caused by a rapid decline in labor "quantity." Specifically, this study utilized the growth rate of the per capita human capital level as a proxy variable for labor quality changes. This variable was categorized into low and high groups ($lnhc\_dummy$) based on quantile thresholds for subgroup regression analysis. The existence of moderating mechanisms was verified by examining whether the regression coefficients exhibited significant differences between subgroups. The per capita human capital data were sourced from the China Human Capital Index Report database.

The regression results of the above analysis indicate that as the growth rate of the human capital level increases, the negative effects of $fap1$ and $fap2$ on $lnpagerank$ significantly weaken, with an empirical p-value of 0 for the corresponding intergroup coefficient difference test.[1] This demonstrates that improvements in human capital levels aimed at enhancing labor skills and quality can effectively mitigate the adverse trade effects caused by rapid labor quantity loss. The moderating effect regression results of human capital are shown in the online Appendix.

6.2.2. The Moderating Effect of New Industrialization Development

In recent years, China has accelerated its transition into the digital era. As a crucial component of new industrialization, the digital economy and digital development have increasingly demonstrated their transformative impact on social production. They have significantly altered interregional factor resource allocation patterns and emerged as key forces driving economic growth and reshaping trade development frameworks. From this perspective, against the backdrop of new industrialization, this paper further examined whether digital dimension can significantly moderate the economic effects of declining factor allocation.

Specifically, referencing the representative indicators proposed by Huang *et al*. (2019) and Zhao *et al*. (2020), this paper selected five indicators: the number of internet broadband users per 100 people, the proportion of computing services and software industry employees to total employees, the total telecom service volume per

[1] The empirical p-values of the inter-group coefficient difference test are obtained using Fischer's combination test after 500 bootstrap resampling.

capita, the number of mobile phones per 100 people, and the regional digital inclusive finance index. Based on standardization, a principal component analysis was conducted to obtain the digital development index for the region. After the digital growth rate was divided into low and high groups based on quantiles and a dummy variable (dig_dummy) was generated for empirical analysis, Table 4 reports the corresponding group regression results. It can be seen that with the rapid advancement of new industrialization, the adverse effects caused by the outflow of traditional production factors significantly decrease. Thus, Hypothesis 2 is validated.

Table 4. The Moderating Effect Regression Results of New Industrialization Development

	(1)	(2)	(3)	(4)
	Low	High	Low	High
	lnpagerank	*lnpagerank*	*lnpagerank*	*lnpagerank*
*fao*1	–0.291***	–0.161***		
	(0.042)	(0.050)		
*fap*2			–0.301***	–0.199***
			(0.042)	(0.051)
Sample size	423644	419864	423644	419864
Adjusted R^2	0.522	0.478	0.522	0.478
Industry × Year	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes
Experience p–value	0.022**		0.050*	

6.2.3. The Moderating Effect of Market Mechanisms

Economic development requires a stable market environment as its foundation, and market entities anticipate a favorable business environment that serves as robust support for the current advancement of new industrialization. To address this, this paper selected the provincial marketization index (market) to measure regional market development with specific data sourced from the China Provincial Marketization Index Database. Building on this, the marketization level was divided into high and low groups based on quantiles, followed by group-wise regression. The moderating effect regression results of market mechanisms are shown in the online Appendix. The results show that, consistent with the theoretical analysis, although the regression coefficients of the core explanatory variable are significantly negative in both the low- and high-marketization groups, the empirical p-value from the intergroup coefficient difference test indicates that the regression coefficient in the latter group is significantly larger than that in the former. This suggests that the improvement of market forces can effectively mitigate the resource misallocation caused by declining factor allocation efficiency in the manufacturing sector, optimize resource allocation structures, enhance resource utilization efficiency, and reduce its adverse effects on trade networks.

6.2.4. The Moderating Effect of Industrial Policy Support

Beyond market cultivation, proactive industrial policies adopted by the government can effectively reduce production costs for enterprises and enhance their productivity, operational capabilities, and confidence, thereby adjusting the impact of factor allocation on enterprises' "hub" status and providing robust support for the development of new industrialization. Following this logic, this study drew on Song and Wang's (2013) research approach, measuring industrial policy support by examining the stance toward the manufacturing sector in the Five-Year Plan outlines issued by the central and provincial governments during the study period. Specifically, for manufacturing industries explicitly associated with positive terms such as "develop," "promote," "support," "encourage," or "foster" in the previous Five-Year Plan text at either the central or provincial level, it is considered that the corresponding industry in that province received supporting industrial policy measures during the subsequent planning period. Furthermore, these industries were divided into low- and high-policy-intensity groups ($policy\_dummy$) based on the total number of HS6-digit industries covered by all supportive policies, followed by a group-wise regression analysis. The regression results indicate that compared to the high-intensity group, the low-intensity group exhibits a smaller regression coefficient (with a larger absolute value) and higher significance. This suggests that under weaker industrial policy support, the adverse effects caused by declining factor allocation efficiency are more severe and pronounced. Thus, Hypothesis 3 is empirically validated.

Table 5. The Moderating Effect Regression Results of Industrial Policy

	(1)	(2)	(3)	(4)
	Low	High	Low	High
	lnpagerank	*lnpagerank*	*lnpagerank*	*lnpagerank*
*fap*1	–0.432***	–0.102**		
	(0.046)	(0.046)		
*fap*2			–0.453***	–0.097**
			(0.046)	(0.047)
Sample size	469659	454094	469659	454094
Adjusted R^2	0.534	0.445	0.534	0.445
Industry × Year	Yes	Yes	Yes	Yes
Province × Year	Yes	Yes	Yes	Yes
Experience p–value	0.000***		0.000***	

7. Research Conclusions and Implications

Using China's provincial-HS6 industry-level data from 2002 to 2021, this study measured the trade position of provincial industries within global trade networks and quantified their factor allocation conditions, based on the existing literature. Through theoretical and empirical analyses, it examined how changes in factor allocation levels affect trade network positions during industrial development. Overall, the findings demonstrate that the rapid deterioration in factor allocation efficiency significantly undermines Chinese industries' positions in trade networks, particularly in export networks. Mechanism analysis indicated that the influence channels are through worsening labor and capital misallocation and diminished regional entrepreneurial activity. However, improvements in labor quality, advancements in new industrialization, relatively mature factor market mechanisms, and proactive government industrial policies significantly mitigate these adverse effects.

Overall, this study not only provides new theoretical perspectives for understanding industrial position changes in the context of globalization but also offers valuable references for policymakers on optimizing factor allocation and enhancing industrial competitiveness during economic transitions. Through in-depth analysis and empirical testing, this research highlights the importance of continuously optimizing and upgrading industrial structures, strengthening technological innovation and talent cultivation, and improving market mechanisms and industrial policies in the era of economic globalization.

References

Bai, J., & Liu, Y. (2018). Can Outward Foreign Direct Investment Improve the Resource Misallocation of China. *China Industrial Economics (Zhongguo Gongye Jingji)*,(1), 60–78.

Ballester, C., Calvó-Armengol, A., & Zenou, Y. (2006). Who's Who in Networks. Wanted: The Key Player. *Econometrica*, 74(5), 1403–1417.

Brandt, L., Van Biesebroeck, J., Wang, L. H., & Zhang, Y. (2017). WTO Accession and Performance of Chinese Manufacturing Enterprises. *American Economic Review*, 107(9), 2784–2820.

Cai, F. (2021). Productivity, Growth Momentum, and Manufacturing——How China Can Regain Its Resources Reallocative Efficiency. *China Industrial Economics (Zhongguo Gongye Jingji)*, (5), 5–18.

Chen, S., & Chen, D. (2018). Air Pollution, Government Regulations and High-quality Economic Development. *Economic Research Journal (Jingji Yanjiu)*, (2), 20–34.

Dhyne, E., Kikkawa, A. K., Mogstad, M., & Tintelnot, F. (2021). Trade and Domestic Production Networks. *Review of Economic Studies*, 88(2), 643–668.

Hsieh, C. T., & Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India. *Quarterly Journal of Economics*, 124(4), 1403–1448.

Huang, Q., Yu, Y., & Zhang, S. (2019). Internet Development and Productivity Growth in Manufacturing Industry: Internal Mechanism and China Experiences. *China Industrial Economics (Zhongguo Gongye Jingji)*, (8), 5–23.

Huang, Y., Lin, C., Liu, S., & Tang, H. (2023). Trade Networks and Enterprise Value: Evidence from the US-China Trade War. *Journal of International Economics*, 145, 103811.

Lee, Y. H., & Schmidt, P. (1993). *A Production Frontier Model with Flexible Temporal Variation in Technical Efficiency*. The Measurement of Productive Efficiency: Techniques and Applications. Oxford University Press.

Liu, J., Che, W., & Xia, F. (2021). Network Analysis of Global Value Chain and Coping with International Risk Transmission. *Journal of Management Sciences in China (Guanli Kexue Xuebao)*, (3), 1–17.

Nunn, N. (2007). Relationship-Specificity, Incomplete Contracts, and the Pattern of Trade. *Quarterly Journal of Economics*, 122(2), 569–600.

Rodrik, D. (2016). Premature Deindustrialization. *Journal of Economic Growth*, 21(1), 1–33.

Song, L., & Wang, X. (2013). Priority Industrial Policy, Resource Reallocation and Industrial Productivity. *Management World (Guanli Shijie)*, (12), 63–77.

Wang, X., Zhou, Y., Zhu, D., & Huang, H. (2023). Deindustrialization and Enterprises' Domestic Value-added Rate. *The Journal of Quantitative & Technical Economics (Shuliang Jingji Jishu Jingji Yanjiu)*, (10), 71–92.

Zhao, T., Zhang, Z., & Liang, S. (2020). Digital Economy, Entrepreneurship, and High-Quality Economic Development: Empirical Evidence from Urban China. *Management World (Guanli Shijie)*, (10), 65–75.