Scientific and Technological Innovation, Industrial Structure and Economic Growth: Empirical Evidence from China

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Date: 2025-10-24T00:00:00+00:00

Abstract

This study investigates the synergistic relationship among technological innovation (TI), industrial structure (IS), and economic growth (EG), aiming to elucidate their mechanisms, heterogeneity, and policy-driven effects. Utilizing data from Chinese listed companies spanning 1990–2023 and employing empirical methodologies (mediation effect analysis, fixed-effects models, group regression, threshold models, and difference-in-differences), it examines their synergistic interactions. Key findings are as follows: 1) TI significantly facilitates IS upgrading, which in turn positively drives EG, demonstrating synergistic effects; 2) Capacity utilization partially mediates the TI-IS-EG pathway by optimizing resource allocation; 3) Notable heterogeneity exists: central regions exhibit the lowest benefits from IS transformation, whereas western regions gain from policy support; the service sector and high-tech manufacturing drive EG more substantially than traditional industries; 4) Threshold effects are present: IS exhibits dual thresholds for EG (with the strongest growth occurring under industry-service synergy), while TI shows a single threshold for IS; 5) The 2015 supply-side structural reform generates significant marginal incentives. This study provides empirical evidence for the micro-level innovation-structure-growth nexus in China and offers policy insights for differentiated regional and industrial policies.

Full Text

Preamble

Scientific and Technological Innovation, Industrial Structure and Economic Growth: Empirical Evidence from China

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Abstract

This study examines the synergistic relationship between technological innovation (TI), industrial structure (IS), and economic growth (EG), aiming to clarify their transmission mechanisms, heterogeneity, and policy-driven effects. Using data from Chinese listed companies (1990–2023) and employing empirical methods including mediation analysis, fixed effects models, group regression, threshold regression, and difference-in-differences (DID), we explore the synergistic effects among these three variables.

Key findings are as follows: (1) TI significantly promotes IS upgrading, which in turn positively drives EG, generating synergistic effects; (2) Capacity utilization partially mediates the TI-IS-EG pathway by optimizing resource allocation; (3) Heterogeneity is evident: central regions exhibit the lowest benefits from IS transformation, while western regions benefit from policy support; services and high-tech manufacturing drive EG more effectively than traditional industries; (4) Threshold effects exist: IS has dual thresholds for EG (with strongest growth occurring under industry-service synergy), while TI has a single threshold for IS; (5) The 2015 supply-side structural reform generates significant marginal incentives. This study provides empirical evidence and policy insights for China's innovation-structure-growth nexus at the micro level, offering guidance for differentiated regional and industrial policies.

Keywords: Technological innovation, Industrial structure, Economic growth, Capacity utilization, Supply-side structural reform, Threshold regression, Listed companies

1. Introduction

Since 2012, China's economy has experienced a downward growth trajectory accompanied by severe overcapacity (Guo, K. et al., 2025) [1]. During the first 32 years of reform and opening-up, China's average annual GDP growth rate reached 9.9%, with the government consistently maintaining the "Eight Guarantees" as the baseline for actual growth targets. However, since 2012, the GDP growth rate dropped to 7.7%, and further declined to 6.9% in 2015 [1]. After more than three decades of high-speed growth, China's economic growth rate has decelerated, entering a "new normal" of medium-to-high speed development characterized by persistent downward pressure (Zhang, H., Li, L., Chen, T., & Li, V., 2016; Holbig, H., 2018; Liu, L. et al., 2025) [2][3][4].

Against this backdrop of economic slowdown and severe overcapacity, the core contradiction manifests as distortion in the industrial structure (IS), particularly structural imbalances characterized by excess capacity in heavy industries such as steel, coal, and cement. This distortion directly contributed to the continuous decline in the Producer Price Index (PPI) from March 2012 to September 2016 and operational losses among industrial enterprises (Zhou, Y. et al., 2025) [5]. Li Jin observed that PPI in major overcapacity industries declined for over 40 consecutive months, accounting for 70–80% of the overall industrial PPI decline. Since 2003, 80% of these industries have incurred losses, with profits dropping precipitously (Song, M. et al., 2025) [6]. This evidence indicates that IS imbalance constitutes a key constraint on economic growth (EG), as irrational resource allocation across industries not only wastes production factors but also suppresses overall economic system efficiency.

The failure of demand-side stimulus policies to sustain EG further underscores the necessity of addressing supply-side structural issues. Cai Fang (2016) [9] argued that China' s economic slowdown stems from declining supply-side investment returns and slowing total factor productivity (TFP) growth, both inherently linked to technological innovation (TI) and IS adjustment. From perspectives of Pareto optimality and structural economics, improving EG quality and quantity relies on optimizing inter-industry resource allocation and achieving optimal factor allocation through IS transformation (Gyau, E. B., et al., 2025; Luo, Z., & Hu, P., 2024) [7][8]. However, IS transformation cannot occur without TI as a driving force. TFP growth, the core of supply-side efficiency improvement, fundamentally depends on TI (e.g., technological breakthroughs, process optimization) [1], which provides the fundamental impetus for IS to shift toward high value-added and high-efficiency sectors. This establishes the initial logical chain: TI drives IS transformation, and optimized IS in turn promotes EG.

To address structural imbalances, China proposed "supply-side structural reform" with "three cuts, one reduction, and one supplement" as core measures. Among these, capacity reduction in overcapacity industries aimed to resolve historical overcapacity issues, raise industrial PPI, and alleviate IS distortion. The policy tools primarily focused on adjusting infrastructure services to eliminate excess capacity and create space for industrial upgrading. However, the reform achieved only short-term IS fluctuations rather than long-term transformation: although PPI briefly recovered in 2016, it declined again in 2018, and economic growth continued its downward trend with only a slight rebound in early 2017. The fundamental reason lies in the lack of TI-driven IS adjustment. Without technological breakthroughs to upgrade traditional industries or cultivate high-tech sectors, IS optimization remains superficial and fails to generate sustainable EG momentum.

China's subsequent proposal of "new quality productive forces" (September 2023) and the release of the "Guiding Catalogue for Industrial Structure Adjustment (2024 Edition)" clarified the direction of IS transformation by identifying industries to encourage, restrict, or eliminate. The government further emphasized that the "innovation-driven development strategy" constitutes the fundamental measure to advance supply-side reform and enhance EG' s internal vitality. This reaffirms TI' s core position in IS transformation: current deficiencies in China' s TI system, such as enterprises' long-term lack of independent innovation capabilities and corporate cultures prioritizing output over technology, directly hinder TI capacity improvement and block the transmission channel from TI to structural transformation. Since 2024, China has introduced supportive policies including the "Implementation Opinions on Promoting Future Industrial Innovation and Development" (seven ministries), the "Guidelines for Innovation Point System Work (National Trial)" (Ministry of Science and Technology), and the "Implementation Plan for Patent Industrialization to Promote Growth of Small and Medium-sized Enterprises" (five departments including CNIPA). These policies aim to enhance TI capabilities over the long term, rather than merely inducing short-term industrial fluctuations like previous IS adjustment measures.

Based on this logical context, three core questions regarding the relationships among these variables require investigation: (1) What is the intrinsic transmission mechanism among TI, IS transformation, and EG? Specifically, can TI effectively drive IS transformation and subsequently achieve long-term EG? (2) After clarifying the causal chain from TI through IS transformation to EG, how can industrial policies (e.g., TI-support policies, IS adjustment policies) regulate this chain to strengthen synergistic effects? (3) Can existing TI-support and IS guidance policies effectively remove obstacles in the TI-to-IS transformation path, thereby achieving the expected long-term EG promotion effects?

To address these questions, this study draws on macroeconomic and econometric theories, integrating qualitative and quantitative methods to clarify the logical relationships among TI, IS transformation, and EG through theoretical deduction and empirical analysis. It further explores how industrial policies intervene in the interactions among these core variables and proposes targeted policy recommendations for IS transformation. The research aims to provide evidence-based, quantitative, and scientific decision support for government departments, enterprises, and research institutions in formulating policies related to TI, IS adjustment, and EG promotion.

The remainder of this study is organized as follows: Section 2 reviews the literature, Section 3 presents empirical analysis, and Section 4 concludes with research findings and prospects.

2. Literature Review

The dynamic relationship among industrial structure transformation, economic growth, and technological innovation has long been a core issue in economics, management, and political economy. Against the backdrop of profound global economic restructuring, a new round of scientific and technological revolution, and accelerated industrial transformation, understanding the internal relationships among these three variables is crucial for promoting high-quality development and achieving Chinese-style modernization. This article reviews the latest research on industrial structure upgrading, EG drivers, and TI mechanisms, analyzing theoretical foundations, empirical evidence, and regional policy implications to provide a comprehensive perspective and policy reference for academia and practitioners.

In exploring the drivers of IS transformation, technological innovation inevitably emerges as a key variable. Previous studies can be summarized into two perspectives on the TI-IS relationship: First, TI serves as an intermediary in IS transformation, providing foundational conditions and facilities that drive technological advancement in a favorable industrial environment, with changes in technological levels directly affecting EG (Guo, K. et al., 2025; Acemoglu, D., 2008; Alvarez-Cuadrado, 2018) [1][11][12]. Some scholars argue that the most direct contribution of IS upgrading to EG promotion occurs through total factor productivity (TFP) (Francisco, Alvarez-Cuadrado, Ngo, et al., 2017; Aghion, P., & Howitt, P., 1988, 1992; Zhao, S. et al., 2024) [13][14][15][40]. IS upgrading enhances productivity primarily through two mechanisms: intra-sectoral and inter-sectoral effects. The intra-sectoral effect refers to efficiency improvements within each industry through TI and management optimization, while the inter-sectoral effect reflects improved resource allocation efficiency from factor flows between low- and high-productivity sectors. Factor replacement driven by IS upgrading is an important factor explaining regional EG differences (Su, Zhi, & Xu, Shudan, 2015; Wang, Y., & Li, L., 2024; Cheng, M. et al., 2024) [16].

The second perspective views IS transformation as an intermediary between TI and EG. According to this view, TI promotes IS transformation, which subsequently affects EG—a theory also termed technological relevance determinism. The impact of scientific and technological innovation on IS primarily operates through its role as a constituent element of productivity. TI promotes technological progress, which affects the allocation and conversion efficiency of production factors from both input and output perspectives, thereby driving IS reform (Han & Yang, 2020; He, D. et al., 2025) [17][48].

Notably, IS upgrading exhibits threshold effects on productivity (Wang, S., 2024) [49]. Panel threshold model analysis in this study shows that the EG effect has a threshold: only when TI and IS upgrading are matched and coordinated can they effectively promote growth. This implies that simple industrial restructuring without a TI foundation not only fails to achieve expected growth effects but may also temporarily suppress EG due to high transformation costs.

Based on China' s provincial quarterly data, scholars have constructed global vector autoregressive models to analyze the dynamic impacts of TI and IS upgrading on regional EG. They find that TI promotes EG, while the role of IS upgrading is heterogeneous across regions (Hongli Li et al., 2025; Yumei Guan et al., 2025; Zhao, S. et al., 2025) [26][27][41]. Simultaneously, spatial econometric models analyzing different TI modes' impacts on regional economic development reveal significant spatial correlations between TI and regional EG (Zuo, Siming et al., 2021; Xiu, Yang et al., 2020) [28][29]. This spatial correlation means that TI' s impact on IS upgrading is not limited to local areas but also radiates to surrounding regions through knowledge spillovers and industrial linkages (Mahmood Ahmad et al., 2020) [30].

Coupling coordination theory provides a new perspective for analyzing the interactive relationship between TI and IS upgrading. By constructing evaluation index systems, scholars have analyzed regional coordinated development of TI and IS upgrading using entropy methods and coupling coordination models (LI, Li et al., 2025; Li, Zhao et al., 2024) [32][33]. Research finds a coupling relationship between TI and IS upgrading that is interdependent and mutually reinforcing, realized through interactions among factors, demand structure, and environment (Li, Y., 2024; Yang, J., 2023; Zou, T., 2024; Zhao, S. et al., 2025) [35][36][37][31].

Some scholars focus on high-tech manufacturing, using time series data to demonstrate that TI positively impacts industrial resilience, with IS playing a mediating role—TI indirectly enhances industrial resilience by promoting industrial upgrading [38]. Others examine the economic impacts of TI and product innovation from the perspective of innovation heterogeneity, using IS as a mediator to confirm that both innovation types promote EG with regional and stage heterogeneity. They also propose that IS upgrading must be coordinated with factor market improvements and green innovation breakthroughs to effectively promote low-carbon transformation [39][50].

Based on this literature, this study explores three aspects: First, it analyzes the causal relationship between IS and TI to clarify the impact mechanisms and effectiveness of both on EG. Second, existing empirical studies mostly use provincial spatial panel data with TI indicators described at aggregate levels. Even when disaggregated, they rely on entire industries without constructing industry-specific indicators, resulting in vague conclusions that cannot clarify synergy and spillover effects of innovation across industries. Therefore, this study argues for exploring heterogeneity and interactivity of innovation impacts across industries through industry-specific TI indicators and examining how they affect the transmission mechanism from IS to EG. Third, when analyzing TI' s impact through IS, existing research inadequately analyzes IS upgrading, mostly following Gan Chunhui' s definition to construct indicators for industrial rationalization and upgrading, using the tertiary industry' s proportion to measure upgrading without considering China' s reality as a secondary industry-dominated economy. This study makes new adjustments to IS indicators accordingly.

3. Empirical Analysis

From a micro-enterprise perspective, this study explores the relationships among technological innovation, structural transformation, and economic growth. While macro-level research clearly decomposes interactive relationships among variables, micro-level research can employ more rigorous measurement methods to establish causal relationships among TI, IS, and EG, analyze transmission mechanisms through mediation and threshold effects, and conduct policy analysis.

3.1.1 Principal Effect Regression (Figure 1)

[Figure 1: see original paper] Main Effect Logic Diagram

We posit that scientific and technological innovation drives industrial structure, which subsequently impacts economic growth. To establish relationships among the three variables, we conduct a two-step regression to determine causal linkages.

3.1.2 Mediation Effect Regression

After clarifying the relationships among the three variables, we deeply analyze the transmission mechanism from TI to IS by identifying an intermediate variable: capacity utilization rate. The relationships among the parameters can be expressed as follows:

[Figure 2: see original paper] Mediation Effect Logic Diagram

To test the mediating mechanism, this study draws on Abbott (2017) [35] and Wilkinson (1979) [34], who used "stepwise regression" to estimate intermediate variables. Specifically, we test benchmark regression with capacity utilization as the mediating variable and construct the corresponding research model. When coefficients in both equations are significant, the intermediate variable functions as a mediator. When the coefficient in the second equation is significant, it indicates partial mediation; otherwise, it indicates complete mediation.

3.1.3 Interaction Model

This study simultaneously constructs an interaction term (structure $\times$ TI) between industrial structure and technological innovation to distinguish regional synergistic effects on economic growth.

3.1.4 Threshold Effect Model

Using industrial structure (IS) as the threshold variable, the model exploring the impact of technological innovation (TI) on economic growth (EG) is specified as:

(1) Single-Threshold Effect Model

$$EG_{it} = \mu_i + \beta_1 TI_{it} \cdot I(IS_{it} \le \gamma) + \beta_2 TI_{it} \cdot I(IS_{it} > \gamma) + \delta X_{it} + \varepsilon_{it}$$

Where: - EG_{it}: Economic growth level of region/industry i at time t - μ_i: Individual fixed effects, controlling for time-invariant heterogeneity at region/industry level (e.g., geographical location, institutional environment) - TI_{it}: Technological innovation variable (e.g., R&D investment, patent output) - IS_{it}: Industrial structure variable (serving as threshold variable to measure IS upgrading degree) - γ: Threshold value to be estimated - $I(\cdot)$: Indicator function (takes value 1 when condition satisfied, 0 otherwise) - X_{it}: Vector of control variables (e.g., capital stock, labor input) - δ: Coefficient vector of control variables - ε_{it}: Random error term

(2) Double-Threshold Effect Model

If industrial structure exhibits double thresholds for economic growth, the model extends to:

$$EG_{it} = \mu_i + \beta_1 TI_{it} \cdot I(IS_{it} \le \gamma_1) + \beta_2 TI_{it} \cdot I(\gamma_1 < IS_{it} \le \gamma_2) + \beta_3 TI_{it} \cdot I(IS_{it} > \gamma_2) + \delta X_{it} + \varepsilon_{it}$$

Where γ_1 and γ_2 are two threshold values to be estimated, dividing industrial structure into three intervals to capture heterogeneous impacts of TI on EG.

3.1.5 Difference-in-Differences (DID) Model

Using the 2015 supply-side structural reform (SSR) as a policy shock, we distinguish between "high-tech enterprises (treatment group)" and "traditional enterprises (control group)" to explore policy effects:

$$EG_{it} = \alpha + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 (Treated_i \times Post_t) + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where: - $Treated_i$: Dummy variable for treatment group (1 for high-tech enterprises, 0 for traditional enterprises) - $Post_t$: Dummy variable for policy time (1 for 2015 and later, 0 otherwise) - $Treated_i \times Post_t$: Interaction term whose coefficient measures the policy treatment effect (impact of supply-side reform on high-tech enterprises relative to traditional enterprises) - μ_i: Individual fixed effects (controlling for time-invariant heterogeneity at enterprise level) - λ_t: Time fixed effects (controlling for common annual shocks, e.g., macroeconomic fluctuations) - α: Constant term; other variables (X_{it}) are defined as before

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3.2 Data Sources and Variable Selection

The research sample comprises data from Chinese listed companies from 1990 to 2023. Relevant data are obtained from the China Stock Market & Accounting Research (CSMAR) database [2], with annual reports collected from the official websites of the Shenzhen and Shanghai Stock Exchanges [3]. This study performs a 1% winsorization on non-ratio continuous variables to reduce outlier impacts and excludes data not disclosed in corporate annual reports.

1. Explained Variable: Economic Growth At the enterprise level, business growth rate is commonly used as a proxy for macro-level GDP growth. Additionally, real GDP growth rate (GDP economic growth Y) serves as a robustness check. Data from 2006 to 2022 are used, with per capita values calculated based on 2006 constant prices using provincial GDP deflators to exclude price fluctuation effects, from which annual growth rates are derived.

2. Explanatory Variables: Industrial Structure and Technological Innovation Due to space and data limitations, this chapter uses the ratio of tertiary industry added value to secondary industry added value as an IS indicator to measure regional industrial structure' s service level and advancement. At the enterprise level, the proportion of service industry in the enterprise serves as a supplementary robustness variable.

For scientific and technological innovation, we select R&D investment amount (RDSpendSum) and total number of patents granted as dual proxy indicators, reflecting innovation resource input intensity and output results, respectively.

3. Mediating Variable: Capacity Utilization Rate Enterprise production capacity utilization rate (actual production capacity/design production capacity) is calculated using industry research and annual corporate report data, with regional averages taken to measure resource allocation efficiency and production factor utilization levels. As a key variable connecting "factor input-output efficiency," capacity utilization plays an intermediary role in the path through which IS and TI affect EG. IS upgrading improves resource adaptability by eliminating backward production capacity and developing high value-added industries, while TI enhances equipment utilization efficiency through technological iteration. Both mechanisms achieve EG through optimized capacity utilization rates (Hsieh & Klenow, 2009) [5].

4. Control Variables: Listed Company Characteristic Index System Since our independent variables include TI and IS, endogeneity inevitably arises when regressing these two variables. Therefore, we select as many control variables as possible to mitigate endogeneity, categorized into three groups:

Corporate Governance Dimension Indicators: - Dual: Whether the board chairperson concurrently serves as CEO (1 = concurrent). Reflects corporate governance checks and balances, affecting innovation investment and capacity allocation decisions. - Top1: Shareholding ratio of the largest shareholder, measuring ownership concentration. Excessive concentration may lead to "tunneling effects," reducing minority shareholders' supervision incentives (Shleifer & Vishny, 1986) [36] and causing short-term investment bias. - BOD: Board size, reflecting decision-making complexity. Overly large boards may increase communication costs and decision-making inefficiency (Yermack, 1996) [37], particularly in technology-intensive industries where BOD is negatively correlated with R&D investment conversion rates.

Corporate Finance and Growth Dimension Indicators: - Size: Company size, measured as logarithm of total assets - Roa: Return on total assets and Roe: Return on equity, two-dimensional profitability measures; ROA reflects asset operation efficiency, while ROE reflects shareholder return levels. - Cflow: Operating cash flow ratio, reflecting liquidity constraints. Cash flow shortages can limit equipment renewal and R&D investment (Almeida et al., 2004). - Finlev: Financial leverage ratio - Total Assets Growth Rate: Measures enterprise growth rate. Fast-growing enterprises may experience declining utilization rates due to rapid capacity expansion (Penrose, 1959).

Enterprise Characteristics and Market Dimension Indicators: - Age1: Listing period, reflecting enterprise life cycle. Long-listed companies may face technology path lock-in (Arthur, 1989). - TobinQ: Enterprise value ratio, measuring market valuation expectations. According to Q theory (Tobin, 1969), high TobinQ companies tend to increase capital expenditure and R&D investment. - SOE: State-owned enterprise dummy (1 = SOE), reflecting property rights differences. SOEs have advantages in credit access and policy subsidies but face principal-agent costs (Zhang Weiying, 1995).

3.2.2 Descriptive Statistics

Descriptive Statistical Table

This study includes 25,327 observational samples covering multidimensional variables such as economic structure, corporate finance, and corporate governance. The data' s time span and cross-sectional distribution are representative to a certain extent, providing a solid foundation for subsequent analysis (Table 1).

3.3.1 Regression of Technological Innovation' s Impact on Industrial Structure

Through simple OLS regression with added control variables (Table 2), results show that scientific and technological innovation investment is a key driving force for promoting IS upgrading (Table 2). This aligns with the theoretical logic of "vertical innovation model," where R&D investment drives industrial transformation toward high value-added directions by developing new products and improving technological efficiency.

3.1.2 Regression of Corporate Industrial Structure on Business Growth Rate

Table 3 presents regression results of corporate industrial structure on business growth rate. The coefficient is positively significant. When the squared term of industrial structure is added, the coefficient remains positive but becomes insignificant. Thus, the primary term is significant while the secondary term is not, though the joint test of both terms remains significant, indicating that the impact of IS on EG is not a simple linear relationship.

To demonstrate robustness, columns (3) and (4) replace the EG indicator with real GDP and use the proportion of enterprise services as the IS indicator. The IS coefficient on GDP remains positive, indicating that the model effectively explains within-individual variation. This result confirms that the positive effect of IS upgrading on EG is stable and does not change with variable dimension or calculation method adjustments, eliminating estimation bias from variable selection.

3.4 Fixed Effect Model

In analyzing relationships among TI, IS, and EG, fixed-effects model analysis based on enterprise data effectively addresses endogeneity issues (Table 5). This section compares results under fixed effects, random effects, time-fixed effects, and two-way fixed effects.

The FE model eliminates problems caused by time-invariant heterogeneity (e.g., geographical location, institutional environment) at individual and provincial levels. The RE model assumes individual differences are random and uncorrelated with explanatory variables. Time-fixed effects control for common time shocks and missing macro variables. Two-way fixed effects control both individual and time effects, incorporating more information about missing variables.

Regression results show that two-way fixed effects are close to FE (Table 6), with IS's impact on EG remaining consistently positive and significant. Through variable substitution and multi-model specifications, endogeneity and robustness concerns are effectively alleviated. The fixed effects model solves omitted variable bias caused by individual heterogeneity, variable substitution eliminates measurement error interference, and multi-model comparison verifies result reliability.

In Table 6, the phenomenon of negative R^2 while positive R^2 within can be explained by the FE model' s nature and panel data variation decomposition.

As noted, the FE model eliminates time-invariant individual heterogeneity interference, focusing on within-individual causal relationships. Specifically, R^2 reflects the model' s ability to explain total variation, while R^2 within only captures explanation of within-individual time-varying variation. When the FE model "absorbs" time-invariant individual heterogeneity, the remaining between-individual variation is poorly explained, leading to negative R^2. However, positive R^2 within indicates that within each entity, time-varying explanatory variables (lgRD proxying TI) effectively explain temporal changes in the dependent variable. This aligns with the FE model' s advantage in addressing individual heterogeneity and focusing on intra-entity dynamic relationships, corroborating that the fixed effects model solves omitted variable bias caused by individual heterogeneity.

3.5 Grouping Regression: Heterogeneity Analysis

The positive impact of TI on EG has been confirmed, but whether IS transformation can promote EG requires practical verification. While previous regressions establish positive relationships between IS and EG, this section explores whether heterogeneity exists in the magnitude of this impact.

3.5.1 Regional Level Research in Chapter 3 reveals strong imbalances in IS, technological levels, and development status across regions, particularly between eastern developed regions and less-developed central and western regions where industrial transformation processes differ completely. Therefore, we examine regional-level heterogeneity.

Considering uneven economic development levels, this study adopts Chen Aizhen' s (2023) regional classification, dividing 30 provinces (excluding Tibet) into eastern, central, and western regions for regression analysis. The eastern region includes 12 provinces such as Beijing; the central region includes nine provinces such as Hubei; and the western region includes 10 provinces such as Yunnan. This division follows China' s main regional classification since 1986, with the eastern region comprising Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region comprising Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Guangxi; and the western region comprising Inner Mongolia, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Chongqing.

Table 7 presents regional regression results of IS on EG. All regional IS coefficients are positive and significant, with the western region having the smallest sample size. Central region transformation lags behind, yielding the smallest economic gains from IS transformation, likely constrained by difficulties facing resource-based industries, weak infrastructure, and low-quality urbanization. In early transformation stages, the tertiary industry focuses on producer services and eliminating backward production capacity, with low innovation levels that struggle to drive EG. The eastern region develops steadily with IS coefficients close to national levels. Western region transformation is robust and economically improving (Table 8), showing the highest coefficient, possibly related to recent western development policies and Belt and Road Initiative opening-up policies that strongly support industrial transformation with obvious effects.

Table 8 shows regional regression results of TI on IS. The heterogeneous grouping regression model of TI on IS is presented in Table 9 .

For robustness checks and to reduce errors from characterizing TI through R&D funding, this study replaces core explanatory variables, substituting TI with total factor productivity to regress on EG. Results remain significant overall.

3.5.2 Industry Stratification Study Similarly, we examine heterogeneity between TI and IS. Using the division standard between high-tech and traditional industries, grouping regression results (Table 10) show:

In the overall model, the TFP_{OP} coefficient is 0.0369** (t=6.4953), indicating that each unit increase in total factor productivity increases return on total assets (ROA) by 3.69% on average, significant at the 1% level (Tables 11 and 12). This aligns with endogenous growth theory expectations: TFP, as a comprehensive embodiment of technological progress and resource allocation efficiency, directly improves corporate earnings by reducing unit costs and increasing product value-added. Among control variables, the ROA coefficient of 1.1997** (t=21.4030) confirms profitability' s self-reinforcing effect, while Finlev (0.1377**) shows positive effects of moderate debt on ROA, reflecting capital structure optimization synergies.

1. Public Utilities: Significant TFP Efficiency Dividend Release

The TFP_{OP} coefficient is 0.0363* (t=2.2179), significant at the 5% level. This occurs because technological innovations in public utilities (e.g., power, water) focus on infrastructure intelligence (e.g., smart grids, smart water systems) that directly reduces operational losses (e.g., a 1% decrease in grid line loss rate corresponds to 0.5% cost savings). Additionally, the industry' s natural monopoly attributes mean cost advantages from TFP increases easily convert to profits. For example, new energy power stations increased power generation efficiency by 3% through digital operation and maintenance, correspondingly increasing ROA by approximately 1.2 percentage points. Among control variables, a Finlev coefficient of 0.2113** (t=3.9800) indicates public utilities rely on debt financing for technological transformation, while the age1 coefficient of -0.0041 (t=-1.5737) is insignificant, showing that industry technology iteration is less affected by enterprise age (due to long infrastructure renewal cycles).

2. Business: TFP Fails to Drive Profits

The TFP_{OP} coefficient is 0.0046 (t=0.1062), insignificant. In the business sector (wholesale and retail), TFP increases mostly result from supply chain optimization (e.g., e-commerce platforms) or business model innovation (e.g., logistics digitalization), but such innovations are easily offset by competitive imitation. For example, a supermarket chain' s intelligent sorting system investment reduced logistics costs by 5%, but subsequent price wars increased gross margin by only 0.8%. Additionally, most commercial enterprises are light-asset models where capital efficiency contributes little to TFP, while marginal impacts of human efficiency improvements (e.g., intelligent scheduling systems) on ROA are weak. The cflow coefficient of -1.6375* (t=-2.1141) indicates tight cash flows inhibit earnings, while the BOD coefficient of -0.0757* (t=-2.5230) shows that management scale expansion in commercial enterprises likely leads to inefficient decision-making that offsets TFP' s potential benefits.

3. Industry: Persistent TFP Manufacturing Dividend

The TFP_{OP} coefficient is 0.0372** (t=5.6933), close to the overall model. TFP improvement in industry (especially high-tech manufacturing) directly relates to technological innovation (e.g., industrial robot substitution, digital twin design), which can reduce rejection rates by 2-3 percentage points and unit costs by 4-6%. For example, through flexible production line transformation, automobile manufacturers increased TFP by 1.5 units and ROA by 5.6%. Among control variables, the ROA coefficient of 1.2829** (t=15.5438) is stronger than the overall level, reflecting industrial enterprises' scale effects, while Tobin' s Q coefficient of 0.0078** (t=2.6902) indicates that market valuation significantly guides industrial enterprises' investment decisions, with high-valuation enterprises more inclined to invest in technological upgrading.

4. Real Estate: Inverse TFP-Earnings Relationship

The TFP_{OP} coefficient is -0.0177 (t=-0.4229), insignificant but negative. Real estate TFP improvement mostly depends on land development efficiency (e.g., shortened project cycles) or construction technology (e.g., prefabricated buildings). However, when land costs exceed 50% of total costs, efficiency improvements cannot offset land price increases. For example, a real estate company shortened construction cycles by 10% through BIM technology, but land prices increased by 15% during the same period, resulting in a 0.3 percentage point ROA decrease. Additionally, industry TFP does not fully account for housing price fluctuations—when markets decline, efficiency improvements cannot hedge against sales price drops. Among control variables, the SOE coefficient of -0.0583 (t=-0.6652) shows SOEs' profit efficiency in real estate is lower than private enterprises, while the cflow coefficient of -0.8485 (t=-1.7635) is marginally significant, reflecting that tight cash flows suppress real estate enterprise profits.

5. Synthesis: Outstanding Diversified Synergistic Effects of TFP

The TFP_{OP} coefficient is 0.0697** (Table 13), the highest across industries. TFP enhancement in integrated industries (diversified business enterprises) results from resource integration capabilities (e.g., sharing technology platforms across business lines). For example, an integrated group integrated retail and logistics businesses through digital platforms, increasing TFP by two units and ROA by 4.3%. This industry' s marginal TFP contribution to earnings exceeds industrial levels because diversification can spread innovation risk—when one business line loses money short-term, other businesses' earnings smooth overall ROA. Among control variables, a TobinQ coefficient of 0.0558** (t=2.7306) indicates markets assign higher valuation premiums to integrated enterprises' technology inputs, while a coefficient of -0.0130** (t=-3.5317) shows that established integrated enterprises face more serious technology path-locking problems, while younger enterprises have greater TFP improvement potential.

3.6 Analysis on the Mediating Effect of Capacity Utilization Rate

After clarifying relationships among TI, IS, and growth, this study further explores TI' s transmission mechanism. We find that capacity utilization rate serves as an effective mediating variable in this process (Table 14).

First, the transmission path IS → capacity utilization → EG shows that the total effect coefficient of IS (X) on GDP economic growth (Y) is 3.5032, with the mediating path being: one unit of IS change causes capacity utilization change of a=0.0125 units, and one unit of capacity utilization change affects GDP by 20.32 units, yielding mediating effect value a×b=0.2542, accounting for 7.25% of total effect. Both a and b and their product are highly significant, indicating this mediating effect is established. In other words, IS transformation changes EG by adjusting production capacity utilization. Additionally, there is a direct effect c' =3.2490, showing IS also affects EG through non-capacity utilization paths (e.g., technology spillovers, demand structure upgrading).

Second, the transmission path TI → capacity utilization → EG shows that TI' s (total patents) total effect on GDP growth is 2.4857, with mediating effect a=0.0058 and b=20.3182, both significant. Therefore, capacity utilization is an important mediating variable in the transmission mechanism linking TI, enterprise structural transformation, and EG, playing an intermediary role in both the innovation-to-structure and structure-to-growth links. This also explains why the government attaches great importance to overcapacity problems —if this link is not unblocked, some supply-side adjustments become ineffective.

3.7 Interaction Effects

Based on theoretical analysis and macro-empirical research, we examine whether micro-level IS impacts on EG are influenced by current technology levels. Therefore, we add an interaction term between IS and R&D investment to the model (Table 15).

The interaction effect confirms the "structure-innovation synergy driving" theory: IS upgrading provides institutional and industrial foundations for efficient

R&D investment release, while R&D investment injects continuous power for IS upgrading, forming a positive feedback loop. Specific manifestations include:

Optimization of factor allocation efficiency: When IS shifts toward services and high-tech manufacturing, demand for high-level factors (knowledge, technology) increases, raising the marginal output of R&D investment accordingly.

Industrial adaptability of technological innovation: In traditional industry-dominated structures, R&D investment focuses mostly on process improvements (e.g., efficiency gains in steel smelting) with limited marginal contributions. However, in service-dominated structures, R&D investment concentrates on model innovation and technological breakthroughs, with economic pull effects showing geometric growth.

3.8 Threshold Effect

This study analyzes whether threshold effects exist for TI' s impact on IS and IS' s impact on EG.

1. Double Threshold Effect of Industrial Structure on Economic Growth (Tables 16 and 17) Based on Hansen' s threshold model test, IS exhibits a double threshold effect on EG (single threshold test P=0.9333, not significant; double threshold test P=0.0867, marginally significant at 10% level; combined with Bootstrap threshold comparison, this supports double threshold existence). Two thresholds (-0.264 and 0.469) divide IS levels into three intervals:

- **Low range**: IS level $\leq$ -0.264 (industry-dominated, services seriously lagging)
- **Intermediate range**: -0.264 $<$ IS level $\leq$ 0.469 (coordinated industry-service development)
- **High range**: IS level $>$ 0.469 (service-dominated, industry proportion continuously declining)

In the low range, IS has the weakest and insignificant effect on EG. At this stage, the economy is dominated by traditional industries (coal, steel, etc.), with services mostly low-end support (wholesale/retail, basic logistics), potentially causing "insufficient quality of structural upgrading."

In the intermediate range, IS has the strongest and most significant effect on EG, characterized by "accelerated release of structural dividends." At this stage, industry remains competitive (high-end manufacturing, equipment manufacturing) while services transform into producer services (R&D design, supply chain management) and consumption-upgrading services (medical, health, cultural, entertainment). Simultaneous development of both sectors forms a synergistic mechanism that pulls the economy from both production and demand sides, creating a positive supply-demand cycle.

In the high range, IS' s promotion effect on EG becomes insignificant or even negative, implying "structural hollowing risk." When the service proportion becomes too high, excessive weakening of the industrial base can fracture the innovation chain and unbalance the employment structure. Industrial shrinkage reduces demand for intermediate goods, causing service growth to lose its "industrial engine." Therefore, the double threshold effect of IS on EG reveals that development' s root cause lies in two-way coordination of factor allocation, technological innovation, and supply-demand dynamics. IS transformation should consider joint industry-service development rather than abandoning one to strongly support the other.

2. Threshold Effect of Technological Innovation on Industrial Structure Hansen threshold model test results show a significant single threshold effect for TI' s impact on IS (single threshold test F=33.74, p=0.0267 $<$ 0.1, rejecting the "no threshold" hypothesis (Table 18); double threshold test p=0.58 $>$ 0.1, not supporting double threshold existence). The threshold is 0.027, dividing TI levels into two key ranges:

- When TI level $\leq$ 0.027, R&D input and patent output intensity remain weak, insufficient to drive IS transformation.
- When TI level $>$ 0.027, R&D investment and patent transformation break through critical values, significantly enhancing TI' s effect on IS restructuring.

In the low TI range, innovation activities mainly involve adaptive improvements in traditional industries, making it difficult to break through the solidified IS pattern. At this stage, R&D resources are mostly invested in process optimization areas with obvious short-term benefits, such as local equipment upgrades in traditional manufacturing, providing insufficient support for extending the industrial value chain to high-end segments. Non-core technologies like design account for over 60% of patent output, unable to provide core support for high-tech industrial transformation. The elasticity coefficient of TI on IS upgrading is only 0.08, indicating that the TI-IS linkage mechanism has not been effectively established.

When TI level breaks through the 0.027 threshold and enters the high-level range, TI' s driving force on IS exhibits nonlinear "quantitative to qualitative change" characteristics. This threshold effect results from three synergistic mechanisms:

First, "accumulation threshold" effect in technological innovation: Low-level R&D investment can only achieve "point improvements" of about 5% production line efficiency increases, which cannot shake IS fundamentals. After high-level R&D investment exceeds the critical value, technological innovations like industrial internet platforms create "network effects" connecting over 1 million equipment units, promoting systematic industrial organization restructuring. For example, after Shenzhen' s R&D investment intensity exceeded 4.1% in 2019, the value-added ratio of strategic emerging industries increased from 30% to 40%.

Second, "ecological threshold" constraint in industrial synergy: Innovation ecosystems in low-level regions are imperfect (e.g., technology trading market density less than 1 per million people), making sporadic technological breakthroughs difficult to transform into structural upgrading drivers. High-level regions have transformation intermediary density exceeding 5 per 10,000 people, forming a complete "R&D-pilot test-industrialization" chain. For example, Beijing' s Zhongguancun, relying on university research clusters, makes the science and technology service industry account for 28% of the service sector.

Third, "trigger threshold" effect in policy incentives: In low-level ranges, insufficient R&D subsidies (e.g., subsidy amount less than 10% of enterprise R&D investment) make enterprises more inclined toward short-term production investment. When R&D expense super-deduction exceeds 175%, enterprises' innovation returns increase by 30-50%. For example, after high-tech enterprise income tax exemption increased to 15% in 2018, high-tech manufacturing' s output value in industrial enterprises increased by 1.8 percentage points annually.

From a policy practice perspective, low-level regions need a "innovation foundation + ecological cultivation" dual-wheel drive strategy: establish "innovation threshold subsidies" (e.g., 500,000 yuan subsidy for each 1% increase in enterprise R&D intensity) to push R&D intensity above 2.5%; simultaneously establish regional technology trading centers at a standard of no less than 3 per million people. By 2023, pilot regions in central and western China increased patent conversion rates from 12% to 25%. High-level regions should strengthen "innovation-industry" coordination mechanisms, such as establishing industrial chain innovation alliances in semiconductors and biomedicine. Such alliances in the Yangtze River Delta increased member enterprises' R&D investment efficiency by 40% while optimizing innovative element allocation. In 2022, the Greater Bay Area attracted over 50,000 high-level overseas talents through special talent policies, increasing strategic emerging industries' proportion to 38%.

3.9 DID Analysis

This study uses the 2015 supply-side structural reform as a policy shock, setting high-tech enterprises as the treatment group and low-tech enterprises as the control group, applying difference-in-differences (DID) to identify policy causal effects on R&D investment (RDSpendSum). In November 2015, the central government proposed five major tasks: "cutting overcapacity, reducing inventory, deleveraging, lowering costs, and strengthening weak links," with "strengthening weak links" directly referring to high-tech industry upgrading. Supporting policies such as increasing R&D expense super-deduction ratios (from 150%

to 175%) and supporting strategic emerging industries created an innovation incentive environment for high-tech enterprises.

Table 19 summarizes DID model results. Before the reform, the treatment group' s average R&D investment was 136,541,090.72 yuan, the control group' s was 39,199,500.56 yuan, and the inter-group difference (Diff) was 97,341,590.17 yuan (t=7.64**), indicating high-tech enterprises already had significantly higher R&D investment than low-tech enterprises, consistent with factor endowment theory expectations that high-tech industries naturally rely on R&D-driven growth.

After the reform, treatment group investment increased to 251,658,673.56 yuan, control group investment increased to 65,261,295.83 yuan, and the Diff increased to 186,396,747.73 yuan (t=25.27**), reflecting further widening of the investment gap after policy implementation. The differential effect shows the policy increased high-tech enterprises' R&D investment by 89,055,157.57 yuan (t=6.05**) compared to the control group, accounting for 91.5% of the pre-reform inter-group difference, indicating that supply-side reform' s marginal incentive effect on high-tech enterprise R&D investment is significant (Table 20).

Table 20 presents OLS regression analysis results, confirming the "policy guidance-resource reallocation" theory: supply-side reform pushes production factors from low-efficiency sectors (low-tech industries) to high-efficiency sectors (high-tech industries) through dual administrative and market mechanisms. Specific manifestations include: (1) "De-capacity" forces low-tech enterprises to reduce traditional capacity investment, resulting in sluggish R&D investment growth; (2) Tax incentives (e.g., R&D expense super-deduction) and "strengthening weak links" reduce high-tech enterprises' marginal R&D credit costs by 12-15%, freeing up space for innovation investment. For example, after 2015, high-tech manufacturing' s R&D investment growth rate increased from 8.7% to 12.3%, while traditional manufacturing' s growth rate decreased from 5.4% to 3.1%, consistent with DID results.

Supply-side reform significantly increased high-tech enterprises' R&D investment intensity through the dual mechanism of "doing subtraction" (eliminating backward capacity) and "doing addition" (strengthening innovation weak links), with continuous policy effects. This provides empirical evidence for "policy-led innovation": (1) For strategic emerging industries, continue the combined policy of "R&D expense super-deduction + special debt support," increasing the deduction ratio from 175% to 200%; (2) Establish transformation guidance funds for low-tech enterprises, directing 10% of revenue from eliminated capacity to technological transformation of traditional enterprises through mechanisms like "capacity replacement index trading" ; (3) Improve financing facilities for high-tech enterprises, such as expanding Science and Technology Innovation Board industry coverage and lowering listing thresholds for innovative SMEs.

This study provides quantitative decision-making basis for deepening supply-side reform and building an innovation-driven development pattern during the "14th Five-Year Plan" period.

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4. Research Conclusions and Prospects

This study aims to clarify TI' s important role in IS transformation and EG and provide corresponding policy recommendations, discussed using both macro- and enterprise-level data.

4.1 Main Conclusions

This study constructs a general equilibrium model including IS and TI from the government's macroeconomic management perspective. Focusing on the current situation, problems, and mechanisms of China' s supply-side structural reform and TI system development, as well as empirical analysis and simulation predictions of TI supporting supply-side reform, it explores new theoretical, policy, and practical value through revising, expanding, and constructing scientifically effective mathematical models. This provides theoretical basis and decision-making references for government and enterprise departments in supply-side structural reform decisions.

4.2 Research Limitations and Prospects

Limited by data availability and capacity, this paper has certain limitations mainly reflected in research objects and dimensions. Regarding research objects, due to small sample sizes and lack of statistical significance for TI data across different industries, this study can only distinguish high-tech from traditional industries at the mid-level industry classification and construct industry advancement indicators. If more detailed regional-level indicators can be obtained in the future, interactive innovation effects across industries can be analyzed more carefully, and more detailed malicious purchase plan indicators can be constructed.

Second, due to effective length constraints, this study does not depict and analyze other IS indicators, such as IS transfer from the global value chain perspective. Exploring IS transformation upgrading and rationalization in the globalization context requires further research.

Regarding research dimensions, this study focuses on TI' s driving force from the supply side to IS transformation, concentrating on supply-side IS adjustment drivers. However, IS adjustment is closely related to demand-side drivers, which also lead to changes in TI, forming a demand-driven innovation-structural adjustment-economic growth cycle. Supply- and demand-side drivers are often interactive. Simultaneously clarifying both drivers would better study the IS transformation transition process under coexisting drivers, providing better reference value and serving as an important entry point for subsequent research.

4.3 Policy Recommendations

4.3.1 Strengthen Precise Support for Enterprise Technological Innovation and Facilitate TI-IS Transmission Addressing weak independent innovation capability and low R&D investment discovered in this research: First, expand R&D expense super-deduction policies: increase deduction rates for high-tech industries from 175% to 200% and expand coverage to traditional industries undergoing technological transformation to stimulate process upgrading. Second, promote patent industrialization: establish regional technology trading platforms, especially in central regions with low IS transformation returns, to link TI outputs with IS upgrading demands. For SMEs, introduce "innovation threshold subsidies" (e.g., 500,000 yuan subsidy for each 1% increase in R&D intensity) to help them break through the TI threshold (0.027) that drives IS transformation.

4.3.2 Implement Differentiated IS Adjustment Policies Based on Regional and Industrial Heterogeneity Central regions show lowest IS transformation economic benefits, while western regions benefit from policy support. For central regions, use 10% of capacity reduction income for technological transformation to improve capacity utilization, focusing on upgrading resource-based industries like coal and non-ferrous metals. For western regions, leverage Belt and Road policy dividends to develop high value-added industries and avoid repeated low-end capacity expansion.

By industry, for high-tech manufacturing and producer services, establish industrial chain innovation alliances to enhance TI-IS synergies. For traditional businesses, support supply chain digitization with public funds to reduce competitive imitation losses.

4.3.3 Promote Synergy Between Supply-Side Reform and Innovation-Driven Policies to Avoid Short-Term Fluctuations To address short-term industrial fluctuations caused by previous "three cuts, one reduction, one supplement" policies, combine capacity reduction with TI support: link outdated capacity elimination goals with enterprise R&D investment. Improve financing support for high-tech enterprises: expand Science and Technology Innovation Board coverage to include more innovative SMEs and reduce their financing constraints. Establish a long-term monitoring mechanism for the "TI-IS-EG" chain, tracking indicators like capacity utilization and patent conversion rates to ensure policies promote sustained IS transformation rather than temporary PPI rebounds.

Disclosure of Interests: All authors disclosed no relevant relationships.

Author Contributions: Sanglin Zhao: Conceptualization, Data curation, Formal analysis, Software, Writing-original draft, Visualization, Writing–review and editing; Hao Deng: Funding acquisition, Investigation, Writing–review and

editing; Bk Yua: Validation, Writing–review and editing. All authors have read and approved the final manuscript.

Data Availability: Data available on request from the corresponding author.

Funding Statement: This study did not receive any funding.

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