Decomposition of Total Factor Productivity and Industry Spillover Effects
——Based on input-output matrix

Abstract

Against the backdrop of a global transition from factor-driven to efficiency-driven growth, Total Factor Productivity (TFP) stands as a pivotal metric for evaluating sustainable development. Focusing on the forward spillover effects of TFP growth across industries, this paper seeks to open the "black box" of inter-industry productivity transmission mechanisms. By identifying and quantifying the heterogeneous transmission paths from upstream sectors to downstream TFP growth, the paper deepens the theoretical understanding of technology diffusion patterns in production networks. To achieve this, the paper constructs an analytical framework that integrates an Input-Output model with a Cobb-Douglas production function incorporating intermediate inputs. Utilising intermediate goods as the transmission medium, it delineates the TFP spillover paths along the industrial chain and innovatively disentangles inter-industry TFP transmission into two heterogeneous channels, namely "pure technology spillover" and "factor expansion pull". Consequently, It decomposes downstream TFP growth into four distinct sources comprising indigenous technological progress, scale effects, upstream technology spillovers, and factor pull effects. This framework effectively overcomes the limitations of traditional patent-based and R&D-based methods in underestimating indirect spillovers, achieving a leap from correlation analysis to the identification of transmission channels. The empirical results indicate that Chinese sectoral TFP growth exhibits a significant "scale-efficiency divergence", with spillover intensity showing a gradient attenuation along the industrial chain. Based on the sectoral characteristics identified in the empirical results, policy support should prioritise generic technology R&D in upstream sectors with high spillover potential to extend spillover chains, while the focus for midstream sectors with weak absorption capacity must shift from capacity expansion to strengthening absorption capabilities. Furthermore, digital transformation should be leveraged to integrate "isolated" sectors into the main industrial chain. Ultimately, optimising factor allocation curbs the efficiency squeeze on downstream sectors induced by upstream extensive expansion, thereby fostering sustainable productivity growth.

Keywords: Total factor productivity; Input-output matrix; Industry spillover effects; Economic growth

1. Introduction

Total Factor Productivity (TFP), serving as the core indicator of new quality productive forces, has seen its growth rate decline, serving as the primary driver of the recent macroeconomic slowdown (Shen & Chen, 2024). To promote the growth of TFP, existing literature has explored the factors influencing TFP changes from multiple perspectives. Studies have identified technology diffusion (Evenson 1997; Sakurai, Papaconstantinou, and Ioannidis 1997), infrastructure (Liu & Gong, 2022; Zhou et al., 2025), optimization of resource allocation efficiency (Yang, 2015; Liu & Zhang, 2023; Xie & Zhang, 2024; Nie et al., 2025), international trade spillovers and inter-industry spillovers (Gu and Rennison 2005; Hanel 2000; Jorgenson and Nomura 2007; Vuori 1997), and digitalization (Jorgenson et al., 2007; Li et al., 2024; Zhao et al., 2021; Yang et al., 2023; Huang & Gao, 2023; Li & Xu, 2024) as key determinants. Despite these extensive explorations, relying on empirical studies regarding the correlations of influencing factors makes it difficult to compare their respective contributions. The impact of various factors on TFP growth is not strictly monotonic or linear and is accompanied by complex dynamic interaction mechanisms, rendering aggregate analysis based on linear assumptions unable to disentangle the deep-seated drivers of growth from the key bottlenecks impeding it. Thus, it is essential to systematically decompose the TFP growth rate to accurately identify the key bottlenecks constraining its growth and the critical leverage points for promoting it.

Given that the modern economy is essentially a complex production network interconnected by input-output linkages, this paper focuses on decomposing the TFP growth rate from a production network perspective. The paper argues that the TFP growth rate is characterized by significant inter-industry spillover effects. Specifically, technological breakthroughs, efficiency improvements, or even changes in production scale within an industry can generate positive or negative spillovers to its upstream and downstream sectors through the production network. Positive spillover effects have been widely documented. For instance, logistics standardization in the transportation industry not only enhances the sector's TFP but also significantly promotes TFP growth in upstream and downstream industries (He et al., 2025). Similarly, the construction of intelligent computing centers in the digital sector generates significant positive spillovers on the TFP of downstream enterprises by unleashing the value of computing power factors (Xu et al., 2025). However, negative shocks and transmission impediments should not be overlooked. Recently, the rapid advances in information and communication technology (ICT) and electronic technology in industrialized countries have not been matched by an increase in TFP, owing to obstructed technology diffusion and excessive disparities in cross-industry innovation. When an imbalance in TFP growth among upstream industries cannot be reconciled, it exerts adverse effects on the TFP growth and innovation of the industries themselves (Acemoglu, Autor, and Patterson 2023).

In this regard, this paper interprets the phenomenon as follows: when upstream TFP improves, it not only directly embeds into downstream production functions through intermediate goods with higher technological content but also compels downstream industries to proactively undertake responsive adjustments and adaptive innovations—such as optimizing R&D paths, restructuring management processes, and innovating business models—to achieve efficient coordination with new upstream technologies and products. The speed and effectiveness of these adjustments vary, which, in the short run, manifests as differences in the magnitude or even the sign of the marginal effect of upstream shocks on downstream TFP. For instance, the IT sector provides technical services as intermediate inputs to the retail industry. When these services are optimized—reflecting an improvement in the IT sector's TFP—the outcome depends on downstream responses. If downstream retailers can swiftly synchronize effective adaptive measures with the new system, their TFP growth is a superposition of their own optimization and the positive shock from upstream, thereby achieving synergistic growth across the industrial chain. Conversely, if downstream retailers lack corresponding actions or their improvements fail to align with upstream technologies, the transmission of TFP growth is impeded, potentially resulting in negative effects. Additionally, if new technological products cannot effectively interface with other intermediate inputs in retail—for example, where certain products require specialized handling incompatible with the system—retail TFP growth is similarly hindered, termed "adjustment pains". Moreover, when upstream industries enhance their scale efficiency, downstream search costs and intermediate goods prices correspondingly decrease, thereby optimizing downstream resource allocation efficiency (Bernard, Moxnes, and Saito 2019; Boehm and Oberfield 2020). Since these impacts are typically positive, failing to isolate them would lead to an underestimation of the negative marginal effects and mask the issues regarding TFP propagation within the industrial chain.

To decompose the marginal effects of these impacts and compare their propagation across nodes within the production network, this paper draws on the insights of Jones(2011) regarding inter-industry linkages and complementarities based on intermediate goods. By integrating the aggregate production function incorporating intermediate goods with the input-output model, the paper decomposes industry-level TFP growth rates using intermediate goods as the medium. Given that the intermediate inputs of downstream industries constitute the final outputs of upstream industries, the paper maps the intermediate inputs in the downstream TFP growth formula to the outputs of corresponding upstream industries. This effectively embeds upstream TFP into the downstream TFP growth rate, thereby enabling the identification and quantification of the marginal impacts arising from upstream scale efficiency gains as well as the cross-industry spillover effects generated by upstream TFP improvements. By embedding upstream TFP into the downstream TFP growth rate, the paper identifies and quantifies the marginal impacts of upstream scale efficiency gains and the cross-industry spillover effects of upstream TFP improvements. Separately, accounting for the relationship between the value-added production function and aggregate production functions, the paper isolates industry-specific scale effects. Ultimately, the downstream TFP growth rate is decomposed into four components: (a) indigenous technological progress; (b) scale effects resulting from the sector's own factor inputs; (c) inter-industry spillover effects stemming from upstream TFP improvements; and (d) pull effects generated by the expansion of upstream factor inputs.

Based on this decomposition framework, the empirical analysis spans 37 sectors over the period from 1981 to 2024. Our measure of labor input is the number of employed persons (OECD 2009). For capital input, following the theory that depreciation equals the transfer of capital stock value to output, the paper select depreciation of fixed assets as a proxy variable (He, 2023), defining the portion not converted into output as capital utilization efficiency loss. In addition, the decomposition of industry-level TFP growth rates is based on the 2023 non-competitive input–output table.

The empirical results indicate that sectoral TFP growth in China exhibits a significant characteristic of "scale-efficiency divergence", with spillover intensity displaying a gradient decay pattern along the industrial chain characterized as "broad in the upstream, sparse in the midstream, and approaching zero in the downstream". Although upstream TFP spillovers and indigenous technological progress constitute the primary positive drivers, factor expansion acts as an overall drag, where the cost squeeze caused by upstream factor expansion severely offsets the benefits of technology spillovers. Meanwhile, the volatility of TFP growth is negatively correlated with the position in the industrial chain, with upstream sectors exhibiting violent fluctuations. Based on the decomposition results, the paper further classifies industries into three types: high spillover potential, absorption-constrained, and industrial chain "islands". Accordingly, differentiated policy recommendations are proposed to clear the blockages in technology diffusion and promote the synergistic upgrading of the entire industrial chain.

This paper is closely related to two strands of literature: one on TFP decomposition methods and the other on inter-industry spillover paths.

Regarding TFP decomposition, although existing research is relatively mature, most scholars have focused on decomposition along the dimensions of technological progress, technical efficiency, and returns to scale (Solow, 1957; Diewert & Morrison, 1986; Kumbhakar et al., 2000; Ren & Sun, 2009; Li & Cui, 2021; Li et al., 2024; Zhang et al., 2024), or the empirical analysis influencing factors (Liu & Gong, 2022; Chen & Feng, 2024), while limited attention has been paid to the decomposition of the inter-industry spillover dimension within TFP growth. Even though some studies have introduced industrial structure and production network perspectives (Kendrick 1961; Diewert and Morrison 1986; Bigio and La'O 2020), pointing out that upstream intermediate usage significantly affects downstream TFP growth (Dietzenbacher & Los, 1998; Liu et al., 2023) and confirming the critical role of intermediate input linkages as a transmission mechanism for productivity shocks (Acemoglu et al. 2012; Acemoglu, Akcigit, and Kerr 2016; Baqaee and Farhi 2018), they often treat the production network as an aggregate factor or a shock transmission tool, focusing on examining how sectoral distortions or productivity shocks alter aggregate TFP by affecting overall resource allocation efficiency. This approach fails to delve into the linkage mechanisms among disaggregated sectors, rendering it difficult to precisely trace production network bottlenecks to specific industries. Consequently, it hinders the formulation of targeted industrial policies and makes it challenging to implement precise structural interventions and regulations for specific sectors. Distinct from the aforementioned studies, the paper does not rest content with treating the production network as an aggregate factor or a shock transmission tool. Instead, it endeavors to delve into the network's interior to investigate transmission mechanisms and diagnose structural issues. In light of this, the paper attempts to break through traditional research paradigms by adopting a production network perspective to innovatively decompose the production network structure and quantify the impact of individual nodes within the network on TFP growth.

Regarding research on inter-industry spillover paths, transmission mechanisms exhibit significant asymmetry across different directions. The existing literature has largely reached a consensus on backward spillover paths, suggesting that downstream enterprises can robustly pull the technological progress of upstream suppliers by setting technical standards and providing guidance; in contrast, the effects and mechanisms of forward spillovers are more critical and complex. Forward spillover paths primarily operate by embedding upstream technological advancements into the intermediate goods supplied to downstream sectors, thereby enhancing their quality and driving downstream technological progress. Coe & Helpman (1995) pioneered the confirmation that imported intermediate goods are a key channel for international R&D spillovers, laying the theoretical foundation for forward spillovers; the meta-analysis by Fan et al. (2022) and the empirical study by Zhu et al. (2016) further confirmed the diffusion effect of upstream technological progress on downstream sectors. Particularly in the digital economy era, the "empowerment effect" generated by upstream digital infrastructure through forward linkages has unprecedentedly amplified the economic significance of forward spillover paths (Xie et al., 2021; Liu, 2022). However, despite the widespread confirmation of the existence and importance of forward spillover paths, there is still a lack of systematic decomposition and quantitative research regarding the heterogeneous composition of their sources and transmission mechanisms. Theoretically, there exist dual heterogeneous paths for the push from upstream industries to downstream sectors; on the one hand, scale benefits brought by the expansion of upstream factor inputs optimize downstream resource allocation efficiency by reducing downstream search costs and intermediate goods prices (Bernard et al. 2019; Boehm and Oberfield 2020)； on the other hand, upstream technological progress directly pushes the downstream technological frontier outward by embedding in high-quality intermediate goods and stimulating downstream learning effects (Liu et al., 2023; Ma & Wang, 2024). Regrettably, most existing studies treat the TFP transmission paths from upstream to downstream as a single "black box", failing to effectively distinguish between technology spillovers stemming from upstream technological progress and the indirect impacts arising from the scale effects of upstream factor expansion, thus making it impossible to clarify whether downstream TFP growth originates from the price dividend of upstream factor expansion or the spillover effect of upstream technological progress. Such conflation of sources constrains a refined understanding of inter-industry productivity transmission mechanisms, preventing relevant policy recommendations from accurately pinpointing key bottlenecks. To this end, the paper takes forward spillover paths as the entry point to reveal and decompose the heterogeneous paths through which different sources of upstream growth (factor scale expansion and technological progress) affect downstream TFP via industrial linkages. By doing so, the paper makes a marginal contribution by not only confirming the existence of forward spillovers, but more importantly, quantifying the marginal contributions of these two heterogeneous paths through a decomposition method, thereby providing a new perspective for understanding the coordinated development of upstream and downstream industries.

The remainder of this paper is organized as follows: Section 2 presents the model construction; Section 3 describes the data and variable processing methods; Section 4 outlines the empirical methodology, analyzes the TFP growth across China's 37 sectors and the decomposition results for 2023, and proposes corresponding policy implications; Section 5 provides the conclusions and implications.

2. Model

This section develops a multi-sector TFP growth decomposition framework integrating the aggregate production function and the input-output model. In an economy with *n* sectors, the output of any sector *j* (*j*=1, 2, …, n) is produced by a representative producer using Cobb-Douglas technology, satisfying:

$$X_j(t) = A_j(t)\left(K_j(t)^{\sigma_j} L_j(t)^{1-\sigma_j}\right)^{1-\gamma_j} M_j(t)^{\gamma_j} \tag{1A}$$

where $K_j(t)$ and $L_j(t)$ denote the capital and labor inputs of sector *j* in period *t*, respectively, and σ_j represents the output elasticity of capital in the sector's value added; the capital and labor inputs combine to form a production unit that transforms the intermediate inputs $M_j(t)$ into the gross output $X_j(t)$ of sector *j* in period *t*, with γ_j representing the output elasticity of intermediate inputs with respect to gross output; $A_j(t)$ captures the efficiency with which capital, labor, and intermediate inputs are transformed into output for sector *j* in period *t*, namely the TFP estimated using the Solow residual approach; and the parameters are restricted such that $\sigma_j \in (0,1)$ and $\gamma_j \in (0,1)$.

By defining $\alpha_j = \sigma_j(1-\gamma_j)$ and $\beta_j = (1-\sigma_j)(1-\gamma_j)$ as the output elasticities of capital and labor inputs in sector *j*, respectively, the nested structure of Equation (1A) can be simplified to:

$$X_j(t) = A_j(t)K_j(t)^{\alpha_j}L_j(t)^{\beta_j}M_j(t)^{\gamma_j} \tag{1B}$$

To eliminate the influence of units of measurement and explore the dynamic adjustment process of the variables, this paper takes the natural logarithm of both sides of Equation (1B) and differentiates with respect to time *t*, yielding the following expression for the TFP growth rate:

$$TFP_j(t) = g_{x_j}(t) - \alpha_j g_{k_j}(t) - \beta_j g_{l_j}(t) - \gamma_j g_{m_j}(t) \tag{2}$$

where $TFP_j(t)$ is the TFP growth rate of sector *j* at time *t*, $g_{x_j}(t)$ is the growth rate of gross output, $g_{k_j}(t)$ is the growth rate of capital input, $g_{l_j}(t)$ is the growth rate of labor input, and $g_{m_j}(t)$ is the growth rate of intermediate inputs.

To characterize the contribution of other sectors to sector *j* in the production process of period *t*, the paper examines the gross output of sector *j*, $X_j(t)$, from a value distribution perspective. Based on the column balance of the input-output table, $X_j(t)$ is decomposed into two components: intermediate inputs $X_{ij}(t)$ and value added $V_j(t)$. Specifically, the intermediate inputs reflect the consumption of products from other sectors by sector *j*, while $V_j(t)$ represents the value added used to pay labor compensation and production taxes, account for the depreciation of fixed assets, and generate operating surplus. Furthermore, under the non-competitive input-output framework, the products from sector *i* consumed by sector *j* can be broken down into domestic supply $X_{ij}^D(t)$ and imports $X_{ij}^M(t)$. Accordingly, the column balance equation for sector *j* in period *t* can be expressed as:

$$X_j(t) = V_j(t) + \sum_{i=1}^{n}(X_{ij}^D(t) + X_{ij}^M(t)) \tag{3}$$

By tracing the intermediate inputs of sector *j* in Equation (3) ($X_{ij}^D(t)$ and $X_{ij}^M(t)$) back to the gross $X_i(t)$ output of the corresponding upstream sectors, differentiating both sides with respect to time *t*, and substituting with the domestic direct input coefficient ($a_{ij}^D = \frac{X_{ij}^D}{X_j}$), the imported direct input coefficient ($a_{ij}^M = \frac{X_{ij}^M}{X_j}$), and the value-added coefficient ($a_{v_j} = \frac{V_j}{X_j}$), we ultimately derive the relationship between the output growth rates across sectors:

$$g_{x_j}(t) = a_{v_j} g_{v_j}(t) + \sum_{i=1}^{n}(a_{ij}^D + a_{ij}^M) \cdot g_{x_i}(t) \tag{4}$$

Substituting Equation (4) into the sectoral TFP formula (2) decomposes $TFP_j(t)$ into four components:

$$\begin{aligned}
TFP_j(t) = {} & \frac{a_{v_j}}{1-a_{jj}^D-a_{jj}^M}\left[g_{v_j}(t) - \alpha_j g_{k_j}(t) - \beta_j g_{l_j}(t)\right] && \text{(a)}\\
& + \frac{a_{v_j}}{1-a_{jj}^D-a_{jj}^M}\left[\alpha_j g_{k_j}(t) + \beta_j g_{l_j}(t)\right] - \left[\alpha_j g_{k_j}(t) + \beta_j g_{l_j}(t) + \gamma_j g_{m_j}(t)\right] && \text{(b)}\\
& + \frac{1}{1-a_{jj}^D-a_{jj}^M}\sum_{i\neq j,i=1}^{n}(a_{ij}^D + a_{ij}^M) \cdot TFP_i(t) && \text{(c)}\\
& + \frac{1}{1-a_{jj}^D-a_{jj}^M}\sum_{i\neq j,i=1}^{n}(a_{ij}^D + a_{ij}^M) \cdot \left[\alpha_i g_{k_i}(t) + \beta_i g_{l_i}(t) + \gamma_i g_{m_i}(t)\right] && \text{(d)}
\end{aligned} \tag{5}$$

From a production network perspective, Equation (5) decomposes the sources of TFP growth for sector j at time t into two major dimensions: internal drivers and external spillovers. Specifically, terms (a) and (b) constitute intra-sectoral effects, while terms (c) and (d) capture forward spillover effects.

Internally, term (a) measures the direct contribution of pure technological progress within the sector. More precisely, $\left[g_{v_j}(t) - \alpha_j g_{k_j}(t) - \beta_j g_{l_j}(t)\right]$ represents the Solow residual at the value-added level, capturing the initial technology shock net of factor accumulation. Acting as an "internal circulation multiplier", the coefficient's denominator ($1 - a_{jj}^D - a_{jj}^M$) captures the cascading amplification driven by intra-sectoral self-consumption, while its numerator (a_{v_j}, the value-added rate) serves as a "value anchor" that prevents the artificial inflation of intermediate input scale, ensuring the amplification of the technology shock is grounded in genuinely created value.

Term (b) corresponds to the contribution of sector jj's own factor input growth to its TFP changes. The former part, $\frac{a_{v_j}}{1-a_{jj}^D-a_{jj}^M}\left[\alpha_j g_{k_j}(t) + \beta_j g_{l_j}(t)\right]$, captures the asymmetric factor growth effect amplified by the "internal circulation multiplier" in that when the combined growth of capital and labor inputs is out of sync with changes in intermediate inputs, the resulting output increase essentially reflects an improved utilization rate of existing intermediate inputs. The latter part, $-\left[\alpha_j g_{k_j}(t) + \beta_j g_{l_j}(t) + \gamma_j g_{m_j}(t)\right]$, strictly nets out the conventional output variation generated by movements along the given production function surface, ultimately isolating the pure efficiency improvement derived from asymmetric factor growth.

Turning to the forward spillover effects, term (c) captures the cross-sectoral spillover effect of TFP changes in sector j's upstream sectors on its TFP growth, while term (d) represents the pulling effect of their output expansion on sector j's TFP growth. Specifically, an increase in TFP or production expansion in domestic sector i can affect sector j through two channels. It directly supplies intermediates to sector j (with a marginal contribution of $\frac{a_{ij}^D}{1-a_{jj}^D-a_{jj}^M}$), and it may also boost sector j's TFP through processing trade, where intermediates are exported for foreign processing and subsequently re-imported (with a marginal contribution of $\frac{a_{ij}^M}{1-a_{jj}^D-a_{jj}^M}$). Crucially, unlike term (b), term (d) only accounts for the movement along the upstream production function driven by factor expansion. Any scale efficiency improvements arising from asymmetric factor growth are already embedded in the gross-output-based TFP of the upstream sectors, meaning their downstream impact is fully subsumed within the TFP spillover captured by term (c).

3. Variable Processing and Data Description

The empirical analysis of inter-industry spillovers is based on the 2023 national non-competitive input-output table comprising 42 sectors. Due to adjustments in sectoral classification, these 42 sectors are merged into 37 sectors. For the estimation of industry-level aggregate production functions and elasticities, the study utilizes a balanced panel dataset covering these 37 sectors from 1981 to 2024 (a total of 44 years), with data on total output $X_j(t)$, capital input $K_j(t)$, labor input $L_j(t)$, and intermediate input $M_j(t)$. Data sources include the CSMAR database, the

National Bureau of Statistics, the *China Statistical Yearbook*, the *China Industry Statistical Yearbook*, and the time-series input-output tables compiled by Zhang Hongxia et al.(2021). The mapping between the 42-sector and 37-sector classifications and the corresponding major industry groups is provided in Appendix 1.

Data on total output $X_j(t)$ and value added $V_j(t)$ were obtained following the methods in Zhang et al. (2021), with intermediate inputs $M_j(t)$ derived as the difference between the two. The selection of labor and capital inputs follows the variable selection and data processing methods for TFP estimation in He(2023) and OECD(2009): Given that changes in labor quality and working hours are minimal in the short run, and that the regression of the aggregate production function utilizes labor growth rates for adjacent years, the number of employed persons is directly used as the labor input variable $L_j(t)$ to calculate the growth rate. Due to significant gaps in the statistical data on employment for certain sectors, the paper estimates sectoral employment figures by dividing total labor compensation by the average wage for each industry, which are subsequently adjusted proportionally to align with the total labor force data from the National Bureau of Statistics. Data on total labor compensation by sector were drawn from the time-series input-output tables at current prices(Zhang et al. 2021)and the non-competitive input-output tables for 2020 and 2023. Data on average wages for input-output sectors were assigned based on the corresponding industry average wages, with the industry-level data obtained from the CSMAR database. To address missing data for certain sectors prior to 2002, the paper employs a linear fitting method: the ratio of the sectoral average wage to the overall average wage from 2002 onwards is used to fit the corresponding ratios for 1981–2001, which are then used to estimate and complete the missing wage data. Theoretical economics posits that depreciation represents the transfer of capital to output, while in the context of TFP calculation, the portion not transferred to output can be interpreted as inefficient capital utilization captured by TFP variations, making it reasonable to use fixed asset depreciation data as a measure of capital input. Data on the depreciation of fixed assets are sourced from the time-series input-output tables, as well as the 2020 and 2023 input-output tables. For the years 2019, 2021, 2022, and 2024, the total depreciation is distributed across sectors based on the proportions observed in adjacent years.

4. Empirical Analysis

To effectively estimate the factor elasticities of the production function and control for unobserved price trends, this paper estimates the aggregate production function using log-transformed data on gross output, capital stock, labor, and intermediate inputs. Specifically, the paper employs four estimation strategies (first-differencing, GMM, OLS, and models incorporating a time trend) and compares the regression results across sectors under each method. During the model selection stage, the paper imposes economic priors by retaining only those estimates where the elasticities of capital, labor, and intermediate inputs are strictly non-negative (α, β, $\gamma \geq 0$), ensuring they align with the fundamental tenets of production theory. Ultimately, by maximizing the adjusted R-square and minimizing the AIC in conjunction with the specific data characteristics of each sector, the paper identifies the optimal estimation method on a sector-by-sector basis to derive the final factor elasticity estimates and TFP measurements. The regression methods and detailed results for each sector are presented in Appendix 2.

4.1. Sectoral TFP Levels and Growth Rates

4.1.1. Sectoral TFP Levels and Gross Output in 2024

Figure 1 presents the cross-sectional data for 2024 TFP levels and gross output growth multiples (indexed to 1981), with sectors ranked by their TFP levels.

The data indicate that sectors represented by Research and Experimental Development (TFP: 55.67, output multiple: 746.13), Wholesale and Retail Trades (16.40, 135.02), and Finance (13.87, 431.66) have built their significant output expansion upon relatively high TFP improvements. With cumulative TFP increases far exceeding the social average, these sectors form the vanguard of technical efficiency enhancement. Meanwhile, resource-based sectors such as Metal Ore Mining and Dressing Products (6.77, 86.67) and Petroleum and Natural Gas Extraction Products (4.25, 53.48) also exhibit synergistic growth between efficiency and scale. Yet, a pronounced gap remains between their TFP advancements and those of frontier sectors, indicating that their growth trajectories are predominantly underpinned by resource endowment advantages and cyclical technological upgrades.

However, a larger number of sectors exhibit a stark contrast between drastic scale expansion and marginal efficiency gains. Within manufacturing, technology-intensive industries represented by Communication Equipment, Computers and Other Electronic Equipment (TFP: 1.07, output multiple: 544.63), Electrical Machinery and Equipment (1.51, 277.80), Instruments and Meters (1.90, 149.90), and Special Purpose Machinery (1.26, 180.89) have achieved tens or even hundreds of times expansion in total output; yet, their TFP levels have long hovered around the base period, forming a massive disconnect with their nominal "high-tech" attributes. The service sector presents a similar picture: Real Estate (TFP: 1.10, output multiple: 403.74) and Transport, Storage and Post (1.73, 295.39) show massive output surges while their TFP remains persistently low. This "high-growth, low-efficiency" paradigm indicates that the development of these sectors relies primarily on the continuous accumulation of factor inputs such as capital and labor. Trapped in a traditional factor-driven trajectory, their growth is now constrained by bottlenecks like rising labor costs and diminishing marginal returns to capital. Meanwhile, public utility sectors, represented by Production and Supply of Water (2.65, 240.06) and Production and Supply of Gas (1.03, 1379.12), similarly display explosive scale expansion with negligible TFP gains, indicating a severely lagging efficiency improvement process. In summary, over the past 44 years, the primary centers of TFP growth have been concentrated in modern service sectors that directly benefited from the IT revolution and the deepening of knowledge capital. Conversely, manufacturing, the backbone of the real economy, along with certain modern service sectors has exhibited glaring efficiency lags, characterized by a distinct "scale-efficiency disconnect". Particularly, high-tech manufacturing, classified as technology-intensive, has failed to pull away from other manufacturing sectors in terms of TFP growth, falling short of the TFP surge that empirical expectations would suggest. This implies that these sectors may have been long locked into low value-added processing and assembly nodes within global value chains. Their innovation investments have failed to effectively translate into efficiency gains, thereby trapping them in a "large but not strong" development paradigm. Consequently, transitioning economic development from factor-driven scale expansion to high-quality growth driven by TFP improvements remains a formidable challenge.

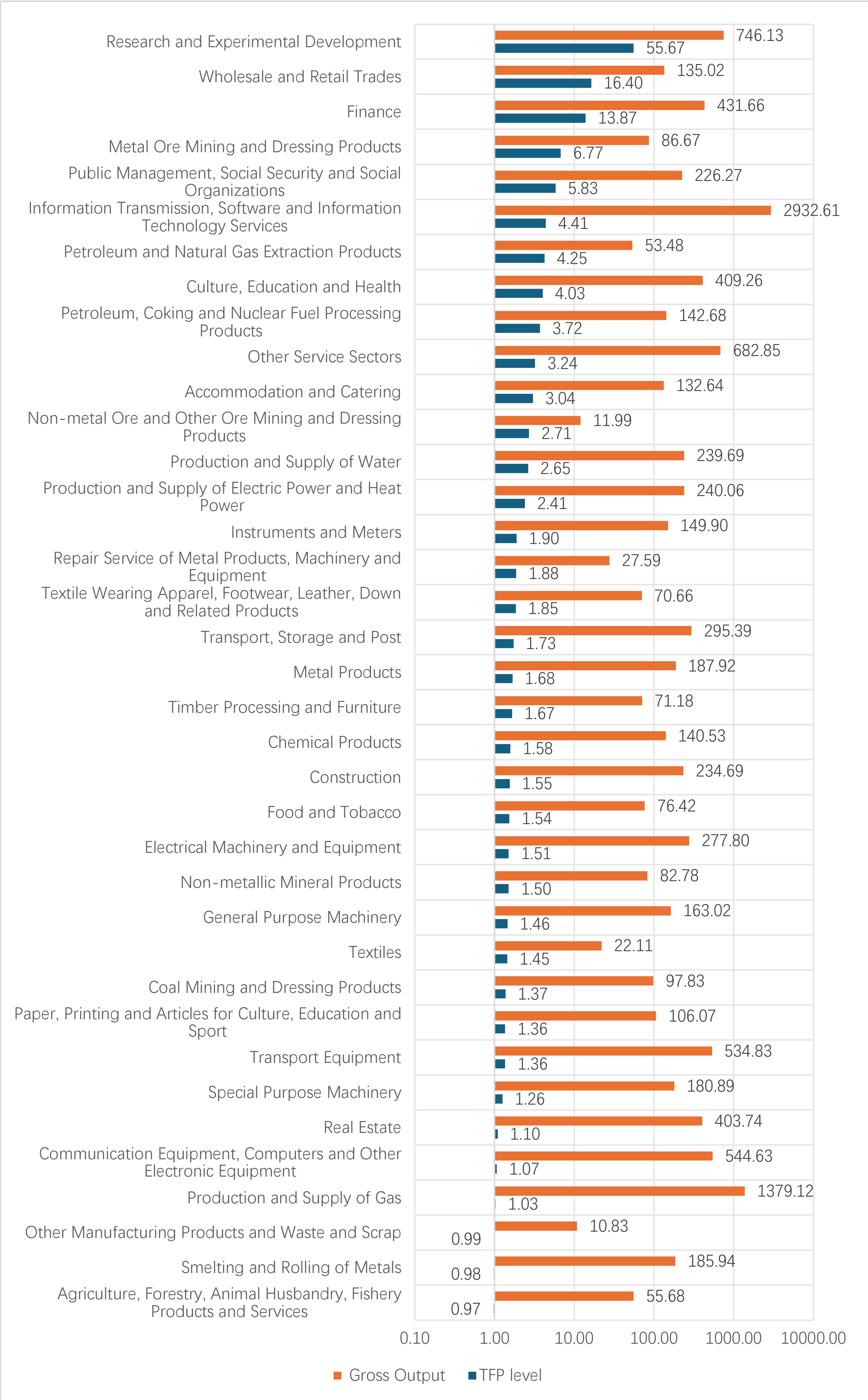

Figure 1 TFP Levels and Gross Output Growth Multiples of 37 Sectors in 2024 (Base Year: 1981)

4.1.2. TFP Growth and Volatility Across 25 Industrial Sectors

Figure 2 depicts the volatility of TFP growth and the sectoral rankings for 25 industrial sectors between 1982 and 2024.

The three sectors with the highest volatility are Other Manufacturing Products and Waste and Scrap (standard deviation of 33.0%), Petroleum and Natural Gas Extraction Products (22.0%), and Coal Mining and Dressing Products (12.0%), significantly higher than those of other sectors. Closely following are resource-processing sectors such as Repair Service of Metal Products, Machinery and Equipment, and Non-metal Ore and Other Ore Mining and Dressing Products, which also report standard deviations in the 9%–10% range. At the lower end of this spectrum, downstream industrial sectors like Textiles, Electrical Machinery and Equipment, and Chemical Products exhibit a standard deviation of merely 0.5%. From the perspective of the industrial chain, this volatility exhibits a significant negative correlation with a sector's position—specifically, sectors closer to the upstream (extraction, primary processing, and renewable resources) experience greater volatility as their TFP is more susceptible to shocks from external pricing, resource endowments, and environmental policies; conversely, further downstream sectors see weaker volatility, driven by mature technological paths and full market competition, which allow TFP growth to enter a steady state.

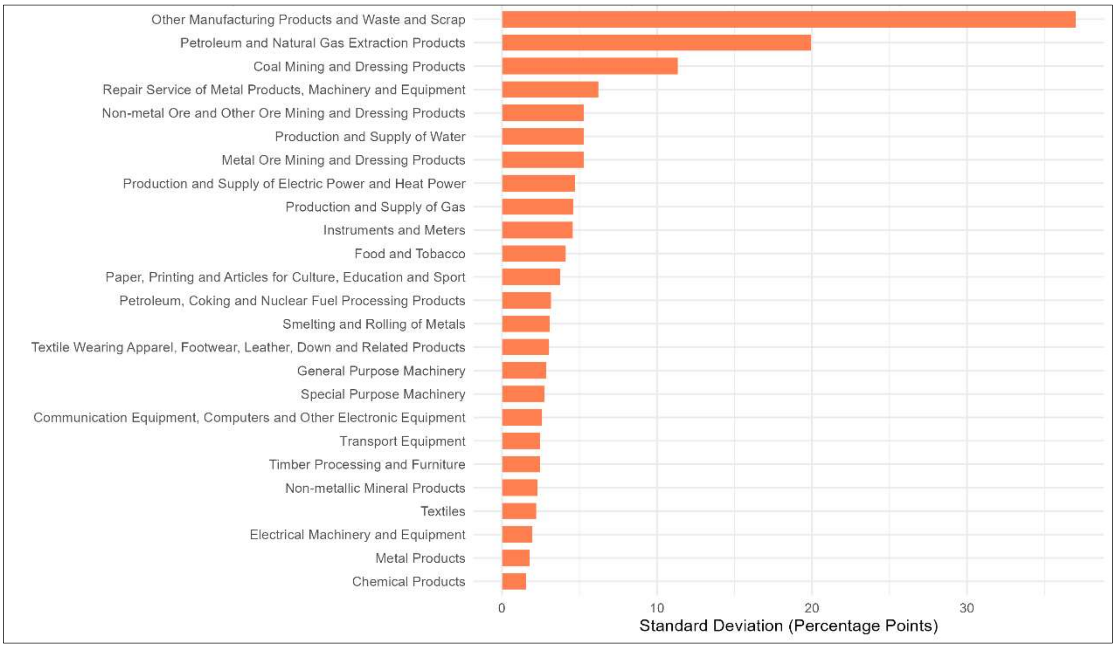

Figure 2 Volatility of TFP Growth (Standard Deviation) in 25 Industrial Sectors, 1982–2024

Figure 3 presents the time series and HP-filtered cyclical components of the three most volatile sectors, with the first row showing the TFP growth trajectories and the second row showing their corresponding cyclical components.

The sector with the highest volatility is Other Manufacturing Products and Waste and Scrap, whose TFP growth rate exhibits an extreme spike pattern. Between 2000 and 2002, the TFP growth rate surged from +60% to +70% before plummeting to -85%, registering an amplitude exceeding 150 percentage points within three years, while fluctuations in the remaining years were relatively muted. The short-term disturbances in its HP-filtered cyclical component oscillated widely between -100% and +130%, forming a classic "V-shaped" reversal during 2001–2002. This indicates that the sector lacks a significant long-term growth trend in its TFP; all fluctuations are driven by short-term policy interventions and changes in the statistical system, with the shocks exhibiting strong memory.

Petroleum and Natural Gas Extraction Products displays a pronounced cyclical pattern in its TFP growth. Its experienced deep contractions during 1985–1986, 1998–1999, 2008–2009, 2014–2015, and 2020–2021, periods that closely align with international crude oil price crashes; conversely, the Russia-Ukraine conflict drove energy prices higher in 2022, synchronously pushing the sector's TFP growth rate to +75%. The sector's cycle length spans approximately 8–12 years, moving in lockstep with the international commodity supercycle. These patterns indicate that the volatility in this sector's TFP growth primarily stems from the price-output-investment nexus: rising oil prices elevate the value of marginal reserves, stimulating production and driving TFP upward, whereas falling prices trigger a negative spiral. Consequently, its TFP growth is largely decoupled from genuine technological progress.

Compared to the previous two sectors, the Coal Mining and Dressing Products sector exhibits significantly subdued TFP growth volatility, fluctuating within a narrow ±10% range for the majority of the time. The peaks of its HP-filtered cyclical component in 1993 and 2016 correspond to the partial deregulation of coal prices and the short-term output expansion and price increases induced by supply-side reform, respectively; the troughs in 2009 and 2020 align with the demand slumps triggered by the financial crisis and the pandemic. This indicates that, unlike the market-driven cycles of the oil and gas sector, coal TFP volatility is a direct product of administrative supply management. Specifically, loose policies trigger capacity releases that propel brief TFP spikes, whereas tight policies enforce production cuts that drive TFP down, meaning the amplitude of volatility directly mirrors the intensity of policy interventions.

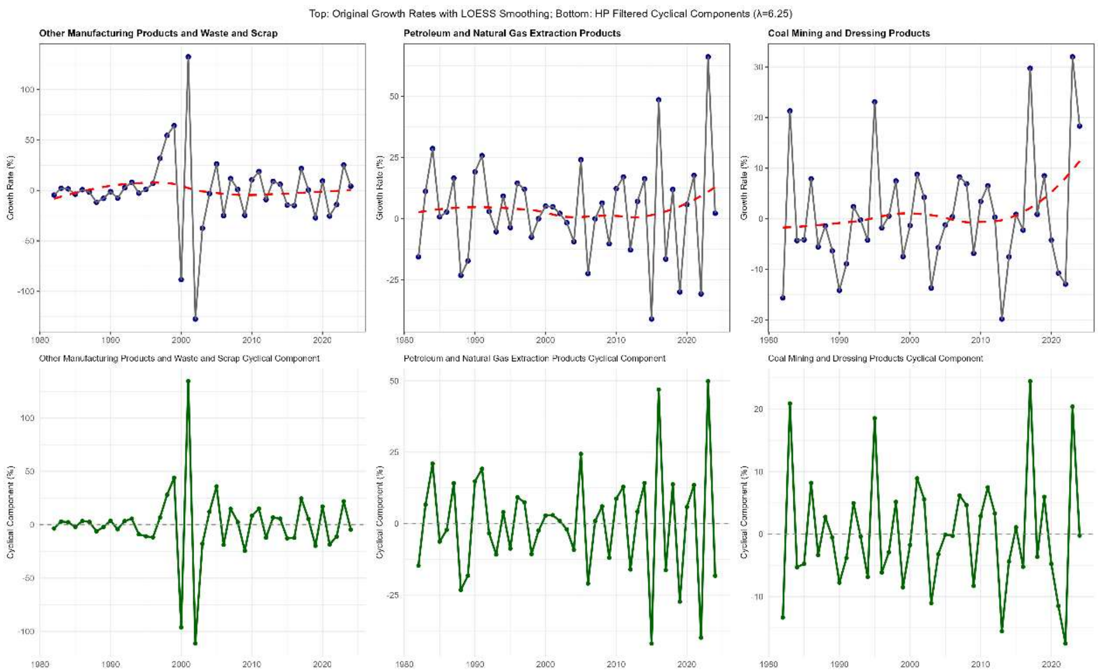

Figure 3 TFP Growth and HP-Filtered Cyclical Components of the Top Three Most Volatile Industrial Sectors, 1982–2024

4.2. Inter-sectoral Decomposition of TFP in 2023

4.2.1. Sectoral Decomposition of TFP Growth Rates in 2023

Table 1 presents the sources of sectoral TFP growth in 2023. Structurally, own technological progress and upstream technology spillovers serve as the primary positive drivers, whereas own factor inputs and upstream factor expansion generally constitute a drag, with significant heterogeneity observed across sectors.

(1) The contribution from own technological progress (a) shows a pronounced sectoral divergence. Notably, the extractive and high-tech manufacturing sectors stand out for their innovation edge, with Petroleum and Natural Gas Extraction Products (34.804), Coal Mining and Dressing Products (24.491), Research and Experimental Development (21.277), Instruments and Apparatus (14.622), and Communication Equipment (13.725) registering high values. This signals active R&D and an advancing technological frontier. Conversely, sectors such as Agriculture, Forestry, Animal Husbandry and Fishery (1.467), Metal Smelting (0.871), Real Estate (0.421), and Non-metallic Mineral Mining and Dressing (-1.988) show negligible or negative values, pointing to a lack of technological breakthroughs or declining efficiency.

(2) The contribution from own factor inputs (b) exhibits a similarly polarized structure. The (b) values for sectors such as Petroleum and Natural Gas Extraction Products (77.658), Coal Mining and Dressing Products (48.281), and Finance (51.295) are substantially positive, indicating that factor expansion still effectively supports TFP growth. However, as many as 17 sectors register negative (b) values, with Transport Equipment (-12.739), Gas Production and Supply (-22.236), Accommodation and Catering (-14.968), Information Transmission (-15.174), Real Estate (-14.785), and Metal Products Repair Services (-23.803) showing particularly sharp negative values. This implies a widespread decline in factor marginal returns: even where technological progress is positive, over-rapid capital deepening and labor redundancy are collectively creating a systemic drag on TFP.

(3) The upstream TFP spillover effect (c) is predominantly positive, corroborating the validity of the forward spillover transmission mechanism within industrial chains. Energy processing and public utility sectors such as Petroleum and Coking Products (40.412), Gas Supply (41.936), and Electricity and Heat (11.356) exhibit the deepest reliance on upstream technology, while mid-stream manufacturing including Chemical Products (9.541), Communication Equipment (9.278), and Metal Smelting (8.816) also reaps substantial benefits. Conversely, the (c) values for Real Estate (1.305), R&D Services (1.271), Agriculture, Forestry, Animal Husbandry and Fishery (1.969), and Public Administration (2.103) all remain at low levels, reflecting either short industrial chains or insufficient absorptive capacity for upstream technologies.

(4) The upstream factor input pulling effect (d) is negative in the vast majority of sectors, acting as a major drag on TFP growth in 2023. The negative contributions are particularly pronounced in sectors such as Petroleum and Coking Products (-48.031), Gas Supply (-34.527), Coal Mining and Dressing Products (-12.170), and Chemical Products (-10.596). This indicates that upstream factor expansion (such as increases in capital stock and labor input) exerts a distinct squeeze on downstream TFP by elevating intermediate input costs or deteriorating resource allocation. Conversely, only a handful of sectors register positive (d) values (Transport Equipment 6.125, Information Transmission 6.822, Public Administration 2.492, and Wholesale and Retail Trade 1.099). Capable of neutralizing or even capitalizing on upstream cost pressures, these sectors exhibit superior cost pass-through and supply chain synergy.

In summary, sectoral TFP growth patterns can be categorized into three main types. The first is the “technology-driven” type, represented by Coal Mining and Dressing, Petroleum Extraction, Communication Equipment, Instruments and Apparatus, and R&D Services. These sectors feature high (a) values and robust overall growth, though some show signs of declining factor efficiency.

The second is the “upstream-dependent” type, represented by Petroleum and Coking Products, Gas Supply, and Electricity and Heat. Their (c) values are extremely high while (d) values are substantially negative, indicating that TFP growth relies heavily on upstream technological innovation but remains vulnerable to shocks from upstream factor expansion. The third is the “positive-linkage” type, where only a few sectors, such as Transport Equipment, Information Transmission, Public Administration, and Wholesale and Retail Trade, register positive (d) values, exhibiting a virtuous dynamic of synergistic development with upstream sectors. Furthermore, sectors such as Agriculture, Forestry, Animal Husbandry and Fishery, Real Estate, and Non-metallic Mineral Products show sluggish performance on both the own-technology and upstream-spillover fronts. Falling into a “low-innovation, low-transmission” category, these sectors urgently require technological innovation and industrial chain integration to reshape their growth momentum.

Table 1 Source Decomposition of Sectoral TFP Growth Rates in 2023 (%)

Sector	(a)	(b)	(c)	(d)
Agriculture, Forestry, Animal Husbandry, Fishery Products and Services	1.467	-4.056	1.969	-1.828
Coal Mining and Dressing Products	24.491	48.281	9.312	-12.170
Petroleum and Natural Gas Extraction Products	34.804	77.658	0.549	-0.718
Metal Ore Mining and Dressing Products	12.020	12.224	4.193	-3.718
Non-metal Ore and Other Ore Mining and Dressing Products	-1.988	4.616	3.854	-2.618
Food and Tobacco	8.216	10.740	2.254	-0.404
Textiles	6.044	12.835	5.064	-7.272
Textile Wearing Apparel, Footwear, Leather, Down and Related Products	12.600	14.209	4.782	-5.965
Timber Processing and Furniture	11.999	3.223	5.781	-1.819
Paper, Printing and Articles for Culture, Education and Sport	7.696	8.835	5.562	-4.393
Petroleum, Coking and Nuclear Fuel Processing Products	4.768	4.296	40.412	-48.031
Chemical Products	8.533	9.191	9.541	-10.596
Non-metallic Mineral Products	1.904	8.284	6.020	-6.492
Smelting and Rolling of Metals	0.871	-1.378	8.816	-7.678
Metal Products	7.382	4.148	3.570	-0.925
General Purpose Machinery	11.721	-0.004	4.648	0.456
Special Purpose Machinery	11.131	1.189	4.646	-0.123
Transport Equipment	10.267	-12.739	5.404	6.125
Electrical Machinery and Equipment	8.623	-5.171	4.425	-0.137
Communication Equipment, Computers and Other Electronic Equipment	13.725	2.789	9.278	-3.085
Instruments and Meters	14.622	2.571	5.223	-1.284
Other Manufacturing Products and Waste and Scrap	14.877	27.489	5.950	-5.475
Repair Service of Metal Products, Machinery and Equipment	24.585	-23.803	2.713	2.196
Production and Supply of Electric Power and Heat Power	11.248	-0.002	11.356	-8.990
Production and Supply of Gas	5.107	-22.236	41.936	-34.527
Production and Supply of Water	15.831	4.569	3.675	-2.734
Construction	2.857	5.992	3.243	-0.826
Wholesale and Retail Trades	11.088	0.270	1.530	1.099
Transport, Storage and Post	3.253	-14.964	3.972	0.809
Accommodation and Catering	10.620	-14.968	3.095	-1.860

Information Transmission, Software and Information Technology Services	4.607	-15.174	4.866	6.822
Finance	4.938	51.295	2.837	-4.362
Real Estate	0.421	-14.785	1.305	-0.630
Research and Experimental Development	21.277	9.084	1.271	0.273
Culture, Education and Health	4.130	-5.756	2.527	-0.896
Public Management, Social Security and Social Organizations	7.298	-6.221	2.103	2.492
Other Service Sectors	7.674	-11.905	4.180	1.306

4.2.2. Inter-industry TFP Growth Spillover Effects Across 25 Industrial Sectors in 2023

Figure 4 presents the marginal TFP spillover effects among 25 industrial sectors in 2023. It illustrates the marginal spillover impact of each source sector (vertical axis) on the TFP growth rate of the target sectors (horizontal axis). The corresponding names for Sectors 2 through 26 are provided in Appendix 2. The cell values reflect the marginal contribution of a unit of technological advancement from the source sector to the target sector's TFP growth.

The paper finds that inter-industry spillover intensity exhibits a clear gradient decay pattern characterized by "extensive upstream, sparse midstream, and negligible downstream" effects. Upstream energy and basic raw material sectors constitute the core sources of technological spillovers along the industrial chain. Sectors such as Coal Mining and Dressing Products, Petroleum and Natural Gas Extraction Products, and Metal Mining and Dressing Products generate positive marginal spillovers ranging from 0.4 to 0.5 across multiple downstream processing and manufacturing sectors. This indicates that technological progress in the extractive industries exerts a widespread transmission effect through intermediate input supply channels, serving as a vital upstream driver of industrial TFP growth. Although a few sectors, such as Non-metallic Mineral Mining and Dressing, Paper and Printing, and Communication Equipment, exhibit limited spillovers of 0.1 to 0.3 to specific downstream sectors, mid-to-high-end equipment manufacturing sectors—including General Purpose Machinery, Special Purpose Machinery, Transport Equipment, and Electrical Machinery—generally record marginal values below 0.1 as spillover recipients, or even fall below the observable threshold. This distributional characteristic suggests that current technological transmission chains predominantly cover the preceding stages from upstream to midstream, struggling to penetrate deeply into the tail end of the industrial chain.

Furthermore, due to their positioning and functional attributes, certain sectors lie on the periphery of the technology spillover network, or even exist as "islands." In the figure, this is reflected in sectors such as Metal Products, Repair Services of Machinery and Equipment, and Production and Supply of Water, which fail to form significant spillover linkages on either the source or receiving side. Specifically, sectors at the tail end of the industrial chain supporting functions—primarily undertaking equipment maintenance, repair, and operational safeguards—have a natural disconnect from core R&D and intermediate goods manufacturing chains. Meanwhile, typical localized public service sectors lack cross-regional mobility, making it difficult to achieve cross-sectoral technology transmission through input-output linkages. Consequently, these sectors struggle to integrate into the main channels of industrial chain technology diffusion, which are carried by intermediate goods trade. Their technological progress relies primarily on intra-sectoral improvements or specific investments, rendering them largely immune to upstream and downstream technological innovation spillovers.

In summary, given the constraints of limited technological investment resources, enhancing industrial TFP growth efficiency requires a differentiated policy strategy: "strengthening sources, clearing nodes, and bridging islands." Specifically, for high-spillover upstream source sectors like Coal Mining and Dressing and Petroleum Extraction, policy support should be directed toward generic technology R&D and pilot-scale testing platforms. This aims to extend their spillover intensity, currently at 0.4 to 0.5, further down the industrial chain, enabling upstream innovation investments to generate a multiplier effect on TFP growth through supply chain transmission mechanisms. Conversely, for midstream sectors with weak technological receptivity, such as General Purpose Machinery and Transport Equipment, technological investments should be prioritized for building absorptive capacity through digital design tools, process testing platforms, and joint R&D centers, rather than simply expanding production capacity. This enables them to more fully harness upstream TFP spillovers, thereby improving growth efficiency. For spillover "island" sectors, such as Repair Services of Metal Products and Production and Supply of Water, the entry point should be digital transformation. By leveraging models like the Industrial Internet and Product-Service Systems (PSS), efforts should be made to integrate their functional modules into the intermediate goods trade network of the main industrial chain, thereby closing diffusion breakpoints. Ultimately, these targeted interventions can achieve the optimal allocation of limited resources to maximize overall industrial TFP growth efficiency.

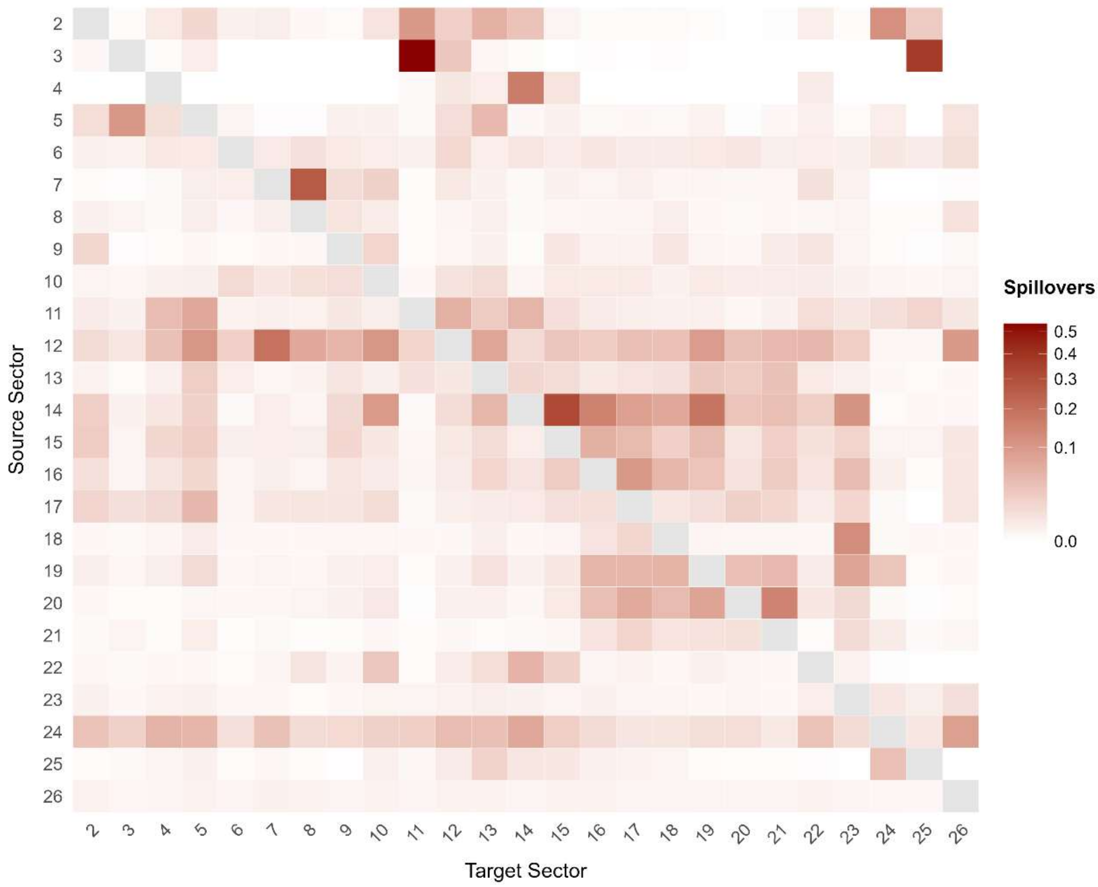

Figure 4 Inter-industry TFP Spillovers Among 25 Industrial Sectors (2023)

5. Conclusions and Implications

In the context of China's transition towards high-quality economic development, spillover pathways based on production networks provide a crucial basis for identifying technological innovation breakthroughs, optimally allocating limited resources to maximize the economy's overall TFP, and fostering new quality productive forces. Therefore, identifying inter-industry TFP spillover pathways—thereby locating the critical nodes, weak links, and isolated sectors in the production network—holds profound significance for designing precise industrial policies and bolstering economic resilience. Focusing on forward TFP spillover pathways, this paper innovatively integrates the input-output framework with an intermediate-input-inclusive Cobb-Douglas production function, using intermediate goods as the transmission medium to characterize these inter-industry linkages. Furthermore, it decomposes the forward spillover of TFP growth into four dimensions—own technological progress, own factor inputs, upstream TFP spillovers, and upstream factor expansion—precisely quantifying their marginal contributions to sectoral TFP.

The research reveals that sectoral TFP growth in China exhibits a pronounced "scale-efficiency divergence." Along the industrial chain, transmission presents an unbalanced pattern characterized by "severe upstream volatility and downstream squeeze." Technological spillovers attenuate gradiently along the chain, indicating that growth momentum remains trapped in a factor-driven path. The root cause lies in the high reliance of upstream resource-based sectors on price cycles and policy interventions. This non-technology-driven model induces severe internal volatility, which is then transmitted downstream via cost channels, leaving downstream sectors to face a dual dilemma of impeded technological transmission and cost squeeze. The source decomposition results corroborate this mechanism: although upstream TFP spillovers and intra-sectoral technological progress serve as the primary positive drivers, factor expansion—both within the sectors themselves and upstream—generally constitutes the main drag. This indicates that the majority of sectors remain deeply mired in a factor-driven trajectory, where the negative squeeze from upstream factor expansion offsets the technological spillover dividends. Only a handful of sectors, such as transport equipment and information transmission, achieve "positive synergy" through supply chain collaboration. Furthermore, the spillover intensity among industrial sectors exhibits a pattern of "broad upstream, sparse midstream, and near-zero downstream," leading to the cascading erosion of technological dividends and stranding certain supporting services and public utility sectors as "islands" within the technology diffusion network. Overall, the cost squeeze induced by extensive upstream expansion severely counteracts the technological spillover dividends, trapping the industrial chain in an inefficient equilibrium where "scale expansion diverges from efficiency improvement." Therefore, to facilitate an efficient transition of China's economic growth from factor inputs to efficiency enhancements, it is imperative to first unclog technological spillover channels and dismantle the negative squeeze effect of factor expansion.

Based on the above analysis, this study provides the following policy implications for fostering new quality productive forces and promoting high-quality economic development:

First, reinvigorate the growth momentum of high-tech industries to escape the "scale-efficiency divergence" trap. Addressing the paradox of surging output alongside stagnant TFP in technology-intensive sectors such as communication equipment and electrical machinery, policy orientation must shift from mere scale expansion toward breakthroughs in core technologies and moving up the value chain. Efforts should prioritize supporting enterprises in breaking their path dependency on low-value-added stages such as processing and assembly. This is essential to translate innovation inputs into tangible technical efficiency improvements, thereby avoiding the factor-driven "large but not strong" development trap.

Second, unclog technology spillover channels along the industrial chain and implement differentiated sectoral support strategies. Given the gradient attenuation of spillovers, characterized by "broad upstream, near-zero downstream", policies should be precisely tailored based on a sector's position within the production network. For upstream source sectors like coal and oil and gas, support for generic technology R&D should be strengthened to amplify their positive spillover effects. For mid- and downstream equipment manufacturing sectors, the focus should be on enhancing technology absorption capacity, such as by building digital R&D platforms to capture upstream technological dividends. For sectors stranded as "islands" in the technology diffusion network, such as water utilities and repair services, efforts should be made to reintegrate them into the main industrial chain via digital transformation and the industrial internet, thereby eliminating breakpoints in technology transmission.

Third, optimize the allocation structure of production factors to eliminate the negative downstream squeeze caused by upstream expansion. As the findings indicate that factor expansion, both within the sectors themselves and upstream, generally acts as a drag on TFP growth, it is imperative to curb the extensive factor inputs in resource-based sectors. This is necessary to prevent upstream cost pressures from propagating down the industrial chain, which would otherwise squeeze downstream profit margins and innovation space. Policies should guide capital and labor flows toward highly efficient and high-spillover sectors, increase the marginal returns on factors, improve resource allocation efficiency, and break the inefficient equilibrium of "high input, low output".

Fourth, mitigate severe volatility in upstream sectors to enhance the resilience of the industrial chain. To address the drastic fluctuations in the TFP growth of upstream resource-based sectors caused by price cycles and policy interventions, efforts should be made to improve the reserve adjustment and market-oriented pricing mechanisms for critical energy and raw materials. This aims to minimize the severe shocks stemming from administrative supply management. By stabilizing upstream supply expectations, a conducive environment for technological innovation can be created for mid- and downstream manufacturing sectors, thereby safeguarding the robust operation of the economic system.

Limited by the availability of sectoral data, this study has not yet constructed the transmission mechanism of total factor productivity (TFP) growth at the micro-enterprise level, relying primarily on macroscopic data and empirical facts to explain the causes of spillover effects. Future research could attempt to utilize micro-enterprise data to further uncover the formation mechanisms of inter-industry TFP spillovers, thereby verifying the robustness of our conclusions. Regarding model specification, this study adopts a short-term perspective, assuming that trade substitution behaviors do not occur; that is, the market share coefficients or regional self-sufficiency rates remain fixed. Although this assumption is reasonable for short-term analysis, future research could extend the model to long-term analyses or policy simulation scenarios. This could involve employing dynamic regional input-output models or computable general equilibrium (CGE) models, and introducing Constant Elasticity of Substitution (CES) functions or gravity models to endogenize the relevant trade coefficients. Such an approach would reflect their dynamic adjustment characteristics in response to changes in relative prices, technological progress, and trade costs. At the macroeconomic level, subsequent studies could also integrate inter-regional input-output and input-occupancy-output relationships to conduct a deeper decomposition of TFP to trace its ultimate sources. Furthermore, this study has not fully considered the feedback effects of intermediate goods purchasing behaviors in downstream sectors on upstream sectors, a limitation that remains to be addressed in future research.

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II. Appendix

Appendix I : Correspondence of the 42 Sectors and 37 Sectors of the Input-Output Table with the National Economy Industry Classification

42-Sector Code and Name		Major Category Code	37-Sector Code and Name	
01	Agriculture, Forestry, Animal Husbandry, Fishery Products and Services	01~05	01	Agriculture, Forestry, Animal Husbandry, Fishery Products and Services
02	Coal Mining and Dressing Products	06	02	Coal Mining and Dressing Products
03	Petroleum and Natural Gas Extraction Products	07	03	Petroleum and Natural Gas Extraction Products
04	Metal Ore Mining and Dressing Products	08、09	04	Metal Ore Mining and Dressing Products
05	Non-metal Ore and Other Ore Mining and Dressing Products	10~12	05	Non-metal Ore and Other Ore Mining and Dressing Products
06	Food and Tobacco	13~16	06	Food and Tobacco
07	Textiles	17	07	Textiles
08	Textile Wearing Apparel, Footwear, Leather, Down and Related Products	18、19	08	Textile Wearing Apparel, Footwear, Leather, Down and Related Products
09	Timber Processing and Furniture	20、21	09	Timber Processing and Furniture
10	Paper, Printing and Articles for Culture, Education and Sport	22~24	10	Paper, Printing and Articles for Culture, Education and Sport
11	Petroleum, Coking and Nuclear Fuel Processing Products	25	11	Petroleum, Coking and Nuclear Fuel Processing Products
12	Chemical Products	26~29	12	Chemical Products
13	Non-metallic Mineral Products	30	13	Non-metallic Mineral Products
14	Smelting and Rolling of Metals	31、32	14	Smelting and Rolling of Metals
15	Metal Products	33	15	Metal Products
16	General Purpose Machinery	34	16	General Purpose Machinery
17	Special Purpose Machinery	35	17	Special Purpose Machinery
18	Transport Equipment	36、37	18	Transport Equipment
19	Electrical Machinery and Equipment	38	19	Electrical Machinery and Equipment
20	Communication Equipment, Computers and Other Electronic Equipment	39	20	Communication Equipment, Computers and Other Electronic Equipment
21	Instruments and Meters	40	21	Instruments and Meters
22	Other Manufacturing Products and Waste and Scrap	41、42	22	Other Manufacturing Products and Waste and Scrap
23	Repair Service of Metal Products, Machinery and Equipment	43	23	Repair Service of Metal Products, Machinery and Equipment
24	Production and Supply of Electric Power and Heat Power	44	24	Production and Supply of Electric Power and Heat Power
25	Production and Supply of Gas	45	25	Production and Supply of Gas
26	Production and Supply of Water	46	26	Production and Supply of Water
27	Construction	47~50	27	Construction
28	Wholesale and Retail Trades	51、52	28	Wholesale and Retail Trades

29	Transport, Storage and Post	53~60	29	Transport, Storage and Post
30	Accommodation and Catering	61、62	30	Accommodation and Catering
31	Information Transmission, Software and Information Technology Services	63~65	31	Information Transmission, Software and Information Technology Services
32	Finance	66~69	32	Finance
33	Real Estate	70	33	Real Estate
34	Leasing and Business Services	71、72	37	Other Service Sectors
35	Research and Experimental Development	73	34	Research and Experimental Development
36	Comprehensive Technical Services	74、75	37	Other Service Sectors
37	Management of Water Conservancy, Environment and Public Facilities	76~78	37	Other Service Sectors
38	Services to Households, Repair and Other Services	79~81	37	Other Service Sectors
39	Education	82	35	Culture, Education and Health
40	Health and Social Work	83、84	35	Culture, Education and Health
41	Culture, Sports and Entertainment	85~89	35	Culture, Education and Health
42	Public Management, Social Security and Social Organizations	90~95	36	Public Management and Social Organizations

Appendix II Regression Methods and Results for the 37-Sector Production Functions

Sector		Capital Coefficient	Labor Coefficien	Intermediate Input Coefficient	Returns to Scale	Adjusted R^2	Estimation Method
01	Agriculture, Forestry, Animal Husbandry, Fishery Products and Services	0.0493	0.1560	0.9026	1.1079	0.9965	GMM
02	Coal Mining and Dressing Products	0.0454	0.0556	0.9151	1.0162	0.9943	OLS
03	Petroleum and Natural Gas Extraction Products	0.0740	0.1482	0.7480	0.9702	0.9892	Time Trend Control
04	Metal Ore Mining and Dressing Products	0.0101	0.2590	0.6626	0.9317	0.9993	Time Trend Control
05	Non-metal Ore and Other Ore Mining and Dressing Products	0.0191	0.2028	0.7346	0.9565	0.9338	First-Differencing
06	Food and Tobacco	0.0575	0.1391	0.8554	1.0520	0.9995	Time Trend Control
07	Textiles	0.0396	0.1511	0.8624	1.0531	0.9997	Time Trend Control
08	Textile Wearing Apparel, Footwear, Leather, Down and Related Products	0.0312	0.1930	0.8437	1.0679	0.9997	Time Trend Control

09	Timber Processing and Furniture	0.0204	0.1120	0.8754	1.0079	0.9998	Time Trend Control
10	Paper, Printing and Articles for Culture, Education and Sport	0.0000	0.1475	0.9173	1.0648	0.9997	Time Trend Control*
11	Petroleum, Coking and Nuclear Fuel Processing Products	0.0083	0.1501	0.7215	0.8799	0.9993	Time Trend Control
12	Chemical Products	0.0179	0.0953	0.8669	0.9801	0.9999	Time Trend Control
13	Non-metallic Mineral Products	0.0605	0.1831	0.8266	1.0701	0.9884	First-Differencing
14	Smelting and Rolling of Metals	0.0360	0.0400	0.9220	0.9980	0.9996	OLS
15	Metal Products	0.0024	0.1302	0.8710	1.0036	0.9999	Time Trend Control
16	General Purpose Machinery	0.0035	0.0399	0.9026	0.9460	0.9998	Time Trend Control
17	Special Purpose Machinery	0.0100	0.0153	0.9353	0.9606	0.9726	First-Differencing
18	Transport Equipment	0.0079	0.0735	0.9234	1.0048	0.9999	Time Trend Control
19	Electrical Machinery and Equipment	0.0062	0.0784	0.8932	0.9779	0.9999	Time Trend Control
20	Communication Equipment, Computers and Other Electronic Equipment	0.0080	0.0433	0.9539	1.0052	0.9998	OLS
21	Instruments and Meters	0.0016	0.1545	0.8302	0.9863	0.9209	First-Differencing
22	Other Manufacturing Products and Waste and Scrap	0.0629	0.0601	1.0379	1.1609	0.9505	GMM
23	Repair Service of Metal Products, Machinery and Equipment	0.0056	0.2136	0.8421	1.0612	0.9975	Time Trend Control
24	Production and Supply of Electric Power and Heat Power	0.0086	0.3104	0.6862	1.0052	0.9993	Time Trend Control
25	Production and Supply of Gas	0.1460	0.0779	0.9053	1.1293	0.9997	OLS
26	Production and Supply of Water	0.0385	0.3096	0.7224	1.0705	0.9084	First-Differencing

27	Construction	0.0071	0.1738	0.8898	1.0708	0.9999	Time Trend Control
28	Wholesale and Retail Trades	0.2215	0.1893	0.3077	0.7185	0.9952	Time Trend Control
29	Transport, Storage and Post	0.0171	0.1251	0.7910	0.9332	0.9994	Time Trend Control
30	Accommodation and Catering	0.0893	0.1281	0.6617	0.8791	0.9994	Time Trend Control
31	Information Transmission, Software and Information Technology Services	0.0798	0.2039	0.5911	0.8748	0.8412	First-Differencing
32	Finance	0.0751	0.1743	0.5344	0.7839	0.9984	Time Trend Control
33	Real Estate	0.0163	0.5146	0.7517	1.2825	0.9920	OLS
34	Research and Experimental Development	0.0181	0.3345	0.3850	0.7376	0.9996	Time Trend Control
35	Culture, Education and Health	0.0139	0.2803	0.7490	1.0432	0.9997	Time Trend Control
36	Public Management, Social Security and Social Organizations	0.1807	0.3506	0.4759	1.0072	0.9994	Time Trend Control
37	Other Service Sectors	0.0161	0.0784	0.7732	0.8677	0.9998	Time Trend Control

* A non-negativity constraint was imposed on the regression for Sector 10 (Paper, Printing and Articles for Culture, Education and Sport).