Growth of the Service Sector and Economic Fluctuations: A Production Network Perspective

Dazhong Cheng, Yutong Tang, Xinyi Shao*

This paper examines the impact of growth of the service sector on economic fluctuations and its underlying mechanisms from the perspective of global production networks. We analyze this mechanism by constructing general equilibrium model of production networks and empirically test it by using nearly three decades of global input-output data and simultaneous equations model. The results show that 10% increase in the share of initial inputs and final consumption in the service sector leads to reduction in the sparsity of the production network by 0.42% to 1.34%; 10% reduction in the sparsity of the production network results in decrease in the magnitude of economic fluctuations by 0.79 to 1.56 units. This indicates that the rise in the share of initial inputs and final consumption in the service sector associated with the growth of the service sector tends to reduce the sparsity of production network linkages, thereby helping to smooth economic fluctuations. Counterfactual analysis reveals that if China's service sector share, industry intermediate input share, service sector productivity fluctuations are replaced with the corresponding data from the United States, China's overall economic fluctuations would decrease to varying degrees, with the largest contributions coming from changes in the service sector share and industry intermediate input share (69.8% and 73.6%, respectively). This study implies that actively promoting the development of the service sector has profound strategic significance for stabilizing growth, adjusting structures, and reducing fluctuations in the Chinese economy.

Keywords: growth of the service sector, economic fluctuations, production network

1. Introduction

In *The Service Economy*, Fuchs (1968) posited that the cyclical fluctuations in output and employment within the industrial sector are more pronounced than those in the service sector. This suggests that as the proportion of the service sector increases, the cyclical fluctuations of the overall economy tends to diminish. Empirical economic

* Dazhong Cheng, Professor, Department of World Economy and Institute for World Economy, Fudan University. Yutong Tang, PhD student, Department of World Economy, Fudan University. Xinyi Shao, PhD. student, Department of World Economy, Fudan University.

performance corroborates this assertion. Figure 1 illustrates the economic fluctuations of various sample economies by measuring the standard deviation of their GDP growth rates[1]. The results demonstrate a negative correlation between the proportion of the service sector in GDP and the magnitude of economic fluctuations across different sample periods (1990–2018 and 2000–2018). Taking China and the United States as examples, from 1990 to 2018, the GDP fluctuations of the two countries were 2.48% and 1.56%, respectively, while the average service sector shares were 41.62% and 74.91% for the same period. From 2000 to 2018, the GDP fluctuations of the two countries were 2.05% and 1.48%, respectively, with average service sector shares of 45.15% and 75.33%. It is clear that the higher the proportion of the service sector in an economy, the smaller the magnitude of its economic fluctuations.

Why does the growth of the service sector lead to a tendency for economic fluctuations to diminish? This paper explores this issue from the perspective of the production network. Firstly, by constructing general equilibrium model that incorporates production network, we seek to understand the mechanism through which the growth of the service sector affects economic fluctuations, and thereby propose two interrelated theoretical hypotheses: (1) When the elasticity of substitution between initial inputs and intermediate inputs is greater than that between different intermediate inputs, the lower the sparsity of the production network, the smaller the magnitude of economic fluctuations; (2) The increase in the proportion of the service sector, through the rise in the share of initial inputs and the share of final consumption, leads to decrease in the sparsity of the production network. Secondly, this paper conducts empirical analysis by using simultaneous equations model based on nearly three decades of global input-output data and other relevant data. The results show that if the share of initial inputs in the service sector increases by 10%, the sparsity of the production network will decrease by 0.42%, and if the sparsity of the production network decreases by 10%, the magnitude of economic fluctuations will decrease by approximately 1.56 units. If the share of final consumption in the service sector increases by 10%, the sparsity of the production network will decrease by 1.34%, and if the sparsity of the production network decreases by 10%, the magnitude of economic fluctuations will decrease by approximately 0.79 units. In other words, the increase in the share of initial inputs and final consumption associated with the growth of the service sector leads to the decrease in the sparsity of production network linkages in the economy, thereby exerting a dampening effect on economic fluctuations. This fundamental conclusion remains valid after a series of endogeneity and robustness tests. Counterfactual

[1] We also attempted to measure economic fluctuations by using different indicators (such as the standard deviation of the cyclical component of GDP logarithm and the standard deviation of the error term between actual and fitted GDP values), and the results remained robust.

analysis indicates that if China's service sector share, industry intermediate input share, and service sector productivity fluctuations are replaced with the corresponding data from the United States, China's economic fluctuations would decrease to varying degrees. Among these, changes in the service sector share and the total output-to-value-added ratio (i.e., the industry intermediate input share) contribute the most to the overall economic fluctuations, with contribution rates of 69.8% and 73.6%, respectively. This further confirms that the growth of the service sector and the increase in the share of initial inputs help to smooth out economic fluctuations.

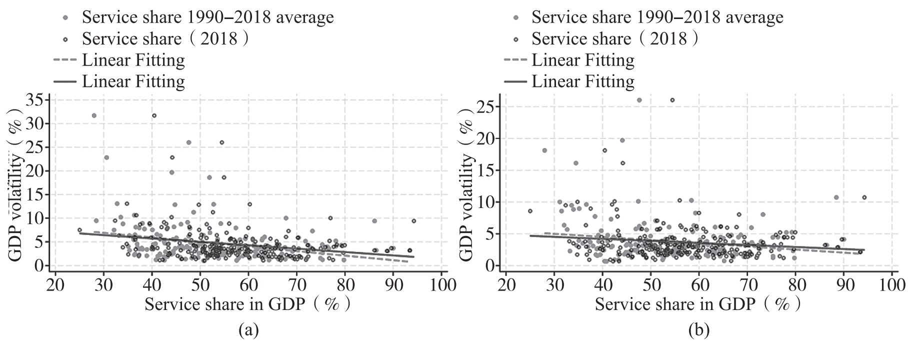

Figure 1. The Relationship Between the Service Shares and Economic Volatility

Note: In subfigures (a) and (b), the GDP volatility of each economy are measured by the standard deviation of annual GDP growth rates, covering the periods 1990–2018 and 2000–2018, respectively. The proportion of the service sector is calculated based on the 2018 share and the average share during the respective periods. The sample sizes for the correlation between GDP volatility and the 2018 service sector share are 199 for both subfigures; the sample sizes for the correlation between GDP volatility and the average service sector share are 203 for subfigure (a) and 202 for subfigure (b). Data source: World Bank database.

Regarding the question of how the growth of the service sector affects economic fluctuations, early research primarily analyzed the issue from the perspective of the characteristics of service sector products. For instance, Fuchs (1968) argued that the stability of service production stems from the non-storability of service products and the inflexibility of consumption. Non-storability implies that the service sector rarely holds inventory, thereby avoiding economic fluctuations; the inflexibility of consumption maintains the stability of actual consumption. The flexibility of employment in the service sector further reinforces this function. In summary, these characteristics mean that the increase in the proportion of the service sector acts as a "stabilizer" for economic fluctuations. This conclusion has been corroborated by subsequent research (Eggers and Ioannides, 2006; Carvalho and Gabaix, 2013). However, these studies overlooked the role of production networks.

In fact, research exploring the network origins of economic fluctuations can be traced back at least to Long and Plosser (1983), who were the first to introduce production networks and construct multi-sector general equilibrium model to explain business cycles and macroeconomic fluctuations.[1] Acemoglu *et al.* (2012) discovered that the rate of decay of aggregate fluctuations depends on the structure of the production network, emphasizing that sectoral heterogeneity shocks only lead to large-scale aggregate fluctuations when significant asymmetry is present, but the sparsity of the input-output matrix is not related to the characteristics of aggregate fluctuations. Some studies (e.g., Gabaix, 2011; Carvalho and Gabaix, 2013; Carvalho, 2014; Atalay, 2017) analyzed the role of sectoral Domar weights and their distribution in the impact of micro shocks on macro fluctuations based on Hulten's theorem (Hulten, 1978), but Acemoglu *et al.* (2012) emphasized that Domar weights and their distribution depend on the input-output structure of the production network. Baqaee and Farhi (2018) extended the first-order scenario of Hulten's theorem to capture nonlinearities, thereby demonstrating that even if two sectors have equal Domar weights, their impact on aggregate TFP may not be equal.[2] In the context of China, some studies explored the propagation of exogenous shocks within production networks and their impact on macroeconomic fluctuations (Yan and Wu, 2017; Xiao and Hou, 2023; Xu and Tian, 2023). This paper focuses on how the growth of the service sector within economic (industrial) structural changes affects the structural changes of production networks, and how these structural changes in production networks, in turn, influence economic fluctuations.

The literature branch most closely related to this paper analyzes the impact of the service sector on economic fluctuations from the perspective of input-output linkages. Moro (2015) found that the increase in the proportion of the service sector reduces both GDP growth and its fluctuation, with the proportion of intermediate inputs playing a significant role. Miranda-Pinto (2021), considering CES production technology and the cost of complexity of intermediate inputs in multi-sector model, showed that when intermediate inputs and labor inputs are substitutable, the diversification of the production network reduces economic fluctuations, and that service-dominated economies experience smaller economic fluctuations due to the more diversified providers of intermediate inputs in the service sector. Building on Moro (2015), Lv

[1] Subsequent research following Long and Plosser (1983) can be broadly categorized into two types based on the existence of efficient equilibrium: one type posits that efficient equilibrium exists (e.g., Gabaix, 2011; Acemoglu *et al.*, 2012; Acemoglu *et al.*, 2017); the other type introduces market frictions, arguing that no efficient equilibrium exists (e.g., Jones, 2011; Baqaee, 2018; Baqaee and Farhi, 2018; Liu, 2019; Bigio and La'O, 2020; Fadinger *et al.*, 2022).

[2] Horvath (1998) found that aggregate fluctuations are related to the degree of sectoral segmentation; the more segmented the sectors, the more likely the input-output matrix is to contain zeros. Koren and Tenreyro (2013), based on the law of large numbers, argued that the increase in the variety or quantity of intermediate inputs in the production process disperses economic fluctuations. Acemoglu and Azar (2020) analyzed the relationship between the sparsity or dispersion of production networks and economic growth based on endogenous production networks. Herskovic (2018) investigated the role of the sparsity or dispersion of production networks in asset pricing.

and Deng (2018), Wang and Man (2022) studied the smoothing effect of industrial structure upgrading and economic servitization on China's economic fluctuations, emphasizing the impact of the proportion of intermediate inputs in sectoral production on economic fluctuations. Compared to these studies, this paper makes two main advances: Firstly, in theoretical modeling, to capture the final demand motivation (i.e., the Engel effect) for the rise in the service sector's proportion, this paper employs the Linear Expenditure System (LES) demand function and its corresponding Stone-Geary utility function, combined with supply-side factors highlighted in existing literature, to reveal the mechanism by which service sector growth affects the production network and economic fluctuations; Secondly, considering the complexity of the relationship between changes in the service sector's proportion and economic fluctuations at the empirical level, we adopt a series of econometric processing methods, including addressing endogeneity issues, controlling for as many influencing factors as possible, and conducting counterfactual analysis, to identify the causal relationship between the two. Finally, this paper is also related to the literature that studies China's industry/firm-level production networks and related issues (such as industrial policy, fiscal and tax policy, innovation, income distribution, etc.) (Liu, 2019; Shi *et al.*, 2019; Qi and Li, 2020; Sun and Liu, 2020; Bao and Dan, 2021; Bian *et al.*, 2021; Chen and Liu, 2021; Ni 2021; Qi and Li, 2021; Liu, 2022; Liu, 2022; Chu *et al.*, 2023). However, this paper focuses on exploring the impact of service sector growth on production networks and the resulting economic fluctuation effects, thereby analyzing general laws applicable to universal economies including China.

The remaining content is organized as follows: Section 2 provides the theoretical analysis, revealing the intrinsic mechanism by which service sector growth affects economic fluctuations and proposing two hypotheses to be tested; Section 3 constructs the econometric equations based on the theoretical model and introduces the main indicators and data used to characterize the production network, presenting preliminary characteristic facts; Section 4 reports the empirical analysis results in detail, including baseline analysis, endogeneity issue handling, robustness checks, and counterfactual analysis; Section 5 concludes with implications and insights.

2. Theoretical Analysis

The theoretical model of this paper is primarily based on Miranda-Pinto (2021), but unlike that study, we employ the LES function on the demand side. This approach is mainly adopted due to the following characteristic fact: as income levels rise, the proportion of household consumption allocated to services tends to increase. The LES demand function and its corresponding Stone-Geary utility function can effectively capture the final demand motivation (i.e., the Engel effect) leading to the rise in the service sector's proportion, whereas the CES utility function and its derived demand function assume that households' expenditure shares on different products are independent of changes in their income levels. This paper integrates demand and supply to explore the mechanism by which service sector growth affects economic fluctuations, including changes in the input structure of the service sector, changes in the production network, and the Engel effect.

2.1. Firm

Assume there are n sectors in the economy, and each sector i has a representative firm that produces according to CES technology[1], namely:

$$y_i = z_i \left(a_i L_i^{\frac{\varepsilon_y - 1}{\varepsilon_y}} + (1 - a_i) M_i^{\frac{\varepsilon_y - 1}{\varepsilon_y}} \right)^{\frac{\varepsilon_y}{\varepsilon_y - 1}} \tag{1}$$

In Equation (1), the intermediate input bundle M_i is equal to:

$$M_i = \left(\sum_{j=1}^{n} \omega_{ij} M_{ij}^{\frac{\varepsilon_M - 1}{\varepsilon_M}} \right)^{\frac{\varepsilon_M}{\varepsilon_{M-1}}} \tag{2}$$

Among them, y_i, z_i, L_i represent the output, total factor productivity, and initial input (labor) of the representative firm in sector i, respectively. M_{ij} denotes the intermediate input that sector i purchases from sector j. a_i signifies the importance of the initial input (labor) to total output, while ($1-a_i$) indicates the importance of intermediate inputs to total output. ω_{ij} represents the importance of sector j as a provider of intermediate inputs to sector i, hence the square matrix Ω (i.e., $n \times n$ matrix containing elements ω_{ij}) represents the input-output structure (network structure) of the economy. ε_y denotes the elasticity of substitution between the initial input (labor) and intermediate inputs, and ε_M represents the elasticity of substitution among different intermediate inputs.

2.2. Household

The representative household maximizes utility:

[1] The theoretical model of this paper adopts the CES production function setting on the supply side (such as Atalay, 2017; Baqaee and Farhi, 2018; Carvalho and Tahbaz-Salehi, 2019; Carvalho *et al.*, 2021; Miranda-Pinto, 2021, etc.). In contrast, Acemoglu *et al.* (2012, 2016) use the Cobb-Douglas production function, the limitation of which is that the proportion of intermediate inputs is an exogenous parameter. The CES model, however, allows for richer pattern of propagation of exogenous shocks through input-output linkages. For example, under negative productivity shock, the CES production function includes not only the downstream propagation effect similar to that in the C-D model but also the reallocation effect among sectors.

$$u(\mathbf{c}) = \sum_{i=1}^{n} \beta_i \ln(c_i - \underline{c}_i) \tag{3}$$

The budget constraint is:

$$\sum_{i=1}^{n} p_i c_i = I = w\overline{L} + \sum_{i=1}^{n} \pi_i \tag{4}$$

Among them, $\mathbf{c}$ is the vector of consumption quantities, where c_i represents the consumption of product or service i, and p_i denotes the price of product or service i. $\underline{c}_i$ indicates the exogenously given basic subsistence consumption level for product or service i, below which consumption does not "generate utility. This setting ensures that the fitting line between the "income (I)" and "product consumption expenditure" has a positive intercept, thereby approximately reflecting the Engel effect. β_i represents the marginal expenditure share (marginal consumption amount) for different products, i.e., $\beta_i = \frac{\mathrm{d}(p_i c_i)}{\mathrm{d}I}$. Let the share of consumption of different products in the household utility function be $\gamma_i = \frac{p_i c_i}{I}$, and $\sum_{i=1}^{n} \gamma_i = 1$, then the income elasticity of demand for that product or service is $\varepsilon_{d,i} = \frac{\beta_i}{\gamma_i}$. This implies that when $\varepsilon_{d,i} = 1$, the marginal expenditure share of the product or service equals the average expenditure share; when $\varepsilon_{d,i} > 1$, the marginal expenditure share of the product or service exceeds the average expenditure share. $\overline{L}$ represents the total labor supply of the household, w denotes the price of the initial factor (labor), and π_i represents the profit of sector i.

2.3. Market Equilibrium

The competitive equilibrium in the economy is constituted by the set of price levels $\{w, (p_i)_i^n\}$ the set of resource allocations $\{c_i, L_i, y_i, M_i\}_i^n$、$\{M_{ij}\}_{ij}^n$. Given sectoral productivity shocks and price levels, the representative household maximizes utility under the budget constraint; firms maximize profits; and the product and labor markets clear ($y_i = c_i + \sum_{j=1}^{n} M_{ji}$, $\overline{L} = \sum_{i=1}^{n} L_i$).[1]

[1] For additional derivations related to the theoretical model, please refer to Appendix 1 on the Journal's website.

2.4. Production Network Structure and Economic Fluctuations

We follow the method of Carvalho and Gabaix (2013) to express the overall economic fluctuation σ as:[1]

$$\sigma = \sqrt{\sum_{i=1}^{n}\left(\frac{Sales_i}{GDP}\right)^2 \sigma_i^2} = \sqrt{\sum_{i=1}^{n}\lambda_i^2\sigma_i^2} \tag{5}$$

Among them, σ_i represents the idiosyncratic fluctuation of sector i.[2] λ_i is the Domar weight of sector i, equal to the sales value of sector i ($Sales_i$) divided by GDP. According to Hulten's theorem, in efficient economy, the impact of (productivity) shock (z_i) on sector i on total output (Y) is equal to the Domar weight (λ_i) of that sector, i.e., $\frac{\mathrm{d}\log Y}{\mathrm{d}\log z_i} = \lambda_i = \frac{Sales_i}{GDP}$. In other words, the Domar weight of a sector reflects the sufficient statistic of how shocks to the sector affect GDP. The higher the Domar weight of sector, the greater the amplification of shocks propagated through the production network.

Based on the market clearing conditions and the general equilibrium solution, the sector Domar weight matrix can be obtained as:

$$\boldsymbol{\lambda} = \left[\mathbf{I} - (\mathbf{p}^{1-\varepsilon_M}\mathbf{1}') \circ \left((\mathbf{z}\circ\mathbf{p})^{\varepsilon_y - 1}\mathbf{1}'\right)' \circ \left(\mathbf{p}^{\mathbf{M}(\varepsilon_y-\varepsilon_M)} \circ (\mathbf{1}-\mathbf{a})^{\varepsilon_y}\mathbf{1}'\right)' \circ \boldsymbol{\Omega}^{\varepsilon_M}\right]^{-1} \boldsymbol{\gamma} \tag{6}$$

Among them, $\circ$ denotes the Hadamard product. $\boldsymbol{\Omega}$ ($n\times n$ matrix with elements ω_{ij}) represents the economy's input-output structure (production network structure). $\mathbf{p^M}$, $\mathbf{p}$, $\mathbf{z}$, $\boldsymbol{\gamma}$ and $\mathbf{a}$ denote the intermediate goods price vector, price vector, sectoral productivity vector, consumption share vector, and the vector of the importance of primary factors (labor) in the production process, respectively. The exponent ε_M of $\boldsymbol{\Omega}$ can also reflect the cost of complexity. In summary, the production network structure, consumption expenditure shares, primary factor input shares, and the two substitution elasticities ε_y and ε_M all influence the Domar weights, thereby affecting aggregate economic fluctuations. Clearly, depending on the specific assumptions about z, ε_y and ε_M, Equation (6) can take different forms.

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[1] According to Hulten's theorem, Equation (5) can be derived.

[2] Assuming that the productivity of each sector follows random walk form: $\log z_{i,t+1} - \log z_{i,t} = \log \bar{z} + \upsilon_{i,t}$. Here, $\bar{z}$ represents the technological level of each sector in the steady state, and let $\bar{z} = 1$. $\upsilon_{i,t}$ follows normal independent distribution with the mean of 0 and the variance of σ_i^2.

Case 1: Let z_i=1 and $\bar{L}=1$. When $\varepsilon_y \neq \varepsilon_M$, Equation (6) becomes:[1]

$$\boldsymbol{\lambda} = [\mathbf{I} - \left(\mathbf{S}^{\varepsilon_y - \varepsilon_M} \circ (\mathbf{1}-\mathbf{a})^{\varepsilon_y} \mathbf{1}'\right)' \circ \boldsymbol{\Omega}^{\varepsilon_M}]^{-1} \boldsymbol{\gamma} \tag{7}$$

Among them, **S** is the sparsity vector of the production network, with its elements $S_j = (\sum_{i=1}^{n} \omega_{ji}^{\varepsilon_M})^{\frac{1}{\varepsilon_M - 1}}$. The sparsity of the production network can measure the distribution of connections (edges) in the input-output network. The lower the sparsity of the production network, the higher the degree of diversification in intermediate inputs and the lower the degree of specialization, leading to more uniform distribution of input-output linkages across sectors.[2]

Specifically, when $\varepsilon_y \neq \varepsilon_M$=1, Equation (7) simplifies to: $\boldsymbol{\lambda} = [\mathbf{I} - (\mathbf{S}^{\varepsilon_y - 1} \circ (\mathbf{1}-\mathbf{a})^{\varepsilon_y} \mathbf{1}')' \circ \boldsymbol{\Omega}]^{-1} \boldsymbol{\gamma}$ Here, **S** is the sparsity vector of the production network, with its elements $S_j = \prod_{i=1}^{n} \omega_{ji}^{\omega_{ji}}$, representing the sparsity of sector j.

Taking the partial derivative of Equation (7) with respect to S_j yields:

$$\frac{\mathrm{d}\boldsymbol{\lambda}}{\mathrm{d}S_j} = [\mathbf{I} - (\mathbf{S}^{\varepsilon_y - \varepsilon_M} \circ (\mathbf{1}-\mathbf{a})^{\varepsilon_y} \mathbf{1}')' \circ \boldsymbol{\Omega}^{\varepsilon_M}]^{-1} (\varepsilon_y - \varepsilon_M) \begin{pmatrix} S_j^{\varepsilon_y - \varepsilon_M - 1} (1-a_j)^{\varepsilon_y} \boldsymbol{\omega}_{j,i\in n} & \mathbf{0} & \mathbf{0} \end{pmatrix} \boldsymbol{\lambda} \tag{8}$$

[1] To illustrate the relationship between the production network structure and Domar weights, assume that the production network is symmetric. When the production network structure is symmetric, meaning that the outdegree of each sector is the same, and given the elasticity coefficients ε_y, ε_M, and a, the prices across all sectors will be identical.

[2] The sparsity of the production network corresponds to the diversification of network connections. Sparsity describes the distribution of edges (node connections) in the production network, reflecting whether sectors in the input-output matrix rely on a few important intermediate inputs or a diverse set of intermediate inputs (input bundles $\boldsymbol{\Omega}_i = \{\omega_{ij}\}$). It measures the degree of input specialization in the economy, as well as the density or congestion of network connections (industrial chains). The higher the degree of input specialization in the economy, the more important the single input is to specific sector, and the more concentrated the sources of inputs for production relies on, the higher the sparsity of the production network. Conversely, when the demand for different intermediate inputs across sectors is relatively uniform, the sparsity of the production network is lower. For example, consider two networks: $\boldsymbol{\Omega}_1 = \begin{pmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$ and $\boldsymbol{\Omega}_2 = \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{pmatrix}$. It can be observed that network $\boldsymbol{\Omega}_1$ has higher sparsity, meaning each sector (node) uses only one intermediate input, while network $\boldsymbol{\Omega}_2$ has lower sparsity, meaning each sector (node) uses multiple intermediate inputs more evenly.

Among them, $\boldsymbol{\omega}_{j,i\in n}$ is $1\times n$ dimensional vector representing the importance of intermediate inputs from other sectors i to sector j; $\mathbf{0}$ is $1\times n$ dimensional 0 vector.

If and only if $\varepsilon_y > \varepsilon_M$, then $\mathrm{d}\boldsymbol{\lambda}/\mathrm{d}S_j>0$, which implies that the lower the sparsity of the production network, the smaller the Domar weight, and consequently, the smaller the magnitude of economic fluctuations. Existing research, such as Atalay (2017), estimates that the substitution elasticity between primary inputs (labor) and intermediate inputs, ε_y, is generally greater than the substitution elasticity between different intermediate inputs, ε_M. In other words, the condition $\varepsilon_y > \varepsilon_M$ in Equation (8) generally holds. Appendix 2 of this paper provides further proofs.

Case 2: Let z_i=1 and $\bar{L}=1$. When $\varepsilon_y=\varepsilon_M$, Equation (6) becomes:[1]

$$\boldsymbol{\lambda}=[\mathbf{I}-\left(((\mathbf{1}-\mathbf{a})\mathbf{1}')'\circ\boldsymbol{\Omega}\right)^{\varepsilon_y}]^{-1}\boldsymbol{\gamma} \tag{9}$$

Specifically, when $\varepsilon_y=\varepsilon_M$=1, Equation (9) simplifies to: $\boldsymbol{\lambda}=[\mathbf{I}-\left((\mathbf{1}-\mathbf{a})\mathbf{1}'\right)'\circ\boldsymbol{\Omega}]^{-1}\boldsymbol{\gamma}$. Here, $\mathbf{L}=[\ell_{ji}]=[\mathbf{I}-\left((\mathbf{1}-\mathbf{a})\mathbf{1}'\right)'\circ\boldsymbol{\Omega}]^{-1}$ represents the Leontief inverse matrix of the economy. In this case, although the sparsity metric (**S**) mentioned above no longer appears, the distribution of elements ℓ_{ij} in the Domar weights and the Leontief inverse matrix can still reflect the sparsity of the production network. Specifically, the sparsity of production network connections can influence the transmission path and distribution of upstream sector heterogeneity shocks to downstream sectors, thereby affecting macroeconomic fluctuations. The higher the sparsity of the production network, the greater the impact of upstream sector heterogeneity shocks on individual downstream sectors, leading to larger overall economic fluctuations. Further proof of this is provided in Appendix 3 of this paper.

Integrating the previous two scenarios, we can derive the following hypothesis:

Hypothesis 1: Given other conditions (especially when ε_y is not less than ε_M), the lower the sparsity of the production network, the smaller the magnitude of economic fluctuations.

Furthermore, the structural characteristics and evolution of the production network are also influenced by sectoral structure, with the rise of the service sector being a fundamental feature of sectoral structural changes. Evidence shows that, compared to other sectors, the service sector uses lower share of intermediate inputs and higher share of initial inputs (value-added); longitudinally, as the proportion of the service sector increases, the share of intermediate inputs in the service sector tends to decrease,

[1] To illustrate the relationship between the production network structure and Domar weights, it is assumed that the production network is symmetric.

while the share of initial inputs (value-added) tends to rise.[1] This implies that the rise of the service sector leads to more equalized centrality of nodes within the production network, thereby making the overall production network connections more uniform. We discuss this mechanism further in Appendix 4. Consequently, we get the following hypothesis:

Hypothesis 2: A rising proportion of the service sector leads to a decreasing sparsity of production network. The mechanisms include two aspects: firstly, the increase in the share of initial inputs (the role of the service sector as demander of initial inputs increases); secondly, the increase in the share of final consumption (the role of the service sector as provider of final goods rises).

3. Specification, Indicators and Data

This section first constructs the econometric regression model based on the precious theoretical analysis and hypotheses, then discusses the relevant indicators and data, presenting preliminary characteristic facts.

3.1. Econometric Model Setting

Since Hypothesis 1 concerns how changes in the structure of the production network affect economic fluctuations, and Hypothesis 2 focuses on the impact of the rising proportion of the service sector on the structure of the production network, the variable representing the structure of the production network appears both as explanatory variable and as explained variable. In this case, a system of simultaneous equations model is required, and the iterative three-stage least squares (3SLS) method can be used for estimation. The specific econometric model is specified as:

$$\begin{cases} \sigma_{ct} = \varphi_1 \ln(Sparsity_{ct}) + \mathbf{X}_{ct} + \mu_c + \eta_t + \vartheta_{ct} & (10) \\ \ln(Sparsity_{ct}) = \varphi_2 \ln(Share_{ct}) + \mathbf{X}_{ct} + \mu_c + \eta_t + \nu_{ct} & (11) \end{cases}$$

Among them, $\ln(Sparsity_{ct})$ represents the sparsity of network connections for economy c in year t (logarithmically transformed). σ_{ct} denotes the actual GDP fluctuation of economy c in year t. The explanatory variables $\ln(Share_{ct})$ in Equation (11) include $\ln(PI_{ct})$ and $\ln(FC_{ct})$, which represent the proportion of initial inputs and final

[1] Relevant literature, such as Autor and Dorn (2013), points out that the labor input in service sector production is difficult to substitute with information technology. Therefore, the substitution of information technology for routine production in other sectors leads to increase in wages for low-skill workers in the service sector, and more labor is reallocated to the service sector, resulting in an upward trend in labor input in the service sector. This paper will also present related characteristic facts in Section 3 and Appendix 6.

consumption in the service sector of economy c in year t, respectively (logarithmically transformed). $\boldsymbol{X}_{ct}$ contain control variables, including economic growth rate, openness to trade, government expenditure share, inflation rate, etc. μ_c and η_t represent country fixed effects and year fixed effects, respectively. ϑ_{ct} and v_{ct} are random error terms. If the coefficient φ_1 before $\ln(Sparsity_{ct})$ is positive, Hypothesis 1 holds, indicating that the higher the sparsity of network connections, the greater the magnitude of economic fluctuations. If the coefficient φ_2 before $\ln(Share_{ct})$ is negative, Hypothesis 2 holds, suggesting that the higher the proportion of initial inputs and final consumption in the service sector, the lower the sparsity of production network connections.

3.2. Data and Indicator

The main variables involved in the econometric analysis include the production network structure indicators, economic fluctuation rates, economic growth rates, service sector shares, and the proportions of initial inputs and final consumption in the service sector for various economies. We primarily utilize the input-output data in basic price from the Eora database for the years 1991–2016 and the PWT10.0 database. The former covers 188 economies and 26 sectors/items worldwide, and after matching with the latter, the number of economies included is 170.[1]

3.2.1. Sparsity of Production Network

We construct the sparsity indicator ($Sparsity_c$) for the production network of country c based on the previous theoretical model, with its calculation formula being $Sparsity_c = \sum_{i=1}^{n} \phi_i \prod_{j=1}^{n} {\omega_{ij}}^{\omega_{ij}}$. Here, ϕ_i represents the proportion of sector i output to the total output, and $Sparsity_i = \sum_{j=1}^{n} {\omega_{ij}}^{\omega_{ij}}$ represents the sparsity or specialization degree of intermediate inputs in sector i.[2] The more dispersed the distribution of ω_{ij} values, the higher the sparsity of the production network.

In the robustness analysis, we will also attempt to measure the sparsity of the production network using three methods: Firstly, based on the theoretical model mentioned earlier, we will use the Herfindahl-Hirschman Index (HHI) of Domar

[1] For the descriptive statistics of the variables and the classification of industries, please refer to Appendix 5.

[2] The national-level production network sparsity indicator constructed in this paper is the weighted average of the sector-level sparsity indicators from the theoretical model in Section 2. This indicator is highly correlated with the network sparsity indicator of Herskovic (2018), with correlation coefficient of 0.87.

weights, with the calculation formula being $HHI_c = \sqrt{\sum_{i=1}^{n}(\frac{Sales_i}{GDP})^2}$. As the sparsity of network connections decreases, the Domar weights of each sector and their *HHI* index will also decrease. Secondly, according to theoretical Hypothesis 2, the rise of the service sector leads to more equalized centrality of nodes within the production network, thereby making the overall production network connections more uniform. To this end, we introduce the average centrality indicator of the production network for country *c*, with the calculation formula being $KB_c = \sum_{i=1}^{n} KB_i \log KB_i$. Here, KB_i is element in the vector $\mathbf{KB} = a[\mathbf{I} - (1-a)\mathbf{\Omega}]^{-1}\boldsymbol{\gamma}$, representing the Katz-Bonacich network centrality of sector *i*.[1] The lower the average network centrality, the more uniform the distribution of centrality across sectors. Thirdly, we adopt commonly used indicator to measure the sparsity of the production network—the production network density indicator (*Density*), with the calculation formula being: $Density_c = \frac{k}{n(n-1)}$. In this formula, *k* represents the number of edges in the production network, i.e., the number of input-output connections between sectors, and *n* is the number of sample sectors.[2] When the network density is 0, it indicates that there are no input-output relationships above the threshold between sectors; when the network density is 1, it indicates that there are input-output connections above the threshold among all sectors.[3] The higher the network density, the lower the sparsity of network connections.

3.2.2. Economic Fluctuation Rate (σ)

We measure the economic fluctuation rate using the standard deviation of the actual GDP growth rate (i.e., the rolling standard deviation of fixed sample length). That is, within the sample interval [1, T], the length of the rolling time

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[1] The average centrality indicator KB_c of the production network for country *c* is essentially the weighted average of the Katz-Bonacich centrality of each sector. The Katz-Bonacich centrality of sector *i* is equivalent to the share of sector *i* output in the total output of all sectors (Acemoglu *et al.*, 2012; Herskovic, 2018). Simply put, the output of specific sector in the input-output table is divided into two parts: intermediate use and final use, with the former further participating in the production processes of other sectors. Therefore, the output share vector of sector can be represented as: $\mathbf{\Phi} = [\mathbf{I} - ((\mathbf{1}-\mathbf{a})\mathbf{1}')' \circ \mathbf{\Omega}]^{-1}(\mathbf{a} \circ \boldsymbol{\gamma})$, and the output share of sector *j* can be recursively decomposed into two parts: the preference part (involving final use) and the network part (involving intermediate use): $\phi_j = a\gamma + (1-a)\sum_{i=1}^{n} \omega_{ij}\phi_i$.

[2] This paper sets the threshold at 0.1%, meaning that if the direct input coefficient $a_{ij} \geq 0.1\%$, it is determined that there is a connection or edge between the relevant sectors.

[3] Here, the intermediate inputs of sector to itself are not included.

window is set to κ, and the rolling standard deviation for country c in year t is: $\sigma_{ct}=\sqrt{(\frac{1}{\kappa}\sum_{n=t-\kappa+1}^{t}(\Delta GDP_{ct}-\overline{\Delta GDP_{ct}})^2)}$. In this paper, the length of the time window is set to κ=5. In the robustness checks, we will also use the standard deviation of the GDP cyclical component and the standard deviation of the GDP fitting error term to measure the economic fluctuation rate.

3.2.3. Indicators Related to Service Sector

The share of the service sector (Ser_{ct}) in each country is the proportion of the service sector's value-added to GDP. In the Eora global input-output table, sectors numbered 15–25 are classified as the service sector. The proportion of initial inputs in the service sector (*PI*) is the share of the service sector's (income approach) GDP in its total output. Since the sum of the proportions of initial factor inputs and intermediate inputs equals 100%, the higher proportion of initial inputs implies the lower proportion of intermediate inputs. Similarly, the proportion of final consumption in the service sector (*FC*) is the share of final consumption in the service sector's total output, and the higher proportion of final consumption indicates the lower proportion of intermediate use.

3.2.4. Control Variables

The main control variables include the GDP growth rate at the national level ($\Delta GDP_{ct}=\ln GDP_{ct}-\ln GDP_{c,t-1}$), population size (*Pop*), trade openness (*Open*) (equal to the ratio of total trade to GDP), government expenditure share (*Gov*) (equal to the ratio of government expenditure to GDP), inflation rate (*Inf*), and so on. The relevant data are all sourced from the PWT 10.0 database.

3.3. Stylized Facts[1]

First, observe the relationship between the structure of the production network and economic fluctuations. Figure 2 shows that the sparsity of network connections is positively correlated with economic fluctuations, but network density is negatively correlated with economic fluctuations. This indicates that the higher the sparsity of network connections and the lower the network density, the greater the magnitude of economic fluctuations. This is consistent with the prediction of Hypothesis 1, but the causal relationship between them requires further identification and confirmation.

[1] More stylized facts are portrayed in Appendix 6.

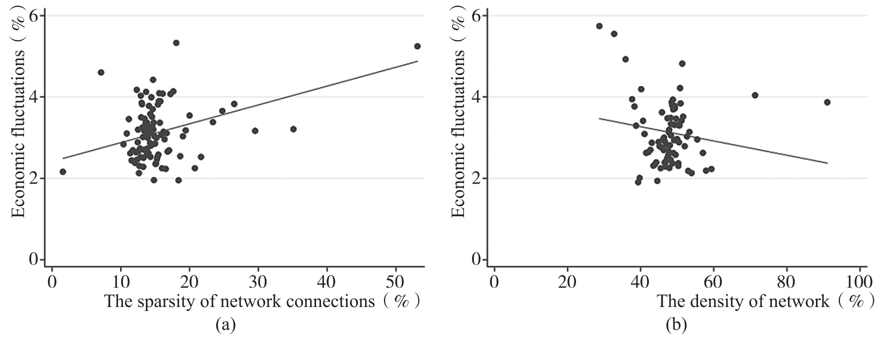

Figure 2. The Relationship Between the Structure of the Production Network and Economic Fluctuations

Note: The authors estimate and produce the data based on PWT data and Eora global input-output data.

Next, we observe the relationship between the structural characteristics of the production network and the proportion of initial inputs and final consumption in the service sector, respectively. As can be seen from Figure 3, the sparsity of network connections is negatively correlated with both the proportion of initial inputs and the proportion of final consumption in the service sector. That is, the higher the proportion of initial inputs and final consumption in the service sector, the lower the sparsity of network connections, which is consistent with the expectation of Hypothesis 2.

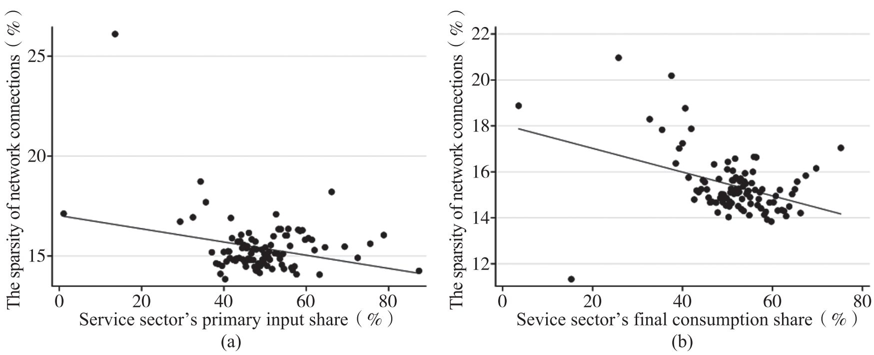

Figure 3. The Relationship Between the Proportion of Initial Input and Final Consumption in the Service Sector and the Structure of Production Networks: Cross-Country Evidence

Note: The authors estimate and produce the data based on Eora global input-output data.

4. Empirical Analysis

Based on the above mentioned characteristic facts, we further conduct econometric analysis on the intrinsic mechanism by which the growth of the service sector affects economic fluctuations, using the constructed system of simultaneous equations model.

This analysis includes baseline regression, endogeneity issue handling, robustness checks, and counterfactual analysis.[1]

4.1. Benchmark Regression

Columns (1) to (4) in Table 1 only control for country and year fixed effects without including other control variables. We consider two simultaneous equation setting. Firstly, with the proportion of initial inputs in the service sector ln(*PI*) as the explanatory variable (columns (1) and (2)), the sparsity of the production network has a significant positive impact on economic fluctuations, with coefficient of 16.606, meaning that 1% increase in the sparsity of the production network leads to 0.166 unit rise in the economic fluctuation rate; the increase in the proportion of initial inputs in the service sector results in the decrease in the sparsity of the production network, with 1% increase in the proportion of initial inputs leading to 0.047% decrease in sparsity. Secondly, with the proportion of final consumption in the service sector ln(*FC*) as the explanatory variable (columns (3) and (4)), the impact of the sparsity of the production network on economic fluctuations remains positive, with coefficient of 8.818, indicating that 1% increase in sparsity leads to 0.088 unit rise in the fluctuation rate; whereas the increase in the proportion of final consumption in the service sector leads to the decrease in the sparsity of the production network, with 1% increase in the proportion of final consumption leading to 0.142% decrease in sparsity.

Columns (5) to (8) in Table 1 further introduce additional country-level control variables on the basis of the first four columns. With the proportion of initial inputs in the service sector as the explanatory variable (columns (5) and (6)), the coefficient for ln(*Sparsity*) is 15.632, meaning that 1% increase in the sparsity of the production network leads to 0.156 unit rise in the economic fluctuation rate; and 1% increase in the proportion of initial inputs in the service sector results in 0.042% decrease in sparsity. When the proportion of final consumption in the service sector is used as the explanatory variable (columns (7) and (8)), 1% increase in sparsity leads to 0.079 unit rise in the fluctuation rate; and 1% increase in the proportion of final consumption in the service sector leads to 0.134% decrease in sparsity.

[1] Although the focus of this paper is to explore how the growth of the service sector affects the sparsity of the production network and how the latter influences economic fluctuations, we have also attempted to use the 2008 global financial crisis as shock event and applied DID analysis. The results show that the Domar weights of the impacted sectors are positively correlated with network sparsity, indicating that reduction in network sparsity helps to mitigate the shock amplification effect within the network. This finding is not contradictory to the regression results of this paper.

Table 1. Services Growth, Production Networks and Economic Fluctuations: A Baseline Regression

	Simultaneous equation setting 1		Simultaneous equation setting 2		Simultaneous equation setting 1		Simultaneous equation setting 2	
	σ	ln(*Sparsity*)	σ	ln(*Sparsity*)	σ	ln(*Sparsity*)	σ	ln(*Sparsity*)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(*Sparsity*)	16.606*** (3.407)		8.818*** (1.352)		15.632*** (3.697)		7.859*** (1.401)	
ln(*PI*)		–0.047*** (0.006)				–0.042*** (0.006)		
ln(*FC*)				–0.142*** (0.008)				–0.134*** (0.008)
Δ*GDP*					0.001 (0.003)	–0.0004*** (0.0001)	–0.002 (0.003)	–0.0003*** (0.0001)
ln(*Pop*)					–1.368** (0.582)	0.085*** (0.018)	–0.664 (0.436)	0.074*** (0.017)
ln(*Open*)					–0.728*** (0.147)	–0.028*** (0.004)	–0.958*** (0.095)	–0.024*** (0.003)
ln(*Gov*)					0.026 (0.188)	0.015** (0.007)	0.151 (0.159)	0.014** (0.007)
Inf					–0.00003 (0.0001)	–0.00003 (0.0001)	–0.001 (0.002)	–0.00002 (0.0001)
Adjusted R^2	0.155	0.861	0.350	0.869	0.199	0.865	0.383	0.872
P Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4420	4420	4420	4420	4420	4420	4420	4420

Note: The control variables for population size (*Pop*), trade openness (*Open*), and government expenditure share (*Gov*) are all taken as their logarithmic values. All regressions control for country and year fixed effects. The values in parentheses below the coefficients are standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% statistical levels, respectively.

The results validate the two hypotheses of the theoretical model presented earlier. In other words, the increase in the proportion of initial inputs and final consumption associated with the growth of the service sector leads to the decrease in the sparsity of production network connections in the economy, thereby reducing economic fluctuations.[1]

4.2. Endogenous Issue

The endogeneity issues mainly include omitted variables and reverse causality. We have already controlled for fixed effects and multiple control variables in the baseline regression, so we primarily employ the instrumental variable method to address the reverse causality problem caused by the mutual influence among the proportion of the service sector, economic fluctuations, and the structure of the production network.[2]

The instrumental variable method requires estimation based on single equation and utilizes the two-stage least squares (2SLS) approach. Drawing on the approach of Autor *et al.* (2013), we use the shift-share method to construct Bartik instrumental variables (Bartik, 1991) for the core explanatory variables. The construction method of this instrumental variable is to use the initial share composition at the national level and the overall growth rate of the corresponding variables at the sectoral level to simulate the estimated values for each year. Specifically, this paper uses the initial share of network sparsity for each sector in each country in the initial year and the inner product of the average growth rate of network sparsity across global sectors as the instrumental variable for production network sparsity, with the formula as follows:

$$Sparsity_{IV,ct} = \sum_{i=1}^{n} \phi_{ci,1990} \times Sparsity_{ci,1990} \times (1+g_{it}) \tag{12}$$

Among them, $\phi_{ci,1990}$ represents the output share of sector i in country c at the beginning of the year 1990; $Sparsity_{ci,1990}$ represents the network sparsity of sector i in

[1] As the economy develops, the proportion of the service sector increases, while the proportion of manufacturing in GDP decreases. The deepening division of labor in manufacturing leads to the increase in the proportion of intermediate inputs and the decrease in the proportion of initial inputs; meanwhile, the rise in income levels results in increased consumption of services and decreased consumption of manufactured goods, which in turn leads to the decline in the proportion of final consumption in manufacturing. Our simultaneous equations regression for the manufacturing sector (Appendix Table 4) shows that the impact of the proportion of initial inputs on the sparsity of the production network is significantly negative, consistent with the regression results for the service sector. In summary, the analysis of the manufacturing sector further corroborates the conclusions of Table 1. Due to space limitations, the relationship between the proportion of the manufacturing sector and economic fluctuations is detailed in Appendix 7.

[2] We also considered using the lagged terms of the core explanatory variables, and the results are consistent with the baseline regression (Appendix Table 6).

country c at the beginning of the year 1990; the product of $\phi_{ci,1990}$ and $Sparsity_{ci,1990}$ is the initial share of network sparsity for sector i in country c; g_{it} represents the growth rate of the average network sparsity of global sector i in year t relative to the beginning of the year.

Similarly, the instrumental variables for the proportion of initial inputs and final consumption in the service sector are the inner product of the initial share of initial inputs or final consumption in the service sector for each country in the initial year and the average growth rate of initial inputs or final consumption in the global service sector.[1] The instrumental variable regression results are shown in Table 2, which are consistent with the baseline scenario.[2]

Table 2. Endogeneity Test: Regression Based on 2SLS

	The second stage returns				The first stage returns		
	σ	ln(*Sparsity*)	ln(*Sparsity*)		ln(*Sparsity*)	ln(*PI*)	ln(*FC*)
	(1)	(2)	(3)		(4)	(5)	(6)
ln(*Sparsity*)	4.725*** (1.792)			ln(SparsityIV)	2.263*** (0.220)		
ln(*PI*)		–0.158*** (0.041)		ln(PIIV)		0.665*** (0.139)	
ln(*FC*)			–0.291*** (0.020)	ln(FCIV)			1.528*** (0.109)
Cragg-Donald Wald F Statistics	209.604^{r}	1514.64^{r}	334.714^{r}	F Statistics	105.63***	23.01***	196.66***
Observations	4420	4420	4420	Observations	4420	4420	4420

Note: All regressions include control variables and control for country and year fixed effects. The values in parentheses below the coefficients are robust standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% statistical levels, respectively. The superscript ^{r} indicates that the Cragg-Donald Wald F statistic exceeds the 10% critical value for rejecting the weak instrument test.

4.3. Robustness Test

This section further examines the robustness of the baseline regression results by altering the calculation method of economic fluctuations, replacing the network connection sparsity indicators, and changing the division of the sample period.[3]

[1] Due to space limitations, the relevance explanation and exogeneity test of the Bartik IV can be found in Appendix 8.

[2] The impact of related control variables is similar to the baseline scenario.

[3] For details on the robustness tests, please refer to Appendix 9.

4.4. Counterfactual Analysis

We first decompose the sources of economic fluctuations into three parts based on the above mentioned theoretical model and Carvalho and Gabaix (2013), namely $\sigma_t = \sqrt{\sum_{i=1}^{n} (\frac{Sales_{it}}{GDP_{it}} \frac{GDP_{it}}{GDP_t})^2 \sigma_i^2}$. In other words, σ_t depends on changes in three components: (1) the ratio of the total output (total sales value) of sector *i* to its value-added $\frac{Sales_{it}}{GDP_{it}}$, (2) the proportion of the value-added of sector *i* to the total value-added of the entire economy $\frac{GDP_{it}}{GDP_t}$, and (3) the productivity fluctuation σ_i of sector *i*. For example, even if $\frac{GDP_{it}}{GDP_t}$ and σ_i remain unchanged, the decrease in $\frac{Sales_{it}}{GDP_{it}}$ can reduce economic fluctuations. Economic fluctuations may also arise from the diversification effect, meaning that, given other conditions, if the value-added shares of sectors $\frac{GDP_{it}}{GDP_t}$ shift from being concentrated in a few sectors to being evenly distributed across different sectors, economic fluctuations will also decrease. This effect reflects changes in the sectoral structure. Additionally, economic fluctuations may stem from the compositional effect, that is, if the Domar weights of sectors with lower fluctuation rates increase while those of sectors with higher fluctuation rates decrease, economic fluctuations will consequently diminish.

To analyze the relative importance of the three sources of economic fluctuations and to assess the contribution of the rise of the service sector to smoothing economic fluctuations, we take China as an example and conduct counterfactual analysis using the WIOD SEA data from 1995–2011.[1] Firstly, we assume that the output-to-value-added ratio of each sector $\frac{Sales_{it}}{GDP_{it}}$ in China does not change over time, thereby isolating the contribution of $\frac{Sales_{it}}{GDP_{it}}$ to China's economic fluctuations. The economic fluctuation of China at this time is $\sigma_t = \sqrt{\sum_{i=1}^{n} (\frac{\overline{Sales_i}}{\overline{GDP_i}} \frac{GDP_{it}}{GDP_t})^2 \sigma_i^2}$, where $\frac{\overline{Sales_i}}{\overline{GDP_i}}$ is the cross-period average of $\frac{Sales_{it}}{GDP_{it}}$.

[1] There are two reasons for using this database: firstly, it provides data on capital and labor inputs, allowing for the calculation of sectoral TFP fluctuations; secondly, it covers the period from the late 1990s to the early 2000s, during which China's sectoral structure underwent significant changes, facilitating our observation of the impact of service sector growth on economic fluctuations. This paper uses the Solow residual method to derive the productivity for each sector. For simplicity, we assume that the productivity fluctuations of each sector do not change over time.

Secondly, we assume that the proportion of each sector in China $\frac{GDP_{it}}{GDP_t}$ does not change over time to isolate the contribution of the diversification effect to China's economic fluctuations. The economic fluctuation at this time is $\sigma_t = \sqrt{\sum_{i=1}^{n}(\frac{Sales_{it}}{GDP_{it}}\frac{\overline{GDP_i}}{\overline{GDP}})^2\sigma_i^2}$. Finally, we examine the role of the compositional effect in China's economic fluctuations. The economic fluctuation at this time is $\sigma_t = \sqrt{\sum_{i=1}^{n}(\frac{Sales_{it}}{GDP_{it}}\frac{GDP_{it}}{GDP_t})^2\sigma^2}$, where σ is the average productivity fluctuation of sectors in the Chinese economy. The final results are shown in Figure 4.

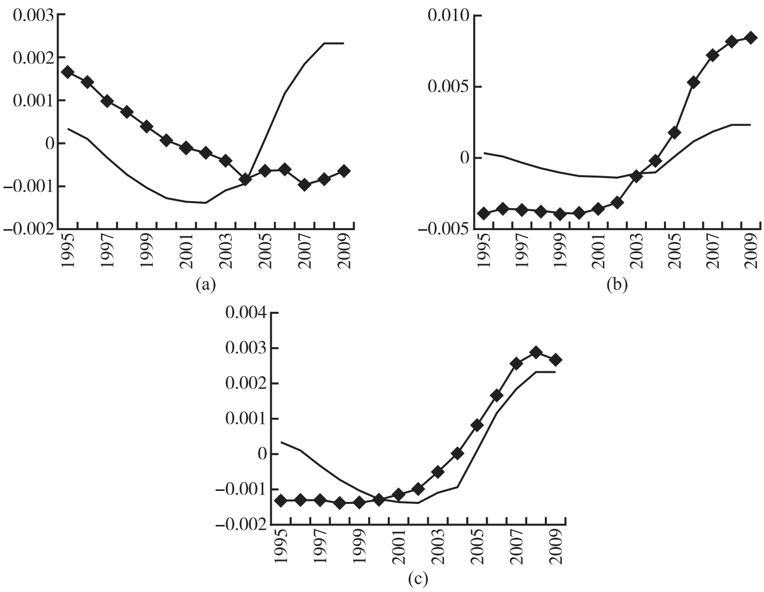

Figure 4. Counterfactual Analysis of the Sources of Economic Fluctuation: the Case of China

Note: The solid line in the graph represents the baseline economic fluctuations calculated by the economic fluctuation decomposition formula, and the diamond line represents the counterfactual economic fluctuations. Among them, (a) shows the counterfactual economic fluctuations after isolating changes in $\frac{Sales_{it}}{GDP_{it}}$; (b) shows the counterfactual economic fluctuations after isolating changes in $\frac{GDP_{it}}{GDP_t}$; (c) shows the counterfactual economic fluctuations after isolating changes in σ_i.

From Figure 4(a), it can be seen that after isolating the impact of changes in $\frac{Sales_{it}}{GDP_{it}}$, the downward trend of China's economic fluctuations from 1995 to 2002 was unaffected. This means that during this sample period, changes in $\frac{Sales_{it}}{GDP_{it}}$ had a minor influence on the trend of China's economic fluctuations. After 2002, when controlling for changes in $\frac{Sales_{it}}{GDP_{it}}$, China's economic fluctuations did not exhibit an upward trend. This indicates that at this time, changes in $\frac{Sales_{it}}{GDP_{it}}$ had a significant contribution to China's economic fluctuations. In contrast, Figure 4(b) shows that after isolating changes in $\frac{GDP_{it}}{GDP_t}$, the changes in $\frac{GDP_{it}}{GDP_t}$ around 2002 had impact on China's economic fluctuations. Meanwhile, Figure 4(c) reveals that after isolating changes in σ_i, the changes in σ_i had greater contribution to China's economic fluctuations before 2002, but smaller impact after 2002.

The results of the above mentioned counterfactual analysis indicate that the primary reasons for the decline in China's economic fluctuations between 1995 and 2002 are the changes in the proportion of value-added across different sectors in the economy ($\frac{GDP_{it}}{GDP_t}$) and the shift in Domar weights towards sectors with lower productivity fluctuations (σ_i), that is, the transformation of the sectoral structure largely contributed to the decrease in China's economic fluctuations. This finding coincides with the fact that China's service sector experienced significant growth from the late 1990s to the early 2000s. This implies that the stability of China's economic fluctuations during this period was mainly due to the rise of the service sector. After 2000, China's economic fluctuations increased, which is primarily attributed to changes in the ratio of total output to value-added in sector i ($\frac{Sales_{it}}{GDP_{it}}$) and changes in value-added across different sectors ($\frac{GDP_{it}}{GDP_t}$), that is, changes in sectoral Domar weights. During this period, the proportion of China's service sector stabilized or even declined, while the proportion of the manufacturing sector increased, leading to the increase in Domar weights and greater economic fluctuations.

We further compare China with the United States, and the results are shown in Table 3. It can be seen that China's GDP fluctuation rate is 18.1%, while that of the United States is 5.2%. This difference mainly stems from three aspects: firstly, the proportion of China's service sector in the overall economy (38%) is much lower than that of the United States (78%); secondly, the ratio of total output to value-added in China's service sector ($\frac{Sales_s}{GDP_s}$) and the ratio of total output to value-added in China's non-service sector ($\frac{Sales_m}{GDP_m}$) are both higher than those in the United States; thirdly, the productivity fluctuation in China's service sector (4.5%) is higher than that in the United States (3.8%).

Based on this, we conduct counterfactual analysis of China's economic fluctuations by replacing China's service sector share, industry intermediate input share, and service sector productivity fluctuations with the corresponding data from the United States while keeping other components unchanged. The results are shown in Table 3. It can be seen that after doing so, China's economic fluctuations decrease to varying degrees. Among them, changes in the service sector share and the ratio of total output to value-added lead to larger changes in overall economic fluctuations, with contribution rates of 69.8% and 73.6%, respectively; whereas the contribution of service sector productivity fluctuations to the overall economic fluctuation changes is smaller, at only 20.2%. This means that the growth of the service sector and the increase in the share of initial inputs help to smooth out economic fluctuations. This further validates the results of the previous econometric analysis.

Table 3. Economic Fluctuations and Counterfactual Analysis: A Comparison Between China and the United States

	GDP_s/ GDP	$Sales_s$/ GDP_s	$Sales_m$/ GDP_m	σ_s	σ_m	Quantitative σ_{GDP}	Contribution rate
China	38%	1.87	4.72	4.5%	6.1%	18.1%	
USA	78%	1.55	2.16	3.8%	5.2%	5.2%	
Counterfactual analysis							
China	78%	1.87	4.72	4.5%	6.1%	9.1%	69.8%
China	38%	1.55	2.16	4.5%	6.1%	8.6%	73.6%
China	38%	1.87	4.72	3.8%	5.2%	15.5%	20.2%

Note: The subscripts *s* for each variable represent the service sector, and *m* represents other sectors. The quantified GDP fluctuation is calculated according to the economic fluctuation decomposition formula in the text. The contribution rate is calculated as (18.1% - China's quantified GDP fluctuation in the counterfactual analysis)/(18.1%–5.2%).

5. Conclusions and Implications

The rise of the service sector signifies the transformation of the economic form from industrial economy to service economy, and studying its impact helps to clarify the patterns of sectoral structural changes in a country. This paper investigates this issue from the perspective of production networks.

In theory, this paper constructs general equilibrium model that includes production networks to understand the mechanism by which the growth of the service sector affects economic fluctuations, and based on this, proposes two interrelated theoretical hypotheses. In brief, the increase in the proportion of the service sector leads to decrease in the sparsity of production networks; and the decrease in production network sparsity results in smaller magnitude of economic fluctuations. By analyzing global data, it is found that 10% increase in the proportion of initial inputs and final consumption in the service sector will reduce production network sparsity by 0.42%~1.34%; while 10% decrease in production network sparsity will reduce the magnitude of economic fluctuations by 0.79~1.56 units. Counterfactual analysis shows that if China's service sector share, industry intermediate input share, and service sector productivity fluctuations are replaced with the corresponding data from the United States, China's economic fluctuations will decrease to varying degrees. Among them, changes in the service sector share and the ratio of total output to value-added lead to larger changes in overall economic fluctuations, with contribution rates of 69.8% and 73.6%, respectively. This once again confirms that the growth of the service sector and the increase in the share of initial inputs help to smooth out economic fluctuations.

This research carries significant policy implications. The lag in the service sector not only hinders the optimization and upgrading of the economy and sectoral structure but also restricts the further development, reform, and opening-up of the overall economy. As this study shows, the backwardness of the service sector also leads to increase in the sparsity of production networks, which in turn causes larger magnitudes of economic fluctuations. Conversely, by promoting employment in the service sector to increase the proportion of initial inputs and by encouraging service consumption to raise the proportion of final consumption in the service sector, it will help to reduce the sparsity of production networks and smooth large economic fluctuations. Therefore, from the perspective of "stabilizing growth, adjusting structure, and reducing fluctuations", actively taking measures to promote the comprehensive development of the service sector is not only of immediate urgency but also of profound strategic significance.

References

Acemoglu, D., & Azar, P. D. (2020). Endogenous Production Networks. *Econometrica*, 88(1), 33–82.

Acemoglu, D., Akcigit, U., & Kerr, W. (2016). Networks and the Macroeconomy: An Empirical Exploration. *NBER Macroeconomics Annual*, 30(1), 273–335.

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The Network Origins of Aggregate Fluctuations. *Econometrica*, 80(5), 1977–2016.

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2017). Microeconomic Origins of Macroeconomic Tail Risks. *American Economic Review*, 107(1), 54–108.

Atalay, E. (2017). How Important are Sectoral Shocks? *American Economic Journal: Macroeconomics*, 9(4), 254–280.

Autor, D. H., & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5), 1553–1597.

Bao, Q., & Dan, J. (2021). Network Centrality, Shared Business Ties and Share of Large Business Partners. *Economic Research Journal (Jingji Yanjiu)*, (10), 189–205.

Baqaee, D. R. (2018). Cascading Failures in Production Networks. *Econometrica*, 86(5), 1819–1838.

Baqaee, D. R., & Farhi, E. (2018). Macroeconomics with Heterogeneous Agents and Input-Output Networks. NBER Working Paper, 24684.

Bartik, T. J. (1991). Who Benefits from State and Local Economic Development Policies? W.E. Upjohn Institute.

Bian, Z., Li, Z., & Xu, M. (2021). Development Zones, Participation in Supply Chains and Firms' Financial Constraints. *Economic Research Journal (Jingji Yanjiu)*, (10), 88–104.

Bigio, S., & La'O, J. (2020). Distortions in Production Networks. *Quarterly Journal of Economics*, 135(4), 2187–2253.

Carvalho, V. M. (2014). From Micro to Macro via Production Networks. *Journal of Economic Perspectives*, 28(4), 23–48.

Carvalho, V. M., & Gabaix, X. (2013). The Great Diversification and Its Undoing. *American Economic Review*, 103(5), 1697–1727.

Carvalho, V. M., & Tahbaz-Salehi, A. (2019). Production Networks: A Primer. *Annual Review of Economics*, 11(1), 635–663.

Carvalho, V. M., Nirei, M., Saito, Y. U., & Tahbaz-Salehi, A. (2021). Supply Chain Disruptions: Evidence from the Great East Japan Earthquake. *Quarterly Journal of Economics*, 136(2), 1255–1321.

Chen, S., & Liu, X. (2021). Innovation Spillovers in Production Networks——Evidence from Quasi-natural Experimental Research of National High-tech Zones. *China Economic Quarterly (Jingjixue Jikan)*, (10), 1839–1858.

Chu, D., Li, Y., & Zhang, T. (2023). Research on the Causes of VAT Burden Difference from the Perspective of Industrial Interconnection. *Economic Research Journal (Jingji Yanjiu)*, (7), 174–190.

Eggers, A., & Ioannides, Y. M. (2006). The Role of Output Composition in the Stabilization of US Output Growth. *Journal of Macroeconomics*, 28(3), 585–595.

Fadinger, H., Ghiglino, C., & Teteryatnikova, M. (2022). Income Differences, Productivity, and Input-Output Networks. *American Economic Journal: Macroeconomics*, 14(2), 367–415.

Gabaix, X. (2011). The Granular Origins of Aggregate Fluctuations. *Econometrica*,

79(3), 733–772.
Herskovic, B. (2018). Networks in Production: Asset Pricing Implications. *Journal of Finance*, 73(4), 1785–1818.
Horvath, M. (1998). Cyclicality and Sectoral Linkages: Aggregate Fluctuations from Independent Sectoral Shocks. *Review of Economic Dynamics*, 1(4), 781–808.
Hulten, C. R. (1978). Growth Accounting with Intermediate Inputs. *Review of Economic Studies*, 45(3), 511–518.
Jones, C. I. (2011). Intermediate Goods and Weak Links in the Theory of Economic Development. *American Economic Journal: Macroeconomics*, 3(2), 1–28.
Koren, M., & Tenreyro, S. (2013). Technological Diversification. *American Economic Review*, 103(1), 378–414.
Kpodar, K., & Imam, P. A. (2016). Does a Regional Trade Agreement Lessen or Worsen Growth Fluctuations? An Empirical Investigation. *Review of International Economics*, 24(5), 949–979.
Kuznets, S. (1973). Modern Economic Growth: Findings and Reflections. *American Economic Review*, 63(3), 247–258.
Liu, E. (2019). Industrial Policies in Production Networks. *Quarterly Journal of Economics*, 134(11), 1883–1948.
Liu, W. (2022). Changes of Production Input Structure and Enterprise Innovation: An Analysis Based on the Endogenous Production Network. *Economic Research Journal (Jingji Yanjiu)*, (4), 50–67.
Liu, W. (2022). Global Production Network and Change of Labor Remuneration Share under New Pattern of Development. *Economic Research Journal (Jingji Yanjiu)*, (10), 86–102.
Long, J. B., & Plosser, C. I. (1983). Real Business Cycles. *Journal of Political Economy*, 91(1), 39–69.
Lv, Y., & Deng, X. (2018). How Does Industrial Structure Upgrading Iron up Macroeconomic Fluctuation in China:DSGE Model Analysis on Internal Structure of Industrial Structure. *Finance and Trade Research (Caimao Yanjiu)*, (2), 1–10.
Lucas, R. E. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, 22(1), 3–42.
Miranda-Pinto, J. (2021). Production Network Structure, Service Share, and Aggregate Fluctuations. *Review of Economic Dynamics*, 39(1), 146–173.
Moro, A. (2015). Structural Change, Growth, and Fluctuations. *American Economic Journal: Macroeconomics*, 7(3), 259–294.
Ni, H. (2021). Production Network Structure, Tax and Fee Reduction and Welfare Effects. *The Journal of World Economy (Shijie Jingji)*, (1), 25–53.
Qi, Y., & Li, Y. (2020). Intersectoral Allocation of Public Expenditure and the Upgrading of China's Industrial Structure: A Production Network Model. *Economic Research Journal (Jingji Yanjiu)*, (4), 86–100.

Qi, Y., & Li, Y. (2021). The Productiveness of Government Consumption in Production Networks Model: Theoretical and Empirical Explorations. *Management World (Guanli Shijie)*, (11), 56–70.

Shi, J., Yang, J., Li, Y., & Zhang, Q. (2019). A Slight Move in One Part May Affect the Situation as a Whole: Supply Network Location, Operational Risk and Corporate Performance. *China Industrial Economics (Zhongguo Gongye Jingji)*, (9), 136–154.

Sun, P., & Liu, Y. (2020). Firm Trade Networks, Bargaining Power and Technological Progress. *Economic Research Journal (Jingji Yanjiu)*, (7), 43–61.

Wang, C., & Man, X. (2022). Research on the Influence Mechanism of Stablization for China's Economic Fluctuations. *Statistical Research (Tongji Yanjiu)*, (3), 52–68.

Xiao, Y., & Hou, C. (2023). Input-Output Networks and Inflation Transmission. *Economic Research Journal (Jingji Yanjiu)*, (11), 24–43.

Xu, X., & Tian, K. (2023). Sectoral Distortions and Macroeconomic Fluctuation: Taking the Financial Crisis as an Example. *The Journal of World Economy (Shijie Jingji)*, (5), 58–89.

Yan, L., & Wu, L. (2017). Input-Output Structure, Industrial Heterogeneity and China's Economic Fluctuations. *The Journal of World Economy (Shijie Jingji)*, (8), 3–28.