Korea and the World Economy
Vol. 27, No. 1 (April 2026) 23-49
https://doi.org/10.46665/kwe.2026.04.27.1.21

Industry Heterogeneity and the Sustainability of China's Capital-Driven Growth

Xuemei Shen*, Kazuo Inaba**, Michael Peneder***, Ei Ei Thein****

This paper reassesses the sustainability of China's capital-driven growth by incorporating industry-level heterogeneity into an extended Cobb-Douglas production framework. Using harmonized input-output tables, industry-level capital stock data, and a quality-adjusted Divisia labor index for 42 industries over the period 2002-2017, we estimate the dynamic elasticity of output with respect to capital within a mixed-effects regression framework.

Our results indicate that capital dependence is stronger than previously suggested by aggregate models, implying the presence of aggregation bias in conventional estimates. At the same time, we document a persistent decline in the elasticity of output with respect to capital, suggesting that the marginal productivity of capital may be diminishing over time.

Rather than affirming sustainability in an unconditional sense, the findings highlight the conditional and evolving nature of China's growth regime. Once industry heterogeneity is explicitly considered, capital-driven growth appears increasingly dependent on improvements in capital efficiency and productivity performance. The study therefore contributes to a reassessment of long-run sustainability under structural transformation.

JEL Classification: O47, O11, C23, O40
Keywords: TFP, capital elasticity, industry heterogeneity, structural transformation, China

* Corresponding author, Xuemei Shen, College of Economics, Ritsumeikan University, 1-1-1 Nojihigashi, Kusatsu, Shiga 525-8577, Japan Email. shin13xm@fc.ritsumei.ac.jp
** Institute of Social System Studies, Ritsumeikan University, 1-1-1 Nojihigashi, Kusatsu, Shiga 525-8577, Japan
*** Austrian Institute of Economic Research (WIFO), Arsenal, Objekt 20, 1030 Vienna, Austria
**** Graduate School of Economics, Ritsumeikan University, 1-1-1 Nojihigashi, Kusatsu, Shiga 525-8577, Japan

1. INTRODUCTION

Since the initiation of economic reforms in the late 1970s, China has sustained rapid economic growth for several decades, particularly accelerating after its accession to the World Trade Organization in 2001. However, in recent years — especially in the post-COVID period — growth has moderated significantly. This slowdown has intensified the debate over whether China's capital-driven growth model remains viable in the long run.

A large body of literature attributes China's growth primarily to factor accumulation, especially capital deepening. Conventional growth accounting approaches, typically based on aggregate production functions, often estimate the elasticity of output with respect to capital at around 0.3 and interpret total factor productivity (TFP) as a residual. However, such aggregate frameworks impose homogeneous technology assumptions across industries and may therefore generate aggregation bias, potentially obscuring structural heterogeneity in capital dependence and productivity dynamics.

This paper reassesses China's growth structure by explicitly incorporating industry-level heterogeneity into an extended Cobb-Douglas production framework. By allowing for cross-industry differences in technological levels and time-varying elasticity of output with respect to capital, we re-examine China's capital-driven growth using disaggregated data for 42 industries over the period 2002-2017.

Importantly, this study does not claim that China's capital-driven growth is sustainable in an unconditional sense. Rather, sustainability is defined here as the capacity of continued capital deepening to generate stable value-added growth without persistent declines in marginal productivity. Under this definition, dynamic changes in the elasticity of output with respect to capital provide an indirect signal regarding the evolving viability of capital-intensive growth.

Using harmonized input-output tables, industry-level capital stock data, and a quality-adjusted Divisia labor index balanced through the RAS procedure, we estimate a multiple linear regression model with mixed effects. This framework allows us to capture unobserved industry heterogeneity while permitting the elasticity of output with respect to capital to evolve over time, thereby relaxing the restrictive homogeneity assumption embedded in aggregate models.

The results show that capital dependence is stronger than suggested by aggregate models, implying that conventional estimates may understate the extent of capital-driven growth. At the same time, we document a persistent decline in the elasticity of output with respect to capital over the sample period. Rather than interpreting this decline as definitive evidence of structural constraint, we view it as raising important concerns regarding the conditional and evolving nature of long-run sustainability.

While the Solow residual and aggregate Cobb-Douglas production functions remain standard tools for measuring productivity, a growing body of literature emphasizes that aggregate measures may obscure substantial technological heterogeneity across industries (Jorgenson *et al.*, 1987; Jorgenson and Schreyer, 2013). Existing studies on China have largely focused on productivity performance at the macro or regional level. For example, Chow (1993) and Li (2003) provided early macro-level estimates emphasizing capital accumulation and labor reallocation, while

Brandt *et al.*(2020) examined regional TFP growth and highlighted inefficiencies such as capital misallocation and the role of state-owned enterprises (SOEs). However, by relying primarily on aggregate or regional data, these studies are limited in their ability to capture sector-specific technological differences and dynamic changes in capital efficiency.

By correcting aggregation bias and explicitly modeling industry heterogeneity, this study provides a more nuanced interpretation of China's growth regime during a period of structural transformation.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and measurement of capital and labor inputs. Section 4 presents the empirical methodology. Section 5 discusses the results. Section 6 concludes.

2. LITERATURE REVIEW

Growth accounting has undergone substantial advancements since the pioneering work of Solow (1957). In his foundational study, Solow conceptualized TFP as the unexplained residual in output growth after accounting for the contributions of capital and labor inputs. This residual captured the efficiency gains and technological progress driving economic growth. Subsequently, Domar (1961) extended Solow's aggregate framework to the sectoral level, allowing for a more granular analysis by explicitly incorporating the proportional changes in capital and labor over time within individual sectors. Arrow *et al.* (1961) further enriched the theoretical underpinnings of growth accounting and introduced the constant elasticity of substitution (CES) production function. This innovation allowed for varying degrees of substitutability between labor and capital, providing a more flexible representation of production processes.

Christensen *et al.* (1973) advanced this line of inquiry by employing the translog production function, a second-order approximation that generalized the CES framework. Unlike earlier models assuming a unitary elasticity of substitution, these approaches facilitated a nuanced examination of the interplay between labor and capital inputs. Together, these contributions have laid a robust theoretical foundation for understanding the dynamics of productivity and the multifaceted drivers of economic growth.

Wallace and Hussain (1969) introduced an error components model designed to account for variability arising from three distinct sources: time, cross-sectional units, and the interaction of both dimensions. The model is formally represented by the following equations: (i) $y_{it} = \alpha + \sum_{j=1}^{p} \beta_j x_{jit} + \varepsilon_{it}$ and (ii) $\varepsilon_{it} = U_i + V_t + W_{it}$. In this framework, U_i, V_t, and W_{it} represent the random error components associated with cross-sectional units, time, and individual observations, respectively. These components are assumed to have zero means, be mutually independent, and possess constant variances denoted as σ_u^2, σ_t^2, and $\sigma_{it,}^2$ respectively. Building on the foundational work of Wallace and Hussain (1969), Swamy and Arora (1972) extended this model by developing an Aitken-type estimator. This estimator was particularly notable for its suitability in small sample contexts, addressing practical challenges often encountered in empirical applications.

Hausman and Taylor (1981), Wansbeek and Kapteyn (1982) advanced the understanding of panel data models by deriving the eigenvalues and eigenvectors of the error term (ε) and defining the variance-covariance matrix of the composite error as: $\Phi = \sigma^2 I_{NT} + \sigma_v^2 I_T \otimes J_N + \sigma_\mu^2 J_T \otimes I_N$ (I denotes the unit matrix of order indicated by its subscript, J is a square matrix of unit elements; $\sigma^2, \sigma_v^2, \sigma_\mu^2$ are respective variances of u_{nt}, μ_n, v_t). Hsiao (1974) decomposed β into three components: $\beta_{ntj} = \beta_j + \mu_{nj} + v_{it}$, indicating that a random coefficient model was particularly useful for analyzing panel data. This framework proved particularly useful for analyzing panel data, as it allowed the parameters to vary across both cross-sectional units and time periods. By accommodating heterogeneity in the data, the random coefficient model enabled more flexible and accurate modeling of complex datasets, addressing the limitations of traditional fixed or random effects models.

Most regression-based productivity models account for differences in the relative scales of operation but do not accommodate technological differences at the industry level (Caves *et al.* 1981). These models often impose stringent assumptions about technology within individual sectors, leading to challenges when aggregated into a production function. In contrast, a multiple linear regression model with random effects can account for technological differences at the industry level and does not require constant input coefficients for capital and labor over time. This approach provides greater flexibility in modeling and analyzing productivity by incorporating variations in technology and input use across industries and time periods.

A significant challenge for empirical research on the Chinese economy has been the lack of reliable capital stock statistics. Pioneering studies by Chow and Li (2002), and Wu (2011), have made notable contributions to address this issue. Furthermore, earlier research comparing productivity performance across industries and over time has been constrained by the absence of a homogeneous data source. This study addresses these limitations by utilizing a combination of datasets, including the Chinese Input-Output (IO) Tables, the National Economic Census (NEC), the Labor Statistical Yearbook, and the Chinese Investments in Fixed Asset Yearbook. These datasets enable the estimation of sectoral capital stock accumulation, sectoral value added at constant prices, and the sectoral Divisia labor index, which incorporates changes in labor quality. Together, these measures facilitate a comprehensive assessment of sectoral TFP.

3. DATA

This study analyzes Chinese productivity growth across industries during the period 2002-2017 by conducting statistical analyses on the distribution of the components of China's production function: labor force, capital stock, and value added by industry. However, detailed micro-level data are not available for all variables, and certain components are observed only at an aggregated level.

3.1. Labor Inputs

Labor force data are sourced from the China Labor Statistic Yearbook (2003, 2008, 2013, 2018) and the National Economic Census (NEC) (2004, 2008, 2013, 2018), both provided by the National Bureau of Statistics (NBS). The NEC is a comprehensive industry survey covering all enterprises in China's secondary and tertiary sectors. This survey has been conducted four times, focusing on enterprise data from the years 2004, 2008, 2013, and 2018.

3.1.1. Labor force in china

Since 2007, China's total labor force has exhibited limited growth, which appears to have had a smaller impact on overall economic growth. The Divisia labor index, however, provides a more detailed analysis by categorizing labor inputs based on location (rural or urban), education level (elementary school or below, high school or below, and college or above), and industry (across 42 categories).

Table 1 Distribution of the Total Labor Force in China for the Period 2002-2017

	2002	2007	2012	2017
	Millions of People			
Total Employment (end of year)	748	790	767	776
Urban Employment	258	313	371	425
Unit Employment[1]	110	120	152	176
Staff and Workers	106	114	87	21
Employment in Urban Private	43	79	132	227
Rural Employment	490	476	396	352
Rural Enterprise	133	151	101	88*
Farmer	357	326	295	263*
	Percentage of Total			
Urban Employment	35	40	48	55
Unit Employment	15	15	20	23
Staff and Workers	14	14	11	3
Employment in Urban Private	6	10	17	29
Rural Employment	65	60	52	45
Rural Enterprise	18	19	13	11*
Farmer	48	41	38	34*

Note: * In 2017, Rural Enterprise and Farmer data were estimated.
Source: Labor statistic yearbook by related years.

Table 1 provides details of China's total labor force from 2002 to 2017. During this period, the total labor force increased from 748 million in 2002 to 776 million in 2017; although recent trends indicate a decline.

[1] Unit Employment: By National Bureau of Statistics of China Unit Employment are defined as employed people registered under work units (danwei), including state-owned enterprises, collective enterprises, private companies, and foreign-invested firms.

The recent decline in the number of employed people occurred entirely in rural areas, specifically in state-owned and collective-owned employment.[2] In contrast, private employment and unit employment with other types of ownership increased. This indicates a movement of labor not only from rural to urban areas but also toward different types of ownership.

3.1.2. Divisia Labor index

The Divisia labor index[3] employed in this study tracks changes in the composition of the workforce by considering various labor force characteristics, including location (rural or urban), education level (elementary school or lower, high school or lower, college and above), and industry (42 categories). The use of a Divisia labor index is particularly important in the context of structural transformation. As labor migrates from rural agriculture to urban manufacturing and services, improvements in educational attainment and sectoral reallocation alter effective labor input beyond simple headcounts. By separating labor quantity from labor quality, the Divisia framework allows us to capture human-capital upgrading consistent with structural transformation theory.

This study quantified the total labor inputs and assessed changes in labor quality at the industry level, distinguishing between rural and urban labor. The China Labor Statistical Yearbook served as the primary data source, providing employment information categorized by registration status. Urban units offered detailed labor information by industry and education level.

The RAS[4] model, implemented following Yamada and Hagiwara (2016),[5] was used to balance the quality of labor inputs. These characteristics related to the region, education, and industry data were sourced from the China Labor Statistical Yearbook (for the years 2003, 2008, 2013, and 2018) and the NEC (for the years 2004, 2008, 2013, and 2018). These years were chosen to align with the Chinese IO base years: 2002, 2007, 2012, and 2017.

The Divisia labor index reflects the changes in the quality of labor inputs across industries and classifications over a specified period. The index includes 252 types of labor, calculated as 2 (rural and urban) × 3 (education levels) × 42 (industries).

Table 2 shows that while the overall labor force decreased, growth in labor quality was driven by improvements in education and the movement of labor between regions and industries. The contribution of education to labor quality was higher in recent years, and the migration of labor from rural to urban areas, as well as across different sectors, steadily increased.

---

[2] The Labor Statistics Yearbook provides data on weekly working hours for 20 industries. Based on this data, this study accounts for 11 legal holidays and 104 general vacation days to calculate total working hours.

[3] The Divisia labor index details are in Section A1 of the Appendix.

[4] RAS method details are in Section A2 of the Appendix.

[5] Yamada and Hagiwara (2016) introduce the RAS method with Scilab software. Scilab is free software that possesses functions similar to those of MATLAB.

Table 2 Divisia labor index classified by quality

Period	Number of Labor force growth rate	Quality Labor change				Divisia Labor Index growth rate
		by education	by labor movement between rural and urban area	by labor movement between industry	by multi inter factor	
	(1)	(2)	(3)	(4)	(5)	(6) = Sum 1 to 5
2002-2007	1.07%	1.00%	0.83%	1.27%	–1.76%	2.41%
2007-2012	–0.03%	0.83%	1.79%	0.92%	–1.74%	1.77%
2012-2017	0.24%	2.16%	1.09%	1.03%	–2.58%	1.94%

Source: Estimated by the author.

3.2. Capital Stock

Capital stock is calculated using the perpetual inventory method, which combines the previous year-end capital stock with current investment net of depreciation. Investment data is collected from the Statistical Yearbook of the Chinese investment in Fixed Assets. Due to variations in data sources covering different target areas, slight discrepancies may exist in the total investment in fixed assets. To address this, this study calculates annual investment as the average of the available data. The Chinese Statistical Yearbook provides sectoral investment detail for rural areas. Based on the total investments reported in the Chinese Statistical Yearbook, this study allocates investments to individual industries to represent the total societal investment. Equation (1) explains the calculation of capital stock.

$$K_{j,t} = (I - \delta_j)K_{j,t-1} + I_{j,t} \tag{1}$$

Where, $K_{j,t}$ is capital stock in year t (Christensen and Jorgenson, 1969). It is calculated by adding the investment $I_{j,t}$ to the remaining capital stock from the end of the previous year, adjusted for depreciation.[6)]

[6)] Sectoral depreciation rates are primarily estimated by combining information on net fixed assets from the census data with depreciation data from the Linked Input-Output Tables (explain in Section 3.3). For sectors where net fixed assets are not directly available, these data are derived from total assets, the original cost of fixed assets, and accumulated depreciation. In addition, to make the sector-specific adjustments: for manufacturing, the average ratio of net fixed assets to total assets within manufacturing, and for service, the corresponding average ratio within services, are applied. These adjustments ensure sectoral consistency in these estimates. For years not covered by the census, capital stock is projected using Equation (1).

Capital stock data is collected from the NEC provided by the NBS. The NEC is a comprehensive industry survey covering all enterprises in China's secondary and tertiary sectors. It was conducted four times, focusing on enterprise data for the years 2004, 2008, 2013, and 2018. For the agriculture sector, access to capital stock was supported by the NBS through the Agriculture Census, which focuses on rural areas and collects information about farmers. The Agriculture Census was conducted in 1996, 2006, and 2016.

3.3. Gross Value-Added Data

Value-added data is extracted from the Chinese IO tables. The analytical period covers 2002-2017, based on the availability of the Chinese IO tables. The base years of Chinese IO tables are 2002, 2007, 2012, and 2017. Nominal GDP data was referenced from the Chinese IO tables. The development of China's national income accounting system can be divided into three stages. The first stage, spanning 1952 to 1984, was marked by the introduction and development of the Soviet-style Material Product System (MPS), which focused on collecting output data in physical terms. The second stage, from 1985 to 1992, featured the coexistence of MPS with the System of National Accounts (SNA). During this period, national income was calculated using MPS, while GDP was calculated using the SNA. The third stage began in 1993 and continues to the present, reflecting the adoption of the SNA as the sole basis of China's national accounts system. This shift was implemented to more accurately reflect the country's transitional economic characteristics.

Despite the introduction of the United Nations' SNA in the Guideline for Measuring GDP and National Income in 1992, China continued to maintain the MPS-based national income system early in the third stage. However, by 2002, China had completed the transition from the MPS to the standard SNA system and revised China's National Accounts (CSNA2002) to align with the 1993 SNA guidelines.

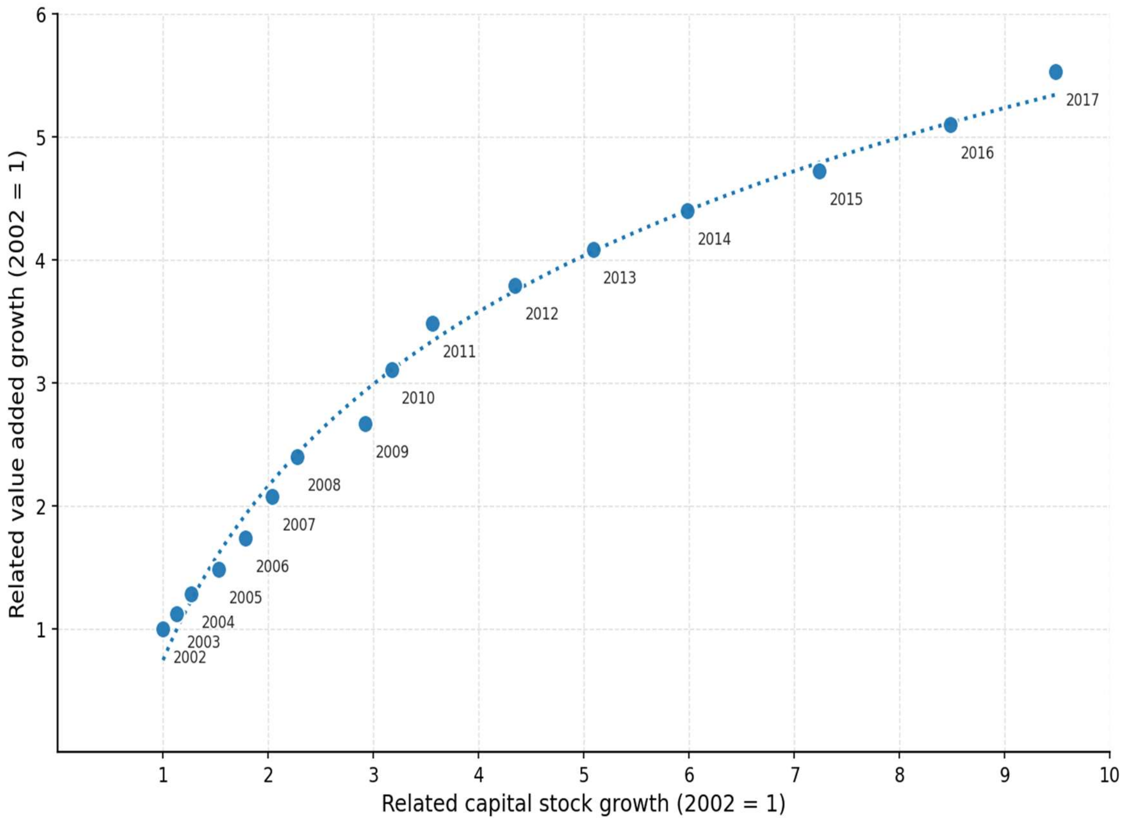
The nominal-to-real GDP ratio provides the implicit price deflator,[7)] which is used to deflate the net exports and imports of goods and services to obtain their real values. The real output is calculated as the nominal total output deflated by the producer price index.

This paper utilized IO tables to estimate the Chinese GDP from 2002 to 2017. Over this period, four basic IO tables were available: 2002 (122 industries), 2007 (135 industries), 2012 (139 industries), and 2017 (139 industries). Additionally, three extended IO tables were used for three years: 2005, 2010, and 2015 (each covering 42 industries). These tables are employed to estimate the "2002-2017 linked Input-Output Tables," and the total sectoral value added in this linked table is treated as real GDP.

Figure 1 presents the relative growth of gross value added and capital stock for the total industry, indexed to 2002 = 1. The pattern suggests a declining elasticity of value added with respect to capital over time.

[7)] The details of the implicit price deflator are given in Appendix A3.

Figure 1 Relative growth of capital and value added (2002=1)



4. ANALYSIS OF CHINA’S PRODUCTION FUNCTION

In this section, the study measures Chinese productivity growth using three complementary analytical approaches: the standard Solow residual, the Cobb-Douglas production function with fixed and random effects, and a multiple linear regression model. The Solow residual provides a macro-level evaluation of productivity by isolating output growth unexplained by capital and labor input, serving as a baseline for comparison. The Cobb-Douglas production function introduces sector-specific and time-dependent factors, enabling a more nuanced understanding of productivity across industries. Finally, the multiple linear regression model allows for time-varying capital and labor elasticities, offering deeper insights into sector-specific productivity.

These three methodologies collectively provide a layered analytical framework, combining aggregate and sectoral perspectives to identify the drivers of China’s economic growth. This integrated approach bridges the gap between macro-level analyses, which often overlook sector-specific variations, and detailed industry-level insights, offering a more holistic and dynamic view of productivity trends across sectors, accounting for both structural and temporal shifts in China's economy.

4.1. The Solow Residual

We begin with the standard Solow (1957) growth accounting framework, in which total factor productivity (TFP) is measured as the residual component of output growth after accounting for the contributions of capital and labor. Under the assumption of constant returns to scale and competitive factor markets, factor shares are typically treated as constant and equal to their income shares.

$$\frac{\dot{Q}}{Q} = \frac{\dot{A}}{A} + w_k \frac{\dot{K}}{K} + w_l \frac{\dot{L}}{L} \qquad (2)$$

Where Q represents output, and dots indicate time derivatives. K and L represent the capital and labor input, respectively. w_k and w_l denote relative shares of capital and labor input. The multiplicative factor A measures cumulative effect of technological shifts over time.

In this study, Equation (2) presents the canonical Solow residual under the assumption of constant factor shares. However, given structural changes in China's economy during the sample period, we allow capital shares to vary over time in the empirical implementation. These time-varying shares are estimated from industry-level regression results and reflect changes in the distribution of income between capital and labor.

This modification does not alter the theoretical foundation of the Solow framework; rather, it improves the measurement of factor contributions by incorporating observed structural dynamics. The time-varying specification should therefore be interpreted as a refinement of the standard growth decomposition rather than a departure from it.

4.2. Cobb-Douglas Production Function with Fixed and Random Effects Models

The second model assumed a standard Cobb-Douglas production function augmented with fixed effect or random effect on the time series or cross-section data. The Cobb-Douglas production function, with capital and labor working hours as the two primary factors of production, was used to estimate the TFP. This study employs two software programs — EViews[8] and MATLAB[9] — to compare the performance results.

The Cobb–Douglas production function can be described by the following formula:

$$\log(V_{it}) = \log(A_i) + \lambda \log(e^t) + \alpha \log(K_{it}) + \beta \log(DL_{it} \times h_{it}) + u_{it} \qquad (3)$$

Where V_{it} denotes the value added of the i-th individual sector at time t, K represents the capital stock, DL is the Divisia labor input, and h is the working hours. A_i is a time-varying

[8] In EViews, there are three options for the random effects model; they are based on Wallace and Hussain (1969), Swamy and Arora (1972), and Wansbeek and Kapteyn (1982).

[9] In MATLAB, the random effects model is based on Pinheiro and Bates (1996).

observable variable that measures the TFP of the i-th individual sector at time t, while λ is a time-invariant variable associated with TFP growth (or technical progress). The error term u_{it} is assumed to be uncorrelated with K, L, and A. The coefficients α and β represent the constant distribution rates for capital and labor, respectively.

In the Wald test, a return to scale is not supported for a homogeneous function ($\alpha + \beta = 1$). Nonetheless, the per capita production function should still be considered by redefining the formula as follows. The per capita Cobb-Douglas production function can be expressed as:

$$\log(V_{it}/(DL_{it} \times h_{it})) = \log(A_i) + \lambda \log(e^t) + \alpha\log(K_{it}/(DL_{it} \times h_{it})) + u_{it} \qquad (4)$$

Where A_i is a time-invariant observable variable, and e^t is assumed to be a time-variant observable variable. α and λ are coefficients associated with time-invariant and time-varying observable variables, respectively. In half of the cases examined (labeled 3 and 4 in Table 4), a trend (t) variable was added to the formula. For this technical change, the value of the trend coefficient should be added to the time-period random effect.

4.3. Multiple Linear Regression Model

Considering the technical changes at the industry level and allowing for variations in the capital distribution rate over time, a multiple linear regression model was adopted as a third methodology. In this model, each individual sector ($i = 1, \dots, N$) can assume a different TFP, allowing for random effects to occur in a time series ($e^{\lambda_i t}$). This multiple linear regression model permits changes in the capital distribution rate over multiple time periods ($t = 1, \dots, T$), thereby allowing the time-series random effect to influence the capital attribution (α^t).

While EViews could only apply random effects to either the cross-section or the time period, MATLAB[10] offered the flexibility to apply random or fixed effects to all independent variables. Therefore, for the implementation of the multiple linear regression model, this study utilized MATLAB, which also provided a helpful multiple linear regression toolbox.

To leverage the variation in growth rates between industries and the variation in the elasticity of capital and labor, the multiple linear regression models were described by the following formula:

$$\log(V_{it}/(DL_{it} \times h_{it})) = \log(A_i) + \lambda_i \log(e^t) + \alpha^t\log(K_{it}/(DL_{it} \times h_{it})) + u_{it}. \qquad (5)$$

In Formula 5, we assume that individual sectors have different rates of technical change growth and that the elasticity of capital with labor with respect to output is a time-varying observable variable (as shown in labels 5 and 6 of Table 5).

[10] For productivity with MATLAB, see Alvarez *et al*. (2020) and Balk *et al*. (2020).

Formula 5 extends the standard Cobb-Douglas production function into a multiple linear regression framework that incorporates industry-level variation. The model allows output to depend on capital input, labor input, and time effects, while capturing cross-industry heterogeneity in technological levels.

To operationalize Formula 5, we employ a mixed-effects specification, as detailed in the Appendix A4. In this framework, industry-specific intercepts account for unobserved technological heterogeneity across industries, while time-varying random slopes permit the elasticity of output with respect to capital to evolve over time. This structure relaxes the restrictive homogeneity assumption embedded in aggregate production-function models and enables us to estimate dynamic changes in capital dependence.

More specifically, the random-effects structure allows the coefficient on capital to vary across years, thereby capturing shifts in the marginal contribution of capital during the sample period. The mixed-effects implementation therefore provides a flexible empirical counterpart to the theoretical specification in Formula 5, while maintaining internal consistency with the extended Cobb–Douglas framework.[11)]

5. COMPARISON OF OUTCOMES FROM THREE APPROACHES TO PRODUCTIVITY

This section provides a comprehensive summary and analysis of the productivity estimates obtained using the three methodologies outlined in Section 4: the Solow residual model, the Cobb-Douglas production function, and the mixed effect regression model. Each method offers unique insights into TFP and its contributions to economic growth, ranging from aggregate-level assessments to industry-specific. The results are discussed in detail below, highlighting the varying perspectives and implications derived from these approaches.

5.1. Results of Solow Residual Model

Table 3 presents the estimated data for China's TFP based on the Solow residual method. The estimation procedure is described in Section 4.1. Over the entire period 2002-2017, real value added grew at an average annual rate of 9.44%, of which capital accumulation accounts for approximately 57.5%, while TFP contributes about 31.9%. The remaining share is explained by labor input, with qualitative labor (qL) contributing 7.6% and employment growth (N) accounting for only 3.0%. This decomposition indicates that China's growth during the sample period remained predominantly capital-driven, although productivity improvements played a non-negligible role.

The declining contribution of TFP is broadly consistent with existing empirical evidence. Using

---

11) The detailed random-effects estimation procedure and model specification are presented in Appendix A4 and Appendix A5.

a similar growth-accounting framework, the World Bank (Brandt *et al*. (2020) reports that China's TFP growth averaged 3.1% during 1979-2008 but fell sharply to 0.7% during 2009-2018. The World Bank also finds that human capital growth remained below 1% per year, implying that productivity contributed only modestly to growth in the post-2008 period. Although the absolute TFP contribution in the present study is somewhat higher, the downward trend in productivity growth is consistent with their findings.

Table 3 Estimated TFP in the aggregate economy

Years	V	qL	N	K	TFP
2002-2007	11.97% (100%)	0.75% (6.30%)	0.61% (5.10%)	6.67% (55.70%)	3.94% (32.90%)
2007-2012	9.30% (100%)	1.20% (12.90%)	–0.02% (–0.20%)	5.46% (58.70%)	2.66% (28.60%)
2012-2017	7.12% (100%)	1.29% (18.20%)	0.19% (2.60%)	4.01% (56.30%)	1.63% (22.90%)
2002-2017	9.44% (100%)	0.71% (7.60%)	0.28% (3.00%)	5.43% (57.50%)	3.02% (31.90%)

Note: V is the real value added based on the official value-added (GDP) data. qL: qualitative labor input; N: number of employees; K: capital stock; TFP: total factor productivity.

Source: Data based on adjusted estimate (capital share was 0.44 in 2002-2007, 0.33 in 2007-2012, and 0.24 in 2012-2017, which is calculated in Table 5 as case 6. For the entire period 2002-2017, refer to the capital share of 0.505 calculated in Table 5 as case 5)

Comparable results are reported by Herd (2020), who estimates TFP growth rates of 3.48% for 2000-2005, 4.21% for 2005-2010, and 1.11% for 2010-2015, alongside capital stock growth rates of 4.95%, 5.77%, and 5.32%, respectively. The relative magnitudes and temporal decline in TFP observed in Table 3 closely mirror these estimates, reinforcing the robustness of the present results.

5.2. Results of the Cobb-Douglas Production Function

Table 4 presents the results of the Cobb-Douglas production function estimates for four cases: using EViews and MATLAB, with and without the trend variable. The fixed effect was applied either to the cross-section or the period. The detailed calculation method is provided in Section 4.2.

The coefficients obtained from EViews and MATLAB showed minimal differences. The capital distribution rate was approximately 0.3 when using the per capita formula. Additionally, the Hausman test did not reject the period random effect.

Table 4 The results of per capita Cobb-Douglas production function

Variables	(1) EViews	(2) MATLAB	(3) EViews	(4) MATLAB
Cross Section	Fixed	Fixed	Fixed	Fixed
Period	Random	Random	Random	Random
Constant	1.560***	1.555***	1.229***	−98.424***
	(17.432)	(18.571)	(9.552)	(−9.711)
ln(K/(DL×h))	0.341***	0.346***	0.312***	0.300***
	(11.867)	(12.491)	(10.425)	(10.585)
Trend	–	–	0.049***	0.052***
	–	–	(3.590)	(9.874)
Observations (n)	672	672	672	672
Adjusted R-squared	0.869	0.925	0.928	0.932

Note: T-values are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

5.3. Results of Multiple Linear Regression Model

This model assumes that individual sectors have different rates of technical change growth and that the elasticity of capital with respect to labor is a time-varying observable variable.

Table 5 presents the coefficients of the multiple linear regression models generated using MATLAB. In case 5,[12] the industry-level TFP was estimated by using a random effect on the industry. The details of TFP estimation in this session are provided in Session 4.3. An additional random effect on capital distribution allowed its rate to vary over time. According to this multiple linear regression model, when incorporating different TFP values at the industry levels, the capital distribution rate was calculated to be 0.5, which was higher than the rate estimated by the Cobb-Douglas production function model.

In case 6, a random effect was applied at both the industry level and capital distribution; however, the capital coefficient was excluded from the constant coefficient. The capital distribution showed a decreasing trend, with averages of 0.44 in 2002-2007, 0.33 in 2007-2012, and 0.24 in 2012-2017. The observed decline in the elasticity of output with respect to capital implies a substantial reduction in the marginal productivity of capital. In a neoclassical framework, such a decline reflects diminishing returns. However, in the Chinese context, this pattern may also signal over-investment and capital misallocation, particularly in capital-intensive industries. The results suggest that the capital-driven growth regime may have approached a structural threshold.

[12] For Multiple linear regression model with MATLAB please refer to Appendix A4.

Table 5 The results of multiple linear regression model

	(5)_MATLAB	(6)_MATLAB
Cross Section	Random	Random
Period	Random	Random
Constant	-40.286*	-155.930***
	(-1.839)	(-5.870)
ln(K/(DL×h))	0.505***	Random
	(13.584)	–
Trend	0.026***	0.132***
	(2.959)	(6.880)
Observations (n)	672	672
Adjusted R-squared	0.970	0.972

Note: T-values are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Figure 2 Comparison of Estimated Productivity and Real Value-added Growth Rate from 2002 to 2017

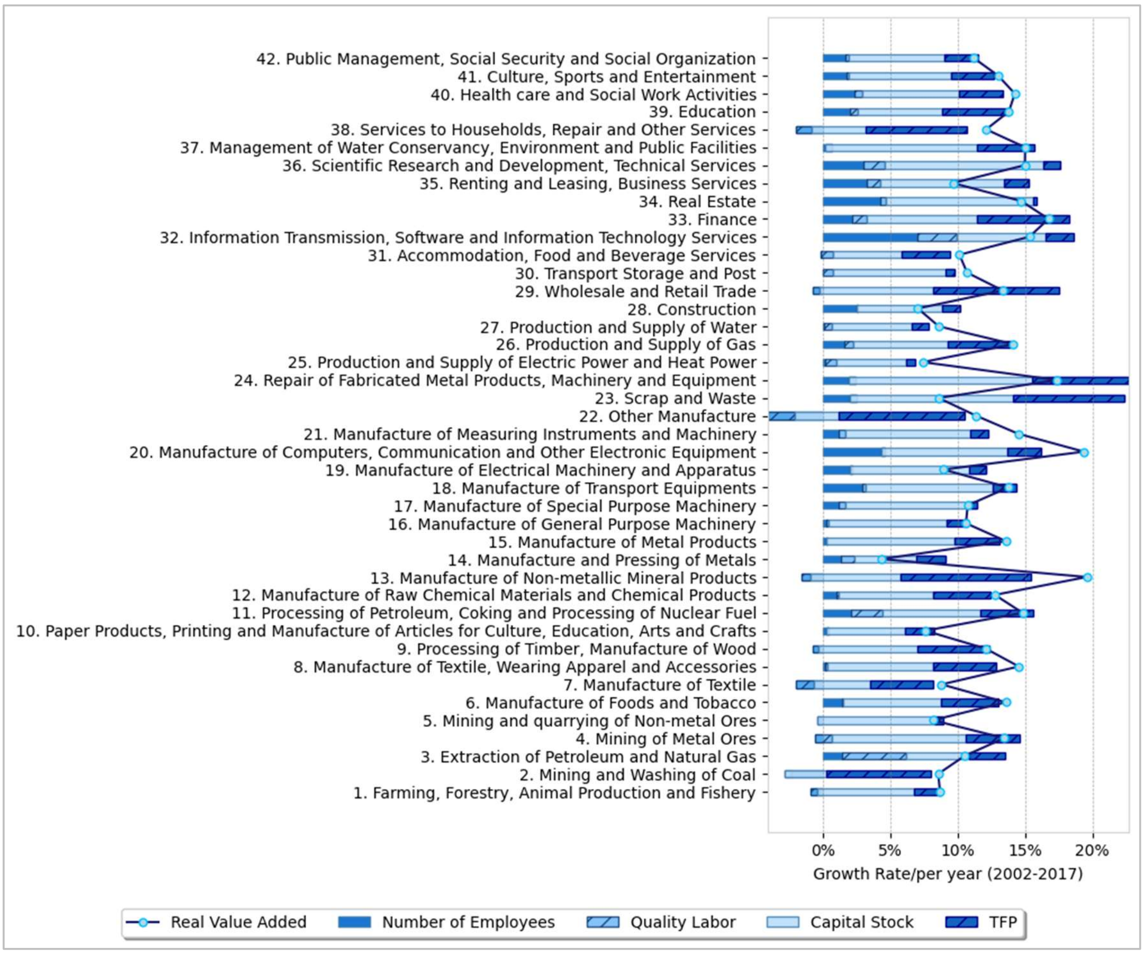


Figure 2 illustrates the comparison of the estimated productivity and real value-added growth rates. The results show that applying random effects at the industry level, along with the Divisia labor index and the growth rate of capital stock accumulation, resulted in a close alignment with industry levels.

At the industry level, capital accumulation significantly contributed to the value-added growth rate across most industries. Among them, the "Manufacture of Computers, Communication, and Other Electronic Equipment" (Industry No. 20) demonstrated the highest value-added growth rate. However, this growth was primarily driven by increases in the number of employees, capital investments, and a modest rise in TFP, with minimal contribution from qualitative improvements in labor. This suggests that the growth relied heavily on low-cost labor.

In contrast, "Real Estate" (Industry No. 34) showed almost no contribution from TFP. Nevertheless, TFP made notable contributions in certain sectors. Specifically, "Information Transmission, Software, and IT Services" (Industry No. 32) and "Finance" (Industry No. 33) demonstrated a well-balanced growth dynamic, supported by both human capital development (labor quality growth and number of employees growth) and increases in TFP.

The estimation results indicate that the elasticity of output with respect to capital increased significantly when industry heterogeneity is taken into account. This finding suggests that aggregate models may underestimate the degree of capital dependence in China's growth process.

Furthermore, we observe a persistent decline in the elasticity of output with respect to capital over the sample period. This decline is statistically significant and appears consistently across most industries. At first glance, this pattern may suggest that the marginal productivity of capital has been decreasing over time.

However, this decline should not be interpreted as definitive evidence of structural constraint. Rather, it indicates that the marginal contribution of capital may be diminishing relative to earlier stages of capital accumulation. While this pattern is consistent with concerns regarding capital efficiency and possible over-investment, alternative explanations — such as structural transformation, sectoral convergence, or resource reallocation — may also contribute to the observed trend.

Accordingly, the empirical results should be understood as raising important questions about the conditional and evolving nature of long-run sustainability, rather than providing a conclusive structural diagnosis.

These findings imply that although China's growth remains capital-intensive, its long-term trajectory may increasingly depend on improvements in capital allocation efficiency and productivity performance.

6. CONCLUSION

This study examined the sustainability of China's growth model by incorporating industry-level technological heterogeneity into a dynamic production-function framework. Applying three complementary approaches — the Solow residual method, the panel Cobb-Douglas specification, and a random-coefficient model with time-varying the elasticity of output with respect to capital — we examined industry-level TFP growth across 42 industries during 2002-2017. By using harmonized input-output tables, industry-level capital stock constructed through the perpetual inventory method, and a quality-adjusted Divisia labor index balanced via the RAS procedure, we decomposed value-added growth into capital accumulation, labor quantity, labor quality, and TFP contributions.

Our findings provide several important insights. First, while China's growth during the sample period remained predominantly capital-driven, the estimated the elasticity of output with respect to capital rises substantially once industry heterogeneity is explicitly incorporated, reaching approximately 0.5 — significantly higher than the conventional estimate of around 0.3 derived from aggregate homogeneous models. This result demonstrates the presence of aggregation bias in traditional growth accounting approaches.

Second, and more importantly, the elasticity of output with respect to capital exhibits a persistent declining trend over time. The reduction in capital's marginal contribution — from earlier to later subperiods — indicates diminishing marginal productivity of capital. In the context of China's post-2008 investment surge, this pattern is consistent with the over-investment hypothesis and suggests that the capital-driven growth regime may have approached a structural threshold. The results therefore reveal not only the central role of capital in China's expansion but also the emerging limits of continued capital deepening.

Third, substantial heterogeneity across industries becomes evident once sectoral differences are explicitly modelled. Knowledge- and service-intensive sectors — such as information transmission and finance — display more balanced growth patterns supported by labor quality upgrading and sustained TFP improvements. In contrast, capital-intensive industries exhibit weaker productivity dynamics. This widening divergence suggests uneven allocation of high-quality labor and productivity-enhancing resources across sectors and highlights structural imbalances within the economy.

In relation to the broader growth debate, our evidence supports neither a purely factor-driven interpretation nor a fully productivity-led transition. Rather, China appears to exhibit a hybrid and transitional growth regime: capital accumulation remains fundamental at the aggregate level, yet its efficiency declines over time, while productivity gains become increasingly relevant within specific industries. By integrating growth accounting with structural transformation analysis, this study offers a more nuanced interpretation of China's development trajectory.

Methodologically, the results confirm the advantages of the random-effects and random-coefficient framework. Consistent with Schurer and Yong (2012) and Bell and Jones (2015), allowing industry-specific heterogeneity and time-varying the elasticity of output with respect to capital improves estimation efficiency and reduces bias associated with restrictive homogeneous-technology assumptions. Modelling unobserved technological differences explicitly yields more economically meaningful industry-level TFP estimates and enables direct evaluation of capital efficiency dynamics.

Overall, our findings indicate that China's growth remains strongly capital-intensive once industry heterogeneity is taken into account. At the same time, we observe a persistent decline in the elasticity of output with respect to capital over the sample period. This pattern should not be interpreted as definitive evidence of structural exhaustion. Rather, it suggests that the sustainability of capital-driven growth may increasingly depend on improvements in capital efficiency and productivity performance.

Accordingly, the contribution of this study lies not in confirming or rejecting sustainability in an absolute sense, but in highlighting its conditional and evolving nature under structural transformation. By explicitly incorporating industry heterogeneity and correcting potential aggregation bias, this paper provides a more nuanced understanding of China's growth dynamics and offers a framework for reassessing long-run sustainability in capital-intensive economies. These refinements do not alter the empirical results but improve their conceptual clarity and internal consistency.

APPENDIX

A1. Divisia Labor Index

Labor inputs can be aggregated according to the following equation:

$$L_t = f(n_{1t}, \ldots, n_{it}) \tag{6}$$

where n_{it} represents employee by type i (labor) in time period t. Assuming efficient labor markets and the linear homogeneity of f,

$$\frac{\partial \ln \ \ _t}{\partial t} = \sum_i s_{it} \frac{\partial \ln L_i}{\partial t} \tag{7}$$

where $s_{it} = \partial \ln f / \partial \ln h_{it} = \mathrm{w_{it}} L_{it} / \Sigma \mathrm{w_{it}} L_{it}$ represents the share of the i-th type in total labor compensation. The total number of employees working for all types of labor is $\mathrm{m_i} = \Sigma n_{it}$, with $b_{it} = n_{it}/\mathrm{m_i}$. The quality growth rate is then defined as

$$\frac{\partial \ln a_t}{\partial t} = \sum_i (s_{it} - b_{it}) \frac{\partial \ln \ \ _i}{\partial t} \tag{8}$$

The labor aggregate is given by

$$d_t = \sum_i v_{it} \Delta \ln n_{it} \tag{9}$$

where $v_{it} = \frac{1}{2}(s_{it} + s_{it+1})$ represents the average share of two consecutive periods without using the Laspeyres and Paasche indices.[13)]

The quality change under a one-factor effect is defined as

[13)] Bergen *et al.* (2006) use Laspeyres and Paasche indices in their study.

$$q_t \equiv d_t - n_t \tag{10}$$

If the labor input is classified by the j-th education (e_j) level and the i-th region (r_j), the total labor input growth becomes

$$d_t = \sum_{ej} \sum_{ri} v_{rit} \Delta \ln n_{rit} \tag{11}$$

In this case, the total labor quality change is given by

$$q_t = d_{ict} - n_t = q_{it} + q_{ct} + q_{ict}, \tag{12}$$

where q_{ict} is the interaction between two factors. In the k-th factor classification, interaction effects can have interactions of an order up to $k-1$.

A2. RAS Method

The initial matrix can be defined using three equations. The X matrix does not require the same dimensions. The new matrix X^t can be estimated by respecting the newly provided row and column totals:

$$\sum_i x_{ij} = Z_j \tag{13}$$

$$\sum_j x_{ij} = Z_i \tag{14}$$

$$\sum_i Z_i = \sum_j Z_j \tag{15}$$

Figure A1 Presents the Framework of the RAS Method.

a. Base Matrix b. New Matrix c. Estimate x_{ij}

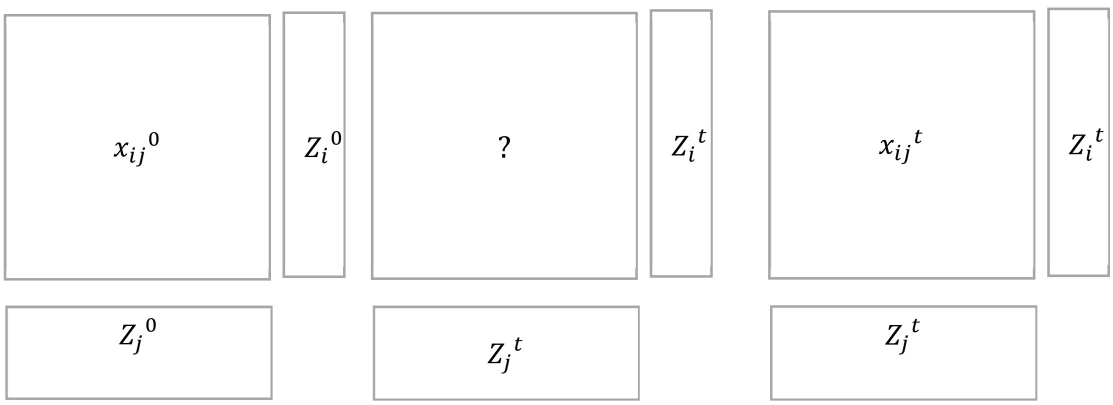


Figure A2 The Framework of the RAS Method

Step 1 Estimate the *R* balance row:

$$r_i{}^k = Z_i / \sum_j x_{ij}{}^k \tag{16}$$

Then, reverse the matrix:

$$X^k = \hat{R} \times X^k \tag{17}$$

where $\hat{R}$ is a diagonal matrix. Here $\mathrm{k} = 0,$ while $\sum_j x_{ij}{}^{k+1} \neq z_i{}'$, so move to Step 2.

Step 2 Estimate S to balance the column:

$$s_j{}^k = z_j / \sum_i x_{ij}{}^k \tag{18}$$

Then, revise the matrix as follows:

$$X^{k+1} = X^k \times \hat{S} \tag{19}$$

where $\hat{S}$ is a diagonal matrix, but the row and column are still unbalanced, $\sum_i x_{ij}{}^{k+1} \neq Z_j{}^t$. Therefore, in the next step, repeated calculation is necessary to balance the total matrix.

Step 3 Using the Lagrange in equation (15), the calculation is repeated until the matrix is balanced:

$$\Sigma_j x_{ij}^t = \Sigma_i x_{ij}^t$$

$$\min_{x_{ij}^t} L = \Sigma_i \Sigma_j \left(\frac{x_{ij}^t - x_{ij}^0}{x_{ij}^0}\right)^2 \tag{20}$$

$$st. ZI_j^t = \Sigma_j x_{ij}^t \ , \ ZJ_i^t = \Sigma_i x_{ij}^t$$

The basic data (x_{ij}^0) are suitable for determining employee numbers across three educational levels for 42 industries and rural and urban classifications. For the new column vector (ZI_j^t), the total compensation of individual industries[14] is considered. Similarly, for the new row vector (ZJ_i^t), the total number of employees multiplied by the wages of employees at the three educational levels is applied.[15]

Simple RAS in MATLAB

```
Z0=[100,200,200;200,100,200]
ZI=[300,300,400]
ZJ=[600;400]
Z=Z0;
eps=1.0e-20;
ssr=10^10
ktry=0
SSR=[]

while(ssr>eps)
ktry=ktry+1
if ktry>1000;
warning('RAS does not converge')
ktry=-ktry
break
end
S=diag(ZI./sum(Z,1));
Z=Z*S;
ssr1=sum((S-eye(3)).^2)
R=diag(ZJ./sum(Z,2));
Z=R*Z;
ssr=sum((R-eye(2)).^2)
SSR=[SSR;[ktry,ssr1,ssr]];
end
```

A3. Implicit Price Deflator

The new deflation was calculated using the formula in equation (6). Finally, the real gross value added was obtained by subtracting the real intermediate input. Real GDP was derived proportionally from the index of real GDP converted to 2012 prices (Hashimoto (2005):

---

[14] For rural areas, there was no information regarding total compensation based on industry, so we used the total individual industrial compensation provided by the Chinese IO table, minus the urban area compensation, to determine the rural industrial compensation.

[15] Employee wage levels by educational level were determined from classified compensation data of five urban and rural groups, which were not precisely based on educational level.

$$I_i'' = \frac{\hat{X}_i - \hat{E}_i + \hat{M}_i}{X_i - E_i + M_i} \tag{21}$$

$$\hat{X}_i = I_i \cdot X_i \tag{22}$$

$$\hat{M}_i = I_i \cdot M_i \tag{23}$$

$$\hat{E}_i = I_i \cdot E_i \tag{24}$$

$$\hat{x}_{ij} = I_i'' \cdot x_{ij} \tag{25}$$

where $\hat{X}_i$ represents the domestically produced real output of sector i after adjustment, and I_i denotes the domestic goods deflator for sector i. $\hat{M}_i$ represents the real import value of sector i after adjustment, and I_i denotes the import goods deflator for sector i. For exports ($\hat{E}_i$), real adjustments are made using the domestic goods deflator. Intermediate demand ($\hat{x}_{ij}$) is treated differently from exports, with real adjustments made using estimated deflators (I_i'').

A4. Random Effects Model

In the standard two-way random effects (RE) model, the coefficients on regressors are assumed fixed across individuals, while unobserved heterogeneity is captured through additive error components (Wallace and Hussain 1969). By contrast, Swamy (1970) proposed a more general framework in which the regression coefficients themselves may vary randomly across units.

In our context, sector-specific technical progress is allowed to differ across sectors. The model can be written as:

$$\log(V_{it}/(DL_{it} \times h_{it})) = \log(A_i) + \lambda_i \log(e^t) + \alpha^t \log(K_{it}/(DL_{it} \times h_{it})) + u_{it} \tag{5}$$

Where,

$$\lambda_i = \lambda + \xi_i, \quad \xi_i \sim \text{i.i.d.}(0, \ \sigma_\xi^2)$$

Here

- λ: average technical progress,
- ξ_i: sector-specific deviations in technical progress,
- α^t: time-varying the elasticity of output with respect to capital.

This specification adopts the random-coefficient logic of Swamy (1970) in a limited form, by allowing technical progress to vary across sectors while allowing the elasticity of output with respect to capital to vary over time.

A5. Multiple Linear Regression Model in MATLAB

Formula 5 allows leveraging the variation in growth rates between industries and the variation in the elasticity of capital and labor.

In case 5 (labeled as 5 in Table 5), the industry-level TFP was estimated by using a random effect on the industry. Another random effect on capital distribution allowed its rate to change. The model was specified as follows:

lme = fitlme(data,'lnvdl ~ sec + lnkdl +year+(1| year) +(lnkdl-1| year)+ (year-1| sec)') (26)

In case 6 (labeled as 6 in Table 5), the constant capital coefficient was dropped but a random effect was applied at industry-level, and capital distribution allowed capital contribution to vary. The model was specified as follows:

lme = fitlme(data,'lnvdl ~ sec + year+(1| year) +(lnkdl-1| year)+ (year-1| sec)') (27)

Here

-sec: represents industry dummies capturing cross-industry heterogeneity in productivity levels,
-year: captures common trend in TFP over time,
-(1| year): introduces a year-specific random intercept,
-(*lnkdl-1| year*): allows the elasticity of capital to vary randomly by year,
-(year-1| sec): allows the coefficient on the time trend TFP to vary randomly across industries, meaning each industry can have its own productivity growth rate.

Acknowledgements
We would like to express our sincere gratitude to the two anonymous reviewers for their valuable comments.

Authors' contributions
Xuemei SHEN contributes to data collection and data analysis and writes the entire manuscript. Kazuo INABA gives advice and comments for the research improvement. Michael PENEDER assists part of the data collection and data calculation. Ei Ei THEIN collects related literature and formatting the manuscript. All authors check and approve the final manuscript.

Authors' information
Xuemei SHEN is an associate professor at the College of Economics, Ritsumeikan University, Japan. Kazuo INABA is a senior researcher of the Institute of Social System Studies, Ritsumeikan University, Japan. Michael PENEDER is a senior economist, Austrian Institute

of Economic Research (WIFO). Ei Ei THEIN is a Ph.D. candidate, Graduate School of Economics, Ritsumeikan University, Japan.

Availability of data

The data generated in the analyses are collected from three main data sources: labor force data from the Labor Statistic Yearbook, capital stock data from the National Economic Census (NEC) https://www.stats.gov.cn/english/, and value-added data from the Chinese Input-Output tables https://www.ceicdata.com/en/china/inputoutput-table-inputoutput provided by the National Bureau of Statistics of China.

Declaration

Competing interests

There are no competing interests regarding this paper.

REFERENCES

Alvarez, I. C., J. Barbero, and José L. Zofío, "A Data Envelopment Analysis Toolbox for MATLAB," *Journal of Statistical Software*, 95, 2020, pp. 1-49 (https://doi.org/10.18637/jss.v095.i03).

Arrow, K. J., H. B. Chenery, B. S. Minhas, and R. M. Solow, "Capital-Labor Substitution and Economic Efficiency," *The Review of Economics and Statistics*, 43, 1961, pp. 225-250 (https://doi.org/10.2307 /1927286).

Balk, B. M., J. Barbero, and José L. Zofío, "A Toolbox for Calculating and Decomposing Total Factor Productivity Indices," *Computers & Operations Research*, 115, 2020, pp. 1-23, (https://doi.org/10.1016/j.cor.2019.104853).

Bell, A. and K. Jones, "Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data," *Political Science Research and Methods*, 3, 2015, pp. 133-153, (https://doi.org/10.1017/psrm.2014.7).

Brandt, L., J. Litwack, E. Mileva, L. Wang, Y. Zhang, and L. Zhao, "China's Productivity Slowdown and Future Growth Potential," *Policy Research Working Paper* 9298, Washington, DC: World Bank, 2020.

Caves, D. W., L. R. Christensen, and J. A. Swanson, "Productivity Growth, Scale Economies, and Capacity Utilization in U.S. Railroads, 1955–74," *American Economic Review*, 71, 1981, pp. 994-1002.

Chen, K.-H. and K. Fujikawa, "A DPG (Deviation from Proportional Growth) Analysis of the Japanese, Korean and Taiwanese Economies," *Journal of Applied Input-Output Analysis*, 1, 1992, pp.71-87

Chenery, H. B., S. Shishido, and T. Watanabe, "The Pattern of Japanese Growth, 1914–1954," *Econometrica*, 30, 1962, pp. 98-139, (https://doi.org/10.230 7/1911290)

Chinloy, P., "Sources of Quality Change in Labor Input," *American Economic Review*, 70, 1980, pp. 108-119.

Chow, G. C., "Capital Formation and Economic Growth in China," *Quarterly Journal of Economics*, 108, 1993, pp. 809-842.

Chow, G. C., and K.-W. Li, "China's Economic Growth: 1952–2010," *Economic Development and Cultural Change*, 51, 2002, pp. 247-256.

Christensen, L. R. and D. W. Jorgenson, "U.S. Real Product and Real Input, 1929–1967," *Review of Income and Wealth*, 16, 1970, pp. 19-50, (https://doi.org/10.1111/ j.1475-4991.1970.tb00695.x)

Christensen, L. R. and D. W. Jorgenson, "The Measurement of U.S. Real Capital Input, 1929–1967," *Review of Income and Wealth*, 15, 1969, pp. 293-320, (https://doi.org/10.1111/j.1475-4991.1969.tb00814.x)

Christensen, L. R., D. W. Jorgenson, and L. J. Lau, "Transcendental Logarithmic Production Frontiers," *The Review of Economics and Statistics*, 55, 1973, pp. 28-45.

Domar, E. D., "On the Measurement of Technological Change," *The Economic Journal*, 71, 1961, pp. 709-729.

Hashimoto, H., “Compilation of 1990–1995–2000 Link Input-Output Tables for Japan,” *Input-Output Analysis*, 13, 2005, pp. 3-15 (in Japanese).

Hausman, J. A., and W. E. Taylor, “Panel Data and Unobservable Individual Effects,” *Econometrica*, 49, 1981, pp. 1377-1398.

Herd, R., “Estimating Capital Formation and Capital Stock by Economic Sector in China: The Implications for Productivity Growth,” *World Bank Group Policy Research Working Paper*, 9317, 2020.

Hsiao, C., “Statistical Inference for a Model with Both Random Cross-Sectional and Time Effects,” *International Economic Review*, 15, 1974, pp. 12-30.

Imamura, H., “The Measurement of Labor Input as the Source of Economic Growth,” *Mita Business Review* (Keio University), 26, 1983, pp. 83-90 (in Japanese).

Jorgenson, D. W., M. Kuroda, and M. Nishimizu, “Japan-U.S. Industry Level Productivity Comparisons,” *Journal of the Japanese and International Economies*, 1, 1987, pp. 1-30, (https://doi.org/10.1016/0889-1583(87)90025-6)

Jorgenson, D. W. and Z. Griliches, “The Explanation of Productivity Change,” *Review of Economic Studies*, 34, 1967, pp. 249-283.

Jorgenson, D. W. and P. Schreyer, “Industry-Level Productivity Measurement and the 2008 System of National Accounts,” *Review of Income and Wealth*, 59, 2013, pp. 185-211, (https://doi.org/10.1111/j.1475-4991.2012.00516.x).

Kim, J.-I. and L. J. Lau, “The Sources of Economic Growth of the East Asian Newly Industrialized Countries,” *Journal of the Japanese and International Economies*, 8, 1994, pp. 235-271.

Krugman, P., “The Myth of Asia’s Miracle,” *Foreign Affairs*, 73, 1994, pp. 62-78, (https://doi.org/10.2307/20046929)

Li, K.-W., “China’s Capital and Productivity Measurement Using Financial Resources,” *Economic Growth Center Discussion Papers*, No. 859, 2003, (https://elischolar.library.yale.edu/egcenter-discussion-paper-series/859)

Meng, R., “The Estimation of Industry-Level Labor Input for China (1): Estimation of Employment by Industry,” *Mita Business Review* (Keio University), 56, 2013, pp. 27-56 (in Japanese).

Schurer, S. and J. Yong, “Personality, Well-Being and the Marginal Utility of Income: What Can We Learn from Random Coefficient Models?,” *Health, Econometrics and Data Group* (HEDG) Working Papers, No. 12/01, 2012, (https://ideas.repec.org/p/yor/hectdg/12-01.html)

Solow, R. M., “Technical Change and the Aggregate Production Function,” *The Review of Economics and Statistics*, 39, 1957, pp. 312-320.

Swamy, P. A. V. B., “Efficient Inference in a Random Coefficient Regression Model,” *Econometrica*, 38, 1970, pp. 311-323.

Swamy, P. A. V. B. and S. S. Arora, "The Exact Finite Sample Properties of the Estimators of Coefficients in the Error Components Regression Models," *Econometrica*, 40, 1972, pp. 261-275.

Wallace, T. D. and A. Hussain, "The Use of Error Components Models in Combining Cross Section with Time Series Data," *Econometrica*, 37, 1969, pp. 55-72.

Wansbeek, T. and A. Kapteyn, "A Class of Decompositions of the Variance-Covariance Matrix of a Generalized Error Components Model," *Econometrica*, 50, 1982, pp. 713-724.

William, H. W., "Quality of Labor in Manufacturing," *The Review of Economics and Statistics,* 55, 1973, pp. 284-290.

Wu, H. X., "Accounting for China's Growth in 1952–2008: China's Growth Performance Debate Revisited with a Newly Constructed Data Set," *RIETI Discussion Paper Series*, No. 11-E-003, 2011, (https://www.rieti.go.jp/jp/publications/dp/11e 003.pdf).

Yamada, S. and T. Hagiwara, "Applied Input–Output Analysis (6): Input Output Analysis with Scilab," *Input–Output Analysis*, 23, 2016, pp. 123-132.

Young, A., "A Tale of Two Cities: Factor Accumulation and Technical Change in Hong Kong and Singapore," *NBER Macroecon. Annu*, 7, 1992.