The Effects of Sectoral TFP on China's Structural Transformation and Growth*

Xilu Chen† Kaiming Guo‡

Abstract

Since the 21st century, China has followed the Kuznets patterns of structural transformation across broad sectors while simultaneously witnessing the transformation and upgrading of industries within them. Intra-sectoral analysis reveals that high-technology manufacturing and nontraditional services exhibit distinct patterns of total factor productivity (TFP) growth, capital deepening, and employment dynamics compared to their traditional counterparts, with these internal disparities often exceeding inter-sectoral differences. While sectoral TFP is a recognized driver of structural change, its dual role in shaping both inter- and intra-sectoral transformation remains under-explored. To isolate these effects, we develop a multi-sector dynamic general equilibrium model. Our quantitative analysis shows that between 2003 and 2020, TFP growth in high-technology manufacturing and traditional services was a critical engine of China's structural transformation and economic growth. Specifically, TFP gains in high-technology manufacturing increased its value added and employment shares within the secondary sector by 7.90 and 8.29 percentage points, respectively, boosting annualized aggregate labor productivity growth by 1.97 percentage points. In comparison, TFP growth in traditional services lifted the value added and employment shares of nontraditional services by 10.85 and 8.51 percentage points while contributing 1.59 percentage points to labor productivity growth. Although capital deepening has been a marginally stronger driver of past development, its role is diminishing with declining investment rates. Therefore, China's future economic trajectory will depend more critically on TFP improvement. Prioritizing TFP improvements in high-technology manufacturing and harnessing untapped TFP potential in nontraditional services are crucial for sustaining high-quality development.

Keywords: Total Factor Productivity; Structural Transformation; Economic Growth

JEL Codes: O11; O14; O53

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†School of Economics and Research Center for Mezzoeconomics, Jinan University; E-mail: chenxilu@jnu.edu.cn.

‡Lingnan College, Sun Yat-sen University; E-mail: guokm3@mail.sysu.edu.cn.

1 Introduction

China's economy since the early 21st century has undergone two parallel structural transformations. Alongside a well-documented inter-sectoral resource reallocation consistent with the Kuznets facts, a profound but less-explored industrial upgrading has been reshaping the economy from within. Between 2003 and 2020, high-technology manufacturing's shares of value added and employment within the secondary sector grew by 7.67 and 12.46 percentage points, respectively, while nontraditional services saw their shares within the tertiary sector rise by 4.40 and 5.12 percentage points. This quantitatively evident intra-sectoral structural transformation highlights industrial modernization as a critical engine for sustained growth.

Further analysis shows that disparities in total factor productivity (TFP) growth, capital deepening, and employment dynamics distinguish the modern subsectors from their traditional counterparts, with intra-sectoral differentials often exceeding inter-sectoral ones. For instance, high-technology manufacturing recorded an annualized TFP growth of 3.05% from 2003 to 2020, outpacing low-technology manufacturing by 1.98 percentage points. Conversely, nontraditional services saw their TFP decline at an annualized rate of -0.64%, lagging traditional services by 4.14 percentage points. These asymmetries underscore the need to understand how TFP improvements at the subsector level drive structural change.

While an extensive literature has identified TFP as a central driver of structural transformation (Ngai and Pissarides, 2007), its application to China has predominantly focused on inter-sectoral dynamics (see, e.g., Brandt et al., 2008; Zhu, 2012), leaving the intra-sectoral dimension underexamined. Our study bridges this gap by jointly investigating China's inter- and intra-sectoral structural transformations.

To do so, we first construct a detailed dataset for five subsectors (agriculture, low- and high-technology manufacturing, traditional and nontraditional services) based on the data from the National Bureau of Statistics (NBS) covering 2003–2020. We then document the stylized facts of China's structural transformation and TFP improvement across the subsectors based on a standard growth accounting framework.

We identify two notable facts that are central to our investigation. The first is a persistent transformation and upgrading process within China's non-agricultural sector, evidenced by the higher growth rates of value added and employment in high-technology manufacturing and nontraditional services compared to their traditional counterparts. The second is a stark divergence in TFP performance between the secondary and tertiary subsectors: high-technology manufacturing outperforms low-technology manufacturing, while nontraditional services lag behind traditional services. These findings reveal the intrinsic differences in the driving forces of the structural transformation, necessitating models that can simultaneously account for these inter- and intra-sectoral dynamics.

To quantify the impact of such sectoral TFP improvements, we develop a multi-sector dynamic general equilibrium framework tailored to Chinese economic characteristics. The model specifies five production sectors. Industrial goods are produced by combining outputs from low- and high-technology manufacturing, whereas services for household consumption are aggregates of traditional and nontraditional services. The system is closed by allocating agricultural, industrial, and service outputs to household consumption and the formation of investment goods, which in turn determines capital accumulation. The incorporation of non-homothetic preferences, sector-specific TFP growth rates, and heterogeneous output elasticities ensures that the framework can capture the income and relative price effects that are essential for modeling structural transformation. The model also explicitly specifies production linkages within the manufacturing and service sectors, allowing us to quantify the effects of intra-sectoral substitution and complementarity.

Our calibration using Chinese data from 2003 to 2020 yields baseline dynamics closely reproducing the observed patterns of both inter- and intra-sectoral structural transformation. The simulated growth rates for aggregate labor productivity and sectoral output per worker deviate from empirical data by less than one percentage point, indicating that the model is a conservative yet reliable representation of China's economic growth.

We leverage this validated model to conduct several counterfactual analyses where sectoral TFP levels are fixed at their 2003 levels. The results indicate that TFP improvements in high-technology manufacturing and traditional services have the most pronounced effects. On the one hand, TFP improvement in high-technology manufacturing during the 2003–2020 period not only raises its share in manufacturing output and employment by 7.90 and 8.29 percentage points, respectively, but also boosts the annualized aggregate labor productivity growth rate by 1.97 percentage points. On the other hand, TFP improvement in traditional services leads to a 10.85 and 8.51 percentage point increase in the output and employment shares of nontraditional services within the tertiary sector, respectively, and contributes 1.59 percentage points to the annualized labor productivity growth rate. Cumulatively, aggregate TFP improvements across all sectors elevated annualized aggregate labor productivity growth by 3.75 percentage points.

A final complementary analysis identifies capital deepening as a driver for the secondary sector's development and confirms its responsibility for 5.61 percentage points of annualized aggregate labor productivity growth. However, declining investment rates suggest that the influence of capital deepening is gradually diminishing. It follows that the sustainability of China's structural transformation and economic growth will pivot increasingly toward a reliance on TFP improvement. Accordingly, further strengthening the role of TFP in high-technology manufacturing and fully unleashing the development potential of TFP in nontraditional services may become the key breakthroughs for advancing China's high-quality future economic development.

Our paper is closely related to a strand of literature focusing on the structural transformation.[1] While prior work has dissected China's inter-sectoral structural transformation through TFP improvements (Brandt and Zhu, 2010; Cao and Birchenall, 2013; Guo et al., 2021), factor accumulation and mobility (Jiang and Shi, 2015; Tombe and Zhu, 2019; Storesletten et al., 2019; Hao et al., 2020; Yao and Zhu, 2021), and government policies (Dekle and Vandenbroucke, 2012; Cheremukhin et al., 2024; Song and Xiong, 2024), the intra-sectoral dimension remains underexplored. As a complement to prior studies, our study simultaneously integrates both the intra- and inter-sectoral structural transformation.

Our work also contributes to the literature on China's growth accounting, which quantifies the contribution of TFP and capital deepening. The methodologies pioneered by Holz (2006), Bosworth and Collins (2008), and Cao et al. (2009) are recently refined with disaggregated data sets (Wu, 2016; Chen et al., 2024; Brandt et al., 2025), permitting more precise measurement of sectoral TFP gains and capital accumulation. While our industrial classifications differ from these works, the productivity growth patterns that we identify corroborate the existing sectoral analyses, further supporting TFP-driven development strategies in China.

Within the above two strands of literature, several studies share similarities with our work by focusing on how TFP improvements and capital deepening influence the structural transformation within China's industries. For example, Liao (2020) traces the role of TFP improvements and capital deepening in the personal services in structural change from 1978–2007. Fang and Herrendorf (2021) categorizes the services into high- and low-skill services, emphasizing that large-scale subsidies in the high-skill service sector have hindered the rise of China's services and overall income growth. Chen et al. (2023) focuses on the development of consumer and producer services in China, finding that during the period from 2005 to 2015, TFP improvements in both sectors exceeded those in the secondary sector.[2] Compared to these studies, our contribution lies in redefining industry taxonomies to capture intra-sectoral structural transformation, providing insights into the transformation and upgrading of traditional subsectors.

The remainder of this paper is structured as follows. Section 2 outlines the sources and processing of the sectoral data for China from 2003 to 2020, presenting the stylized facts. Section 3 formalizes a theoretical framework. Section 4 calibrates the parameters. Section

[1] Theoretical contributions to understanding the fundamental drivers of structural transformation have been made by Echevarria (1997), Kongsamut et al. (2001), Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008), Buera and Kaboski (2012), Comin et al. (2021), and Herrendorf et al. (2020).

[2] While sharing a focus on intra-sectoral dynamics with Chen et al. (2023), our paper offers two key complementary contributions. First, we employ a dynamic general equilibrium framework with endogenous capital accumulation and forward-looking agents, contrasting with their accounting framework. Second, one of our focuses is on the industrial upgrading within the secondary sector, whereas Chen et al. (2023) concentrates on tertiarization.

5 validates the baseline model and evaluates the roles of TFP improvements and capital deepening through counterfactual experiments. Section 6 concludes.

2 Data and Facts

This section presents an overview of the structural transformation within the broad sectors of the Chinese economy. Our analysis begins by documenting the industry classification and data construction processes before proceeding to unveil the driving forces behind this transformation, focusing on sectoral TFP growth. The availability of sectoral value added, price index, and factor input data from the NBS allows for our calculations to be conducted within a parsimonious yet sufficient growth accounting framework.

2.1 Industry Classifications and Data Construction

We start with our classification for the three broad sectors rooted in the standards by NBS. The primary sector consists of agriculture, forestry, animal husbandry, and fishery; the secondary sector includes industry and construction; and the tertiary sector corresponds to services.[3]

We then disaggregate the secondary and tertiary sectors into 36 specific industries using consistent classification codes across the sample period. For narrative simplicity, where no ambiguity arises, we may refer to the primary, secondary, and tertiary sectors as agriculture, manufacturing, and services, respectively. Table 1 presents our complete industry taxonomy.

The intra-sectoral structural transformation, namely the evolution and upgrading of traditional industries within broad sectors, serves as the focus of our investigation. Given China's policy priority on industrial modernization, we divide the secondary sector into low- and high-technology manufacturing and similarly decompose the tertiary sector into traditional and nontraditional services. As official NBS statistics do not report contributions at this subsector level, we operationalize the NBS guidelines to overcome this limitation. High-technology manufacturing industries are identified using the *Statistical Classification of New Industries, New Forms of Business, and New Models*, while nontraditional services are classified based on the *Statistical Classification of Nontraditional Services.*

The decomposition of industries within the secondary sector into low- and high-technology

[3]The NBS updated its sector classifications in 2011 and 2017, revising value added correspondingly but not employment statistics. To ensure data consistency, we adopt the classification of the broad sectors by the NBS in 2002. As noted by Chen et al. (2023), these revisions yield negligible discrepancies in national sectoral value added.

Table 1: Industry Classification

Broad Sector	**Subsector**	**Industry Description**	
Primary	Agriculture	Agriculture, Forestry, Animal Husbandry, and Fishery	
Secondary	Low-Technology Manufacturing	Mining and Washing of Coal	Extraction of Petroleum and Natural Gas
		Mining and Processing of Ferrous and Non-Ferrous Metal Ores	Mining and Processing of Nonmetal Ores, Mining Support Activities, and Other Mining
		Food Processing and Tobacco Manufacturing	Manufacturing of Textile
		Manufacturing of Wood Products and Furniture	Manufacturing of Paper Products and Articles for Culture, Education, and Sport Activities
		Manufacturing of Metal Products	Production and Supply of Gas
	High-Technology Manufacturing	Coking and Processing of Petroleum and Nuclear Fuel	Manufacturing of Chemical Products
		Manufacturing of Non-Metallic Mineral Products	Smelting and Pressing of Metals
		Manufacturing of General and Special Purpose Machinery	Manufacturing of Transport Equipment
		Manufacturing of Electrical Machinery and Equipment	Manufacturing of Electronic Equipment
		Manufacturing of Measuring Instruments and Machinery, Other Manufacturing, and Utilization of Waste Resources	Production and Supply of Electric Power and Heat Power
		Production and Supply of Water	Construction
Tertiary	Traditional Services	Wholesale and Retail	Hotel and Catering
		Household Services, Repair, and Other Services	Education
		Health and Social Work	Public Management and Social Organizations
	Nontraditional Services	Transportation, Storage, and Post	Information Transmission, Computer Services, and Software
		Financial Intermediation	Real Estate
		Leasing and Business Services	Scientific Research and Technical Services
		Management of Water Conservancy, Environment, and Public Facilities	Culture, Sports, and Entertainment

manufacturing proceeds as follows. For the 22 industries in the secondary sector, we calculate two indicators based on the *Statistical Classification of New Industries, New Forms of Business, and New Models*: (1) the proportion of four-digit industries partially engaged in high-technology manufacturing, new energy, or environmental protection activities, and (2) the proportion entirely devoted to such activities. Specific industries with a value exceeding the median in either indicator are classified as high-technology manufacturing.[4] An analogous procedure is applied to the 14 specific industries in the tertiary sector using *Statistical Classification of Nontraditional Services*, which defines four-digit industries

[4]Although not identical in granularity, our classification of low- and high-technology manufacturing aligns broadly with the categorization for manufacturing in the five-sector aggregation proposed by ADB (2021).

related to or exclusively dedicated to nontraditional service activities. These subsector designations are detailed in column 2 of Table 1.

Given the outlined industry classification, we provide a brief overview of the construction methodology for value added, labor, capital stock, capital and labor output elasticities, and TFP for China's specific industries and subsectors over the period 2003 to 2020.[5]

Value Added. Nominal value added for each industry from 2002 to 2020 is calculated based on data from the NBS website and the input-output tables. Price indices are then constructed for each industry from the industrial producer price index and the value added deflator, with the base year 2005 normalized to 1. The real value added is derived by deflating the nominal value added by its corresponding price index. Sectoral value added is obtained by aggregating the value added across all specific industries within a subsector.

Labor. Labor input is measured by employment. Since the NBS website provides annual employment only for the three broad sectors, data for industries and subsectors must be estimated. For this purpose, we use data from the population census and 1% population surveys. Specifically, the employment shares of industries and subsectors within their corresponding broad sector are calculated from the census/survey data. These shares are then applied to the broad sectoral employment totals to derive employment for industries and subsectors.

Capital Stock. We use the perpetual inventory method to compute the capital stock for each industry and subsector. The capital stock for the three broad sectors is first computed from 1978 onward. Subsequently, using available investment data for industries and subsectors, we calculate their capital stock series starting from 2003.

Output Elasticities. These elasticities are derived from input-output tables. Following Bai and Qian (2010), a subsector's labor income share is the ratio of its labor compensation to the sum of labor compensation, fixed asset depreciation, and operating surplus. The labor output elasticity is the arithmetic mean of these income shares over all years. The capital output elasticity is simply one minus the labor output elasticity. Our estimates for the capital output elasticities are 0.5 for agriculture, 0.512 for low-technology manufacturing, 0.516 for high-technology manufacturing, 0.334 for traditional services, and 0.612 for nontraditional services.

Total Factor Productivity. We apply a standard growth accounting framework featuring a Cobb-Douglas production technology, $Y_d(t) = A_d(t)\,[K_d(t)]^{\alpha_d}\,[L_d(t)]^{1-\alpha_d}$, where d is the subsector, t is the year, Y is real value added, K is capital, L is labor, A is TFP, and α is the capital output elasticity. TFP levels are not measured directly but are calculated as the residual from real value-added, capital, labor, and the capital output elasticity.

[5]Supplementary methodological details are provided in Appendix A.

The TFP growth rate is then derived from the resulting time series of TFP levels.

2.2 Stylized Facts

This section documents a set of stylized facts regarding China's structural transformation from 2003 to 2020. Our analysis reveals that this transformation occurred both across and within broad economic sectors, driven by heterogeneous forces. These empirical patterns highlight a notable divergence in the performance of China's manufacturing and service sectors, thereby motivating the quantitative framework developed in the subsequent section.

2.2.1 The Inter- and Intra-Sectoral Structural Transformation

First, the Chinese economy has undergone profound structural transformations, not only between but also within its broad sectors. Table 2 quantifies the shifts in value added and employment shares in each sector during different periods.

Table 2: Structural Transformation in Different Periods in China

	Changes in Output Share			Changes in Employment Share		
	2003–2020	2003–2012	2012–2020	2003–2020	2003–2012	2012–2020
Primary	-4.60%	-3.23%	-1.37%	-25.50%	-15.61%	-9.89%
Secondary	-8.01%	-0.22%	-7.79%	7.10%	8.86%	-1.76%
Low-Technology Manufacturing	-5.58%	-1.08%	-4.50%	-0.54%	1.45%	-1.99%
High-Technology Manufacturing	-2.43%	0.86%	-3.29%	7.64%	7.41%	0.23%
Tertiary	12.61%	3.45%	9.16%	18.40%	6.75%	11.65%
Traditional Services	3.67%	0.41%	3.26%	10.95%	4.97%	5.99%
Nontraditional Services	8.94%	3.04%	5.90%	7.45%	1.79%	5.66%

Consistent with the Kuznets facts, we observe a significant reallocation of economic activity across the three broad sectors. As shown in Table 2, the value added and employment shares of the primary sector have steadily declined between 2003 and 2020, while the tertiary sector has expanded to become the largest contributor to both output and employment. Specifically, the output and employment shares of the tertiary sector increased by 12.61 and 18.40 percentage points, respectively, highlighting the growing importance of services in the Chinese economy and echoing the conclusions of Chen et al. (2023).

A critical and less-explored transformation has occurred simultaneously within the non-agricultural sectors. Within the secondary sector, a clear divergence is apparent. Low-technology manufacturing experienced a notable decline, with its value added share falling by 5.58 percentage points and its employment share by 0.54 percentage points. In contrast, high-technology manufacturing saw its employment share expand by 7.64 percentage points, even as its value-added share registered a decline of 2.43 percentage points. This divergence points to a gradual but steady transition toward high-technology manufacturing.

A similar dynamic is observed in the tertiary sector, where nontraditional services expanded more rapidly than traditional services in terms of value added, with their shares increasing by 8.94 and 3.67 percentage points, respectively. Although traditional services absorbed more labor, the overall expansion in nontraditional services highlights their rising potential as a key driver of the structural transformation, fueled by a rising demand for skilled workers.

The dynamics of this structural transformation shifted notably after 2012, a year marking the 18th National Congress of the Communist Party of China. Table 2 shows that prior to 2012, the secondary sector maintained stable growth and was a primary absorber of labor from agriculture. After 2012, however, both its output and employment shares began to decline, signaling an accelerated pivot toward a service-oriented economy.

The pace of intra-sectoral upgrading also varied across these periods. Before 2012, the shift from low- to high-technology manufacturing was pronounced, while the expansion of nontraditional services remained relatively limited. After 2012, the upgrading process within the tertiary sector gained momentum, with the value added and employment shares of nontraditional services increasing by 5.90 and 5.66 percentage points, respectively.

Figure 1 further illustrates the sustained process of intra-sectoral upgrading by tracking the evolution of high-technology manufacturing (panel A) and nontraditional services (panel B) as shares of their respective broad sectors. Within the secondary sector, the value added share of high-technology manufacturing rose from 65.92% in 2003 to 73.59% in 2020. Similarly, within the tertiary sector, the share of nontraditional services grew from 51.72% to 56.12% over the same period. This evidence, together with the similar trends of employment shares, points to a sustained process of intra-sectoral upgrading.

Taken together, the evidence from both Table 2 and Figure 1 indicates that an analysis focused solely on the three broad sectors would overlook the primary engines of China's recent structural transformation: the rising prominence of high-technology manufacturing and non-traditional services.

2.2.2 The Inter- and Intra-Sectoral Growth Dynamics

Having established the compositional shifts, we now examine the underlying growth dynamics, revealing systematic disparities between subsectors. While both manufacturing and services are upgrading, the drivers of this transformation are starkly different. We begin by analyzing sectoral trends in nominal labor productivity and capital intensity

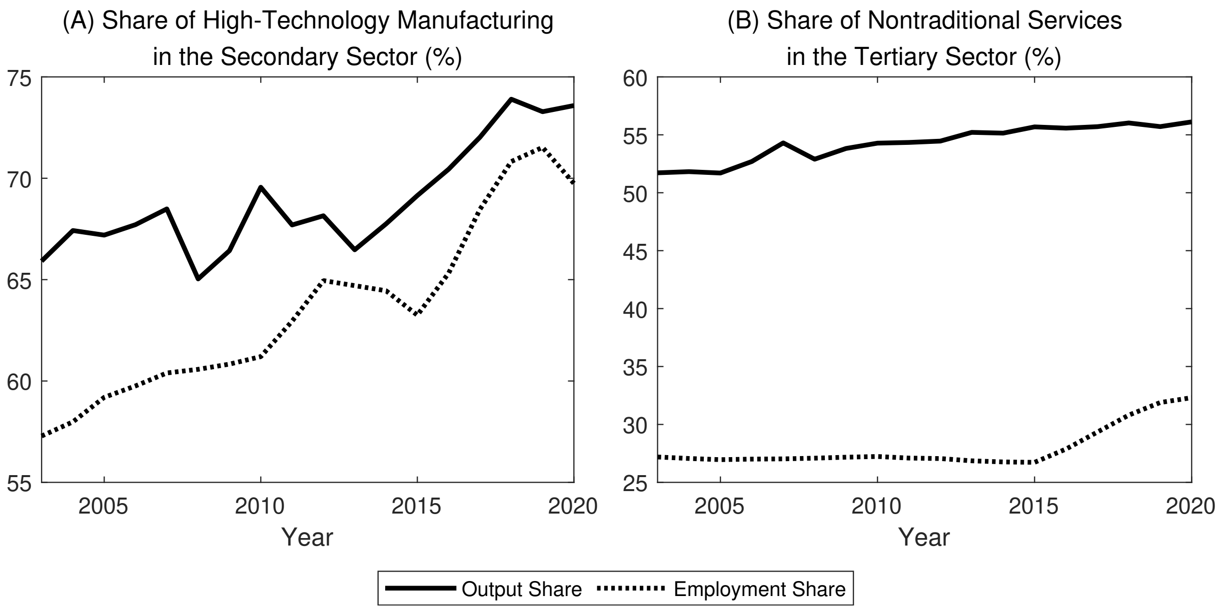

Figure 1: The Shares of High-Technology Manufacturing and Nontraditional Services, 2003–2020

before turning to a growth accounting exercise.

Figure 2 plots the evolution of sectoral labor productivity and capital intensity from 2003 to 2020. To address the influence of price effects, we present both nominal labor productivity (Panel A) and real labor productivity (Panel B, in 2005 prices), alongside the capital–labor ratio (Panel C, also in 2005 prices).

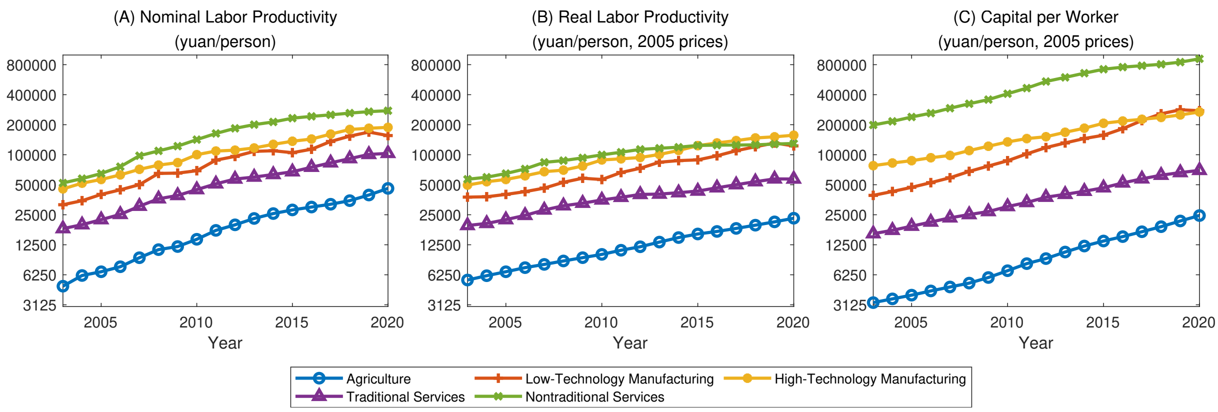

Figure 2: Sectoral Labor Productivity and Capital–Labor Ratio

Regarding nominal labor productivity (Panel A), nontraditional services and high-technology manufacturing consistently maintained the highest levels throughout the period. Although both subsectors started at comparable levels in 2003, nontraditional services grew faster, eventually surpassing high-technology manufacturing.

However, adjusting for price changes reveals a slightly different picture in real labor productivity (Panel B). While nontraditional services initially had higher real productivity, high-technology manufacturing caught up and marginally surpassed it by the end of the period. Notably, low-technology manufacturing also demonstrated strong real labor productivity growth, closing the gap with nontraditional services over time. Agriculture showed the lowest real productivity, while the traditional services remained consistently below their nontraditional counterpart, although the gap narrowed considerably.

Turning to capital–labor ratios (Panel C), a hierarchy similar to productivity initially prevailed, with nontraditional services and high-technology manufacturing having the highest capital–labor ratios. However, low-technology manufacturing experienced rapid capital deepening, steadily closing the gap with high-technology manufacturing and ultimately surpassing it around 2018.

The trends across these three panels reveal two key patterns. First, high-technology manufacturing and nontraditional services generally outperform their low-technology or traditional counterparts in labor productivity, although the convergence within manufacturing is notable. Second, the disparities in labor productivity and capital–labor ratios appear considerably larger within the tertiary sector than within the secondary sector.

To dissect the sources of the above growth, Table 3 presents annualized growth rates of several key sectoral variables. The tertiary sector led in both nominal value added and employment growth, with modern subsectors generally outperforming traditional ones, as shown in columns 1 and 2. A temporal analysis shows that while most subsectors experienced a slowdown in value added and employment growth after 2012, nontraditional services proved to be an exception, with their annualized employment growth accelerating from 2.66% to 5.68%.

Column 3 reports the growth rates of sectoral labor productivity. From 2003 to 2020, agriculture showed the highest annualized growth rate in labor productivity at 14.21%, followed by traditional services (10.76%) and nontraditional services (10.32%). In contrast, low- and high-technology manufacturing recorded the lowest growth rates at 9.85% and 8.72%, respectively. When examining the periods before and after 2012, it is evident that although sectoral labor productivity growth decelerated after 2012, the relative growth trends across subsectors remained largely stable. The notable exception was nontraditional services, whose annualized growth rate of nominal labor productivity fell below that of the manufacturing subsectors, closely relating to the rapid employment increase in nontraditional services during the same period.

The observed differences in labor productivity growth are attributable not only to price growth (column 4) but also to variations in capital deepening. Column 5 presents the growth of capital–labor ratio, indicating that from 2003 to 2020, agriculture and low-technology manufacturing experienced annualized growth rates in their capital–labor ratios of 12.56% and 12.19%, respectively, higher than the other subsectors. While capital–labor ratio growth was relatively rapid across most subsectors before 2012, this trend

Table 3: Annualized Growth Rates of Sectoral Variables, 2003–2020

	Value Added	Employ- ment	Nominal Labor Pro- ductivity	Price Index	Capital– Labor Ratio	TFP
Panel A: Annualized Growth Rate from 2003 to 2020						
Agriculture	9.51%	-4.12%	14.21%	5.01%	12.56%	2.51%
Low-Technology Manufacturing	9.58%	-0.25%	9.85%	2.47%	12.19%	1.07%
High-Technology Manufacturing	11.95%	2.98%	8.72%	1.60%	7.57%	3.05%
Traditional Services	13.61%	2.58%	10.76%	3.98%	8.98%	3.50%
Nontraditional Services	14.80%	4.07%	10.32%	5.08%	9.41%	-0.64%
Panel B: Annualized Growth Rate from 2003 to 2012						
Agriculture	12.60%	-3.80%	17.06%	7.48%	11.96%	2.93%
Low-Technology Manufacturing	15.48%	2.01%	13.20%	5.13%	13.04%	1.12%
High-Technology Manufacturing	16.79%	5.75%	10.44%	2.90%	7.70%	3.30%
Traditional Services	16.67%	2.74%	13.57%	4.87%	9.82%	4.96%
Nontraditional Services	18.11%	2.66%	15.05%	6.56%	11.81%	0.84%
Panel C: Annualized Growth Rate from 2012 to 2020						
Agriculture	6.13%	-4.47%	11.09%	2.30%	13.23%	2.05%
Low-Technology Manufacturing	3.29%	-2.74%	6.20%	-0.44%	11.23%	1.01%
High-Technology Manufacturing	6.75%	-0.05%	6.81%	0.16%	7.41%	2.78%
Traditional Services	10.26%	2.40%	7.68%	3.00%	8.05%	1.88%
Nontraditional Services	11.19%	5.68%	5.22%	3.45%	6.77%	-2.28%

reversed in the subsequent period for all subsectors except agriculture. For instance, the annualized growth rate of the capital-labor ratio in nontraditional services declined from 11.81% to 6.77%. Overall, capital deepening varied substantially across subsectors, with intra-sectoral differences being more pronounced than inter-sectoral ones.

Column 6 presents the sectoral annualized TFP growth rates, revealing notable differentials. Specifically, high-technology manufacturing (3.05%) and traditional services (3.50%) emerged as the leaders. In contrast, agriculture and low-technology manufacturing posted much lower TFP growth rates of 2.51% and 1.07%, respectively. Strikingly, nontraditional services recorded negative TFP growth of -0.64%, indicating that their output expansion was driven entirely by factor accumulation rather than efficiency gains. These findings underscore considerable disparities in TFP growth, both between and within broad sectors, with intra-sectoral divergences, particularly within the secondary sector, exceeding inter-sectoral variations.

Despite methodological differences, our estimated TFP growth rates are consistent with the existing literature. For example, Chen et al. (2024) reported an annualized TFP growth rate of 2.44% for the secondary sector from 2003 to 2022, while Chen et al. (2023) estimated a rate of 2.23% for the same sector from 2003 to 2015. For the tertiary sector, Chen et al. (2024) provided annualized TFP growth rates of 1.46% for producer services and 0.06% for consumer services from 2003 to 2022. Both numbers fall within the range of our estimates for traditional and nontraditional services.[6]

To further explore the disparities in sectoral TFP growth patterns, we present the annualized TFP growth rates before and after 2012 in Panels B and C of Table 3, and the evolution of sectoral TFP in Figure 3 with TFP levels normalized to 1 in 2003. Between 2003 and 2012, TFP grew in all sectors. High-technology manufacturing and traditional services led, while nontraditional services grew slower but positively. However, after 2012, the data in Table 3 and Figure 3 reveal particular challenges for the nontraditional services sector, whose TFP contracted at an annual rate of 2.28%, contrasting sharply with the sustained TFP growth in other sectors.

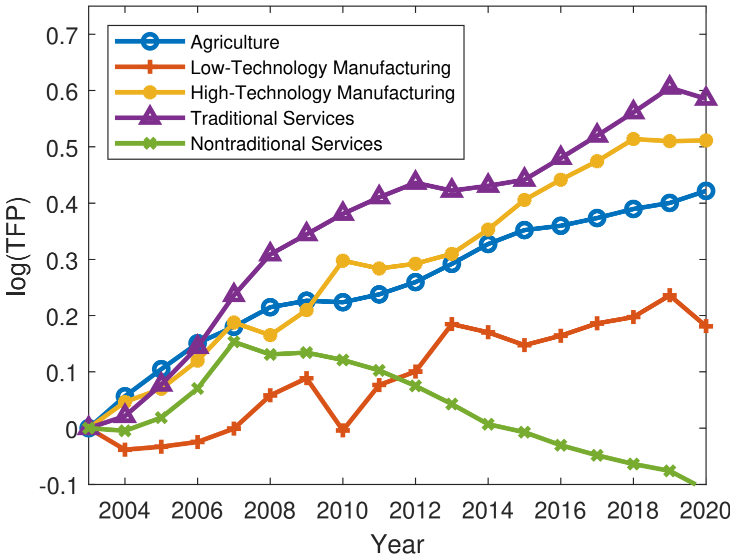

Figure 3: Evolution of Sectoral TFP, 2003–2020

We attribute the divergence in service sector TFP to distinct driving forces. The strong performance in traditional services is likely driven by technology diffusion and scale economies. In contrast, the post-2012 decline in nontraditional services is likely associated with capital and labor misallocation stemming from policy distortions and market access barriers. We provide a detailed discussion of these mechanisms and supporting literature in Appendix B.

In summary, our findings indicate that both the secondary and tertiary sectors are undergoing a transformation and upgrading from traditional to modern activities. However, the underlying driving forces are distinct. Specifically, high-technology manufacturing and nontraditional services differ from their low-technology or traditional counterparts in

[6]Chen et al. (2023) estimated that China's tertiary TFP growth rate is around 4.37% from 2005 to 2015. The differences between their estimates and ours stem from three aspects. First, Chen et al. (2023) assume a higher tertiary labor output elasticity, estimated at around 0.8 using the firm survey data from the Chinese State Taxation Administration. Second, our study covers a longer time period, revealing a decline in the TFP growth of nontraditional services from 2016 to 2020, as shown in Figure 3. Third, our broader scope for the tertiary sector includes public services, whereas Chen et al. (2023) excluded public services from their estimates.

terms of TFP improvement, capital deepening, and employment allocation. Therefore, an investigation into how sectoral TFP improvements simultaneously influence inter- and intra-sectoral structural transformation is crucial. Such an analysis will provide theoretical insights and practical guidance for the upgrading of traditional industries, thereby contributing to industrial structure optimization and sustainable development.

It is also important to clarify the scope of our following investigation. We take the documented sectoral TFP paths as given. Our primary objective is not to endogenously model the causes of these TFP paths, which are likely rooted in policy-driven capital misallocation and other factors, but rather to develop a quantitative framework capable of tracing the implications of these TFP improvements for China's structural transformation and growth. Such an analysis will provide theoretical insights and practical guidance for the upgrading of traditional industries, thereby contributing to industrial structure optimization and sustainable development.

3 Quantitative Model

We develop a general equilibrium model with three features to explain the stylized facts of China's economy. First, drawing on Boppart (2014); Fan et al. (2023), we model household non-homothetic demand using a utility function in the class of Price-Independent Generalized Linearity (PIGL) preferences. Second, we incorporate an investment structure based on Herrendorf et al. (2020) and Guo et al. (2021) and introduce sectoral differences in output elasticities as in Acemoglu and Guerrieri (2008). Third, moving beyond existing settings, we explicitly scrutinize the structure within sectors to comprehensively capture how TFP improvement and capital deepening affect both inter- and intra-structural transformation and economic growth.

3.1 Household Preferences

Consider a model economy inhabited by a continuum of heterogeneous households indexed by $i \in [0, 1]$. Each household i is composed of N_t identical members in period t, and N_t expands at an exogenous rate $n \geqslant 0$.

Every member of household i is endowed with ℓ_i units of labor and an initial wealth of $a_{i,0} \in (0, \infty)$. Labor is supplied inelastically, making the total labor supply at time t equal to $L_t \equiv N_t \int_0^1 \ell_i di$, which grows at rate n. A normalization of the time-invariant constant $\int_0^1 \ell_i di = 1$ implies $L_t = N_t$. To ensure tractability, we make the simplifying assumption that all households share the same relative factor endowments, i.e., $\frac{a_{i,0}}{\ell_i} = \frac{K_0}{L_0}$, where K_0 and L_0 are the economy's initial aggregate wealth and labor (Boppart, 2014).

This assumption prevents the joint distribution of $\{a_{i,0}, \ell_i\}$ from being a state variable.

Household consumption choices are made across three categories corresponding to the economy's three broad sectors, denoted as agricultural products (F), industrial goods (G), and services (S). Let $\mathcal{J} = \{F, G, S\}$ represent these categories. The lifetime utility of a household i is formulated as:

$$U_{i,0} = \sum_{t=0}^{\infty} \beta^t N_t V(P_{F,t}, P_{G,t}, P_{S,t}, e_{i,t}), \tag{1}$$

where the discount factor is $\beta \in (0, \frac{1}{1+n})$. The term $V(\cdot)$ represents the indirect utility function, which depends on the prices of agricultural products ($P_F(t)$), industrial goods ($P_G(t)$), and services ($P_S(t)$) and on the household's total consumption expenditure, $e_{i,t} = \sum_{j\in\mathcal{J}} P_{j,t} c_{i,j,t}$, where $c_{i,j,t}$ is the quantity of category j consumed by household i in period t.

The functional form for the indirect utility of household i is taken from the PIGL class of preferences:

$$V(P_{F,t}, P_{G,t}, P_{S,t}, e_{i,t}) = \frac{1}{\mu}\left(\frac{e_{i,t}}{\prod_{\tilde{j}\in\mathcal{J}}\left(P_{\tilde{j},t}\right)^{\omega_{\tilde{j}}}}\right)^{\mu} - \sum_{\tilde{j}\in\mathcal{J}} \upsilon_{\tilde{j}} \ln P_{\tilde{j},t}. \tag{2}$$

Applying Roy's Lemma yields the demand function for consumption $c_{i,j,t}$:

$$c_{i,j,t} = \frac{e_{i,t}}{P_{j,t}}\left(\omega_j + \upsilon_j\left(\frac{e_{i,t}}{\prod_{\tilde{j}\in\mathcal{J}}\left(P_{\tilde{j},t}\right)^{\omega_{\tilde{j}}}}\right)^{-\mu}\right), \tag{3}$$

where ω_j is the asymptotic household expenditure share on category j with the constraint $\sum_{j\in\mathcal{J}} \omega_j = 1$, υ_j determines whether category j is a necessity ($\upsilon_j > 0$) or a luxury ($\upsilon_j < 0$) satisfying $\sum_{j\in\mathcal{J}} \upsilon_j = 0$, and μ is the income elasticity capturing the income effect.

Households finance their consumption by earning wages from labor and rental income from assets. The intertemporal budget constraint of household i is given by

$$e_{i,t} = (1 + r_t(1 - \tau_t^r))\, a_{i,t} + w_t \ell_i + T_t - (1+n) a_{i,t+1}, \tag{4}$$

where w_t is the wage rate, r_t is the capital return, τ_t^r is the tax rate imposed by the government on asset returns, and T_t includes the lump-sum government transfers and exogenously given net capital outflows.

Additionally, the following transversality condition must hold:

$$\lim_{t\to\infty} a_{i,t} \cdot \frac{(1+n)^t}{\prod_{s=1}^{t}(1+r_s(1-\tau_s^r))} = 0. \tag{5}$$

Solving the household's intertemporal optimization problem yields the following Euler equation:

$$\beta\left(1+r_{t+1}(1-\tau_{t+1}^r)\right)\left(\frac{e_{i,t+1}}{e_{i,t}}\right)^{\mu-1} = \left[\prod_{j\in\mathcal{J}}\left(\frac{P_{j,t+1}}{P_{j,t}}\right)^{\omega_j}\right]^{\mu}. \tag{6}$$

Finally, we aggregate demand across the continuum of households to obtain the expenditure share on category j in the model economy:

$$\eta_{j,t} \equiv \frac{P_{j,t}C_{j,t}}{E_t} = \omega_j + \upsilon_j\phi\left(\frac{E_t/N_t}{\prod_{\tilde{j}\in\mathcal{J}}\left(P_{\tilde{j},t}\right)^{\omega_{\tilde{j}}}}\right)^{-\mu}, \tag{7}$$

where $C_{j,t} \equiv N_t\int_0^1 c_{i,j,t}di$ denotes aggregate consumption of category j, $E_t \equiv N_t\int_0^1 e_{i,t}di$ is aggregate expenditure, and $\phi \equiv \int_0^1\left(\frac{e_{i,0}N_0}{E_0}\right)^{1-\mu}di$ is a time-invariant constant measuring inequality in household expenditure.

A key result from equation (6) is that the expenditure growth rate is identical across all households, being equal to the growth rate of the economy's per capita expenditure, E_t/N_t. It allows us to write the corresponding Euler equation for the model economy as

$$\beta\left(1+r_{t+1}(1-\tau_{t+1}^r)\right)\left(\frac{E_{t+1}/N_{t+1}}{E_t/N_t}\right)^{\mu-1} = \left[\prod_{j\in\mathcal{J}}\left(\frac{P_{j,t+1}}{P_{j,t}}\right)^{\omega_j}\right]^{\mu}. \tag{8}$$

3.2 Firm Production

In the model economy, production unfolds across five perfectly competitive sectors: agriculture (F), low-technology manufacturing (TG), high-technology manufacturing (AG), traditional services (TS), and nontraditional services (MS), which we group into the set $\mathcal{D} = \{F, TG, AG, TS, MS\}$. The production process begins in each sector $d \in \mathcal{D}$ with a Cobb-Douglas technology:

$$Y_{d,t} = A_{d,t}\left(K_{d,t}\right)^{\alpha_d}\left(L_{d,t}\right)^{1-\alpha_d}, \tag{9}$$

where Y_d is output, A_d is the TFP, K_d is the capital stock, L_d is the labor input, and α_d is the capital output elasticity. Firms maximize profits given by:

$$\pi_{d,t} = P_{d,t}Y_{d,t} - \left(1 + \tau_{d,t}^{K}\right) R_t K_{d,t} - \left(1 + \tau_{d,t}^{L}\right) w_t L_{d,t}, \tag{10}$$

where P_d is the output price for sector d, R is the capital rental price, and $\tau_{d,t}^{K}$ and $\tau_{d,t}^{L}$ are the capital and labor wedges, respectively. The first-order conditions imply that

$$R_t \left(1 + \tau_{d,t}^{K}\right) = \alpha_d \frac{P_{d,t}Y_{d,t}}{K_{d,t}}, \tag{11}$$

$$w_t \left(1 + \tau_{d,t}^{L}\right) = (1 - \alpha_d) \frac{P_{d,t}Y_{d,t}}{L_{d,t}}. \tag{12}$$

The outputs from the manufacturing sectors serve as intermediates for a final industrial good, which is produced with a constant elasticity of substitution (CES) technology:

$$Y_{G,t} = \left[\theta^{\frac{1}{\sigma}} (Y_{TM,t})^{\frac{\sigma-1}{\sigma}} + (1-\theta)^{\frac{1}{\sigma}} (Y_{AM,t})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{13}$$

where σ represents the elasticity of substitution and θ is the weighting parameter for low-technology manufacturing. The CES structure in equation (13) explicitly models the input-output linkages within the secondary sector, where the sectoral outputs serve as inputs for the broad sector's final good.[7] The solution to the aggregator's profit maximization problem yields:

$$P_{G,t} (Y_{G,t})^{\frac{1}{\sigma}} = P_{TM,t} \left(\frac{Y_{TM,t}}{\theta}\right)^{\frac{1}{\sigma}} = P_{AM,t} \left(\frac{Y_{AM,t}}{1-\theta}\right)^{\frac{1}{\sigma}}. \tag{14}$$

An analogous process occurs in the service sector, where traditional and nontraditional service inputs are combined via a CES production function:

$$Y_{S,t} = \left[\psi^{\frac{1}{\rho}} (Y_{TS,t})^{\frac{\rho-1}{\rho}} + (1-\psi)^{\frac{1}{\rho}} (Y_{MS,t})^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{15}$$

where ρ is the elasticity of substitution and ψ captures the weight of traditional services. Profit maximization then implies

$$P_{S,t} (Y_{S,t})^{\frac{1}{\rho}} = P_{TS,t} \left(\frac{Y_{TS,t}}{\psi}\right)^{\frac{1}{\rho}} = P_{MS,t} \left(\frac{Y_{MS,t}}{1-\psi}\right)^{\frac{1}{\rho}}. \tag{16}$$

The final stage of production involves crafting investment goods by using agricultural

[7] A similar input-output linkage structure is also featured in Chen et al. (2023), who model industrial goods as an aggregate of manufacturing goods and producer services. We thank the referee for this helpful clarification.

products, industrial goods, and services by

$$I_t = A_{I,t} \left[\sum_{j \in \mathcal{J}} (\gamma_{j,t})^{\frac{1}{\varepsilon}} (I_{j,t})^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{17}$$

where $A_{I,t}$ is investment-specific TFP and $\gamma_{j,t}$ defines the time-varying technology structure, with the constraint $\sum_{j \in \mathcal{J}} \gamma_{j,t} = 1$. The corresponding first-order conditions are

$$P_{I,t} (I_t)^{\frac{1}{\varepsilon}} (A_{I,t})^{\frac{\varepsilon-1}{\varepsilon}} = P_{j,t} \left(\frac{I_{j,t}}{\gamma_{j,t}} \right)^{\frac{1}{\varepsilon}}. \tag{18}$$

As a numeraire, we normalize the price of capital in each period, $P_{I,t}$, to 1.

While our baseline model abstracts from explicit inter-sectoral input–output linkages such as those in Chen et al. (2023), our framework implicitly captures essential inter-sectoral linkages from the demand side. Specifically, our model and Chen et al. (2023) share a fundamental structural isomorphism in how sectors interact. Whereas Chen et al. (2023) use a CES technology to bundle manufacturing and producer services into industrial goods, our specification uses a CES technology to bundle broad sectoral outputs into the final investment good, alongside a PIGL preference for consumption aggregation. In both frameworks, the sectors act as inputs, either for intermediate production or for final demand formation. The above demand-side aggregation effectively generates similar relative price and income effects that drive inter-sectoral transformation. Adopting such a parsimonious specification allows us to maintain analytical tractability and focus on our primary innovation regarding intra-sectoral structural changes. Because cross-sector linkages primarily affect the relative sizes of broad sectors rather than the relative trends within them, the abstraction does not compromise our core findings regarding intra-sectoral dynamics. Furthermore, as input–output linkages typically amplify TFP shocks (Jones, 2011), abstracting from them implies that our later quantitative results regarding TFP's contribution to economic growth should be viewed as conservative lower bounds.

3.3 Solving the Model

A competitive equilibrium in this economy is defined by a sequence of allocations and prices that satisfy a set of market clearing conditions. For each consumption category $j \in \mathcal{J}$, the goods market must clear:

$$Y_{j,t} = C_{j,t} + I_{j,t} + X_{j,t}, \tag{19}$$

where X_j is the net exports of category j. The share of net exports in total output, $x_{j,t} = \frac{X_{j,t}}{Y_{j,t}}$, is treated as exogenously given.

Additionally, the market clearing conditions for labor and capital are:

$$N_t = N_t \int_0^1 \ell_i di \equiv L_t = \sum_{d \in \mathcal{D}} L_{d,t}, \tag{20}$$

$$N_t \int_0^1 a_{i,t} di \equiv K_t = \sum_{d \in \mathcal{D}} K_{d,t}. \tag{21}$$

The government maintains a balanced budget in every period, such that:

$$N_t T_t = \sum_{d \in \mathcal{D}} \left(\tau^K_{d,t} R_t K_{d,t} + \tau^L_{d,t} w_t L_{d,t} \right) + r_t \tau^r_t K_t - \sum_{j \in \mathcal{J}} P_{j,t} X_{j,t}. \tag{22}$$

The relationship between the return on capital and its rental price is given by the standard no-arbitrage condition:

$$R(t) = r(t) + \delta, \tag{23}$$

where δ is the capital depreciation rate. Combining equations (4) and (21), we derive the law of motion for aggregate capital:

$$K_{t+1} = (1 - \delta) K_t + I_t. \tag{24}$$

To summarize, the equilibrium conditions for our general equilibrium model consist of 37 equations, including the production functions (9), (13), (15), (17), first-order conditions (11), (12), (14), (16), (18), sectoral expenditure shares (7), market clearing conditions (19), (20), (21), (22), (23), the Euler equation (8), the capital accumulation equation (24), and the condition that capital prices are normalized to 1.

The solution to this system determines the equilibrium paths of 37 endogenous variables, including aggregate capital (K), expenditure (E), investment (I), sectoral outputs (Y_d), quantities of industrial goods and services (Y_G, Y_S), consumption and investment allocations (C_j, I_j), sectoral factor inputs (K_d, L_d), prices (P_d, P_G, P_S, P_I), the wage rate (w), the rental price (R), and capital returns (r).

The model's behavior is governed by 19 parameters: sectoral output elasticities (α_d), CES parameters (σ, θ, ρ, ψ, ε), preference parameters (ω_j, υ_j, μ), the discount factor (β), and the depreciation rate (δ). Following Fan et al. (2023), we calibrate $\upsilon_j \phi$ directly rather than calibrating υ_j and ϕ separately.

Given an initial value for capital (K_0) and exogenous paths for TFP levels (A_d, A_I), wedges

(τ_d^K, τ_d^L, τ^r), net export shares (x_j), and investment technology shares (γ_j), the system of equilibrium conditions can be solved to find the paths of all endogenous variables.

4 Calibration

We outline our calibration strategy in this section. Table 4 provides a comprehensive summary of the parameter values, sources, and target moments. As detailed in the table, our calibration procedure distinguishes between three categories, including time-invariant parameters set externally based on existing literature (Panel A), time-invariant parameters estimated jointly by matching model moments to data (Panel B), and time-varying exogenous series calibrated to match specific historical paths (Panel C). We describe the identification of each category in turn below.

Table 4: Parameters and Calibrated Exogenous Series

Parameter	Description	Value	Source or Target Moments
	Panel A: Externally Set Time-Invariant Parameters		
δ	Depreciation rate	0.09	Brandt et al. (2012)
β	Discount factor	0.96	Guo et al. (2021)
μ	Income elasticity	0.375	Chen et al. (2023)
α_F	Capital share in agriculture	0.5	Brandt et al. (2008)
α_{TM}	Capital share in low-technology manufacturing	0.512	Data average
α_{AM}	Capital share in high-technology manufacturing	0.516	Data average
α_{TS}	Capital share in traditional services	0.334	Data average
α_{MS}	Capital share in nontraditional services	0.612	Data average
	Panel B: Jointly Estimated Time-Invariant Parameters		
θ	Weight in industrial goods production	0.319	Sectoral value added shares
σ	Elasticity of substitution within the secondary sector	1.680	Sectoral value added shares
ψ	Weight in service production	0.479	Sectoral value added shares
ρ	Elasticity of substitution within the tertiary sector	0.207	Sectoral value added shares
ε	Elasticity of substitution in investment goods production	0.000	Sectoral investment shares
ξ_1, ξ_2	Trend parameters for industrial investment weights	2.266, 0.078	Sectoral investment shares
ξ_3, ξ_4	Trend parameters for service investment weights	1.349, 0.081	Sectoral investment shares
ω_F	Asymptotic share of agriculture	0.051	Sectoral consumption shares
ω_G	Asymptotic share of industrial goods	0.075	Sectoral consumption shares
ω_S	Asymptotic share of services	0.875	Sectoral consumption shares
$\upsilon_F\phi$	Income effect parameter for agricultural goods	0.111	Sectoral consumption shares
$\upsilon_G\phi$	Income effect parameter for industrial goods	0.290	Sectoral consumption shares
$\upsilon_S\phi$	Income effect parameter for services	-0.400	Sectoral consumption shares
K_{2003}	Initial capital stock	Calibrated	Industrial share in consumption in 2003
	Panel C: Calibrated Exogenous Series		
$A_{j,t}$	Sectoral TFP levels	Time-varying	Solow residuals
$\tau_{j,t}^K, \tau_{j,t}^L$	Sectoral capital and labor wedges	Time-varying	First-order conditions
τ_{t+1}^r	Asset return tax rate	Time-varying	Aggregate investment rate
$x_{j,t}$	Net capital outflow shares	Time-varying	Sectoral trade imbalances

We begin with the externally set parameters reported in Panel A of Table 4. Consistent with Brandt et al. (2012), the depreciation rate is set to $\delta = 0.09$. Following Guo et al. (2021), we set the discount factor to $\beta = 0.96$. The parameter μ in preferences is set to $\mu = 0.375$, which corresponds to the benchmark value in Chen et al. (2023). Then, we calibrate the remaining parameters based on the empirical moments and our model.

Sectoral Capital Output Elasticities. Following the results from Section 2, we set $\alpha_F = 0.5$, $\alpha_{TM} = 0.512$, $\alpha_{AM} = 0.516$, $\alpha_{TS} = 0.334$, and $\alpha_{MS} = 0.612$. These values are all close to 0.5, consistent with the capital output elasticities reported in Brandt et al. (2008).

Parameters in CES Production Functions of Industrial Goods and Services. Specifically, we estimate θ and σ using the following two conditions:

$$\frac{VA_{TM,t}}{VA_{TM,t}+VA_{AM,t}} = \theta\left(\frac{P_{TM,t}}{\left(\theta\left(P_{TM,t}\right)^{1-\sigma}+(1-\theta)\left(P_{AM,t}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}\right)^{1-\sigma},$$

$$\frac{VA_{AM,t}}{VA_{TM,t}+VA_{AM,t}} = (1-\theta)\left(\frac{P_{AM,t}}{\left(\theta\left(P_{TM,t}\right)^{1-\sigma}+(1-\theta)\left(P_{AM,t}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}\right)^{1-\sigma}.$$

The left-hand side of the above equations is the value added shares of low- and high-technology manufacturing in the secondary sector, while the right-hand side is a function of the sectoral prices. Using data on sectoral prices and value added shares, we estimate θ and σ by minimizing the difference between the actual sectoral value added shares and the model predictions based on the feasible generalized nonlinear least squares (FGNLS) method. Our estimation yields $\theta = 0.319$ and $\sigma = 1.680$.[8] Similarly, we estimate $\psi = 0.479$ and $\rho = 0.207$ with the following conditions:

$$\frac{VA_{TS,t}}{VA_{TS,t}+VA_{MS,t}} = \psi\left(\frac{P_{TS,t}}{\left(\psi\left(P_{TS,t}\right)^{1-\rho}+(1-\psi)\left(P_{MS,t}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}}}\right)^{1-\rho},$$

$$\frac{VA_{MS,t}}{VA_{TS,t}+VA_{MS,t}} = (1-\psi)\left(\frac{P_{MS,t}}{\left(\psi\left(P_{TS,t}\right)^{1-\rho}+(1-\psi)\left(P_{MS,t}\right)^{1-\rho}\right)^{\frac{1}{1-\rho}}}\right)^{1-\rho}.$$

Our estimated elasticities of substitution indicate that low- and high-technology manufacturing are substitutes ($\sigma > 1$) and that traditional and nontraditional services are complements ($\rho < 1$). Therefore, the underlying mechanisms driving intra-sectoral structural transformation in the secondary and tertiary sectors are fundamentally distinct.

Parameters in CES Production Functions of Investment Goods. We estimate ε and $\gamma_{j,t}$ based on the following equations:

$$\frac{VA^{I}_{j,t}}{\sum_{\tilde{j}\in\mathcal{J}} VA^{I}_{\tilde{j},t}} = \gamma_{j,t}\left(\frac{P_{j,t}}{\left(\sum_{\tilde{j}\in\mathcal{J}}\gamma_{\tilde{j},t}\left(P_{\tilde{j},t}\right)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}}\right)^{1-\varepsilon},$$

where $P_{G,t}$ and $P_{S,t}$ are derived based on previously estimated production function pa-

[8] We report more calibration details in Appendix C.

rameters and sectoral prices, and $VA^I_{j,t}$ is the investment component from the value added of category j. Following Herrendorf et al. (2013, 2020), we estimate $VA^I_{j,t}$ using input–output tables.[9] To better align with Chinese investment data, we adopt the specification proposed by Guo et al. (2021), assuming that $\gamma_{j,t}$ follows $\log\left(\frac{\gamma_{G,t}}{\gamma_{F,t}}\right) = \xi_1 + \xi_2 t$ and $\log\left(\frac{\gamma_{S,t}}{\gamma_{F,t}}\right) = \xi_3 + \xi_4 t$, where ξ_1, ξ_2, ξ_3, and ξ_4 are constants. Based on the sectoral prices and value added shares, we apply the FGNLS method, resulting in estimates of $\varepsilon = 0.000$, $\xi_1 = 2.266$, $\xi_2 = 0.078$, $\xi_3 = 1.349$, and $\xi_4 = 0.081$.

An elasticity of substitution ε of zero indicates that the production function of investment is Leontief, consistent with findings for the U.S. in Herrendorf et al. (2020). However, examining longer time series of Chinese data may yield a positive elasticity estimate (Guo et al., 2021).

From 2003 to 2020, $\gamma_{j,t}$ is determined by the above calibration. For years after 2020, $\gamma_{j,t}$ is assumed to hold constant at their 2020 levels.

Preference Parameters. To calibrate the asymptotic expenditure share ω_j and the non-homothetic parameter $\upsilon_j\phi$, we use the following conditions:

$$\frac{VA^C_{j,t}}{\sum_{j\in\mathcal{J}} VA^C_{j,t}} = \omega_j + \upsilon_j\phi\left(\frac{\sum_{j\in\mathcal{J}} VA^C_{j,t}/N_t}{\prod_{\tilde{j}\in J}\left(P_{\tilde{j},t}\right)^{\omega_{\tilde{j}}}}\right)^{-\mu},$$

where $VA^C_{j,t}$ is the consumption component of the value added of category j. Using the FGNLS method, we estimate the parameters with $VA^C_{j,t}$ and the sectoral prices. The results are as follows: $\omega_F = 0.051$, $\omega_G = 0.075$, $\omega_S = 0.875$, $\upsilon_F\phi = 0.111$, $\upsilon_G\phi = 0.290$, and $\upsilon_S\phi = -0.400$. The estimated asymptotic expenditure share for agricultural products, ω_F, is slightly higher than the value reported by Fan et al. (2023) for the United States. This discrepancy suggests differences in the consumption structures between China and the United States.

Sectoral TFP Levels. The calibration of $A_{F,t}$, $A_{TM,t}$, $A_{AM,t}$, $A_{TS,t}$, $A_{MS,t}$, and $A_{I,t}$ is based on the following equations:

$$A_{d,t} = \frac{Y_{d,t}}{\left(K_{d,t}\right)^{\alpha_d}\left(L_{d,t}\right)^{1-\alpha_d}}, \qquad d\in\mathcal{D},$$

$$A_{I,t} = \frac{1}{P_{I,t}}\left(\sum_{j\in\mathcal{J}}\gamma_{j,t}\left(P_{j,t}\right)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}.$$

From 2003 to 2020, the TFP levels can be derived using the corresponding sectoral value

[9] Appendix C.1 provides a more detailed estimation process. The same approach is applied to estimate $VA^C_{j,t}$ in subsequent analyses.

added, capital, labor, and prices. Based on the sectoral TFP levels, we pin down the sectoral annualized TFP growth during 2003 and 2020, $\overline{g}_d^{TFP}$, where $d \in \mathcal{D}$. For $t \in [2021, 2040]$, we assume the TFP growth rate for sector d to be $g_{d,t}^{TFP} = \overline{g}_d^{TFP} \times \frac{2040-t}{20}$. The same method is applied to determine $A_{I,t}$ from 2021 to 2040. After 2040, we assumed that the TFP levels no longer grow.

Capital and Labor Wedges. We begin by assuming that $\sum_{d\in\mathcal{D}} \tau_{d,t}^K = 0$ and $\sum_{d\in\mathcal{D}} \tau_{d,t}^L = 0$.[10] For the period from 2003 to 2020, we calculate R_t and w_t with the first-order conditions. Specifically, $R_t = \frac{1}{5}\sum_{d\in\mathcal{D}} \frac{\alpha_d P_{d,t} Y_{d,t}}{K_{d,t}}$, and $w_t = \frac{1}{5}\sum_{d\in\mathcal{D}} \frac{(1-\alpha_d) P_{d,t} Y_{d,t}}{L_{d,t}}$. Then, $\tau_{d,t}^K$ and $\tau_{d,t}^L$ are determined by

$$
\begin{aligned}
\tau_{d,t}^K &= \frac{\alpha_d P_{d,t} Y_{d,t}}{R_t K_{d,t}} - 1, \\
\tau_{d,t}^L &= \frac{(1-\alpha_d) P_{d,t} Y_{d,t}}{w_t L_{d,t}} - 1.
\end{aligned}
$$

From 2021 to 2040, we assume that wedges decrease by a fixed amount each year, linearly converging to zero by 2040. After 2040, all wedges are held constant at zero.

Asset Return Tax Rates. We calibrate τ_{t+1}^r such that the investment rate, $\frac{I_t}{\sum_{d\in\mathcal{D}} P_{d,t} Y_{d,t}}$, in the first 18 periods in the calibrated model matches the data from 2003 to 2020. Starting in 2021, τ_{t+1}^r is assumed to decline annually by a fixed value, reaching zero by 2040. After 2040, the wedge is set to zero permanently.

Net Capital Outflow Shares. For 2003 to 2020, we derive the net capital outflow shares $x_{j,t}$ by

$$
x_{j,t} = 1 - \frac{VA_{j,t}^C + VA_{j,t}^I}{VA_{j,t}}.
$$

From 2021 on, we assume that $x_{j,t}$ converges linearly each year to zero by 2040. Afterwards, the trade is balanced within each sector.

Initial Capital Stock. We anchor the initial capital stock such that the expenditure share of industrial goods in total consumption in the first period of the model precisely matches the observed data in 2003.

5 Quantitative Analysis

This section proceeds as follows. First, we establish the empirical validity of our calibrated theoretical model, demonstrating its success in quantitatively capturing China's inter-

[10] This assumption normalizes the wedge levels. As only the relative wedges matter, changing the sum of wedges to another constant would not affect our model's conclusions.

and intra-sectoral structural transformations and economic growth from 2003 to 2020. Second, we conduct a series of counterfactual experiments to identify the roles of TFP improvement and capital deepening in driving these structural and growth dynamics.

5.1 Dynamics of the Baseline Model

To capture China's historical patterns of structural transformation and economic growth, our simulation of the model economy starts in 2003 and runs for 300 periods, where each period is one year. The model is expected to converge to its steady state after 300 periods of simulation, and our analysis focuses on its performance during the first 18 periods for the calibrated model economy. [11]

Based on the determined model parameters, we solve the model numerically. The first step is to calculate the economy's terminal steady state. We then impose these steady-state values as the terminal conditions for all endogenous variables. Finally, we solve for the entire transition path, finding the evolution of all endogenous variables that satisfies the full set of equilibrium conditions across all 300 periods simultaneously.

We start our evaluation of the baseline model by assessing its performance against the observed inter-sectoral structural transformation. In Figure 4, we compare the model-simulated shares for sectoral value added and employment against the data. Despite not being directly targeted in the calibration, the model's simulated trajectories align well with the empirical trends. Our baseline model correctly captures the persistent shrinkage of the primary sector (panels A and D), the hump-shaped development of the secondary sector (panels B and E), and the sustained expansion of the tertiary sector (panels C and F).

We next evaluate the model's ability to replicate intra-sectoral structural transformation patterns. Figure 5 compares our baseline model's predictions with data for high-technology manufacturing (panels A and C) and nontraditional services (panels B and D) within their respective broad sectors. The model performs well in matching the observed sectoral employment shares. However, it underestimates the rise in the value added share of high-technology manufacturing after 2015.[12]

The divergence likely stems from the abstraction of the endogenous interaction between productivity growth and friction reduction, a simplification consistent with the standard structural transformation and misallocation literature focusing on China (see, for exam-

[11] The 300-period length is chosen to be sufficiently long for the model to attain its steady state, which allows us to concentrate our evaluation on the initial 18-period performance of the calibrated economy.

[12] Appendix Figure A10 provides complete subsector comparisons. To further address concerns regarding the calibration of wedges, Appendix D presents an alternative model specification that perfectly matches all sectoral value added and employment shares. The consistency of TFP effects across both specifications confirms that our main findings are robust to the measurement strategy for distortions.

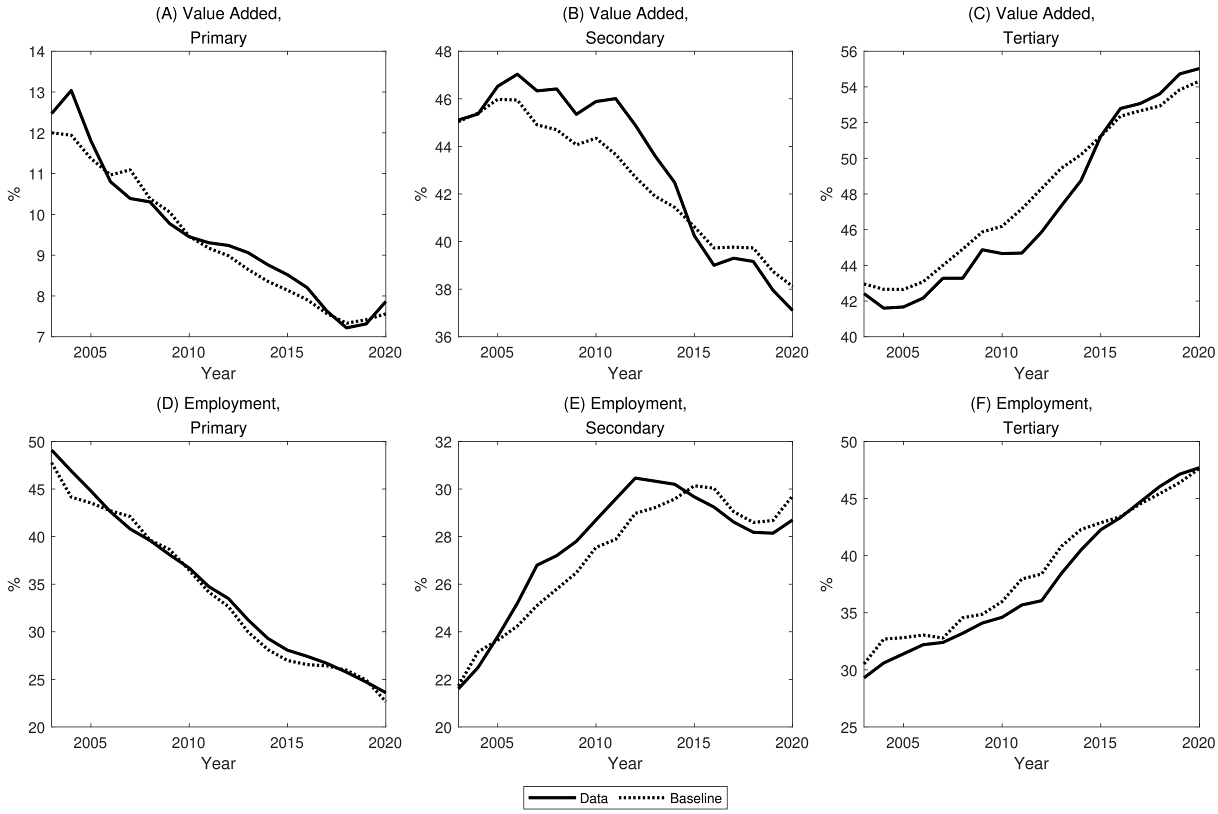

Figure 4: Inter-sectoral Structural Transformation in the Baseline Model

ple, Hsieh and Klenow, 2009; Brandt et al., 2013; Hsieh and Song, 2015; Chen et al., 2023; Cheremukhin et al., 2024), which typically relies on exogenous reduced-form wedges to quantify the macroeconomic consequences of observed distortions. In our baseline calibration, we recover sectoral wedges as residuals to match the first-order conditions. Although we capture the level of sectoral wedges, we treat their evolution as exogenous and independent of TFP.

However, in reality, the rapid expansion of high-technology manufacturing was likely driven by a reinforcing loop. TFP breakthroughs not only increased marginal products but also likely induced institutional reforms or capital inflows that endogenously reduced capital wedges. By treating TFP and wedges as separate exogenous inputs, our model dampens the amplification mechanism, preventing the baseline simulation from fully capturing the growth of the high-technology manufacturing in the most recent years. While endogenizing the interaction between TFP and wedges is theoretically important, structurally identifying this mechanism requires rich firm-level microdata and is thus left as a promising avenue for future research.[13]

A closer look at the data, documented in the first and second rows of Tables 5 and 6, further quantifies the model's fit. The baseline model slightly underestimates the pace of structural transformation, both across and within broad sectors. For example, the

[13]We thank the anonymous referee for this insight.

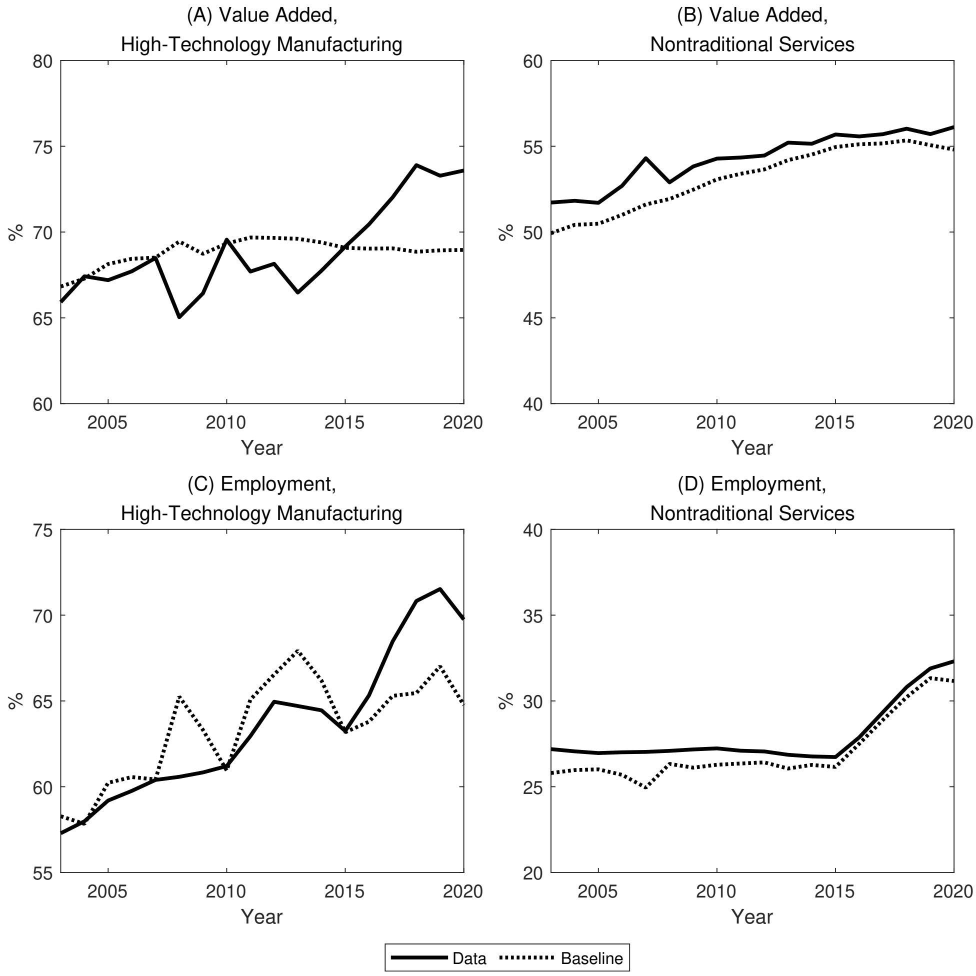

Figure 5: Intra-sectoral Structural Transformation in the Baseline Model

model predicts increases of 11.36 and 17.11 percentage points in the tertiary sector's value added and employment shares, which are smaller than the actual increases of 12.61 and 18.40 percentage points.[14] A similar pattern is found in the analysis of intra-sectoral structural transformation, where the model projects slower growth in high-technology manufacturing's shares, consistent with Figure 5.

Finally, our evaluation extends to growth patterns, specifically those of aggregate labor productivity (total value added per worker, adjusted for capital prices) and sectoral output per worker (sectoral real value added per worker). The first two rows of Table 7 present a direct comparison of the observed and model-simulated annualized growth rates for aggregate labor productivity (column 1) and sectoral output per worker (columns 2–6).

The baseline model closely tracks the growth patterns in the data, though it consistently underestimates the growth rates. Specifically, China's aggregate labor productivity grew at an annual average rate of 9.77% from 2003 to 2020, whereas the baseline model generates a rate of 8.91%. The discrepancies imply that the baseline model successfully

[14] Calculated as $3.04 + 8.32 = 11.36$, $10.14 + 6.97 = 17.11$, $3.67 + 8.94 = 12.61$, and $10.95 + 7.45 = 18.40$ based on the first and second rows of Table 5 and Table 6.

Table 5: Changes of Sectoral Value Added Shares between 2003 and 2020

	Changes of Share in Total Value Added					Changes of Share in Broad Sector Value Added	
	Agriculture	Low-Technology Manufac-turing	High-Technology Manufac-turing	Traditional Services	Non-traditional Services	High-Technology Manufac-turing	Non-traditional Services
Data	-4.60%	-5.58%	-2.43%	3.67%	8.94%	7.67%	4.40%
Baseline Model	-4.44%	-3.11%	-3.81%	3.04%	8.32%	2.14%	4.88%
Counterfactuals:							
Constant Low-Technology Manufacturing TFP	-4.42%	-3.96%	-2.49%	2.71%	8.16%	4.71%	5.08%
Constant High-Technology Manufacturing TFP	-4.20%	0.74%	-5.76%	1.63%	7.59%	-5.76%	5.89%
Constant Traditional Service TFP	-3.83%	-3.51%	-4.81%	9.45%	2.69%	2.13%	-5.97%
Constant Nontraditional Service TFP	-4.45%	-3.06%	-3.69%	4.18%	7.02%	2.14%	2.64%
Constant Primary TFP	-3.86%	-3.17%	-3.94%	2.79%	8.18%	2.13%	5.02%
Constant Secondary TFP	-4.17%	-0.30%	-4.29%	1.33%	7.43%	-2.88%	6.09%
Constant Tertiary TFP	-3.82%	-3.52%	-4.82%	10.68%	1.48%	2.13%	-8.14%
Constant TFP in All Sectors	-3.12%	-0.89%	-5.21%	8.22%	1.00%	-2.88%	-6.96%
No Capital Deepening	-1.58%	-2.63%	-3.39%	-4.44%	12.04%	2.04%	14.30%

Table 6: Changes of Sectoral Employment Shares between 2003 and 2020

	Changes of Share in Total Employment					Changes of Share in Broad Sector Employment	
	Agriculture	Low-Technology Manufac-turing	High-Technology Manufac-turing	Traditional Services	Non-traditional Services	High-Technology Manufac-turing	Non-traditional Services
Data	-25.50%	-0.54%	7.64%	10.95%	7.45%	12.46%	5.12%
Baseline Model	-25.10%	1.41%	6.59%	10.14%	6.97%	6.49%	5.36%
Counterfactuals:							
Constant Low-Technology Manufacturing TFP	-25.00%	0.69%	7.63%	9.77%	6.92%	9.24%	5.54%
Constant High-Technology Manufacturing TFP	-24.65%	4.91%	5.42%	7.86%	6.46%	-1.80%	6.25%
Constant Traditional Service TFP	-24.65%	0.36%	4.48%	16.31%	3.50%	6.48%	-3.15%
Constant Nontraditional Service TFP	-25.36%	1.36%	6.51%	11.32%	6.18%	6.49%	3.47%
Constant Primary TFP	-23.65%	1.24%	6.28%	9.41%	6.72%	6.49%	5.49%
Constant Secondary TFP	-24.51%	4.03%	6.59%	7.50%	6.40%	1.20%	6.44%
Constant Tertiary TFP	-24.85%	0.27%	4.33%	17.43%	2.83%	6.48%	-4.66%
Constant TFP in All Sectors	-23.20%	2.46%	4.26%	14.02%	2.45%	1.19%	-3.85%
No Capital Deepening	-16.42%	1.09%	5.04%	1.34%	8.95%	6.38%	14.29%

captures about 91% of the observed economic growth. We can thus regard our baseline model as a conservative estimate or a lower bound of China's true economic growth.

Despite the aforementioned underestimations in both structural shares and growth rates, the baseline model effectively captures the fundamental patterns of China's structural transformation and economic growth, which validates its effectiveness as a framework for our counterfactual analysis. Therefore, we retain this more parsimonious baseline model in the main text to highlight the fundamental economic mechanisms. As a robustness check, Appendix D presents an alternative model specification with a calibration strategy that better matches the structural transformation data patterns. The counterfactual analyses

Table 7: Annualized Output Growth Rates, 2003–2020

	Aggregate Labor Productivity	Sectoral Output per Worker				
		Agriculture	Low-Technology Manufacturing	High-Technology Manufacturing	Traditional Services	Nontraditional Services
Data	9.77%	8.76%	7.21%	7.01%	6.52%	4.98%
Baseline Model	8.91%	7.98%	6.42%	6.22%	6.01%	4.06%
Counterfactuals:						
Constant Low-Technology Manufacturing TFP	8.60%	7.87%	5.18%	6.10%	5.93%	3.93%
Constant High-Technology Manufacturing TFP	6.94%	7.40%	5.83%	2.49%	5.62%	3.37%
Constant Traditional Service TFP	7.32%	7.57%	6.01%	5.80%	2.16%	3.58%
Constant Nontraditional Service TFP	9.04%	8.03%	6.47%	6.26%	6.04%	4.79%
Constant Primary TFP	8.67%	5.26%	6.34%	6.14%	5.95%	3.96%
Constant Secondary TFP	6.55%	7.28%	4.59%	2.38%	5.55%	3.23%
Constant Tertiary TFP	7.41%	7.60%	6.03%	5.83%	2.18%	4.28%
Constant TFP in All Sectors	5.18%	4.28%	4.22%	2.01%	1.74%	3.46%
No Capital Deepening	3.22%	2.49%	0.88%	0.65%	2.38%	-2.38%

using the alternative specification confirm that our following economic insights, such as the contributions of TFP improvements, are qualitatively the same and quantitatively very similar to the results from the baseline model.

5.2 The Role of Subsector TFP Improvements

Building on the validated baseline model, we conduct a series of counterfactual simulations to quantitatively assess the roles of sectoral TFP growth in shaping China's structural transformation and economic growth.

Our first experiment analyzes counterfactual scenarios where the TFP levels of a specific subsector are held fixed at their initial baseline values. These simulations isolate the contribution of TFP improvement from a given subsector by holding its TFP constant while allowing all others to follow their baseline dynamics.

Inter-Sectoral Structural Transformation Patterns. Figure 6 visualizes the comparison of value added shares (panels A to C) and employment shares (panels D to F) for the three broad sectors across the baseline and counterfactual scenarios, with detailed sectoral share changes reported in Tables 5 and 6.

A notable feature in our counterfactual simulations is that the paths in Figures 6 and 9 do not start from the same position as the baseline in 2003. The difference arises because our framework is a perfect foresight dynamic general equilibrium model. Agents in the model anticipate the different future TFP paths and optimally adjust their initial consumption and investment levels. Since the secondary sector dominates investment while the primary and tertiary sectors dominate consumption, the immediate adjustment in the aggregate investment-to-consumption ratio causes an instant reallocation of sectoral value added and employment shares in the initial period.

Our simulations reveal that subsector TFP growth differentially shapes structural transformation across the broad sectors. In Figure 6, shutting down TFP growth in either high-technology manufacturing (△ line) or traditional services (× line) generates the most significant deviations from the baseline sectoral shares. Specifically, limiting high-technology manufacturing TFP growth elevates the shares of the secondary sector, whereas fixing traditional service TFP increases the shares of the tertiary sector. These opposing effects highlight how sectoral productivity dynamics govern inter-sectoral structural transformation.

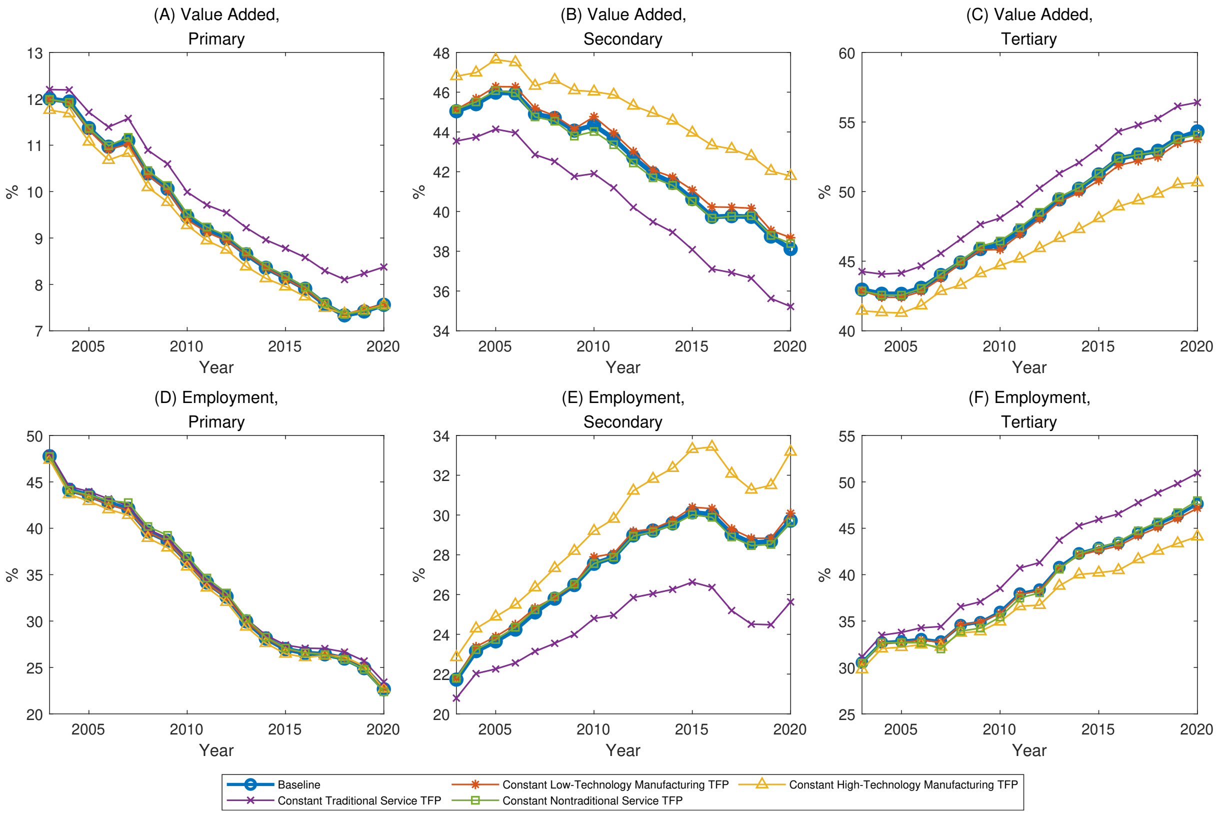

Figure 6: Effects of Subsector TFP Improvements on Inter-sectoral Structural Transformation

We further illuminate how sectoral TFP growth alters the pace and direction of inter-sectoral structural transformation in Tables 5 and 6. In the baseline model, the secondary sector's value added share fell by 6.92 percentage points from 2003 to 2020.[15] In the counterfactual where high-technology manufacturing TFP is held constant, this decline narrows to 5.02 percentage points.[16] Comparing this counterfactual with the baseline reveals that TFP improvements in high-technology manufacturing contributed 1.90 percentage points to the decline of the secondary sector's value added share over the period,

[15]Low- and high-technology manufacturing value added shares fell by 3.11 and 3.81 percentage points, respectively, as shown in row 2 of Table 5.

[16]Calculated as $5.76 - 0.74 = 5.02$ based on row 4 of Table 5.

accounting for approximately 27.46% of the total decline observed in the baseline model.[17] Similarly, for employment shares, TFP improvements in high-technology manufacturing contributed to shifting labor out of the secondary sector, accounting for a 2.33 percentage point difference in the secondary sector's employment share, which is equivalent to approximately 29.13% of the total increase observed in the baseline model.[18] These results quantify how TFP growth in high-technology manufacturing accelerated the economy's transition away from the secondary sector. Likewise, TFP growth in traditional services, by lowering relative prices due to complementarity, led to a 0.78 percentage point smaller increase in the tertiary sector's value added share and a 2.70 percentage point smaller increase in its employment share compared to the scenario without TFP growth, which corresponds to approximately 6.87% and 15.78% of the baseline total tertiary sector expansion. [19]

Our theoretical model attributes the above patterns to the relative price effects. When TFP growth in a subsector ceases, its relative price increases, which in turn raises the relative price of its corresponding broad sector. Higher relative prices for a broad sector's output expand both its value added and labor shares due to the complementarity between secondary and tertiary outputs, particularly within investment goods production.[20]

While relative price changes explain the dominant shifts observed in the secondary and tertiary sectors, understanding the different consequences for the primary sector requires examining how these price shocks propagate through distinct macroeconomic channels.

Specifically, when traditional service TFP is fixed, the primary adjustment channel involves consumption. Rising service prices increase the overall consumption price level, given the large expenditure share of services. The Euler equation (8) then implies that households reduce saving and increase consumption (see Figure A21). Because agriculture has a larger share in consumption expenditures compared to investment goods production (see Figure A19), the aggregate demand shift toward consumption increases the primary sector's overall value added share.

Conversely, when high-technology manufacturing TFP is fixed, the main channel involves investment goods production. Strong complementarity between sectoral inputs in investment production implies that a higher relative price for industrial inputs requires an increased value added share for the secondary sector in investment. Consequently, the value added shares of primary and tertiary sectors within investment decrease (Figure

[17] Calculated as $1.90/6.92 \approx 27.46\%$.

[18] Calculated as $4.91 + 5.42 - 1.41 - 6.59 = 2.33$ based on rows 2 and 4 of Table 6. The relative magnitude is calculated as $2.33/(1.41 + 6.59) \approx 29.13\%$.

[19] The levels are calculated as $9.45 + 2.69 - 3.04 - 8.32 = 0.78$ and $16.31 + 3.50 - 10.14 - 6.97 = 2.70$ based on rows 2 and 5 of Tables 5 and 6. The relative magnitudes are calculated as $0.78/11.36 \approx 6.87\%$ and $2.70/17.11 \approx 15.78\%$.

[20] Our parameter calibration indicates that the complementarity between secondary and tertiary outputs mainly stems from the investment production function.

A19). The negative impact through investment composition drives the decline in the primary sector's overall value added share.

Intra-Sectoral Structural Transformation Patterns. We now turn to the intra-sectoral dynamics. The evolution of high-technology manufacturing's shares within the secondary sector is documented in column 6 of Tables 5 and 6 and illustrated in panels A and C of Figure 7. Parallel results for nontraditional services within the tertiary sector are presented in column 7 of the same tables and in panels B and D of Figure 7.

Our results yield two main findings. First, intra-sectoral structural transformation is primarily driven by TFP improvements occurring within that same broad sector. This is evident, for example, in the negligible variation of high-technology manufacturing's shares when TFP in the tertiary subsectors is held constant, as shown in panels A and C of Figure 7.

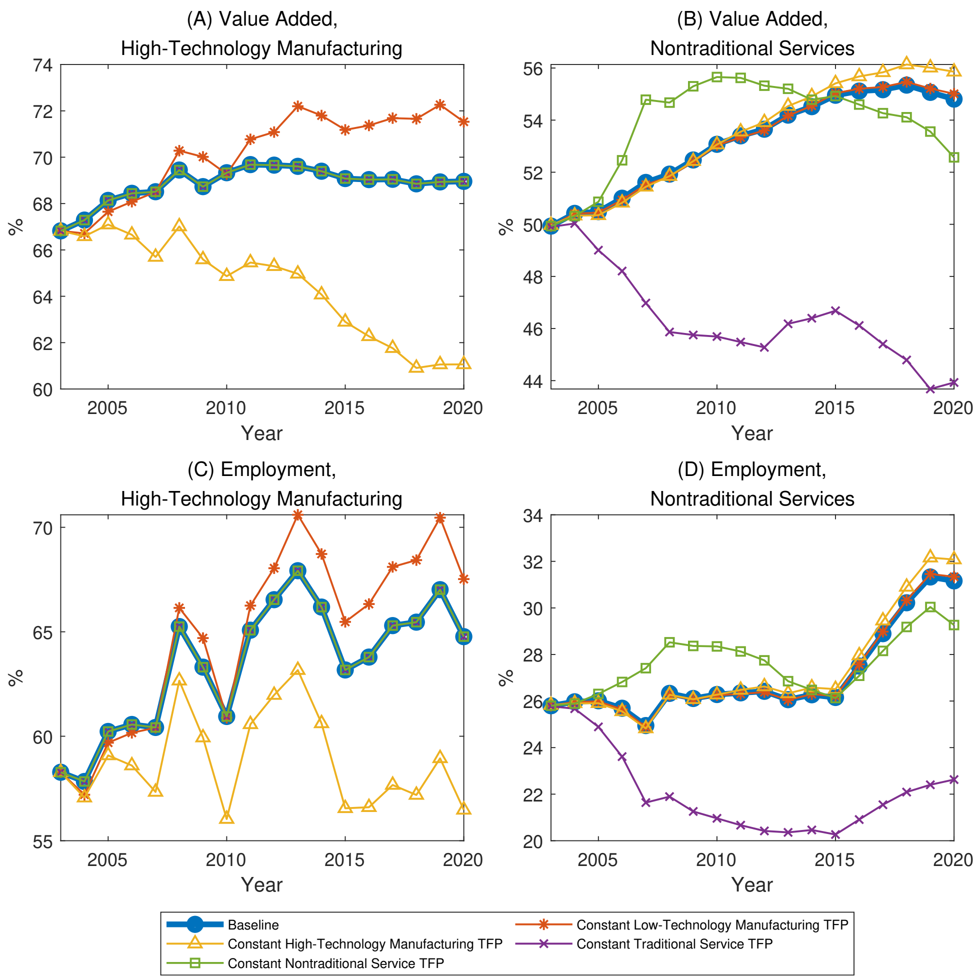

Figure 7: Effects of Subsector TFP Improvements on Intra-sectoral Structural Transformation

Second, and more importantly, the driving forces of intra-sectoral structural transformation are asymmetric across broad sectors. Transformation and upgrading in the secondary sector is driven by TFP growth in the modern subsector itself, as indicated by the △ line in panels A and C of Figure 7. In the baseline model, the value added and employment shares of high-technology manufacturing rise by 2.14 and 6.49 percentage points, respectively (Tables 5 and 6). In the counterfactual scenario without its TFP growth, however, these shares actually fall by 5.76 and 1.80 percentage points. Comparing the baseline and counterfactual scenarios reveals that TFP improvements in high-technology manufacturing contributed 7.90 percentage points to the increase in its value added share and 8.29 percentage points to the increase in its employment share within the secondary sector between 2003 and 2020, equivalent to 369.16% and 127.73% of the net growth in the baseline, respectively.[21]

Conversely, the structural transformation within the tertiary sector is mainly driven by TFP growth in the traditional subsector, as shown by the $\times$ line in panels B and D of Figure 7. Specifically, TFP improvements in traditional services contributed 10.85 percentage points to the increase in the value added share and 8.51 percentage points to the increase in the employment share of nontraditional services within the tertiary sector, equivalent to 222.34% and 158.77% of the net expansion observed in the baseline, respectively.[22]

The key to understanding the above patterns lies in the differences in substitution elasticities between the broad sectors. Our calibration shows that in industrial goods production, the elasticity of substitution σ exceeds 1, suggesting that the low- and high-technology manufacturing outputs are substitutes. When low-technology manufacturing TFP stagnates and its relative price rises, industrial goods producers shift demand toward high-technology manufacturing, increasing its share.

Conversely, in the tertiary sector, the calibrated elasticity ρ is less than 1, implying that traditional and nontraditional services are complements. The complementarity between traditional and nontraditional services resembles Baumol's effect operating within the tertiary sector. The faster TFP growth in traditional services leads to a decline in their relative price. Due to the complementarity, the lower relative price for traditional services results in a declining nominal output share for traditional services, despite their higher productivity growth. Consequently, the TFP gains in the traditional sector effectively boost the nominal output shares of the less productive nontraditional service sector, consistent with our counterfactual findings.

The Panel B in Figure 7 also reveals a non-monotonic pattern when nontraditional service TFP is held constant. The value added share initially rises relative to the baseline before declining. The pattern results from the nontraditional service TFP growth rate changing

[21] Calculated as $7.90/2.14 \approx 369.16\%$ and $8.29/6.49 \approx 127.73\%$.

[22] The contribution levels are calculated as $4.88 - (-5.97) = 10.85$ for value added share and $5.36 - (-3.15) = 8.51$ for employment share based on Tables 5 and 6. The relative magnitudes are calculated as$10.85/4.88 \approx 222.34\%$ for value added share and $8.51/5.36 \approx 158.77\%$ for employment share.

sign during the sample period. Before 2012, nontraditional service TFP grew positively (see Table 3, Panel B). Fixing TFP at the 2003 level thus constituted a negative shock relative to the baseline path. Given the complementarity between traditional and nontraditional services, a negative nontraditional service TFP shock raises its relative price and hence its value added share. After 2012, baseline TFP growth turned negative (see Table 3, Panel C). Fixing nontraditional service TFP now constituted a positive shock relative to the declining baseline scenario. The complementarity implies that a positive nontraditional service TFP shock reduces its relative price and its value added share. The model thus captures the dynamics driven by the observed TFP trend reversal.

Economic Growth Patterns. We now assess the implications of subsector TFP for economic growth and report the annual growth of both aggregate labor productivity and sectoral output per worker from counterfactuals in which TFP is fixed in one subsector at a time. The results are in rows 3 to 6 of Table 7, with the growth trajectories shown in Figure 8.

The central finding is that TFP stagnation in high-technology manufacturing and traditional services has the most pronounced negative effects on aggregate labor productivity. Aggregate labor productivity in 2020 remains below baseline levels in all counterfactuals, with the notable exception of nontraditional services, as shown in the first column of Table 7 and panel A of Figure 8.[23] Our calculations demonstrate that TFP improvements in high-technology manufacturing and traditional services contribute 1.97 and 1.59 percentage points, respectively, to the annualized aggregate labor productivity growth rate, accounting for approximately 22.11% and 17.85% of the baseline total productivity growth.[24] On the one hand, it highlights that high-technology manufacturing has been a crucial driver of China's economic growth, reinforcing the rationale for new industrialization policies. On the other hand, while traditional services have delivered notable TFP gains, future reforms should prioritize TFP growth in nontraditional services to foster sectoral balance and ensure sustainable high-quality development.

A comparison of sectoral output per worker reveals two key transmission patterns, as shown in columns 2 to 6 of Table 7 and panels B to F of Figure 8. First, TFP improvements within each subsector are the primary contributors to its own output per worker growth. Comparing the baseline with counterfactuals underscores the substantial contribution of the TFP improvements within each subsector to sectoral performance. Second, TFP improvements in one subsector generate positive growth spillovers to others. For instance, TFP growth in high-technology manufacturing not only boosted its own output but also

[23]Given the negative TFP growth rate of nontraditional services in the data, the counterfactual scenario corresponding to row 7 of Table 7 and the □ line in Figure 8 assumes no decline in nontraditional service TFP, leading to a higher aggregate labor productivity growth than the baseline.

[24]Calculated as $8.91 - 6.94 = 1.97$ for high-technology manufacturing and $8.91 - 7.32 = 1.59$ for traditional services.

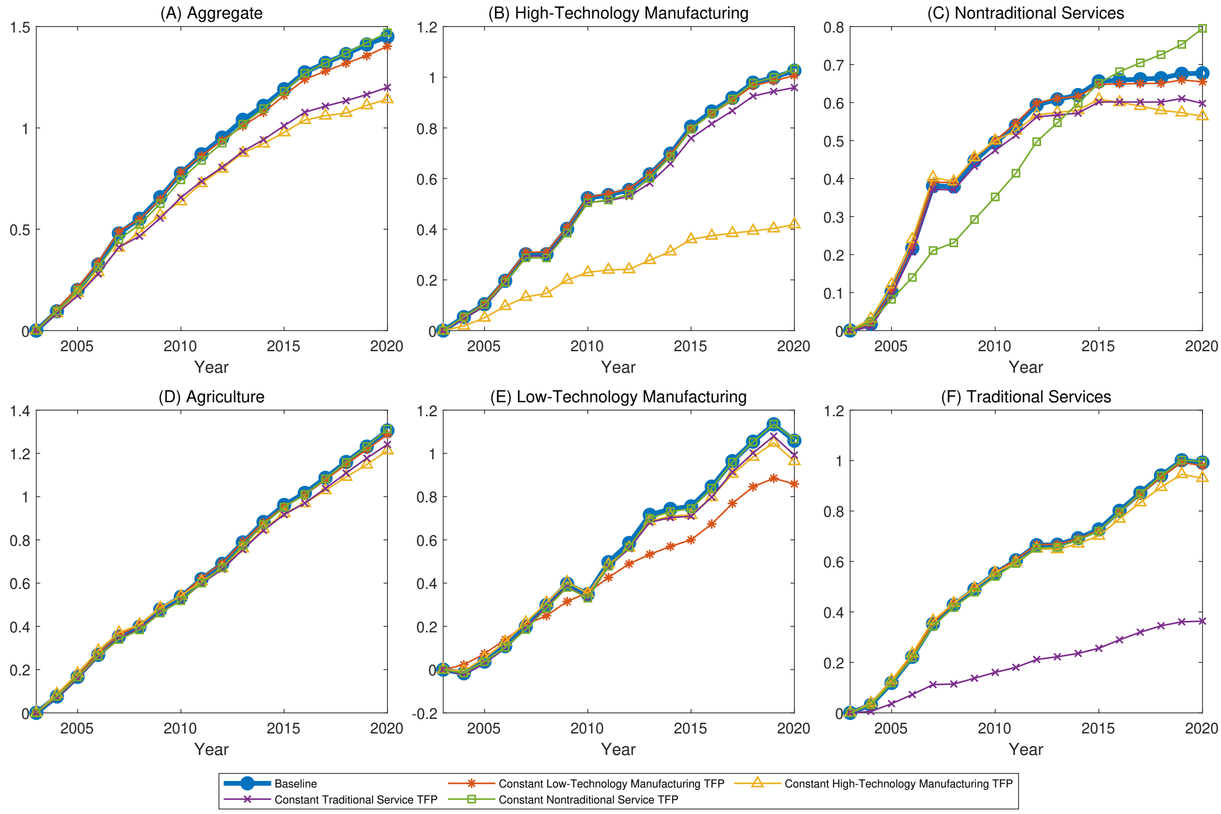

Figure 8: Effects of Subsector TFP Improvements on Economic Growth

contributed positively to output per worker growth across all other subsectors, evidenced by the higher baseline paths compared to the corresponding counterfactual scenario. The above findings imply that fostering coordinated inter-sectoral development is essential for sustained economic growth.

Figure 8 Panel C also shows a non-monotonic growth difference for nontraditional service output per worker relative to the baseline when nontraditional service TFP is fixed. The pattern mirrors the value added share dynamics explained previously and originates from the baseline TFP growth reversal around 2012. Before 2012, fixed TFP represented a negative shock versus the rising baseline TFP, depressing output per worker growth. After 2012, fixed TFP represented a positive shock versus the falling baseline TFP. Therefore, the positive relative TFP effect leads to faster output per worker growth compared to the baseline.

Before moving to the next section, it is important to interpret the above quantitative roles of TFP improvement as conservative estimates due to the independence assumption between TFP and sectoral wedges in our framework. While we treat them as orthogonal, TFP growth and the reduction of distortions are likely positively correlated in reality, often driven by common institutional improvements such as financial liberalization or deregulation. If the stagnation of TFP in our counterfactual scenarios were endogenously accompanied by a halt in the reduction of sectoral wedge dispersion, rather than retaining the historical wedge paths, the counterfactual economy would suffer from severer misallocation and slower growth. For example, for high-technology manufacturing, if the absence of TFP growth also implied persistent financing frictions, its share would contract more sharply in the counterfactual scenario than what we currently report. Consequently, the gap between the baseline and the counterfactuals would widen. By abstracting from the endogenous link between TFP and wedges, our results effectively provide a lower bound on the total contribution of subsector TFP to both China's structural transformation and economic growth.

5.3 The Role of Broad Sectoral TFP Improvements

In this section, we aggregate our analysis to examine how TFP dynamics in the three broad sectors shape structural transformation and economic growth. To do so, we construct counterfactual scenarios where TFP for all subsectors within a single targeted broad sector is fixed at its initial baseline level. This design allows us to capture the systemic impacts of sectoral TFP improvements.

Inter-Sectoral Structural Transformation Patterns. We first investigate the scenario with constant primary TFP. In this case, both the value added and employment shares of agriculture stay above their baseline paths, as indicated by the + line in panels A and D of Figure 9). Quantitatively, TFP improvements in the primary sector contributed 0.58 percentage points to the decline in its value added share and 1.45 percentage points to the decline in its employment share between 2003 and 2020, accounting for approximately 13.06% and 5.78% of the total decline observed in the baseline model, respectively.[25] The finding that agricultural TFP growth accelerates China's transformation away from agriculture is consistent with Brandt et al. (2008) and Cao and Birchenall (2013).

For the non-agricultural sectors, fixing TFP within a broad sector elevates its shares relative to the baseline model due to relative price effects, as shown by the $\diamondsuit$ and $\bigstar$ lines in Figure 9. The aggregate impact of a broad sector's TFP improvement naturally reflects the sum of its parts. For instance, comparing the baseline with the scenario where secondary sector TFP is fixed reveals the contribution of TFP improvements within the secondary sector. Specifically, overall TFP growth in the secondary sector contributed 2.33 percentage points to the decline in its value added share and 2.62 percentage points to the dampening of the expansion in its employment share, equivalent in magnitude to approximately 33.67% and 32.75% of the baseline total changes, respectively.[26]

[25]Calculated as $-3.86 - (-4.44) = 0.58$ for value added shares and $-23.65 - (-25.10) = 1.45$ for employment shares based on rows 2 and 7 of Tables 5 and 6. The contributions are calculated as $0.58/4.44 \approx 13.06\%$ and $1.45/25.10 \approx 5.78\%$.

[26]The contribution are calculated as $-0.30 - 4.29 - (-3.11) - (-3.81) = 2.33$ for value added shares and $4.03 + 6.59 - 1.41 - 6.59 = 2.62$ for employment shares based on rows 2 and 8 of Tables 5 and 6,

Applying the relative price mechanism to the tertiary sector suggests fixing its TFP increases its relative price and value added share, implying accelerated transformation away from the secondary sector compared to baseline. However, the contribution of tertiary TFP improvements needs careful consideration due to internal heterogeneity. Quantitatively, overall TFP improvements in the tertiary sector moderated the structural transformation slightly, contributing to a 0.80 percentage point smaller increase in the tertiary sector's value added share and a 3.15 percentage point smaller increase in its employment share, accounting for approximately 7.04% and 18.41% of the total expansion observed in the baseline model, respectively.[27] The reason involves opposing TFP trends within the tertiary sector baseline, in which traditional services experienced high TFP growth, while nontraditional services experienced TFP decline. Fixing overall tertiary TFP combines halting high growth in traditional services with halting decline in nontraditional services. The positive component partially offsets the negative component. Therefore, the net price increase and resulting acceleration are weaker compared to fixing only traditional service TFP.

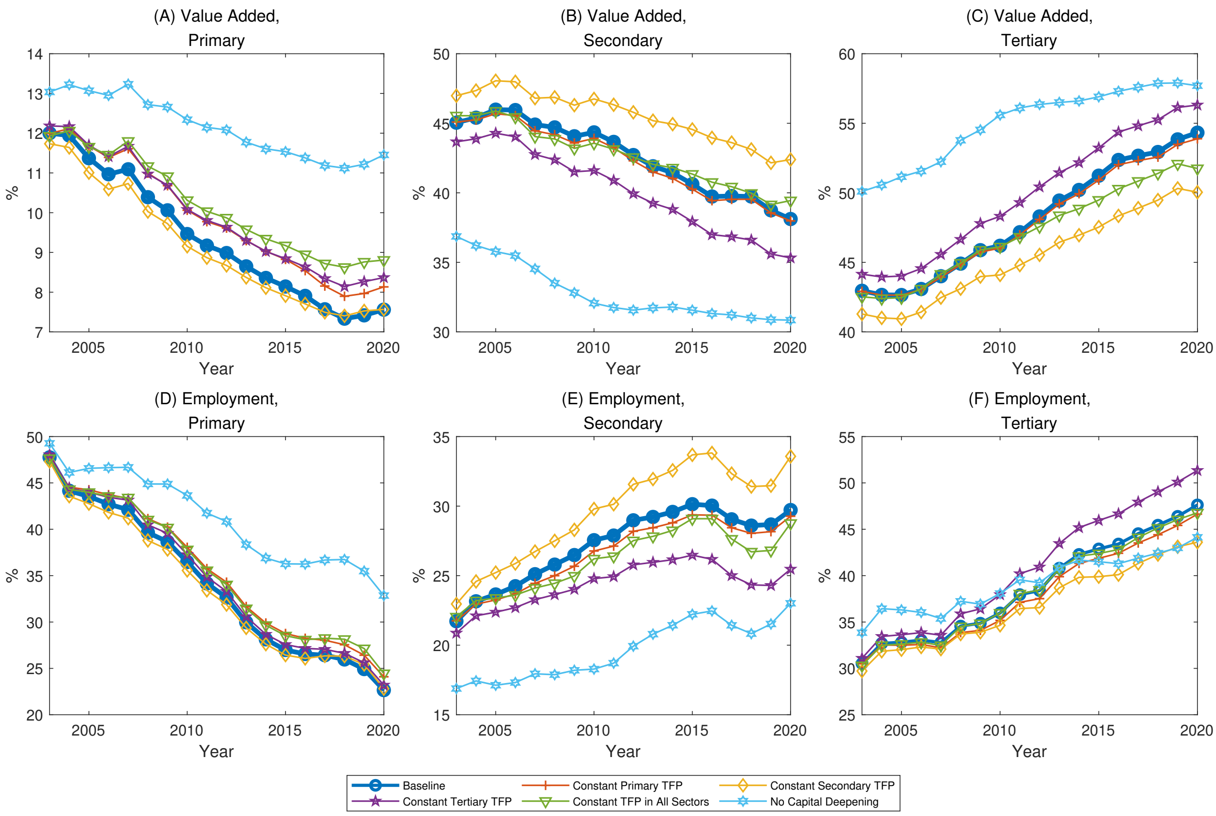

Figure 9: Effects of Broad Sector TFP Improvements on Inter-sectoral Structural Transformation

and they are equivalent in magnitude to $2.33/6.92 \approx 33.67\%$ of the total value added share change and $2.62/8.00 \approx 32.75\%$ of the total employment share change.

[27]The contributions are calculated as $10.68 + 1.48 - 3.04 - 8.32 = 0.80$ for value added shares and $17.43 + 2.83 - 10.14 - 6.97 = 3.15$ for employment shares based on rows 2 and 9 of Tables 5 and 6. The proportions are calculated as $0.80/(3.04 + 8.32) \approx 7.0\%$ and $3.15/(10.14 + 6.97) \approx 18.4\%$.

When holding TFP constant across all three broad sectors, the economy continues to undergo structural transformation. Visually, the counterfactual path trends in the same direction as the baseline, suggesting that TFP growth acts as an accelerator that reinforces other drivers rather than being the sole cause of transformation.

The apparent similarity also masks the complex interactions of sectoral TFP forces. As shown in the previous counterfactuals, TFP growth in individual sectors exerts strong distinct forces on resource allocation. When combined, the sectoral push and pull forces partially offset each other.

Nevertheless, the gap between the baseline and the counterfactual represents a substantial economic reallocation. Overall, aggregate TFP improvements contributed 1.32 percentage points to the primary sector's value added share decline, 0.82 percentage points to the secondary sector's decline, and 2.14 percentage points to the tertiary sector's expansion, equivalent to approximately 29.73%, 11.85%, and 18.84% of the baseline total structural changes for the primary, secondary, and tertiary sectors, respectively.[28] Similar significant contributions are found for employment shares, accounting for 1.90, 1.28, and 0.64 percentage points of the observed changes in the primary, secondary, and tertiary sectors, respectively, which explain approximately 7.57%, 16.00%, and 3.74% of the total labor reallocation in each sector.[29] While these percentage point differences might seem visually modest, they are economically significant. For instance, given China's 2020 GDP and employment, the above percentage point gaps translate to a reallocation of approximately 2.8 trillion RMB in value added and nearly 15 million workers. Therefore, TFP provides economic growth and structural transformation beyond what other forces could achieve.

Intra-Sectoral Structural Transformation Patterns. We compare the value added and employment shares of high-technology manufacturing (panels A and C) and nontraditional services (panels B and D) in scenarios where TFP is fixed at the broad sector level in Figure 10.

Our analysis reveals that intra-sectoral structural transformation depends mainly on the interactions of subsector TFP dynamics within its own corresponding broad sector. Such structural independence stems from the nested CES framework, where factor allocation between subsectors is primarily governed by relative prices driven by divergent subsector

[28]The contributions are calculated as $-3.12-(-4.44)=1.32$ for the primary sector, $-0.89-5.21-(-3.11)-(-3.81)=0.82$ for the secondary sector, and $3.04+8.32-8.22-1.00=2.14$ for the tertiary sector based on rows 2 and 10 of Table 5. The proportions are calculated as $1.32/4.44=29.73\%$ for the primary sector, $0.82/(3.11+3.81)=11.85\%$ for the secondary sector, and $2.14/(3.04+8.32)=18.84\%$ for the tertiary sector.

[29]Calculated as $-23.20-(-25.10)=1.90$ for the primary sector, $1.41+6.59-2.46-4.26=1.28$ for the secondary sector, and $10.14+6.97-14.02-2.45=0.64$ for the tertiary sector based on rows 2 and 10 of Tables 6. The proportions are calculated as $1.90/25.10\approx 7.57\%$ for the primary sector, $1.28/(1.41+6.59)=16.00\%$ for the secondary sector, and $0.64/(10.14+6.97)\approx 3.74\%$ for the tertiary sector.

TFP growth rates. However, external shocks from other broad sectors affect the sector primarily through aggregate income or investment channels, scaling the demand for subsectors proportionally. Consequently, external shocks have limited power to reshape the sectoral internal composition compared to the direct impact of heterogeneous TFP growth within the sector itself.

For example, TFP improvements within the secondary sector as a whole significantly contributed to the intra-sectoral shift towards high-technology manufacturing. Compared to the scenario where overall secondary TFP is fixed, TFP improvements contributed 5.02 percentage points to the increase in high-technology manufacturing's value added share and 5.29 percentage points to the increase in its employment share within the secondary sector, equivalent to approximately 234.58% and 81.51% of the total increases observed in the baseline model, respectively.[30] Since high-technology manufacturing experienced higher TFP growth compared to traditional manufacturing, the overall secondary sector TFP growth introduces the relative price advantage of high-technology manufacturing output, thereby driving resources toward the high-technology manufacturing via the substitution effect.

Economic Growth Patterns. The growth implications of these broad-sector TFP experiments are reported in rows 7 to 10 of Table 7 for annualized rates, with the dynamic trends visualized in Figure 11.

The results show that TFP improvements within each broad sector systematically contributed to aggregate labor productivity and sectoral output per worker growth across all subsectors, as seen in Figure 11. Quantifying the overall impact, aggregate TFP improvements across all three broad sectors contributed 3.73 percentage points to annualized aggregate labor productivity growth between 2003 and 2020, accounting for approximately 41.86% of the baseline total growth. Correspondingly, aggregate TFP growth contributed between 0.60 and 4.27 percentage points to annualized output per worker growth in the various subsectors. [31] These gaps quantify the contribution of TFP improvements throughout the economy to overall growth.

Beyond these general patterns, Figure 11 reveals further issues regarding the comparative impacts of secondary versus tertiary TFP stagnation and the specific effects on subsector growth. Specifically, Panel A shows that TFP improvements in the secondary sector made a larger contribution to aggregate labor productivity growth after 2012 than TFP improvements in the tertiary sector. The explanation lies in the differing nature of TFP

[30] The contributions are calculated as $2.14-(-2.88) = 5.02$ for the value added share and $6.49-1.20 = 5.29$ for the employment share, based on rows 2 and 8 in Tables 5 and 6. The proportions are calculated as $5.02/2.14 \approx 234.58\%$ and $5.29/6.49 \approx 81.51\%$.

[31] The aggregate productivity differential derives from $8.91 - 5.18 = 3.73$, and the proportion is calculated as $3.73/8.91 = 41.86\%$. Subsector output per worker growth declines follow analogous calculations using data from rows 2 and 10 of Table 7.

Figure 10: Effects of Broad Sector TFP Improvements on Intra-sectoral Structural Transformation

trends within sectors. Secondary sector TFP growth was consistently positive across subsectors, meaning its overall contribution reflects purely positive underlying growth. Tertiary sector TFP growth combined high positive growth in traditional services with negative growth in nontraditional services after 2012. The negative trend in nontraditional services partially offset the positive contribution from traditional services, resulting in a smaller net contribution from overall tertiary TFP improvements post-2012 compared to secondary TFP improvements.

Furthermore, Panel C indicates that overall TFP improvements in the tertiary sector made little contribution to nontraditional service output per worker growth by 2020. The result reflects two opposing transmission channels from tertiary TFP growth to nontraditional services. TFP growth in traditional services generated negative spillovers that dampened nontraditional service growth (see also Figure 8, Panel C). Conversely, the negative TFP trend in nontraditional services itself meant that the absence of TFP decline effectively provided a positive boost post-2012. By 2020, the negative spillover contribution from traditional service TFP growth and the positive contribution from avoiding nontraditional

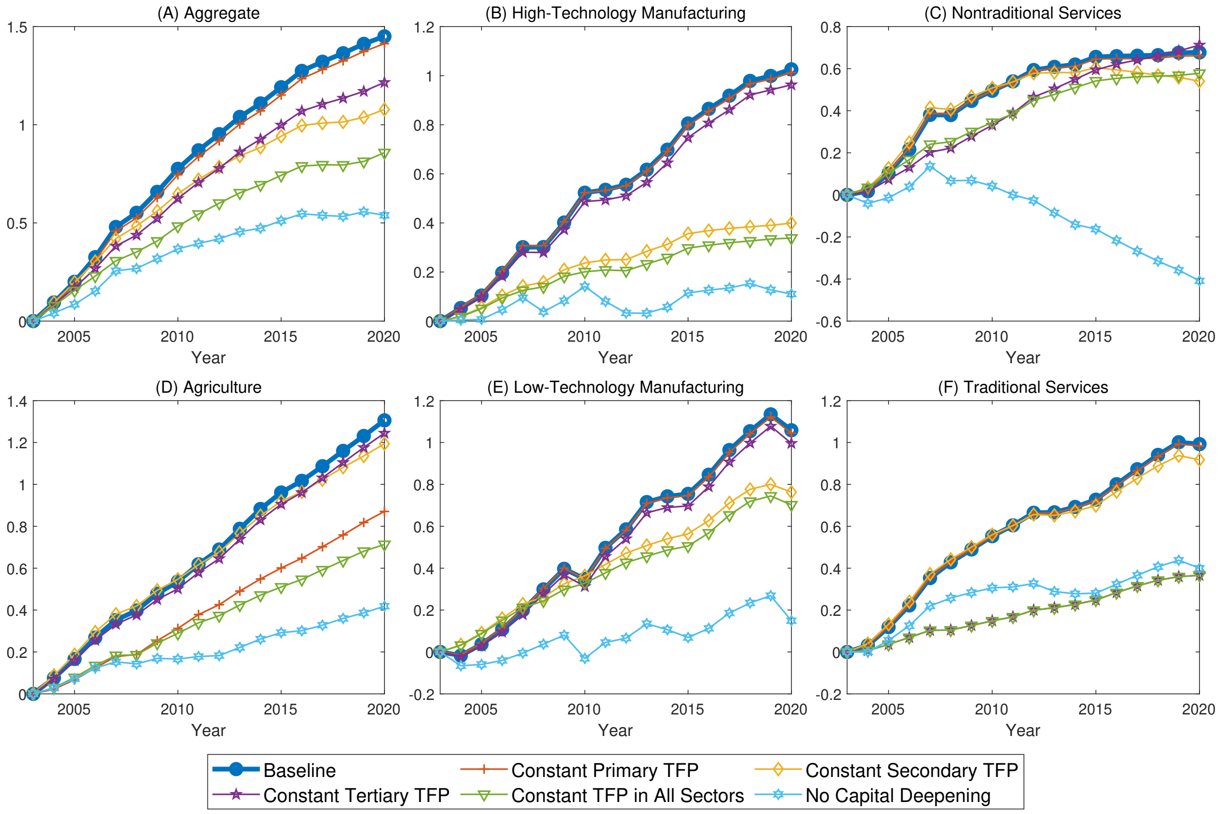

Figure 11: Effects of Broad Sector TFP Improvements on Economic Growth

service TFP decline largely offset each other. The above dynamics further underscore the importance of accounting for intra-sectoral heterogeneity when analyzing the growth implications of broad sector TFP shocks.

5.4 The Role of Capital Deepening

In this section, we conduct a counterfactual experiment to isolate the role of capital deepening. Unlike the sectoral TFP analysis, we focus here on aggregate capital deepening rather than isolating it at the subsector level. The underlying reason is that the sectoral capital–labor ratio is an endogenous outcome determined by factor mobility and equilibrium conditions. Fixing the capital–labor ratio for a specific subsector would require introducing artificial sector-specific wedges to block capital flows, which would confound the effects of capital accumulation with those of increased distortions.

To operationalize the counterfactual scenario that holds the aggregate capital–output ratio constant at its initial level, the asset return tax rates are recalibrated to ensure that investment exactly offsets the capital depreciation for the initial 18 periods, thereby maintaining a constant aggregate capital stock per worker. The subsequent fading of the asset return tax rates follows the same manner as in the baseline model.

Inter-Sectoral Structural Transformation Patterns. Capital deepening significantly shaped the sectoral composition, as depicted by the ★ line in Figure 9. Relative to a scenario without capital deepening, capital accumulation suppressed the shares of the primary and tertiary sectors while boosting the secondary sector's share. The boost to the secondary sector reflects its central role in producing investment goods needed for capital formation.

Furthermore, capital deepening markedly accelerated the pace of inter-sectoral structural transformation. Specifically, comparing the baseline with the counterfactual scenario reveals that capital deepening contributed 2.86 percentage points to the decline in the primary sector's value added share and 0.90 percentage points to the decline in the secondary sector's share, while contributing 3.76 percentage points to the expansion of the tertiary sector's share, accounting for approximately 64.41%, 13.01%, and 33.10% of the total changes observed in the baseline model, respectively.[32] Employment shares follow a similar pattern. Capital deepening accounted for 8.68 percentage points of the primary sector's decline, 1.87 percentage points of the secondary sector's increase, and 6.82 percentage points of the tertiary sector's increase, explaining approximately 34.58%, 23.38%, and 39.86% of the total employment shifts in the primary, secondary, and tertiary sectors, respectively.[33] These results highlight how critical capital deepening has been in shaping China's inter-sectoral structural transformation.

Intra-Sectoral Structural Transformation Patterns. Capital deepening influenced intra-sectoral transformation differently across sectors, as seen in Figure 10. Within the tertiary sector (panels B and D), capital deepening contributed to a lower relative share for nontraditional services compared to the scenario without capital deepening. Nontraditional services, having a higher capital output elasticity, benefit more from capital accumulation, reducing their relative price. Given the complementarity within the tertiary sector, a lower relative price for nontraditional services reduces their value added and employment shares relative to traditional services.

In sharp contrast, capital deepening had little impact on intra-sectoral structural transformation within the secondary sector (panels A and C). The nearly identical capital output elasticities of high-technology and low-technology manufacturing led to almost symmetric responses to capital accumulation, precluding significant shifts in relative shares. The divergent outcomes between the secondary and tertiary sectors highlight how heterogeneous capital intensity across subsectors governs the contribution of capital deepening to

[32]The contributions are calculated as $-1.58 - (-4.44) = 2.86$ for the primary sector, $-2.63 - 3.39 - (-3.11) - (-3.81) = 0.90$ for the secondary sector, and $3.04 + 8.32 - (-4.44) - 12.04 = 3.76$ for the tertiary sector based on rows 2 and 11 of Table 5. The proportions are calculated as $2.86/4.44 \approx 64.41\%$, $0.90/(3.11 + 3.81) \approx 13.01\%$, and $3.76/(3.04 + 8.32) \approx 33.10\%$, respectively.

[33]Calculated as $-16.42 - (-25.10) = 8.68$ for the primary sector, $1.41 + 6.59 - 1.09 - 5.04 = 1.87$ for the secondary sector, and $10.14 + 6.97 - 1.34 - 8.95 = 6.82$ for the tertiary sector based on rows 2 and 11 of Table 6. The proportions are calculated as $8.68/25.10 = 34.58\%$, $1.87/(1.41 + 6.59) = 23.38\%$, and $6.82/(10.14 + 6.97) = 39.86\%$, respectively.

intra-sectoral structural change.

Economic Growth Patterns. The contribution of capital deepening to economic growth was substantial. Comparing the baseline with the counterfactual scenario reveals that capital deepening contributed 5.69 percentage points to the annualized growth rate of aggregate labor productivity between 2003 and 2020, accounting for approximately 63.86% of the baseline growth.[34] The sectoral-level analysis reinforces our result, showing that capital deepening contributed between 3.63 and 6.44 percentage points to annualized output per worker growth across the different subsectors.

While capital deepening has played a more substantial role than TFP improvements in propelling China's past economic growth, its future efficacy is constrained by the consistent decline in investment rates since 2010.[35] Consequently, a reorientation of policy focus toward sectoral TFP improvement as the main engine for sustaining structural transformation and economic growth becomes necessary.

6 Conclusion

This paper constructs a five-sector dataset for the Chinese economy from 2003 to 2020 and uses a calibrated general equilibrium framework to quantify the distinct contributions of TFP improvement and capital deepening to both inter- and intra-sectoral structural transformation. Our work yields three insights with policy implications for China's future growth.

First, while both the secondary and tertiary sectors have observed intra-sectoral structural transformations, the driving forces behind them are different. High-technology manufacturing relies on TFP improvements, whereas nontraditional services depend more on capital deepening. This divergence underscores the necessity of analyzing from inter- and intra-sectoral perspectives for evaluations of structural transformation.

Second, the effects of TFP improvement on structural transformation and economic growth vary across the subsectors. We find that the productivity gains in high-technology manufacturing and traditional services have been the most potent. TFP improvement in high-technology manufacturing increased its shares of value added and employment within the secondary sector by 7.90 and 8.29 percentage points, respectively, while raising annualized aggregate labor productivity growth by 1.97 percentage points. Likewise, TFP improvement in traditional services increases the value added and employment shares of nontraditional services within the tertiary sector by 10.85 and 8.51 percentage points, re-

[34] The contribution is calculated as $8.91 - 3.22 = 5.69$ based on rows 2 and 11 of Table 7. The proportion is calculated as $5.69/8.91 = 63.86\%$.

[35] Appendix Figure A14 illustrates the persistent downward trend of China's investment rate from 2003 to 2020.

spectively, and boosts annualized aggregate labor productivity growth by 1.59 percentage points. In contrast, TFP improvements elsewhere yielded much more limited returns.

Third, capital deepening plays a different role compared to TFP improvement. While capital deepening was historically the stronger driver, accounting for a 5.69 percentage point contribution to annualized aggregate labor productivity growth and preventing declines of 3.63 to 6.44 percentage points in sectoral output per worker, its role is diminishing. China's declining investment rate since 2010 signals an unavoidable transition where future growth must increasingly rely on TFP improvements.

Taken together, our findings reveal that TFP growth, especially in high-technology manufacturing and traditional services, is a robust driver of both structural transformation and economic growth. Yet, addressing remaining challenges, particularly the stagnant TFP in nontraditional services, is now critical. This calls for targeted policies designed to accelerate the transformation and upgrading of traditional industries, specifically by boosting TFP in high-technology manufacturing and unlocking the latent TFP potential in nontraditional services. Although faster nontraditional service TFP growth could slow the expansion of its nominal value added share, it boosts efficiency and welfare, representing a healthier, efficiency-driven structural change even if nominal share growth appears slower.

Future research could build on our analysis in two main directions. First, incorporating richer human capital dynamics, even with limited observed variation, would refine the model's precision. Second, endogenizing technological progress would represent a significant step forward from the current exogenous TFP assumptions. For example, modeling the capital misallocation mechanisms as endogenous drivers of TFP would offer a deeper understanding of the TFP stagnation in nontraditional services and the fundamental drivers of China's growth.

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APPENDIX

Appendix A Data Construction Details

This appendix section outlines the construction of nominal and real value added, employment, physical capital stock, and output elasticities. We use distinct subscripts to denote different data dimensions. The subscript $\mathfrak{i}$ denotes the 37 specific industries described in the body text, the subscript $\mathfrak{i}'$ denotes one-digit industries, and the subscript $\mathfrak{i}''$ denotes two-digit industries. The three broad sectors are indexed by j, $j \in \mathcal{J} = \{F, G, S\}$. The five subsectors are indexed by d, $d \in \mathcal{D} = \{F, TM, AM, TS, MS\}$. Additionally, the subscripts s are used to denote the nine divisions.[A1]

Appendix A.1 Nominal and Real Value Added

We derive the nominal value added for specific industries ($Y_{\mathfrak{i},t}$) and subsectors ($Y_{d,t}$) from 2002 to 2020 using NBS national accounts data and input–output (I–O) tables. Real value added ($Q_{\mathfrak{i},t}$, $Q_{d,t}$) is calculated using sectoral price indices derived from industrial producer prices and value added deflators.

Appendix A.1.1 Nominal Value Added

The NBS publishes nominal value added for nine divisions, $Y_{s,t}$. Seven divisions correspond directly to specific industries ($Y_{\mathfrak{i},t}$). For the remaining two ($s \in \{ind, oth\}$), we need to decompose $Y_{s,t}$ to obtain $Y_{\mathfrak{i},t}$. The decomposition relies on I–O tables from 2002 to 2020 and NBS (2022).

Decomposition of $Y_{oth,t}$. To decompose $Y_{oth,t}$, we use the ratio of value added for specific industries to the total value added for the "others" division ($\frac{\widehat{Y}_{\mathfrak{i},t}}{\sum_{\mathfrak{i}\in oth}\widehat{Y}_{\mathfrak{i},t}}$) for 2002 and 2004 to 2009.[A2] With these ratios, we calculate $Y_{\mathfrak{i},t}$ in the "others" division for 2002 and 2004 to 2009 as follows:

$$Y_{\mathfrak{i},t} = Y_{oth,t} \cdot \frac{\widehat{Y}_{\mathfrak{i},t}}{\sum_{\mathfrak{i}\in oth}\widehat{Y}_{\mathfrak{i},t}}, \quad t \in \{2002\} \cup [2004, 2009]. \tag{A1}$$

For 2003, preliminary estimates $\widetilde{Y}_{\mathfrak{i},2003}$ are computed via logarithmic interpolation between

[A1] The nine divisions includes agriculture (agr), industry (ind), construction (con), wholesale and retail (whr), transportation (tra), hotel and catering (hoc), financial intermediation (fin), real estate (res), and others (oth).

[A2] The ratio in 2002 is derived from the I–O table, while the ratios in other specified years are derived from NBS (2022).

2002 and 2004:

$$\log\left(\widetilde{Y}_{\mathrm{i},2003}\right) = \log Y_{\mathrm{i},2002} + (\log Y_{\mathrm{i},2004} - \log Y_{\mathrm{i},2002}) \cdot \left(\frac{\log Y_{oth,2003} - \log Y_{oth,2002}}{\log Y_{oth,2004} - \log Y_{oth,2002}}\right). \quad \text{(A2)}$$

To ensure consistency at the division level in 2003, we then normalize the interpolated values:

$$Y_{\mathrm{i},2003} = Y_{oth,2003} \cdot \frac{\widetilde{Y}_{\mathrm{i},2003}}{\sum_{\mathrm{i}\in oth} \widetilde{Y}_{\mathrm{i},2003}}. \quad \text{(A3)}$$

Decomposition of $Y_{ind,t}$. We use a similar logic to decompose $Y_{ind,t}$. For 2002, 2004, 2005, 2007, 2008, and 2013, the shares $\frac{\widehat{Y}_{\mathrm{i},t}}{\sum_{\mathrm{i}\in ind} \widehat{Y}_{\mathrm{i},t}}$ calculated from NBS (2022) are used:

$$Y_{\mathrm{i},t} = Y_{ind,t} \cdot \frac{\widehat{Y}_{\mathrm{i},t}}{\sum_{\mathrm{i}\in ind} \widehat{Y}_{\mathrm{i},t}}, \quad t \in \{2002, 2004, 2005, 2007, 2008, 2013\}. \quad \text{(A4)}$$

For 2010, 2012, 2015, 2017, 2018, and 2020, we first decompose $Y_{ind,t}$ using one-digit sector shares ($\frac{\widehat{Y}_{\mathrm{i}',t}}{\sum_{\mathrm{i}'\in ind} \widehat{Y}_{\mathrm{i}',t}}$) from NBS (2022):

$$Y_{\mathrm{i}',t} = Y_{ind,t} \cdot \frac{\widehat{Y}_{\mathrm{i}',t}}{\sum_{\mathrm{i}'\in ind} \widehat{Y}_{\mathrm{i}',t}}, \quad t \in \{2010, 2012, 2015, 2017, 2018, 2020\}. \quad \text{(A5)}$$

We then use I–O tables to decompose $Y_{\mathrm{i}',t}$ into $Y_{\mathrm{i},t}$:

$$Y_{\mathrm{i},t} = Y_{\mathrm{i}',t} \cdot \frac{\widehat{Y}_{\mathrm{i},t}}{\sum_{\mathrm{i}\in \mathrm{i}'} \widehat{Y}_{\mathrm{i},t}}, \quad t \in \{2010, 2012, 2015, 2017, 2018, 2020\}. \quad \text{(A6)}$$

There is another specific adjustment for the industrial sector using I–O tables. The industry classification in 2011 introduced a new two-digit industry: metal products, machinery, and equipment repair services (rep). This industry aggregates repair-related components from five specific industries: manufacturing of metal products (met), manufacturing of general and special purpose Machinery (gsm), manufacturing of transport equipment (trm), manufacturing of electrical machinery and equipment (elm), and manufacturing of measuring instruments and machinery, other manufacturing, and utilization of waste Resources (omw). For 2012, 2013, 2015, 2017, 2018, and 2020, the value added of rep from the I–O tables is reallocated proportionally to these five specific industries. Let $\check{Y}_{\mathrm{i},t}$ denote the reported value added of the above five specific industries and $\check{Y}_{rep,t}$ the value added of *rep*. The adjusted value added for the five specific industries is computed as

$$\widehat{Y}_{\mathrm{i},t} = \check{Y}_{\mathrm{i},t} + \check{Y}_{rep,t} \cdot \frac{\check{Y}_{\mathrm{i},t}}{\sum_{\mathrm{i}} \check{Y}_{\mathrm{i},t}}, \quad \mathrm{i} \in \{met, gsm, trm, elm, omw\}. \tag{A7}$$

For years without I–O tables (2003, 2006, 2009, 2011, 2013, 2014, 2016, 2019), $Y_{\mathrm{i},t}$ in the industrial sector is estimated via logarithmic interpolation between the two closest years with I–O tables, T_1 and T_2. Specifically, we first calculate preliminary estimates:

$$\log\left(\widetilde{Y}_{\mathrm{i},t}\right) = \log Y_{\mathrm{i},T_1} + (\log Y_{\mathrm{i},T_2} - \log Y_{\mathrm{i},T_1}) \cdot \left(\frac{\log Y_{ind,t} - \log Y_{ind,T_1}}{\log Y_{ind,T_2} - \log Y_{ind,T_1}}\right), \quad t \in [T_1, T_2]. \tag{A8}$$

The preliminary estimates are then normalized to ensure consistency with total industrial value added:

$$Y_{\mathrm{i},t} = Y_{ind,t} \cdot \frac{\widetilde{Y}_{\mathrm{i},t}}{\sum_{\mathrm{i} \in ind} \widetilde{Y}_{\mathrm{i},t}}, \quad t \in \{2003, 2006, 2009, 2011, 2013, 2014, 2016, 2019\}. \tag{A9}$$

Appendix A.1.2 Price Index and Real Value Added

Industry-specific price indices ($P_{\mathrm{i},t}$) are constructed to convert nominal to real value added. For non-industrial sectors, the growth rate of the implicit value added deflator in division s is uniformly applied to the specific industries within division s:

$$\frac{P_{s,t}}{P_{s,t-1}} = \frac{Y_{s,t}/Y_{s,t-1}}{Z_{s,t}/100 - 1}, \quad \frac{P_{\mathrm{i},t}}{P_{\mathrm{i},t-1}} = \frac{P_{s,t}}{P_{s,t-1}}, \quad \forall \mathrm{i} \in s, \tag{A10}$$

where $Z_{s,t}$ is the NBS reported the real value added index.

For the specific industries in the industrial sector, we calculate the growth of the price index ($\frac{P_{\mathrm{i},t}}{P_{\mathrm{i},t-1}}$) by weighting the producer price index (PPI) growth rates for the two-digit industries ($\frac{PPI_{\mathrm{i}'',t}}{PPI_{\mathrm{i}'',t-1}}$) using the revenue share of above-scale industrial firms ($AS_{\mathrm{i}'',t}$) as weights:

$$\frac{P_{\mathrm{i},t}}{P_{\mathrm{i},t-1}} = \sum_{\mathrm{i}'' \in \mathrm{i}} \frac{PPI_{\mathrm{i}'',t}}{PPI_{\mathrm{i}'',t-1}} \cdot \frac{1}{2}\left(\frac{AS_{\mathrm{i}'',t-1}}{\sum_{\mathrm{i}'' \in \mathrm{i}} AS_{\mathrm{i}'',t-1}} + \frac{AS_{\mathrm{i}'',t}}{\sum_{\mathrm{i}'' \in i} AS_{\mathrm{i}'',t}}\right). \tag{A11}$$

As the industry classification changed for the data from 2012 on, only 2012 revenue shares are used to calculate $\frac{PPI_{\mathrm{i},2012}}{PPI_{\mathrm{i},2011}}$:

$$\frac{P_{\mathrm{i},2012}}{P_{\mathrm{i},2011}} = \sum_{\mathrm{i}'' \in i} \frac{PPI_{\mathrm{i}'',2012}}{PPI_{\mathrm{i}'',2011}} \cdot \frac{AS_{\mathrm{i}'',2012}}{\sum_{\mathrm{i}'' \in i} AS_{\mathrm{i}'',2012}}. \tag{A12}$$

With 2005 as the base year ($P_{\text{i},2005} = 1$), annual price indices are derived cumulatively with the growth rates in equations (A10), (A11), and (A12). Real value added is then calculated as

$$Q_{\text{i},t} = \frac{Y_{\text{i},t}}{P_{\text{i},t}}. \tag{A13}$$

Nominal ($Y_{d,t}$) and real ($Q_{d,t}$) value added for each subsector are obtained by summing the industry values:

$$Y_{d,t} = \sum_{\text{i}\in d} Y_{\text{i},t}, \quad Q_{d,t} = \sum_{\text{i}\in d} Q_{\text{i},t}. \tag{A14}$$

Sectoral price indices follow:

$$P_{d,t} = \frac{Y_{d,t}}{Q_{d,t}}. \tag{A15}$$

Appendix A.2 Employment

We measure labor input using employment. While annual employment data for the three broad sectors ($L_{j,t}$) are available from the NBS, disaggregated industry-level employment data remain unpublished. To address this, we combine population censuses (2000, 2010, 2020) and 1% population surveys (2005, 2015) to calculate the employment share of each subsector within its corresponding broad sector ($\frac{\widehat{L}_{\text{i},t}}{\sum_{\text{i}\in j}\widehat{L}_{\text{i},t}}$).[A3] Multiplying these shares by $L_{j,t}$ yields employment in specific industries ($L_{\text{i},t}$):[A4]

$$L_{\text{i},t} = L_{j,t} \cdot \frac{\widehat{L}_{\text{i},t}}{\sum_{\text{i}\in j}\widehat{L}_{\text{i},t}}, \quad t \in \{2000, 2005, 2010, 2015, 2020\}. \tag{A16}$$

For non-census years between 2000 and 2020, employment in specific industries is interpolated using a method consistent with value added calculation. Let T_1 and T_2 denote

[A3]For census years (2000, 2010, 2020), employment for two-digit industries ($\widehat{L}_{\text{i}'',t}$) are aggregated to derive specific industry employment ($\widehat{L}_{\text{i},t}$), from which the intra-broad-sector shares ($\frac{\widehat{L}_{\text{i},t}}{\sum_{\text{i}\in j}\widehat{L}_{\text{i},t}}$) are computed. For 2000, micro-level sampling data are additionally used to further disaggregate four two-digit industries (postal/telecommunications, public services, other social services, and miscellaneous sectors) to match our specific industry classifications. For 2005 and 2015, employment data for one-digit industries ($\widehat{L}_{\text{i}',t}$) are refined using micro-level sampling to estimate two-digit industry employment $\widehat{L}_{\text{i}'',t}$. We aggregate $\widehat{L}_{\text{i}'',t}$ to obtain $\widehat{L}_{\text{i},t}$ for calculating the shares $\frac{\widehat{L}_{\text{i},t}}{\sum_{\text{i}\in j}\widehat{L}_{\text{i},t}}$.

[A4]For 2015 and 2020, employment in metal products, machinery, and equipment repair services is allocated to five related specific industries using a method analogous to value added allocation. Let $\check{L}_{\text{i},t}$ denote employment in these specific industries derived from censuses or population surveys following Footnote A3), and $\check{L}_{rep,t}$ denote repair services employment. The adjusted employment ($\widehat{L}_{\text{i},t}$) for the five specific industries is computed as $\widehat{L}_{\text{i},t} = \check{L}_{\text{i},t} + \check{L}_{rep,t} \cdot \frac{\check{L}_{\text{i},t}}{\sum_{\text{i}}\check{L}_{\text{i},t}}, \quad \text{i} \in \{met, gsm, trm, elm, omw\}$.

the closest years with known $L_{\mathfrak{i},t}$. A preliminary estimate ($\widetilde{L}_{\mathfrak{i},t}$) is derived as

$$\log\left(\widetilde{L}_{\mathfrak{i},t}\right) = \log L_{\mathfrak{i},T_1} + (\log L_{\mathfrak{i},T_2} - \log L_{\mathfrak{i},T_1}) \cdot \left(\frac{\log L_{j,t} - \log L_{j,T_1}}{\log L_{j,T_2} - \log L_{j,T_1}}\right), \quad \mathfrak{i} \in j, \quad t \in [T_1, T_2]. \tag{A17}$$

To ensure consistency between broad sector employment ($L_{j,t}$) and the sum of specific industry estimates, $\widetilde{L}_{\mathfrak{i},t}$ is adjusted proportionally:

$$L_{\mathfrak{i},t} = L_{j,t} \cdot \frac{\widetilde{L}_{\mathfrak{i},t}}{\sum_{\mathfrak{i}\in j} \widetilde{L}_{\mathfrak{i},t}} \tag{A18}$$

Finally, subsector employment is obtained by summing corresponding specific industries:

$$L_{d,t} = \sum_{\mathfrak{i}\in d} L_{\mathfrak{i},t} \tag{A19}$$

Appendix A.3 Capital Stock

We construct the capital stock for each specific industry and subsector through three steps: calculating annual investment, determining price indices for investment, and computing capital stock from 2003 to 2020 with initial capital stock and depreciation rate.

Investment by Specific Industry and Subsector. Gross fixed capital formation (FCF) from the NBS website, FCF_t, serves as the benchmark of aggregate investment. Additionally, the NBS has published historical data on the FCF of the three broad sectors from 1978 to 2002 in Hsueh and Li (1999) and NBS (2004), denoted as $\widehat{FCF}_{j,t}$. Then, FCF_t is decomposed into $FCF_{j,t}$ as:

$$FCF_{j,t} = FCF_t \cdot \frac{\widehat{FCF}_{j,t}}{\sum_j \widehat{FCF}_{j,t}}. \tag{A20}$$

However, starting from 2003, the NBS no longer publishes disaggregated FCF. To address this issue, we use the fixed asset investment (FAI) data, another investment-related indicator published by the NBS, assuming that FAI shares of each specific industry approximate its FCF shares. The following paragraphs detail the process of decomposing the FCF using the FAI data.

First, we obtain the latest revised national total FAI, denoted as FAI_t, and non-rural household FAI in three broad sectors, denoted as $FAI^N_{j,t}$, for the years 2003 to 2022 from the NBS website. The rural household FAI, denoted as FAI^R_t, is the difference between FAI_t and the sum of $FAI^N_{j,t}$. The NBS website also provides the growth rates of non-rural household FAI in two-digit industries, denoted as $\frac{FAI^N_{i'',t}}{FAI^N_{i'',t-1}}$, from 2018 to 2022. We also collect rural household FAI by one-digit industry, denoted as $\widehat{FAI}^R_{i',t}$, and non-rural household FAI by two-digit industry, denoted as $\widehat{FAI}^N_{i'',t}$, in 2003–2017 from various issues of *China Statistical Yearbook on Fixed Asset Investment.*

Using these data, we calculate the FAI for each specific industry ($FAI_{i,t}$) from 2003 to 2017. Two-digit industry non-rural household FAI ($FAI^N_{i'',t}$) is estimated from $\widehat{FAI}^N_{i'',t}$ and $FAI^N_{j,t}$ by

$$FAI^N_{i'',t} = FAI^N_{j,t} \cdot \frac{\widehat{FAI}^N_{i'',t}}{\sum_{i'' \in j} \widehat{FAI}^N_{i'',t}}. \tag{A21}$$

For rural households, we calculate FAI for one-digit industries ($FAI^R_{i',t}$) from $\widehat{FAI}^R_{i',t}$ and FAI^R_t by

$$FAI^R_{i',t} = FAI^R_t \cdot \frac{\widehat{FAI}^R_{i',t}}{\sum_{i'} \widehat{FAI}^R_{i',t}}. \tag{A22}$$

By assuming that the composition of rural household FAI mirrors that of non-rural household FAI within each one-digit industry, we calculate FAI for two-digit industries ($FAI^R_{i'',t}$) by

$$FAI^R_{i'',t} = FAI^R_{i',t} \cdot \frac{FAI^N_{i'',t}}{\sum_{i'' \in i} FAI^N_{i'',t}}. \tag{A23}$$

Summing $FAI^R_{i'',t}$ and $FAI^N_{i'',t}$ yields total FAI for two-digit industries ($FAI_{i'',t}$):

$$FAI_{i'',t} = FAI^R_{i'',t} + FAI^N_{i'',t}. \tag{A24}$$

For 2018–2021, we extrapolate the FAI for two-digit industries ($FAI_{i'',t}$) using growth rates of non-rural household FAI ($\frac{FAI^N_{i'',t}}{FAI^N_{i'',t-1}}$):

$$FAI_{i'',t} = FAI_t \cdot \frac{FAI_{i'',t-1} \cdot \frac{FAI^N_{i'',t}}{FAI^N_{i'',t-1}}}{\sum_{i''} \left(FAI_{i'',t-1} \cdot \frac{FAI^N_{i'',t}}{FAI^N_{i'',t-1}} \right)}, \quad t \in [2018, 2022]. \tag{A25}$$

Aggregating across relevant two-digit industries yields FAI for each specific industry

$(FAI_{\mathrm{i},t})$:

$$FAI_{\mathrm{i},t} = \sum_{\mathrm{i}'' \in \mathrm{i}} FAI_{\mathrm{i}'',t}. \tag{A26}$$

Finally, FCF for each specific industry $(FCF_{\mathrm{i},t})$ is calculated as

$$FCF_{\mathrm{i},t} = FCF_t \cdot \frac{FAI_{\mathrm{i},t}}{\sum_{\mathrm{i}} FAI_{\mathrm{i},t}}. \tag{A27}$$

Investment Price Indices. A unified price index (P_t^I) is constructed to deflate nominal investment across all specific industries and subsectors. We normalize the price of capital stock at the beginning of 2005 to 1, which implies $P_{2004}^I = 1$. We calculate P_t^I using three distinct series. For 1978–1989, we apply the FCF deflator from Hsueh and Li (1999). For 1990–2019, we employ the fixed asset investment price indices published by the NBS. For 2020, we use the implicit GFCF deflator derived from NBS (2004).

Capital Stock by Specific Industry and Subsector. Capital stock in 1978 for broad sectors $(K_{j,1978})$ is estimated under the assumption that pre-1978 real investment grew at the 1978–1983 annualized average annual rate. Specifically, for each broad sector,

$$K_{j,1978} = \frac{FCF_{j,1978}/P_{1978}^I}{\left(\frac{FCF_{1983}/P_{1983}^I}{FCF_{1978}/P_{1978}^I}\right)^{\frac{1}{5}} - 1 + \delta}, \tag{A28}$$

where $\delta = 9\%$ is the depreciation rate (Brandt et al., 2012). Then, annual capital stocks from 1979 to 2003 are updated using the perpetual inventory method:

$$K_{j,t+1} = (1-\delta)K_{j,t} + \frac{FCF_{j,t}}{P_t^I}, \quad t \in [1978, 2002]. \tag{A29}$$

Subsequently, we calculate the capital stock for the specific industries in 2003 based on the assumption that the composition of capital stock within a broad sector remains unchanged between the beginning of 2003 and the beginning of 2004. It implies that

$$K_{\mathrm{i},2003} = K_{j,2003} \cdot \frac{FCF_{\mathrm{i},2003}}{\sum_{\mathrm{i} \in j} FCF_{\mathrm{i},2003}}. \tag{A30}$$

The capital stock in the subsequent years follows the perpetual inventory method again:

$$K_{\mathrm{i},t+1} = (1-\delta)K_{\mathrm{i},t} + \frac{FCF_{\mathrm{i},t}}{P_t^I}, \quad t \geqslant 2003. \tag{A31}$$

Subsector capital stocks equal the sum of corresponding specific industries:

$$K_{d,t} = \sum_{\text{i} \in d} K_{\text{i},t}. \tag{A32}$$

Appendix A.4 Output Elasticities of Capital and Labor

We estimate subsector capital output elasticities (α_d) using I–O tables. In the income approach, value added is decomposed into four components: labor compensation (LAC), fixed asset depreciation (FAD), operating surplus (OPS), and net production taxes (NPT). We first extract reported values of of labor compensation ($\widehat{LAC}_{\text{i},t}$), fixed asset depreciation ($\widehat{FAD}_{\text{i},t}$), operating surplus ($\widehat{OPS}_{\text{i},t}$), and net production taxes ($\widehat{NPT}_{\text{i},t}$) for each specific industry in year t. Using the value added derived in previous sections, we refine these items to ensure consistency:

$$LAC_{\text{i},t} = Y_{\text{i},t} \cdot \frac{\widehat{LAC}_{\text{i},t}}{\widehat{LAC}_{\text{i},t} + \widehat{FAD}_{\text{i},t} + \widehat{OPS}_{\text{i},t} + \widehat{NPT}_{\text{i},t}}, \tag{A33}$$

$$FAD_{\text{i},t} = Y_{\text{i},t} \cdot \frac{\widehat{FAD}_{\text{i},t}}{\widehat{LAC}_{\text{i},t} + \widehat{FAD}_{\text{i},t} + \widehat{OPS}_{\text{i},t} + \widehat{NPT}_{\text{i},t}}, \tag{A34}$$

$$OPS_{\text{i},t} = Y_{\text{i},t} \cdot \frac{\widehat{OPS}_{\text{i},t}}{\widehat{LAC}_{\text{i},t} + \widehat{FAD}_{\text{i},t} + \widehat{OPS}_{\text{i},t} + \widehat{NPT}_{\text{i},t}}, \tag{A35}$$

$$NPT_{\text{i},t} = Y_{\text{i},t} \cdot \frac{\widehat{NPT}_{\text{i},t}}{\widehat{LAC}_{\text{i},t} + \widehat{FAD}_{\text{i},t} + \widehat{OPS}_{\text{i},t} + \widehat{NPT}_{\text{i},t}}. \tag{A36}$$

Then, following Bai and Qian (2010), we compute capital income shares ($\alpha_{d,t}$) by subsector d and year t:

$$\alpha_{d,t} = 1 - \frac{\sum_{i \in d} LAC_{\text{i},t}}{\sum_{\text{i} \in d}(LAC_{\text{i},t} + FAD_{\text{i},t} + OPS_{\text{i},t})}. \tag{A37}$$

We assume perfectly competitive capital and labor markets across subsectors, with constant returns to scale Cobb-Douglas subsector production functions. Under these conditions, output elasticities correspond directly to income shares. We therefore calculate capital and labor output elasticities as the arithmetic mean of annual income shares from 2002 to 2020:

$$\alpha_d = \frac{1}{9} \sum_t \alpha_{d,t}, \quad t \in \{2002, 2005, 2007, 2010, 2012, 2015, 2017, 2018, 2020\} \tag{A38}$$

To address potential overestimation of labor output elasticity in agriculture, whose reported labor compensation may incorporate returns to land and other factors, we follow

Brandt et al. (2008) in setting the agricultural labor output elasticity (α_F) to 0.5.

Appendix B Discussion on The TFP Dynamics in Services

In this appendix, we provide a detailed discussion on the potential mechanisms driving the divergent service TFP paths observed in the data. We first qualitatively discuss the drivers for both traditional and nontraditional services based on existing literature, and then provide supplementary quantitative evidence specifically focusing on the capital misallocation issue within nontraditional services.

Appendix B.1 Mechanisms Behind Service Sector TFP Divergence

We attribute the strong TFP performance in traditional services to two factors. The first factor involves the diffusion of technology. For instance, digital technologies have significantly reduced search frictions and transaction costs in healthcare services (Chen et al., 2022), while e-commerce and modern logistics platforms have reshaped wholesale and retail industries by overcoming logistical barriers and improving matching efficiency (Couture et al., 2021). The second factor is related to the scale economies resulting from China's rapid urbanization. The creation of vast, dense urban consumer markets facilitates economic activity and fosters productivity growth through agglomeration economies, particularly benefiting traditional services that often serve local consumers and thrive on urban scale and variety (Glaeser et al., 1992, 2001; Anas et al., 1998; WB and DRC, 2014).

Turning to the decline of nontraditional service TFP after 2012, we argue that stagnant TFP in nontraditional services likely results from several interrelated factors, rather than a single cause. The first factor is capital misallocation. Although the secondary sector also experienced fast capital deepening in the past decades, it was largely a market-driven response to rising labor costs (Cheng et al., 2019), involving investments in automation aimed at improving production efficiency (Li et al., 2024). In contrast, the capital deepening in nontraditional services, especially post-2008, was substantially fueled by government stimulus policies and credit expansion (Bai et al., 2016). The credit expansion was largely driven by local officials' career incentives to boost short-term GDP, channeling funds into large-scale infrastructure and real estate projects (Liu and Xiong, 2020; Song and Xiong, 2024).[A5] Therefore, the capital deepening in nontraditional services is prone to misallocation, which leads to a decline in the measured TFP residual within a growth

[A5] Such policy-driven investment, often geared towards stabilizing asset prices rather than maximizing productive efficiency, has persisted even in recent downturns (Chang et al., 2025).

accounting framework.[A6]

The second factor involves labor misallocation. Although the boom in real estate and finance attracted a significant inflow of labor, it was accompanied by a substantial and growing misallocation of capital and labor within market services, concentrating labor in relatively unproductive firms (Novta et al., 2024). If labor shifted into the inefficiently expanding service activities instead of more productive ones, the sectoral TFP will be further depressed.

The third factor relates to market structure issues, such as market access barriers and a lack of competition. High entry barriers and the significant presence of state-owned enterprises in certain service sectors can lead to resource misallocation and reduce incentives for efficiency gains, contributing to stagnant or declining TFP (Barwick et al., 2025). Such structural issues might also enable incumbent firms to maintain higher prices (Ge et al., 2019).

Appendix B.2 Supplementary Evidence on Nontraditional Services

A striking finding in Section 2 is the negative aggregate TFP growth observed in the nontraditional service sector, contrasting sharply with the positive TFP growth in traditional services and high-technology manufacturing. The negative TFP growth of nontraditional service is counterintuitive, especially given its rising value added and employment shares during the same period.

The aim of this appendix section is to provide supplementary evidence supporting our argument that the poor performance of nontraditional services is likely linked to issues such as capital misallocation, labor misallocation, and market barriers by examining TFP dynamics at a more disaggregated level within the nontraditional service sector. We demonstrate the significant heterogeneity in TFP performance within nontraditional services and explore its relationship with credit allocation, thereby shedding light on the underlying causes of the aggregate TFP stagnation.

Table A1 presents the annualized growth rates of several variables for the sub-sectors within nontraditional services. Focusing on the post-2012 period (Panel C), where the

[A6] See Appendix B for a detailed supplementary analysis validating the capital misallocation argument. First, disaggregated TFP dynamics reveal significant heterogeneity. After 2012, TFP in real estate declined sharply. In contrast, TFP in the information transmission, computer services, and software industry grew robustly. Second, bank loan distribution data show a persistent misalignment. Real estate, for instance, maintained a high loan share while its TFP plummeted. Conversely, the information transmission, computer services, and software industry received a remarkably small loan share. The evidence suggests inefficient, policy-driven capital allocation, contrasting with the market-driven capital deepening in manufacturing.

nontraditional service TFP decline was most pronounced, reveals sharp differences in TFP performance for specific industries.

Most specific industries experienced TFP declines, including financial intermediation (-1.72%), real estate (-6.47%), management of water conservancy, environment, and public facilities (-4.40%), leasing and business services (-5.16%), and scientific research and technical services (-6.05%). In contrast, transportation, storage, and post saw its TFP growth essentially stagnate (0.22%), while information transmission, computer services, and software is the only industry that maintained strong TFP growth (3.31%).

Table A1: Annualized Growth Rates of Variables in Nontraditional Services, 2003–2020

	Value Added	Employment	Nominal Labor Productivity	Price Index	Capital–Labor Ratio	TFP
Panel A: Annualized Growth Rate from 2003 to 2020						
Transportation, Storage, and Post	10.06%	0.88%	9.10%	2.09%	11.39%	0.80%
Information Transmission, Computer Services, and Software	15.43%	8.51%	6.38%	4.88%	-1.39%	2.41%
Financial Intermediation	16.51%	3.35%	12.73%	5.09%	11.13%	0.45%
Real Estate	15.30%	9.68%	5.12%	7.61%	3.85%	-5.28%
Leasing and Business Services	17.59%	9.45%	7.43%	4.88%	9.87%	-1.19%
Scientific Research and Technical Services	17.34%	7.29%	9.37%	4.88%	9.05%	0.92%
Management of Water Conservancy, Environment, and Public Facilities	13.79%	3.22%	10.24%	4.88%	12.03%	0.10%
Culture, Sports, and Entertainment	12.50%	1.79%	10.53%	4.88%	13.80%	0.22%
Panel B: Annualized Growth Rate from 2003 to 2012						
Transportation, Storage, and Post	12.98%	0.68%	12.22%	3.43%	13.49%	1.31%
Information Transmission, Computer Services, and Software	14.93%	7.95%	6.47%	6.00%	-1.70%	1.62%
Financial Intermediation	21.65%	3.38%	17.68%	7.22%	11.75%	2.43%
Real Estate	19.49%	10.09%	8.54%	9.03%	4.82%	-4.21%
Leasing and Business Services	19.99%	5.84%	13.37%	6.00%	11.77%	2.48%
Scientific Research and Technical Services	21.58%	1.92%	19.29%	6.00%	12.72%	7.54%
Management of Water Conservancy, Environment, and Public Facilities	18.30%	0.98%	17.15%	6.00%	14.46%	4.28%
Culture, Sports, and Entertainment	16.33%	1.37%	14.75%	6.00%	14.21%	2.80%
Panel C: Annualized Growth Rate from 2012 to 2020						
Transportation, Storage, and Post	6.86%	1.11%	5.69%	0.60%	9.08%	0.22%
Information Transmission, Computer Services, and Software	16.00%	9.14%	6.28%	3.62%	-1.05%	3.31%
Financial Intermediation	10.98%	3.32%	7.41%	2.74%	10.44%	-1.72%
Real Estate	10.76%	9.23%	1.41%	6.03%	2.76%	-6.47%
Leasing and Business Services	14.95%	13.67%	1.13%	3.62%	7.76%	-5.16%
Scientific Research and Technical Services	12.75%	13.66%	-0.80%	3.62%	5.07%	-6.05%
Management of Water Conservancy, Environment, and Public Facilities	8.92%	5.81%	2.95%	3.62%	9.35%	-4.40%
Culture, Sports, and Entertainment	8.35%	2.26%	5.95%	3.62%	13.34%	-2.61%

The poor TFP performance concentrated in specific industries, particularly pronounced after the post-2008 stimulus plan, motivates a closer look at how loans were allocated across these industries with different productivity trends, which points towards potential issues of allocation efficiency.

Figure A1 provides evidence for potential capital misallocation by plotting log TFP (left axis) against loan balance shares (right axis) for all nontraditional service industries.[A7] Three patterns emerge. First, several industries demonstrate a significant divergence

[A7]To calculate the loan balance shares, we first collected data on the loan balance of financial instibetween credit allocation and productivity performance. Real estate offers the starkest example, in which a persistently high loan share coincides with a dramatic TFP decline after 2012. Similar, though less extreme, misalignments are visible in leasing and business services and management of water conservancy, environment, and public facilities. Second, transportation, storage, and post consistently commanded the highest loan share yet exhibited stagnant TFP growth, indicating substantial credit flowing into a sector with minimal efficiency gains. Third, in sharp contrast, information transmission, computer services, and software, the sector with the strongest TFP growth, received a remarkably small share of loans. While our loan data begin in 2010, potentially missing the peak post-2008 stimulus credit expansion, these figures clearly show a persistent misalignment between credit allocation and TFP performance throughout the subsequent decade.

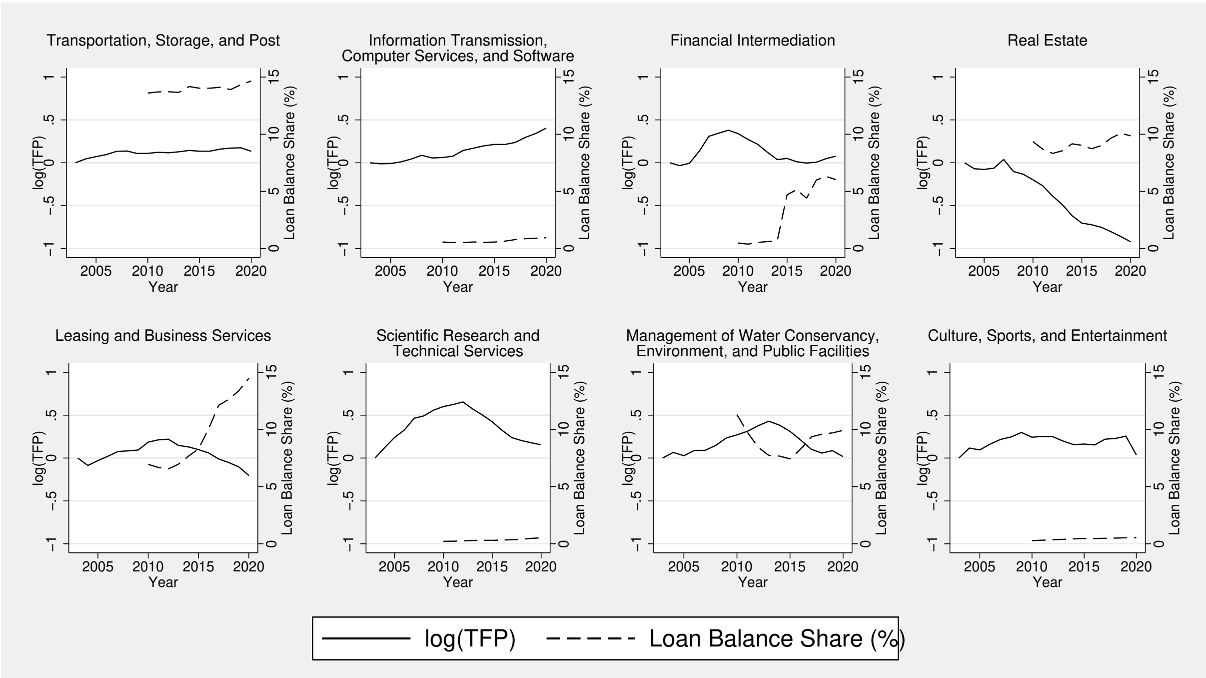

Figure A1: TFP and Loan Balance Share in Nontraditional Service Industries, 2003–2020

To sum up, the disaggregated analysis reveals a persistent misalignment between productivity and credit allocation. Specifically, industries with sharply declining TFP consistently received large loan shares. The above evidence supports our hypothesis attributing the nontraditional service sector's overall poor TFP performance to capital misallocation, potentially linked to policy-driven credit expansion.

tutions by one-digit industry from the *China Financial Yearbook* for the period 2010 to 2020. Then, we calculated the loan balance shares as the shares of each industry's loan balance relative to the aggregate loan balance across all industries.

Appendix C Calibration Details

Appendix C.1 Constructing Consumption and Investment Value Added Vectors

We outline the estimation of sectoral value added generated by consumption ($VA_{j,t}^C$), investment ($VA_{j,t}^I$), and other expenditures ($VA_{j,t}^O$) following Herrendorf et al. (2013, 2020). We assume that imported goods share the same production technology as domestic goods, consistent with Herrendorf et al. (2013), avoiding the need to distinguish between domestic and foreign intermediate inputs.

Using the estimation procedure detailed in Appendix B.2 of Herrendorf et al. (2013), we apply their methodology on United States data before 1972 to Chinese I–O tables, which assume a one-to-one correspondence between industries and commodities.

To address inconsistencies arising from NBS revisions to historical sectoral value added data without corresponding updates to I–O tables, we assume that the inferred value added shares generated by different final demand components in each specific industry are reliable. Specifically, denote the industries in the input-output table by the subscript i'''. Following the above method, we can decompose $\widehat{Y}_{\mathrm{i}''',t}$ into $\widehat{Y}_{\mathrm{i}''',t}^C$, $\widehat{Y}_{\mathrm{i}''',t}^I$, and $\widehat{Y}_{\mathrm{i}''',t}^O$. Then, we aggregate $\widehat{Y}_{\mathrm{i}''',t}$ and $\widehat{Y}_{\mathrm{i}''',t}^C$ to the specific industries. For each specific industry, we calculate the consumption rates and investment rates by

$$\kappa_{\mathrm{i},t}^C = \frac{\sum_{\mathrm{i}''' \in i} \widehat{Y}_{\mathrm{i}''',t}^C}{\sum_{\mathrm{i}''' \in \mathrm{i}} \widehat{Y}_{\mathrm{i}''',t}},$$
$$\kappa_{\mathrm{i},t}^I = \frac{\sum_{\mathrm{i}''' \in i} \widehat{Y}_{\mathrm{i}''',t}^I}{\sum_{\mathrm{i}''' \in \mathrm{i}} \widehat{Y}_{\mathrm{i}''',t}}.$$

$\kappa_{\mathrm{i},t}^C$ and $\kappa_{\mathrm{i},t}^I$ are then multiplied by value added in each specific industry ($Y_{\mathrm{i},t}$) to derive $VA_{i,t}^C$, $VA_{i,t}^I$, and $VA_{i,t}^O$. Aggregating these across subsectors yields $VA_{j,t}^C$, $VA_{j,t}^I$, and $VA_{j,t}^O$.

Appendix C.2 Parameters in CES Production Functions

Table A2 reports the estimated values of parameters σ and θ.

Table A3 reports the estimated values of parameters ϕ and ρ.

Table A2: Parameter Estimates for Industrial Goods Production Function

Parameter	Estimate
σ	1.680***
	(5.13)
θ	0.319***
	(61.83)
AIC	-690.1
RMSE (Low-Technology Manufacturing)	0.0259
RMSE (High-Technology Manufacturing)	0.0259

Note: AIC and RMSE stand for Akaike's Information Criterion and Root Mean Square Error, respectively. Values in parentheses denote t-statistics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3: Parameter Estimates for Service Production Function

Parameter	Estimate
ρ	0.207**
	(5.67)
ψ	0.479***
	(339.99)
AIC	-759.7
RMSE (Traditional Services)	0.00343
RMSE (Nontraditional Services)	0.00343

Note: AIC and RMSE stand for Akaike's Information Criterion and Root Mean Square Error, respectively. Values in parentheses denote t-statistics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix C.3 Parameters in Preferences and Investment Goods Production Function

Tables A4 and A5 present estimates for the parameters in the preferences and investment goods production function.

Table A4: Parameter Estimates for Preferences

	(1)
ω_F	0.0507***
	(9.44)
ω_G	0.0745**
	(3.81)
ω_S	0.875***
	(42.56)
$\upsilon_F\phi$	0.111***
	(15.41)
$\upsilon_G\phi$	0.290***
	(11.92)
$\upsilon_S\phi$	-0.400***
	(-16.29)
AIC	-864.0
RMSE (Primary)	0.00454
RMSE (Secondary)	0.0157
RMSE (Tertiary)	0.0156

Note: AIC and RMSE stand for Akaike's Information Criterion and Root Mean Square Error, respectively. Values in parentheses denote t-statistics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5: Parameter Estimates for Investment Goods Production Function

Parameter	Estimate
ε	2.13×10^{-24}
	(.)
ξ_1	2.266***
	(37.43)
ξ_2	0.0781***
	(15.27)
ξ_3	1.349***
	(27.86)
ξ_4	0.0805***
	(18.66)
AIC	-874.9
RMSE (Primary)	0.00727
RMSE (Secondary)	0.0133
RMSE (Tertiary)	0.00745

Note: AIC and RMSE stand for Akaike's Information Criterion and Root Mean Square Error, respectively. Values in parentheses denote t-statistics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix D Robustness Analysis

The baseline model presented in the main text captures the broad trends of China's structural transformation and economic growth. However, as illustrated in Figure 5, there are some discrepancies between the model's predictions and the actual data, particularly in the post-2010 period for the value added share of high-technology manufacturing. To ensure that our core conclusions are not sensitive to the deviation, we conduct a robustness analysis using an alternative calibration strategy in this appendix section.

Specifically, instead of calculating capital and labor wedges directly from the first-order conditions based on aggregate factor prices as in the baseline, our alternative approach calibrates these wedges for each period. The wedges are chosen such that the model matches the observed time series of value added shares and employment shares for all five sectors from 2003 to 2020. All other parameters, including production function elasticities, preference parameters, and the exogenous TFP paths, remain identical to those used in the baseline calibration. By forcing the model to replicate the observed structural transformation patterns, we can reevaluate the counterfactual impacts of TFP and capital deepening to verify the robustness of our main findings.

Figures A2 and A3 together with the first two rows of Tables A6 and A7 confirm that by construction, our alternative calibration ensures that the model replicates the observed dynamics of both inter-sectoral and intra-sectoral structural transformation in terms of value added shares and employment shares from 2003 to 2020. While calibrated to match sectoral shares, it is important to assess how well the alternative specification captures overall economic growth. Table A6 compares the annualized growth rates of aggregate labor productivity and sectoral output per worker between the data and this alternative model. The alternative model yields an annualized aggregate labor productivity growth rate of 9.08% for 2003-2020, which is slightly higher than the baseline model's 8.91% and remains very close to the actual data's 9.77%. This indicates that the alternative model, while perfectly matching structural transformation patterns, still captures approximately 93% of the observed aggregate growth, confirming its reliability for robustness checks.

Having established the alternative calibration, which replicates both structural transformation and aggregate growth, we now re-evaluate our main counterfactual experiments under this specification to assess the robustness of our core findings.

First, we examine the impact of sector TFP improvements on structural transformation in Figures A4 and A5 and Tables A6 and A7. To test the finding regarding the manufacturing sector, we analyze the scenario where TFP growth in high-technology manufacturing drives its own share increase. Tables A6 and A7 show that in the alternative model, high-technology manufacturing's value added and employment shares within the secondary sector increase by 7.67% and 12.46%, respectively, between 2003 and 2020. However,

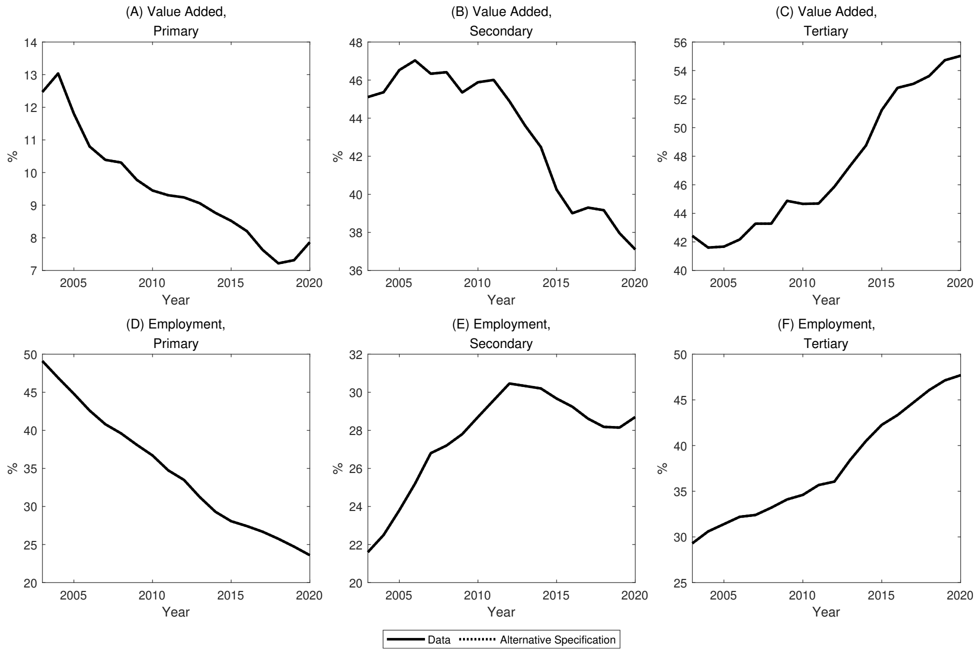

Figure A2: Inter-sectoral Structural Transformation under the Alternative Specification

Table A6: Changes of Sectoral Value Added Shares between 2003 and 2020 under the Alternative Specification

	Changes of Share in Total Value Added					Changes of Share in Broad Sector Value Added	
	Agriculture	Low-Technology Manufac-turing	High-Technology Manufac-turing	Traditional Services	Non-traditional Services	High-Technology Manufac-turing	Non-traditional Services
Data	-4.60%	-5.58%	-2.43%	3.67%	8.94%	7.67%	4.40%
Alternative Model Specification	-4.60%	-5.58%	-2.43%	3.67%	8.94%	7.67%	4.40%
Counterfactuals under the Alternative Specification:							
Constant Low-Technology Manufacturing TFP	-4.66%	-6.24%	-0.91%	3.19%	8.62%	9.99%	4.63%
Constant High-Technology Manufacturing TFP	-4.51%	-2.01%	-3.42%	2.02%	7.92%	0.38%	5.47%
Constant Traditional Service TFP	-4.04%	-5.75%	-3.32%	10.02%	3.09%	7.67%	-6.49%
Constant Nontraditional Service TFP	-4.66%	-5.45%	-2.05%	4.68%	7.48%	7.67%	2.18%
Constant Primary TFP	-3.93%	-5.61%	-2.49%	3.34%	8.69%	7.67%	4.54%
Constant Secondary TFP	-4.53%	-2.92%	-1.83%	1.63%	7.64%	3.07%	5.70%
Constant Tertiary TFP	-4.04%	-5.74%	-3.28%	11.22%	1.83%	7.67%	-8.68%
Constant TFP in All Sectors	-3.38%	-3.38%	-2.99%	8.54%	1.21%	3.06%	-7.42%
No Capital Deepening	-1.62%	-4.48%	-1.85%	-3.90%	11.85%	7.59%	13.40%

as shown in Figure A5, when high-technology manufacturing TFP is held constant, the increase in both its value added and employment shares within manufacturing is reduced by more than half. These results confirm that halting TFP growth in high-technology manufacturing significantly suppresses its expansion within the secondary sector. The magnitudes are comparable to the baseline model's findings, thus supporting the conclusion that TFP improvements in high-technology manufacturing drive its own share growth within manufacturing.

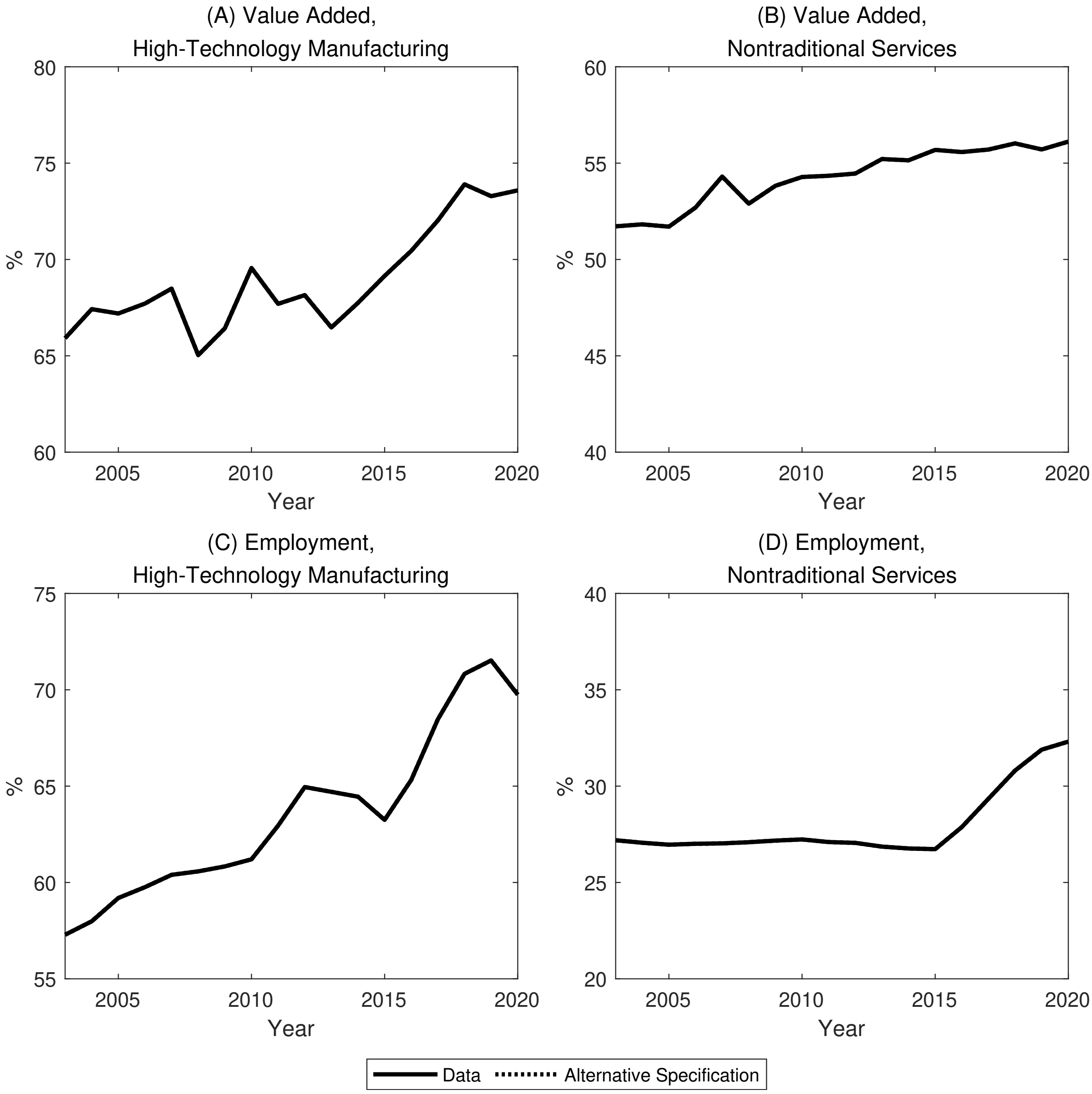

Figure A3: Intra-sectoral Structural Transformation under the Alternative Specification

Next, we test our finding for the services sector, where TFP growth in traditional services pulls up the share of nontraditional services. From Tables A6 and A7, in the alternative model, nontraditional services' value added and employment shares within the tertiary sector increase by 4.40% and 5.12%. When traditional service TFP is held constant, the shares of nontraditional services actually fall by 6.49% and 3.63%, respectively. These results confirm that halting TFP growth in traditional services severely curtails the expansion of nontraditional services. The magnitudes are even slightly larger than the baseline model's findings, thus supporting the conclusion that TFP improvements in traditional services drive the share growth of nontraditional services.

Second, we assess the impact of sub-sector TFP improvements on economic growth using Figure A6 and Table A8. We examine the growth contributions of TFP in high-technology

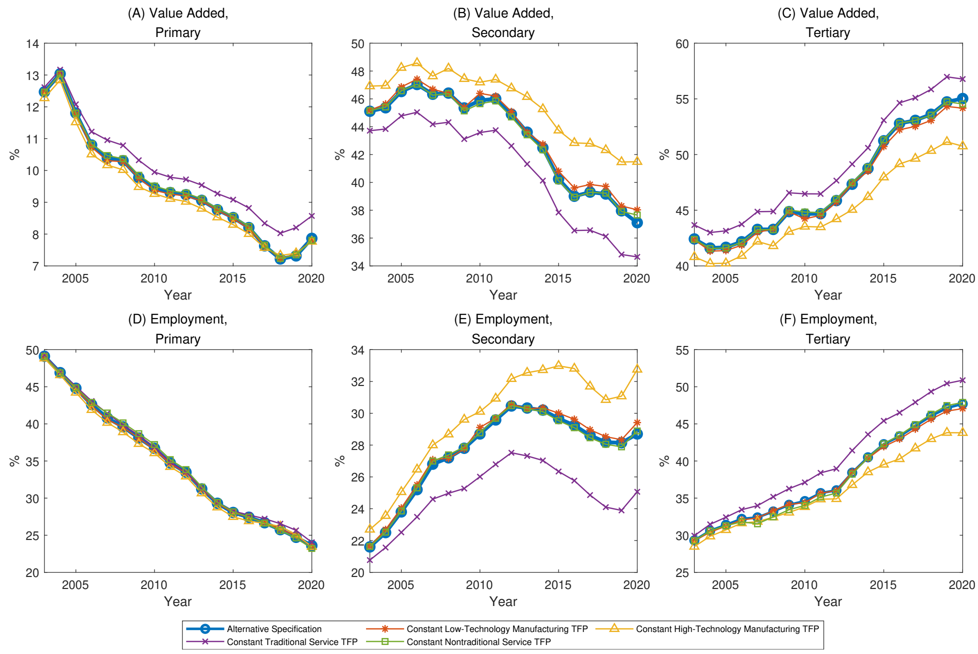

Figure A4: Effects of Subsector TFP Improvements on Inter-sectoral Structural Transformation under the Alternative Specification

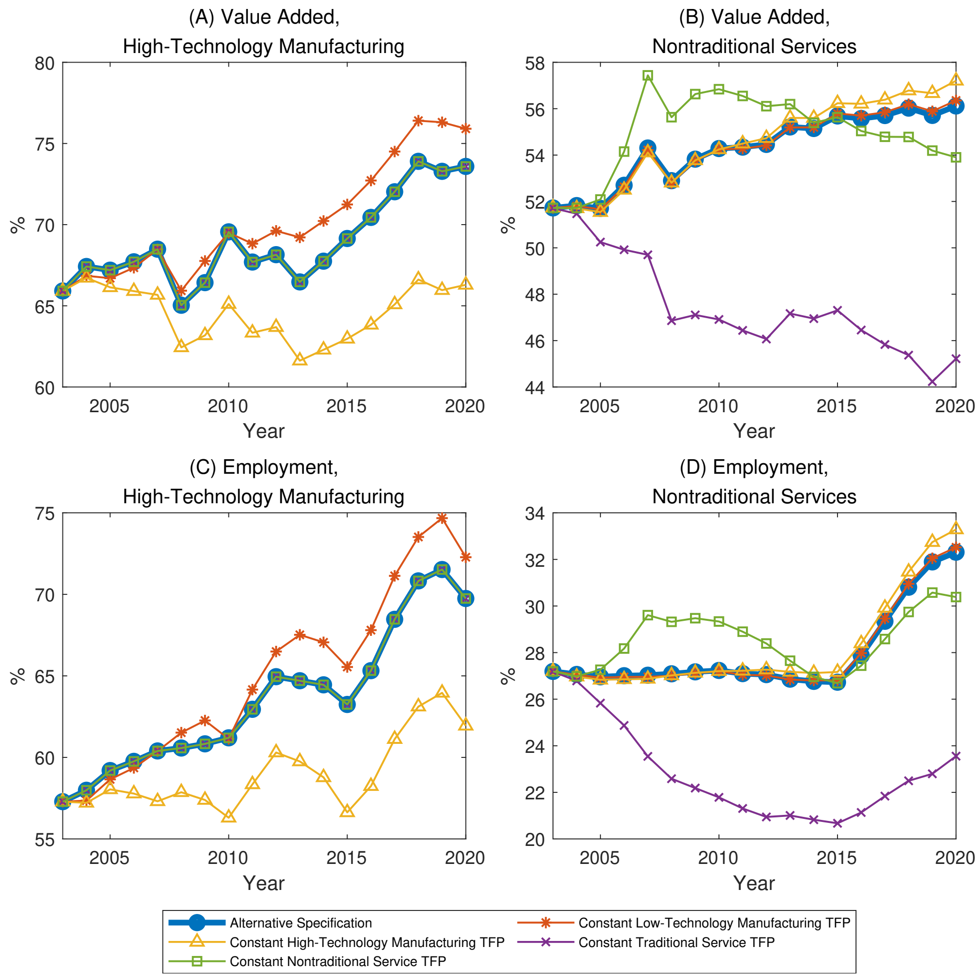

Figure A5: Effects of Subsector TFP Improvements on Intra-sectoral Structural Transformation under the Alternative Specification

Table A7: Changes of Sectoral Employment Shares between 2003 and 2020 under the Alternative Specification

	Changes of Share in Total Employment					Changes of Share in Broad Sector Employment	
	Agriculture	Low-Technology Manufacturing	High-Technology Manufacturing	Traditional Services	Non-traditional Services	High-Technology Manufacturing	Non-traditional Services
Data	-25.50%	-0.54%	7.64%	10.95%	7.45%	12.46%	5.12%
Alternative Model Specification	-25.50%	-0.54%	7.64%	10.95%	7.45%	12.46%	5.12%
Counterfactuals under the Alternative Specification:							
Constant Low-Technology Manufacturing TFP	-25.57%	-1.09%	8.86%	10.45%	7.35%	14.99%	5.33%
Constant High-Technology Manufacturing TFP	-25.39%	2.77%	7.29%	8.49%	6.84%	4.65%	6.09%
Constant Traditional Service TFP	-25.24%	-1.29%	5.58%	17.10%	3.85%	12.45%	-3.63%
Constant Nontraditional Service TFP	-25.87%	-0.50%	7.76%	12.02%	6.59%	12.46%	3.19%
Constant Primary TFP	-23.84%	-0.68%	7.34%	10.07%	7.11%	12.46%	5.25%
Constant Secondary TFP	-25.36%	2.02%	8.57%	8.04%	6.74%	7.51%	6.30%
Constant Tertiary TFP	-25.47%	-1.35%	5.46%	18.22%	3.15%	12.45%	-5.19%
Constant TFP in All Sectors	-23.87%	0.66%	5.91%	14.59%	2.71%	7.50%	-4.30%
No Capital Deepening	-16.57%	-0.36%	6.08%	1.82%	9.02%	12.36%	13.86%

Table A8: Annualized Output Growth Rates under the Alternative Specification, 2003–2020

		Sectoral Output per Worker				
	Aggregate Labor Productivity	Agriculture	Low-Technology Manufacturing	High-Technology Manufacturing	Traditional Services	Nontraditional Services
Data	9.77%	8.76%	7.21%	7.01%	6.52%	4.98%
Alternative Model Specification	9.08%	7.90%	5.17%	7.42%	5.40%	3.61%
Counterfactuals under the Alternative Specification:						
Constant Low-Technology Manufacturing TFP	8.84%	7.76%	3.92%	7.28%	5.31%	3.45%
Constant High-Technology Manufacturing TFP	7.09%	7.27%	4.54%	3.61%	4.99%	2.87%
Constant Traditional Service TFP	7.52%	7.52%	4.78%	7.02%	1.59%	3.16%
Constant Nontraditional Service TFP	9.25%	7.94%	5.20%	7.45%	5.42%	4.32%
Constant Primary TFP	8.84%	5.18%	5.08%	7.33%	5.35%	3.51%
Constant Secondary TFP	6.74%	7.14%	3.30%	3.48%	4.91%	2.72%
Constant Tertiary TFP	7.63%	7.54%	4.80%	7.05%	1.61%	3.85%
Constant TFP in All Sectors	5.36%	4.19%	2.97%	3.15%	1.15%	2.99%
No Capital Deepening	3.49%	2.60%	-0.12%	1.98%	1.92%	-2.58%

manufacturing and traditional services. Holding high-technology manufacturing TFP constant reduces the annualized aggregate labor productivity growth rate from the alternative baseline of 9.08% to 7.09%. This implies a contribution of 1.99 percentage points, which is very close to the baseline model's estimate of 1.97 percentage points. Holding traditional service TFP constant reduces the growth rate to 7.52%, implying a contribution of 1.56 percentage points, almost identical to the baseline model's estimate of 1.59 percentage points. Therefore, the conclusion that TFP growth in high-technology manufacturing and traditional services are the key engines of aggregate growth is robust under the alternative calibration.

Third, we briefly verify the overall contributions of TFP and capital deepening in Figures A6, A7, and A9, and Tables A6, A7, and A8. For the total TFP contribution, holding TFP constant in all sectors reduces the aggregate growth rate to 5.36%. The total TFP contribution is thus 3.72 percentage points, almost identical to the baseline model's estimate of 3.73 percentage points. Regarding the capital deepening contribution, eliminating capital deepening reduces the aggregate growth rate to 3.49%. The contribution of capital deepening is therefore 5.59 percentage points, still very close to the baseline model's estimate of 5.69 percentage points. The finding that capital deepening was historically as important as aggregate TFP remains robust.

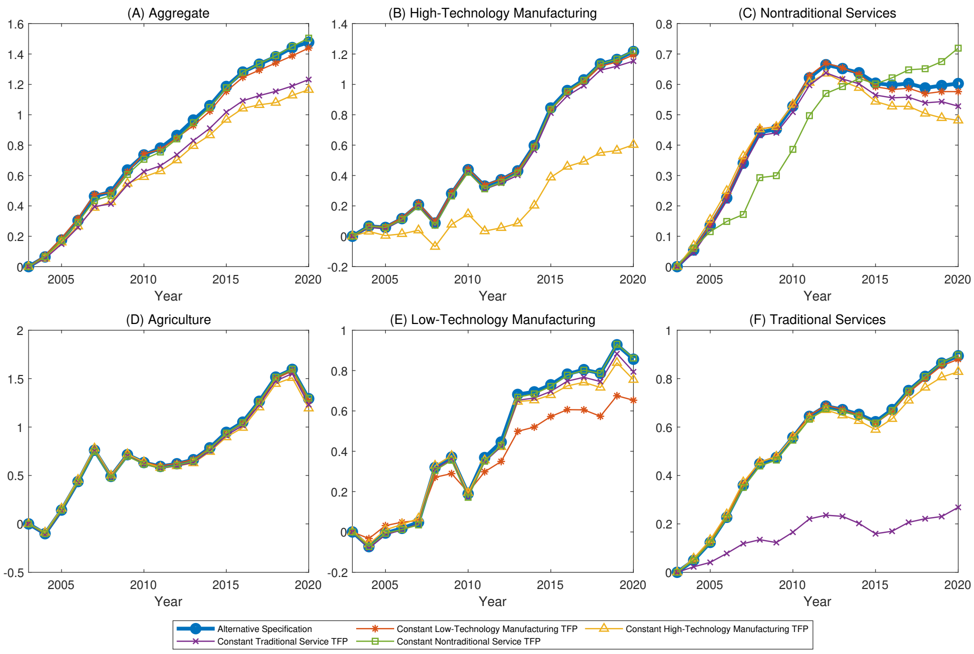

Figure A6: Effects of Subsector TFP Improvements on Economic Growth under the Alternative Specification

In summary, the counterfactual results obtained under the alternative calibration strategy, which matches observed sectoral shares, are quantitatively very similar to those from the baseline model. These results confirm the robustness of our main findings regarding the distinct mechanisms driving intra-sectoral transformation in manufacturing and services, the identification of key TFP growth engines, and the importance of TFP and capital deepening in China's past growth.

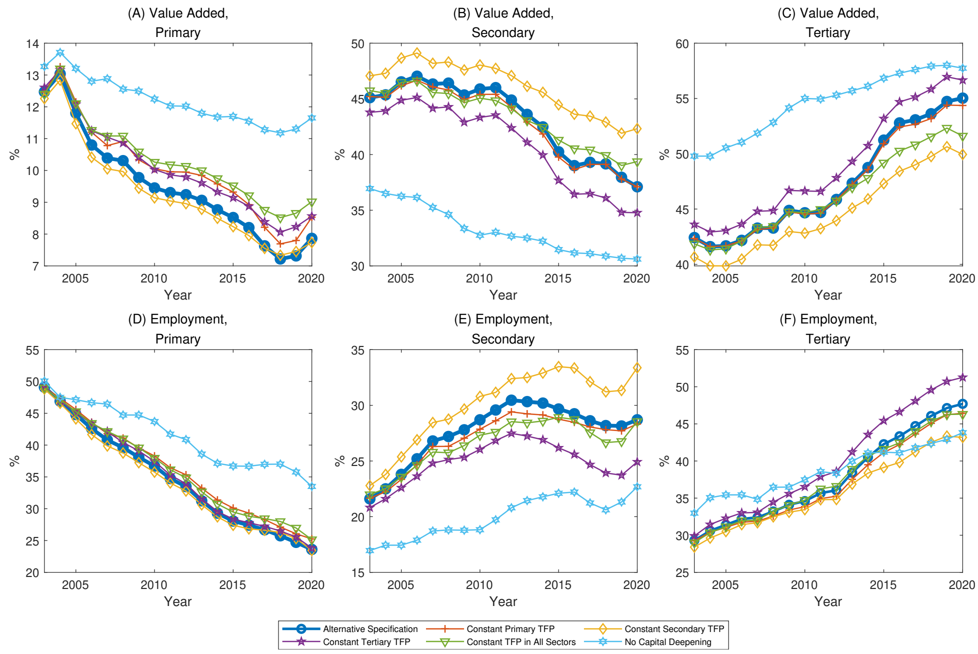

Figure A7: Effects of Broad Sector TFP Improvements on Inter-sectoral Structural Transformation under the Alternative Specification

Figure A8: Effects of Broad Sector TFP Improvements on Intra-sectoral Structural Transformation under the Alternative Specification

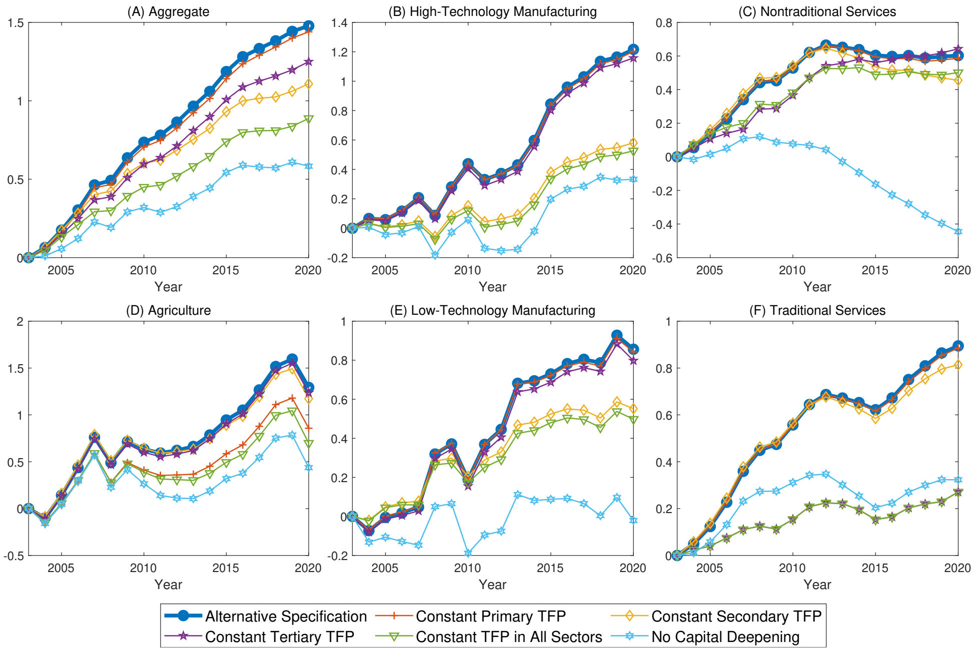

Figure A9: Effects of Broad Sector TFP Improvements on Economic Growth under the Alternative Specification

Appendix E Additional Figures for the Baseline Model

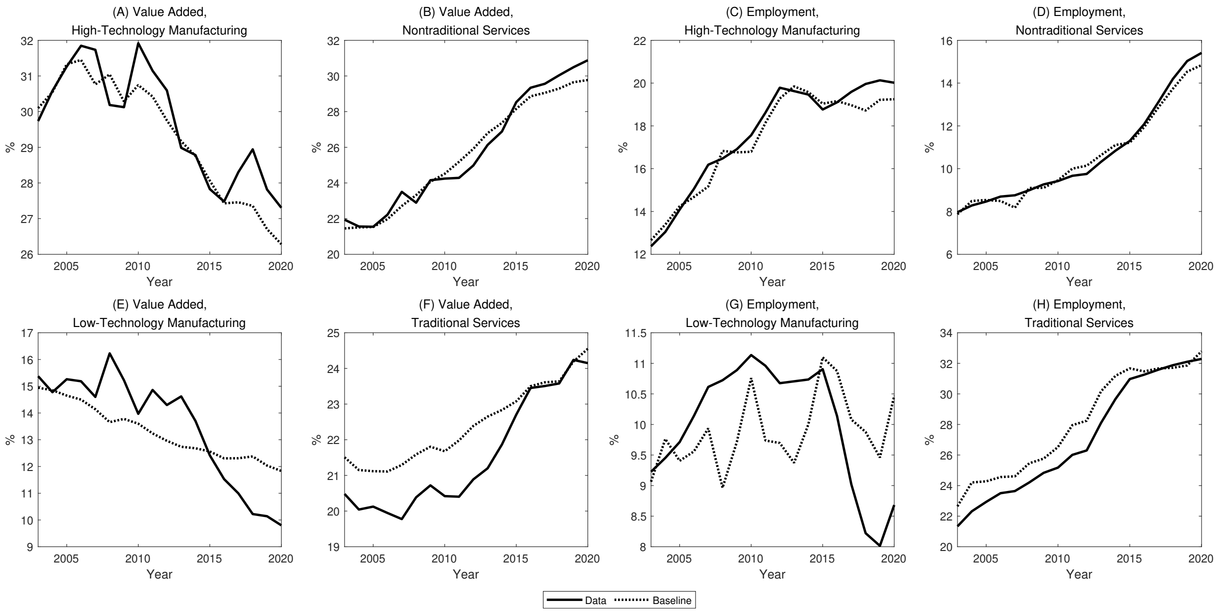

Figure A10: Shares of Non-Agricultural Subsectors in the Baseline Model

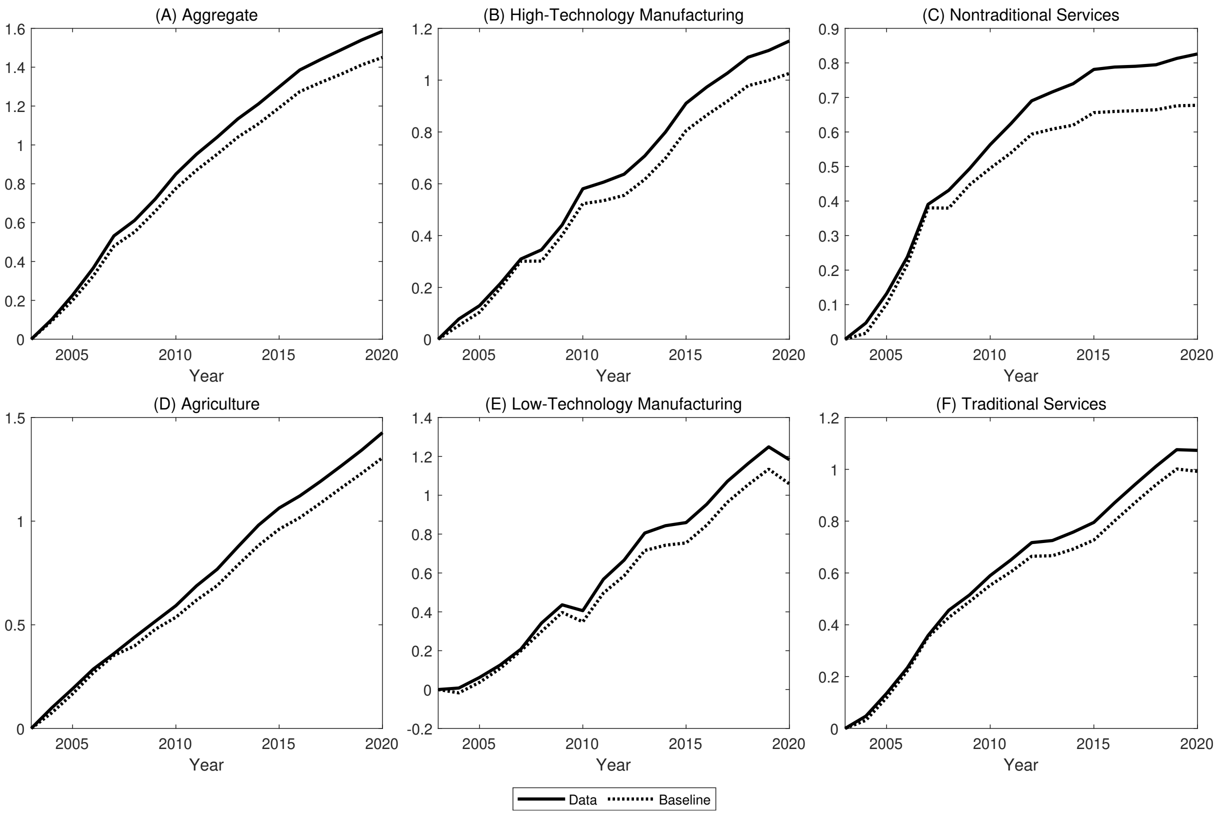

Figure A11: Aggregate Labor Productivity and Sectoral Output per Worker in the Baseline Model

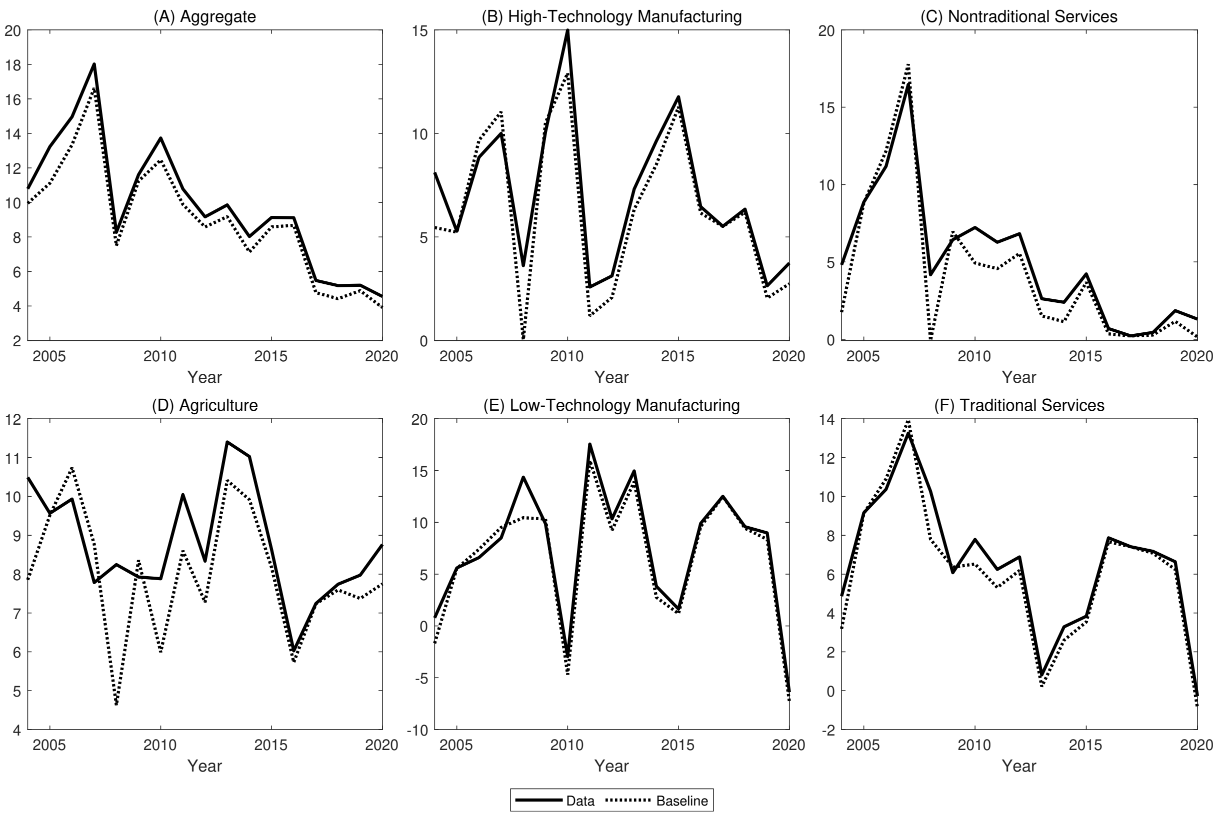

Figure A12: Growth of Aggregate Labor Productivity and Sectoral Output per Worker in the Baseline Model

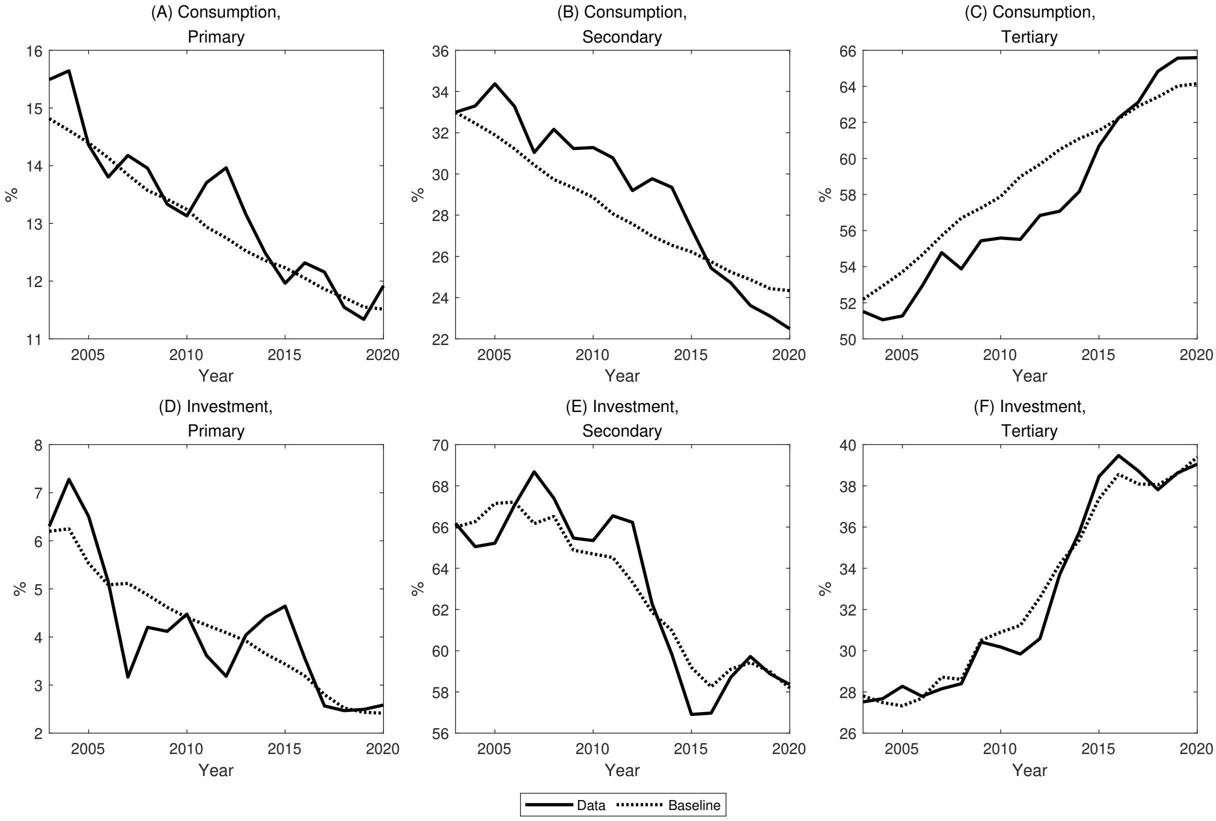

Figure A13: Sectoral Shares in Consumption and Investment in the Baseline Model

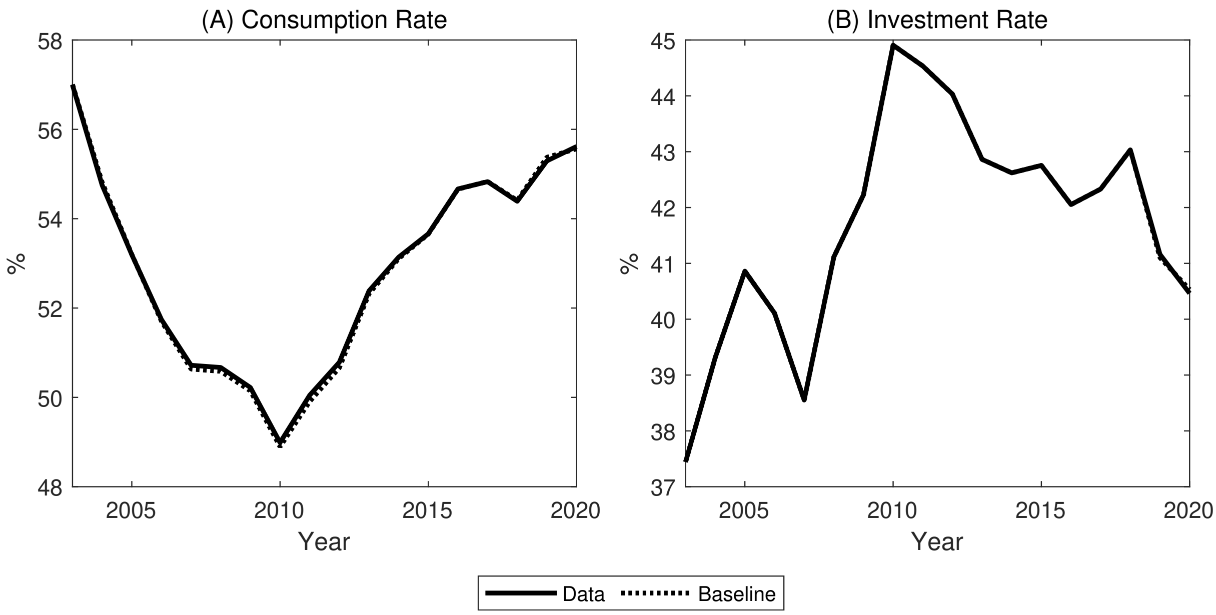

Figure A14: Consumption and Investment Rates in the Baseline Model

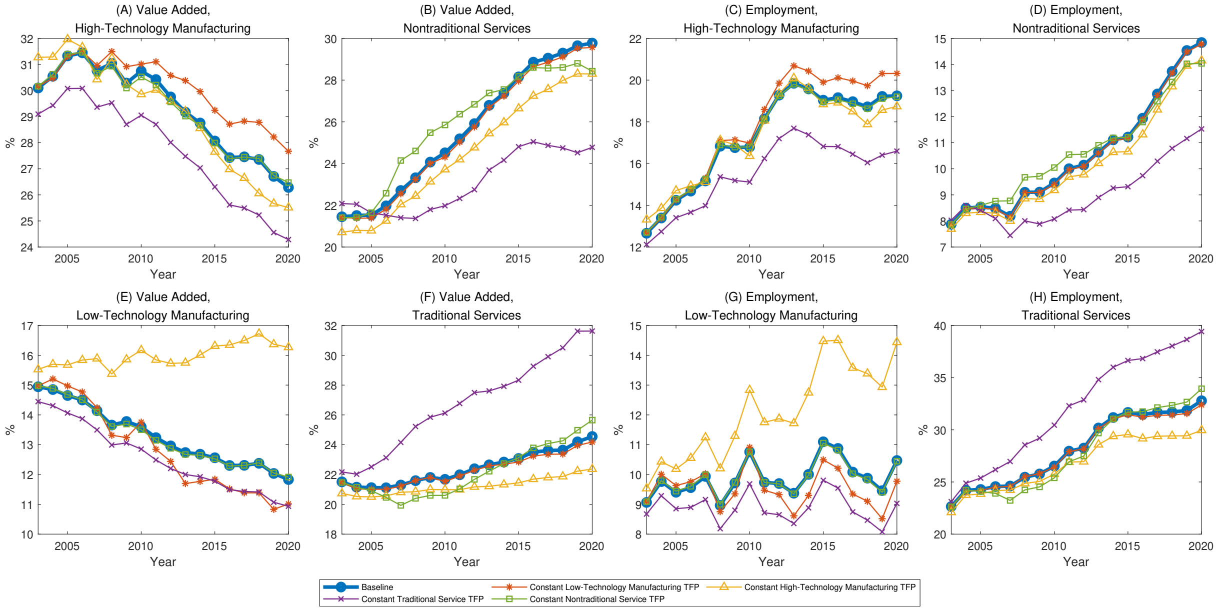

Figure A15: Effects of Subsector TFP Improvements on the Shares of Non-Agricultural Subsectors

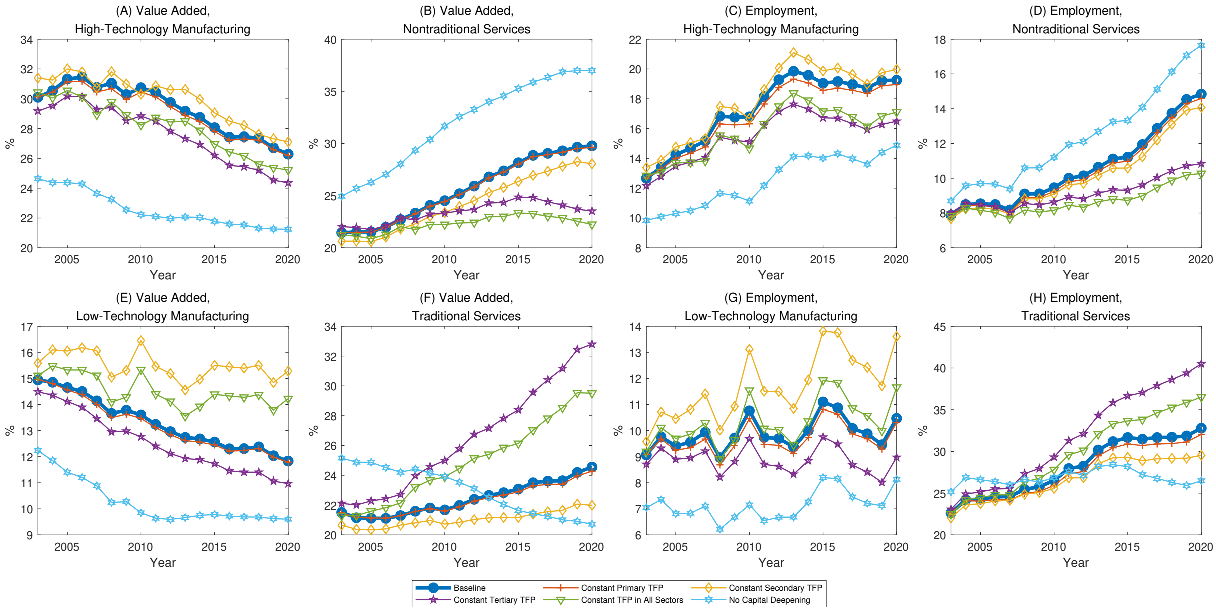

Figure A16: Effects of Broad Sector TFP Improvements on the Shares of Non-Agricultural Subsectors

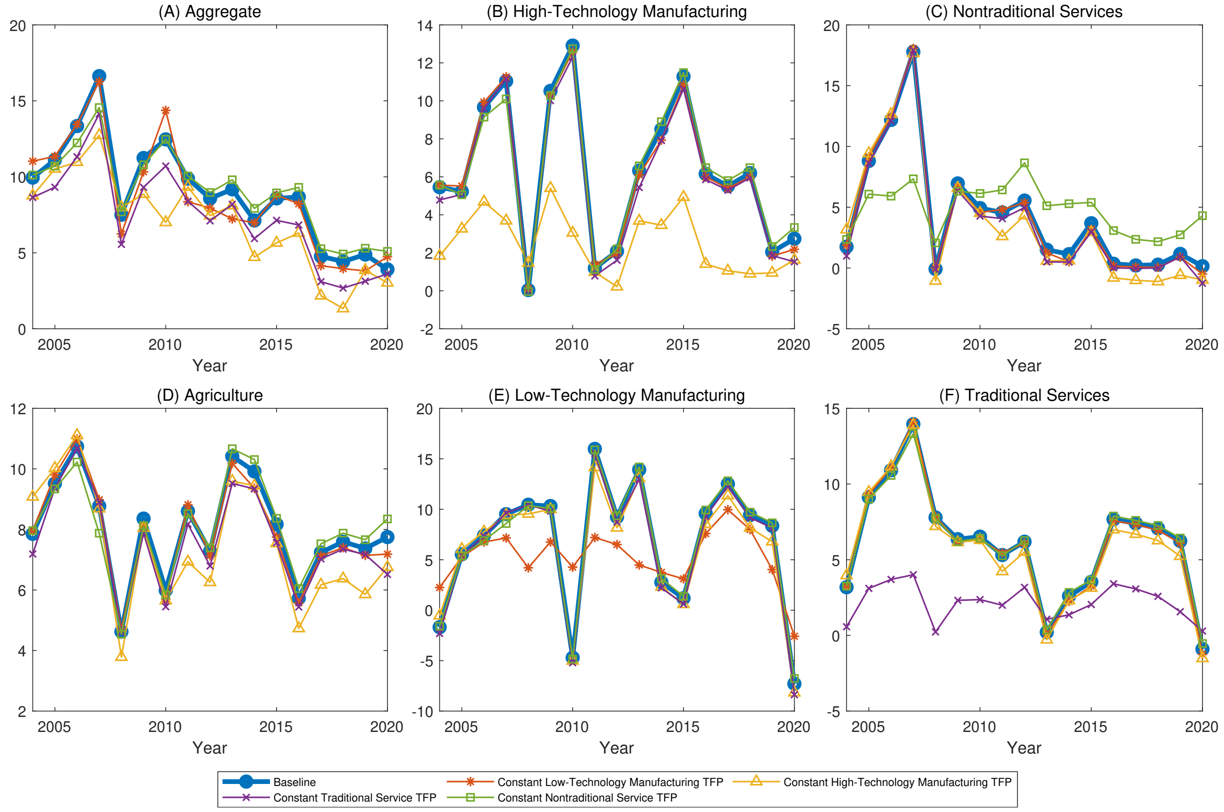

Figure A17: Effects of Subsector TFP Improvements on Growth Rates of Aggregate Labor Productivity and Sectoral Output per Worker

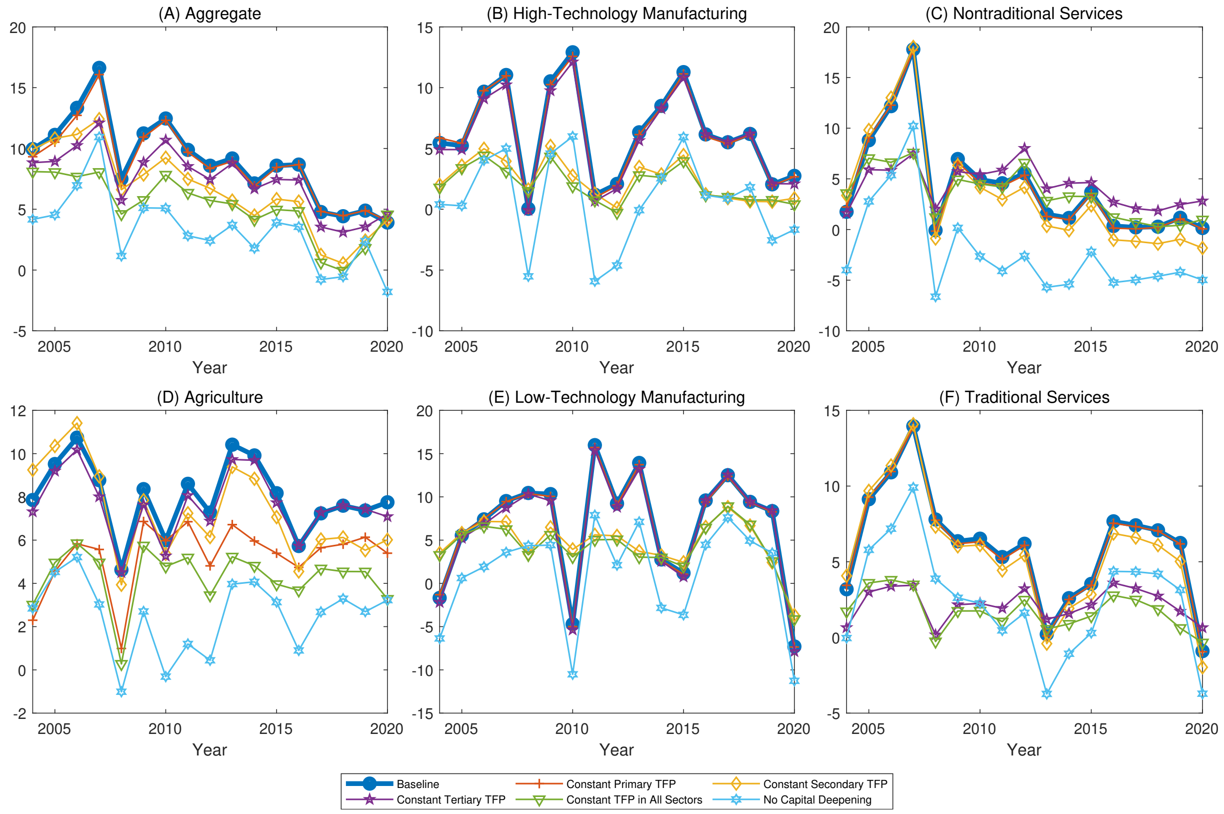

Figure A18: Effects of Broad Sector TFP Improvements on Growth Rates of Aggregate Labor Productivity and Sectoral Output per Worker

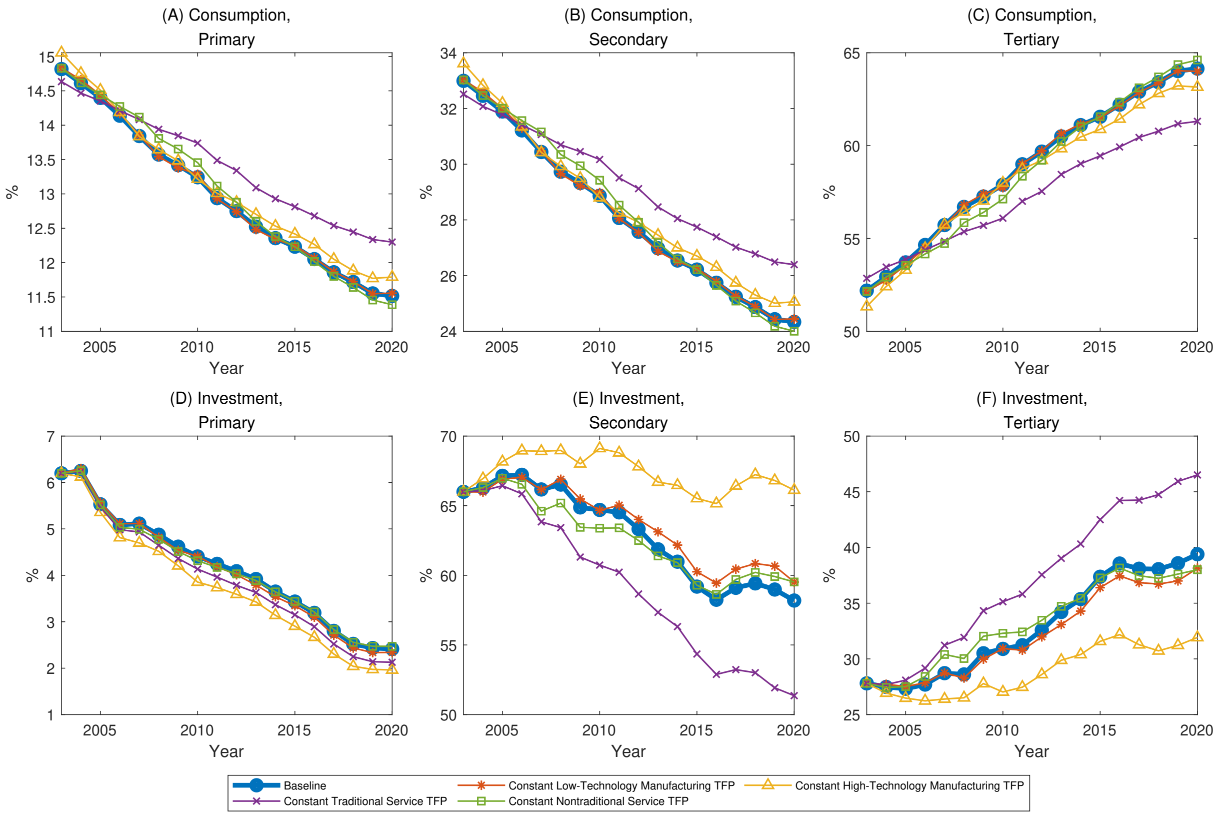

Figure A19: Effects of Subsector TFP Improvements on Sectoral Shares in Consumption and Investment

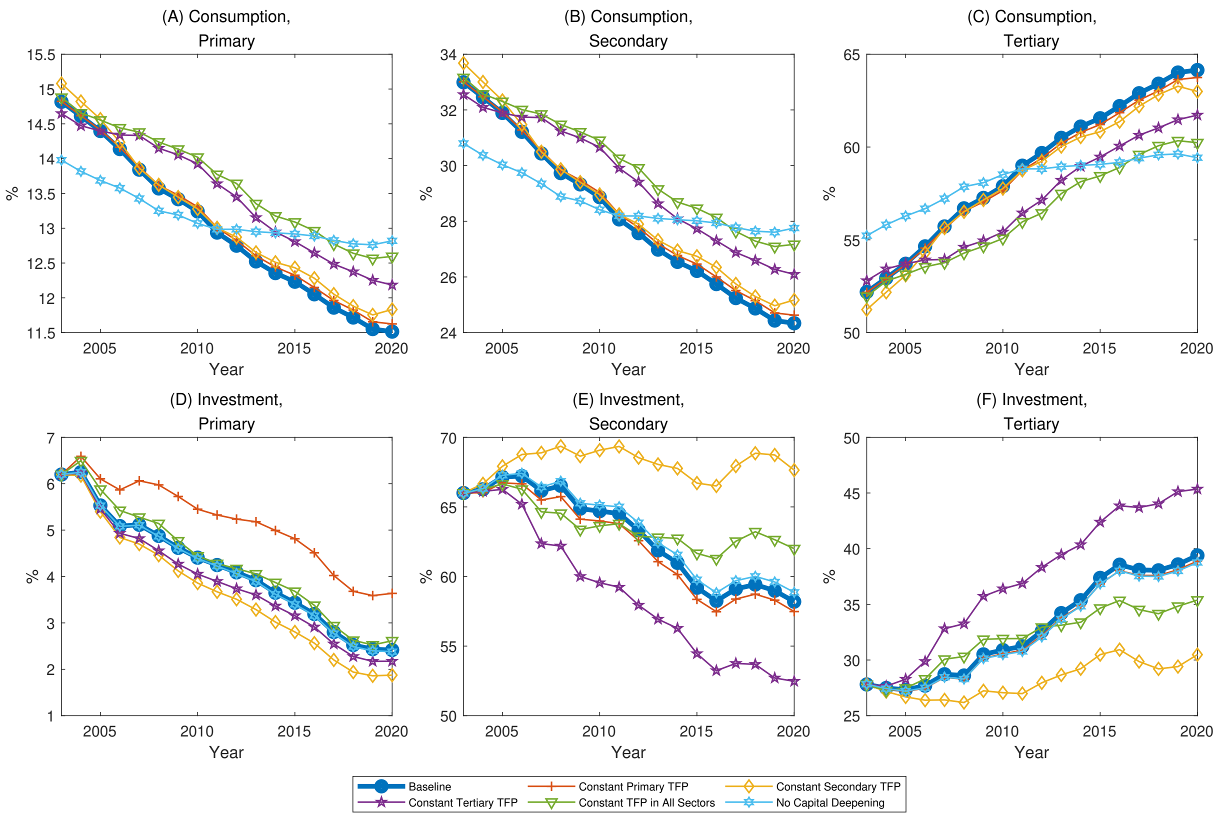

Figure A20: Effects of Broad Sector TFP Improvements on Sectoral Shares in Consumption and Investment

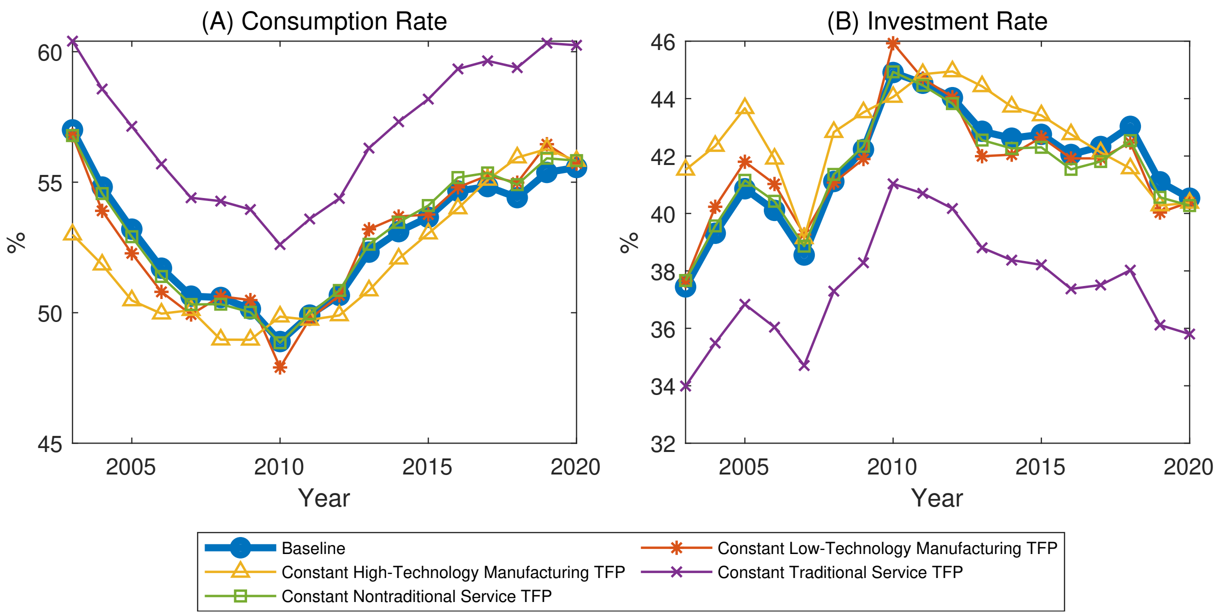

Figure A21: Effects of Subsector TFP Improvements on Consumption and Investment Rates

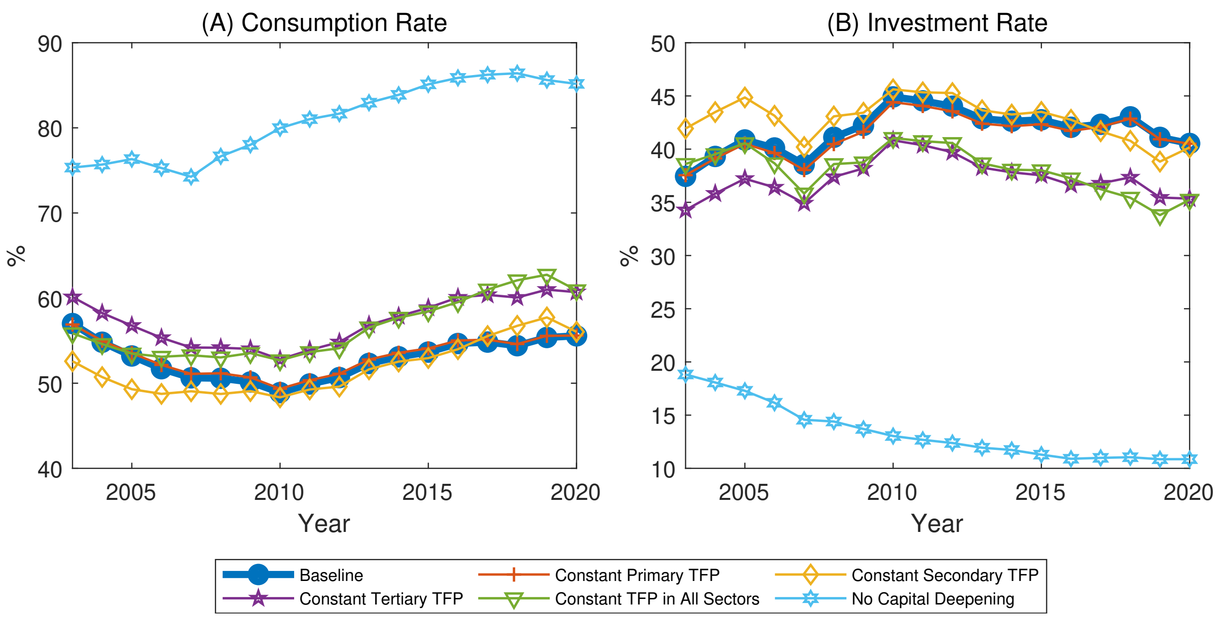

Figure A22: Effects of Broad Sector TFP Improvements on Consumption and Investment Rates

Appendix F Additional Figures under Alternative Specification

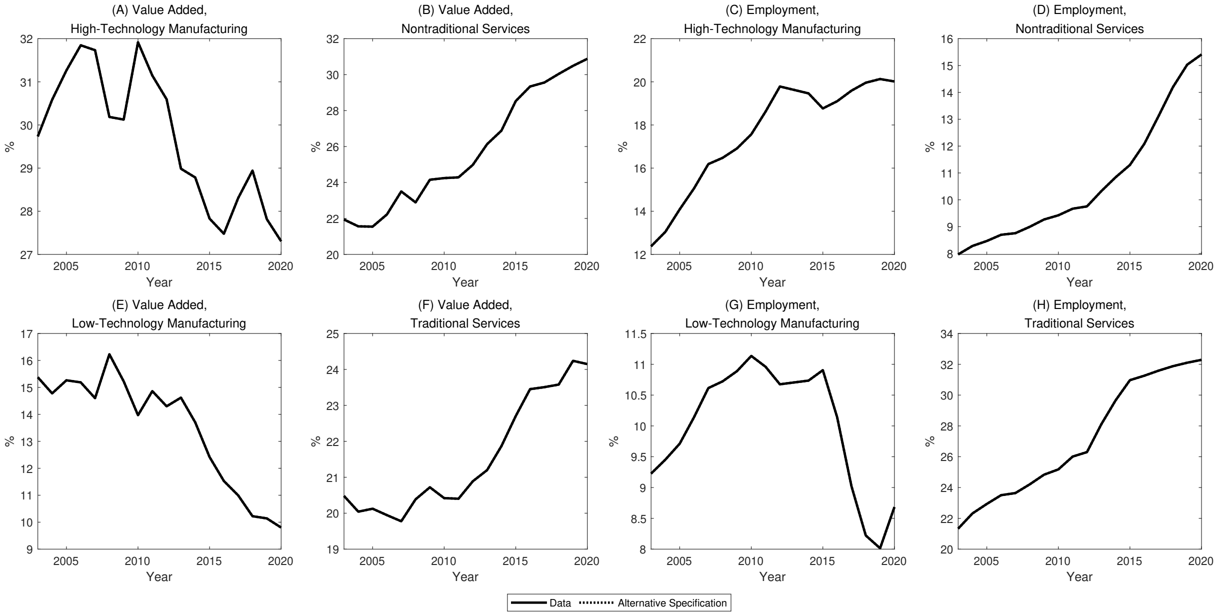

Figure A23: Shares of Non-Agricultural Subsectors under Alternative Specification

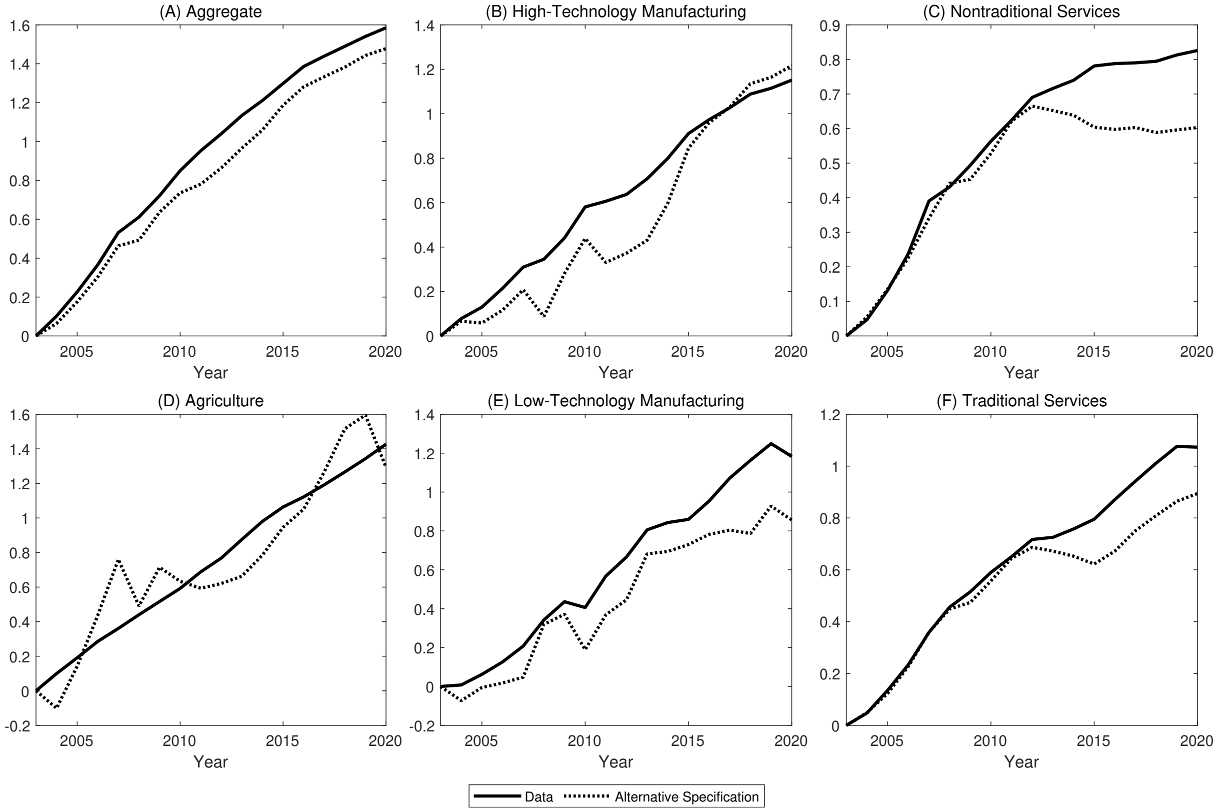

Figure A24: Aggregate Labor Productivity and Sectoral Output per Worker under Alternative Specification

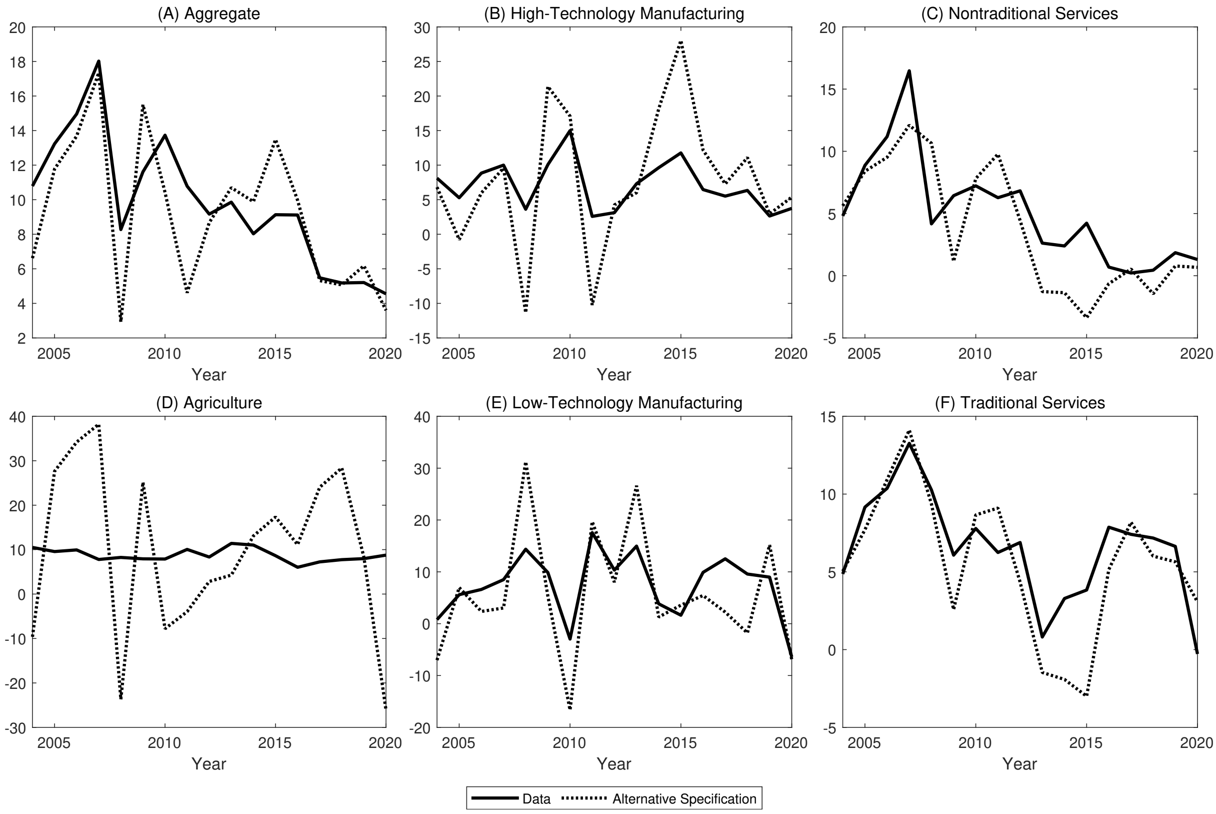

Figure A25: Growth of Aggregate Labor Productivity and Sectoral Output per Worker in the Baseline Model

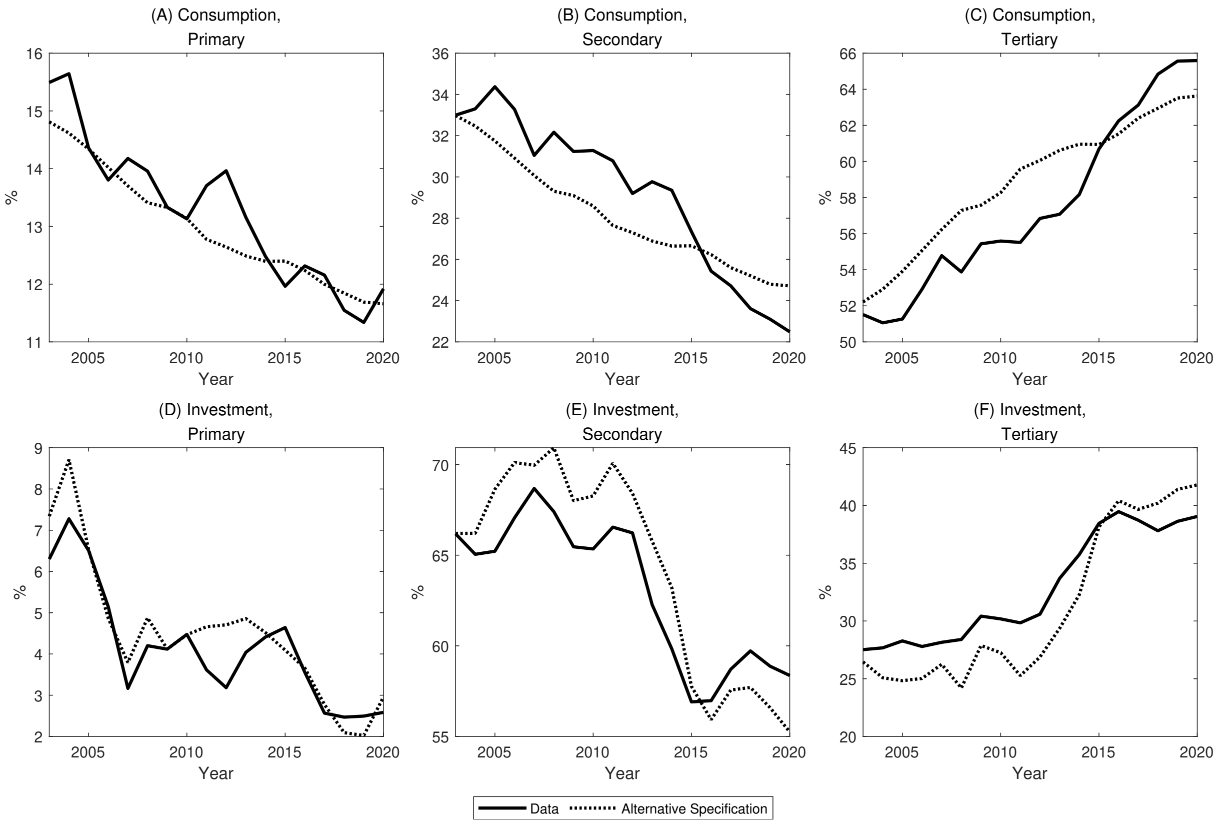

Figure A26: Sectoral Shares in Consumption and Investment under Alternative Specification

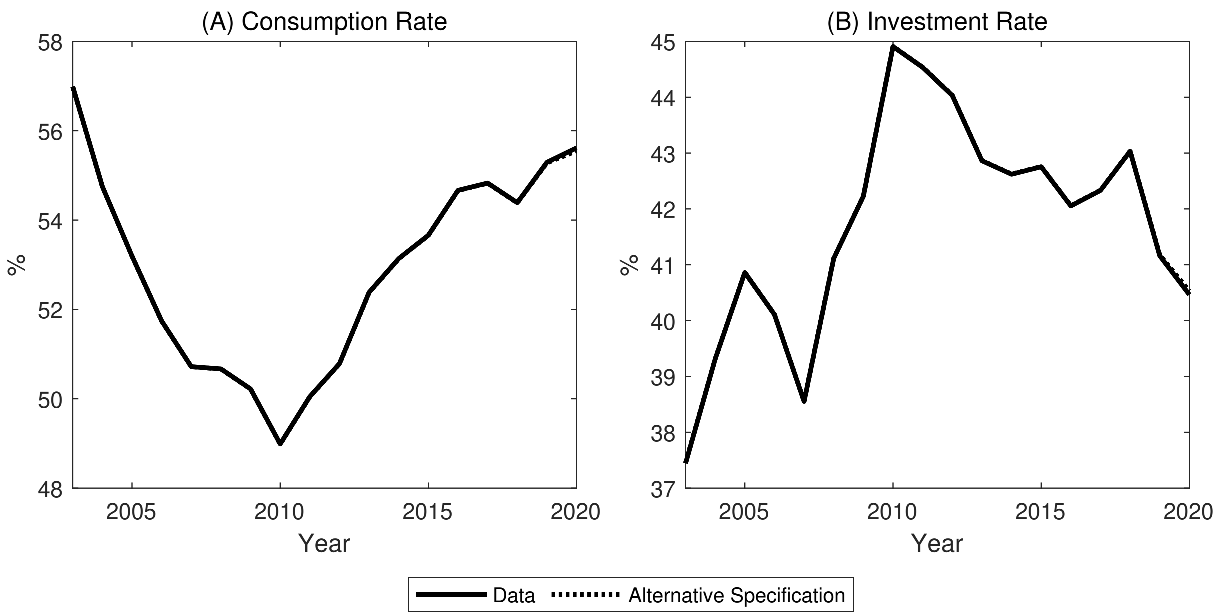

Figure A27: Consumption and Investment Rates under Alternative Specification

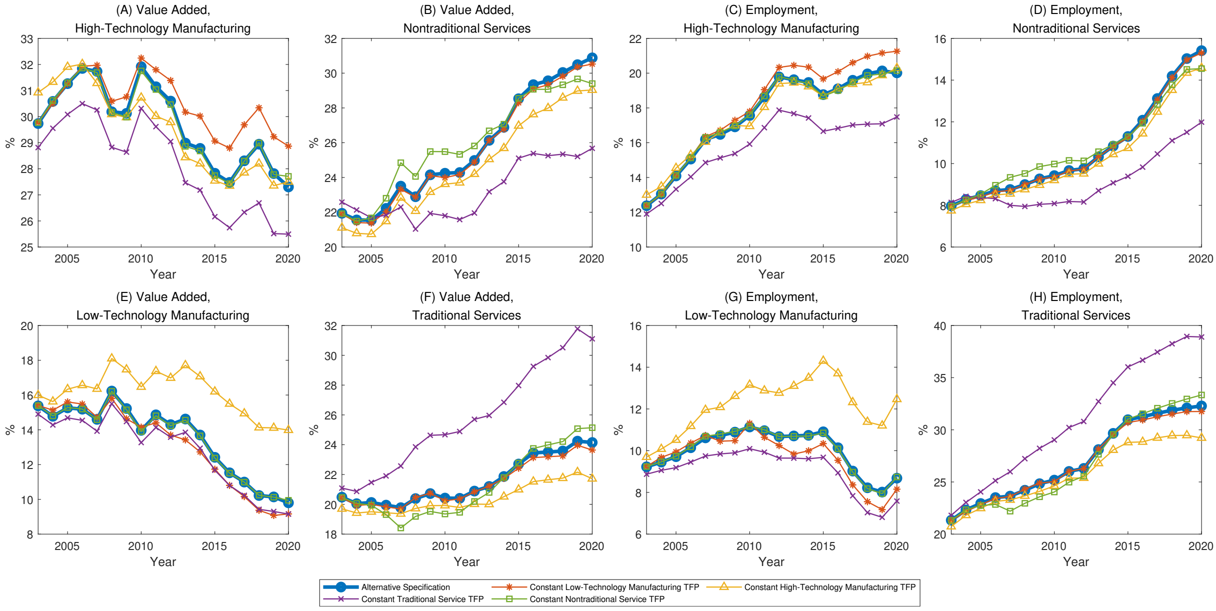

Figure A28: Effects of Subsector TFP Improvements on the Shares of Non-Agricultural Subsectors

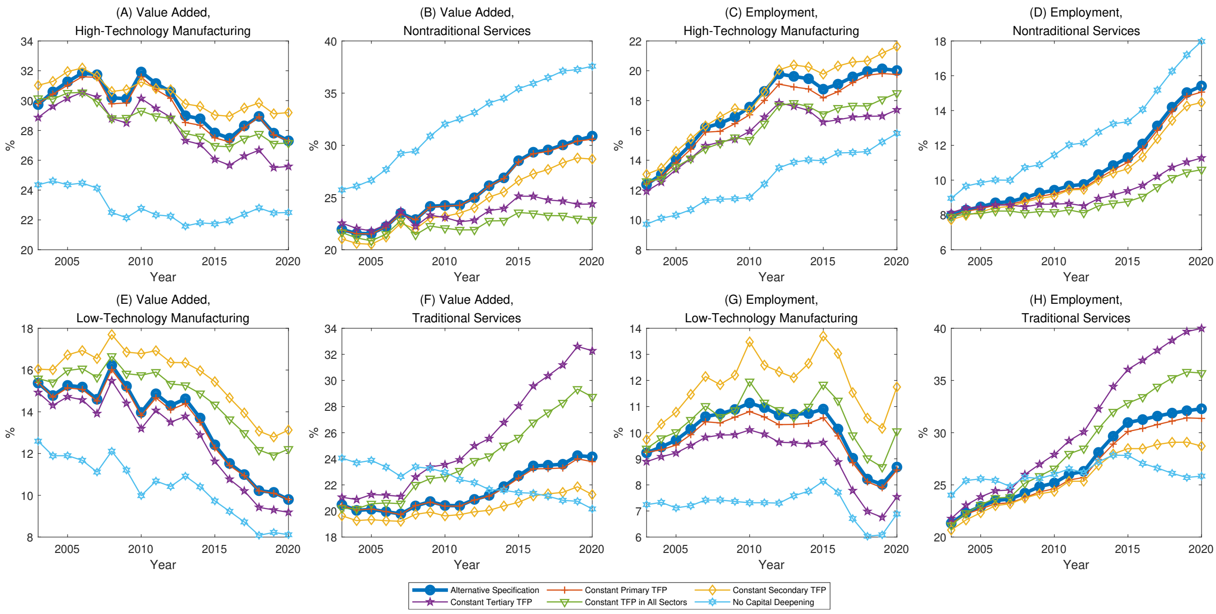

Figure A29: Effects of Broad Sector TFP Improvements on the Shares of Non-Agricultural Subsectors

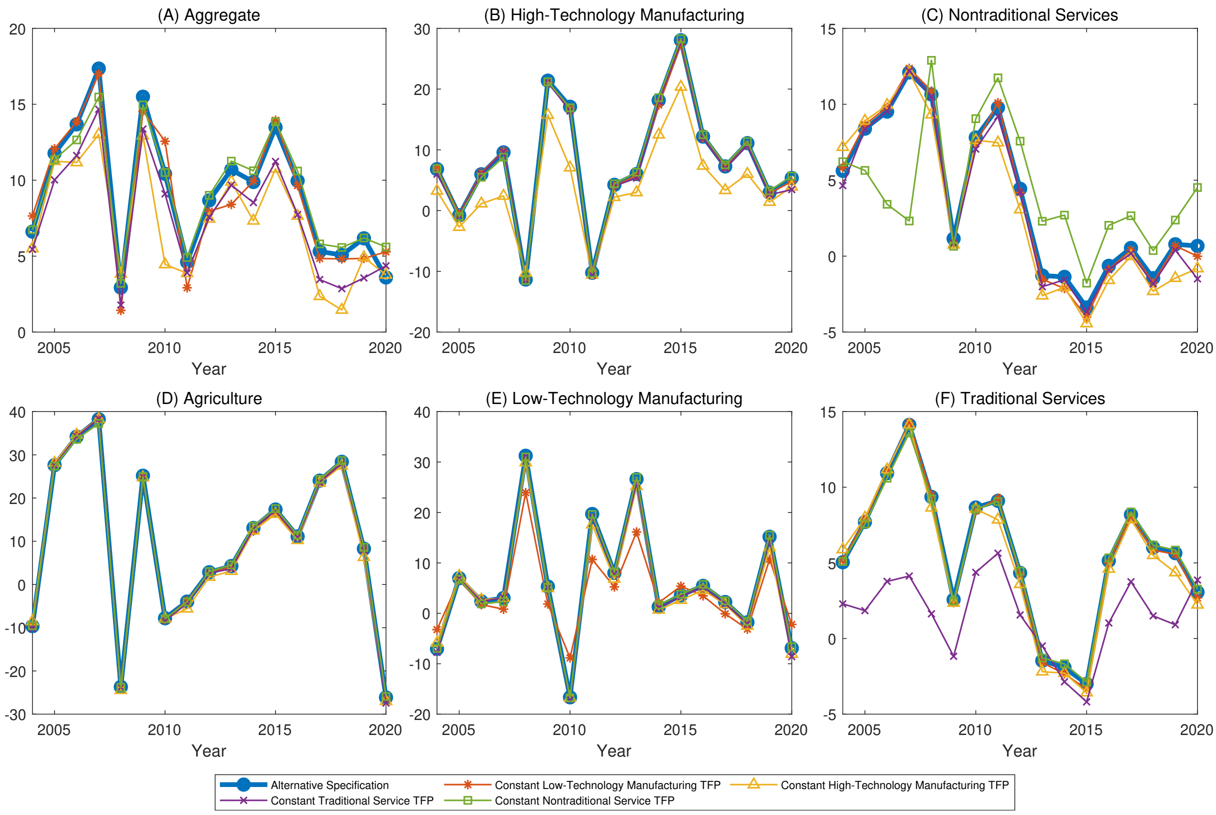

Figure A30: Effects of Subsector TFP Improvements on Growth Rates of Aggregate Labor Productivity and Sectoral Output per Worker

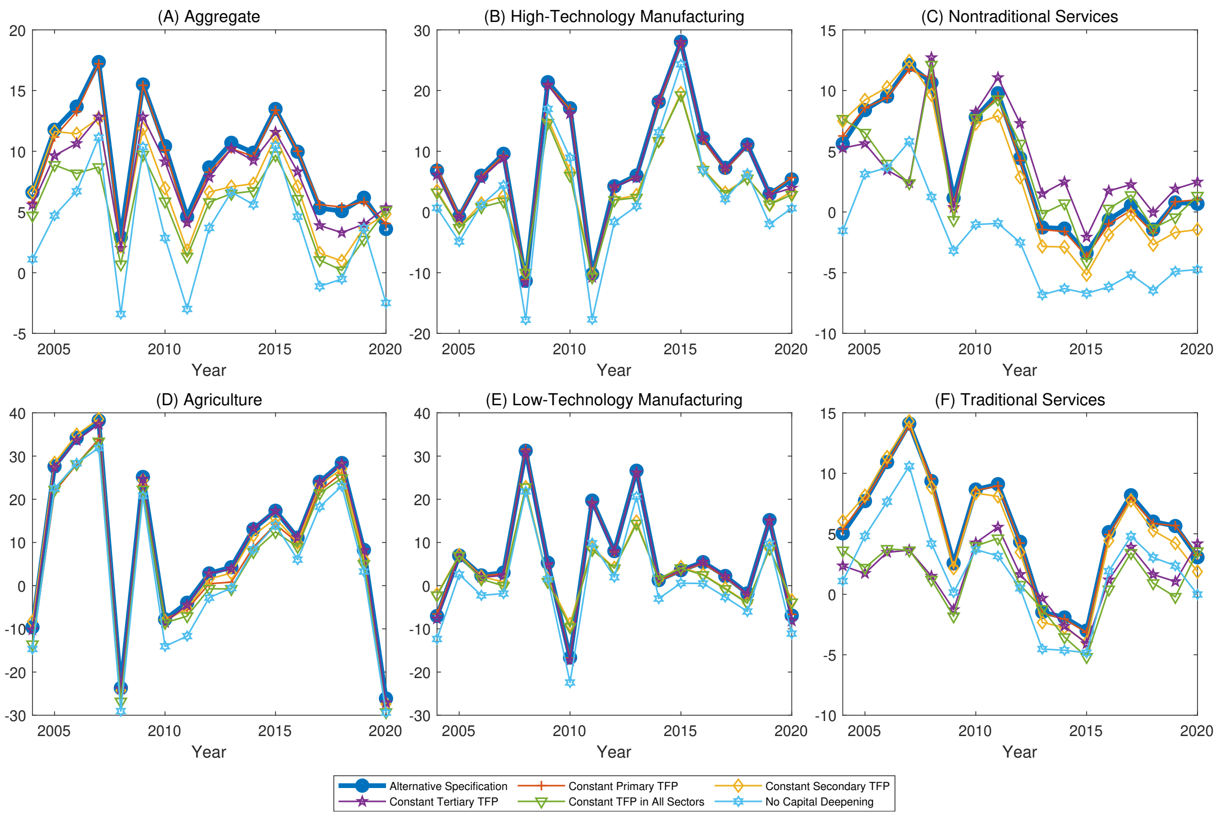

Figure A31: Effects of Broad Sector TFP Improvements on Growth Rates of Aggregate Labor Productivity and Sectoral Output per Worker

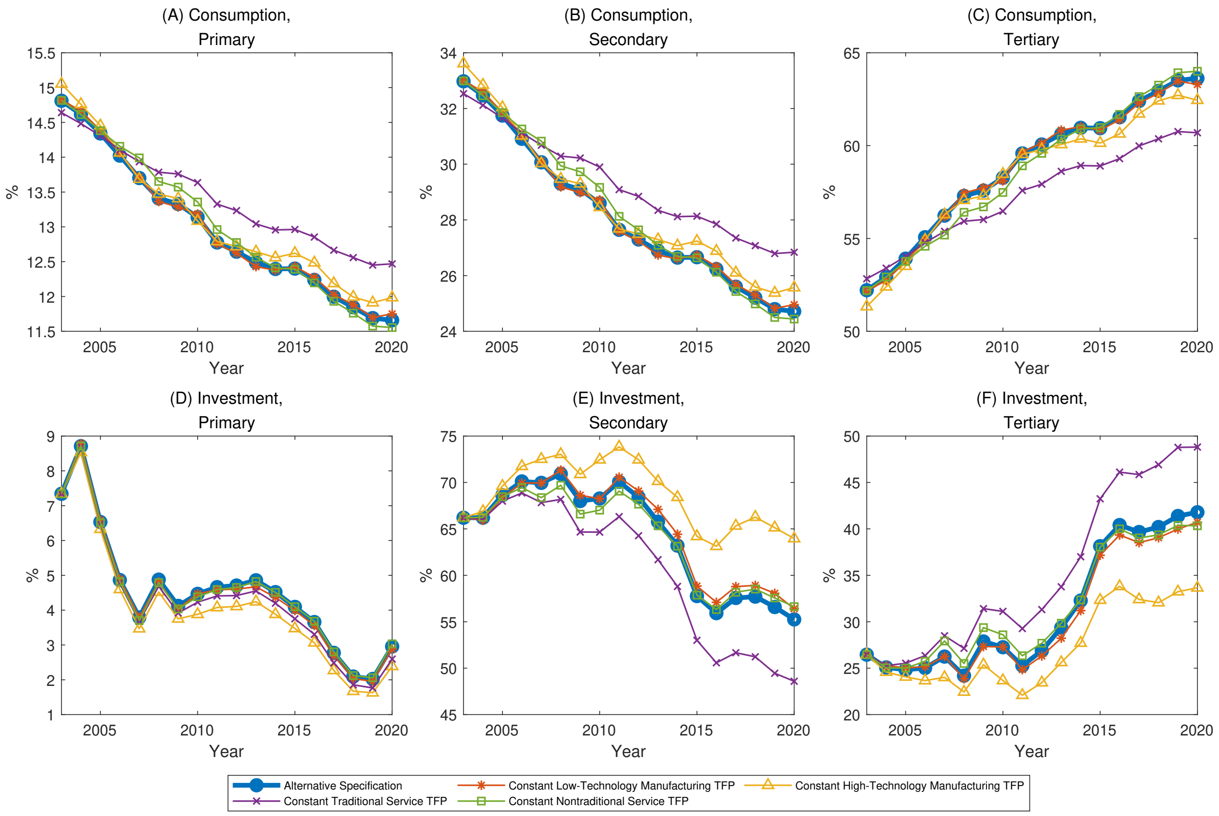

Figure A32: Effects of Subsector TFP Improvements on Sectoral Shares in Consumption and Investment

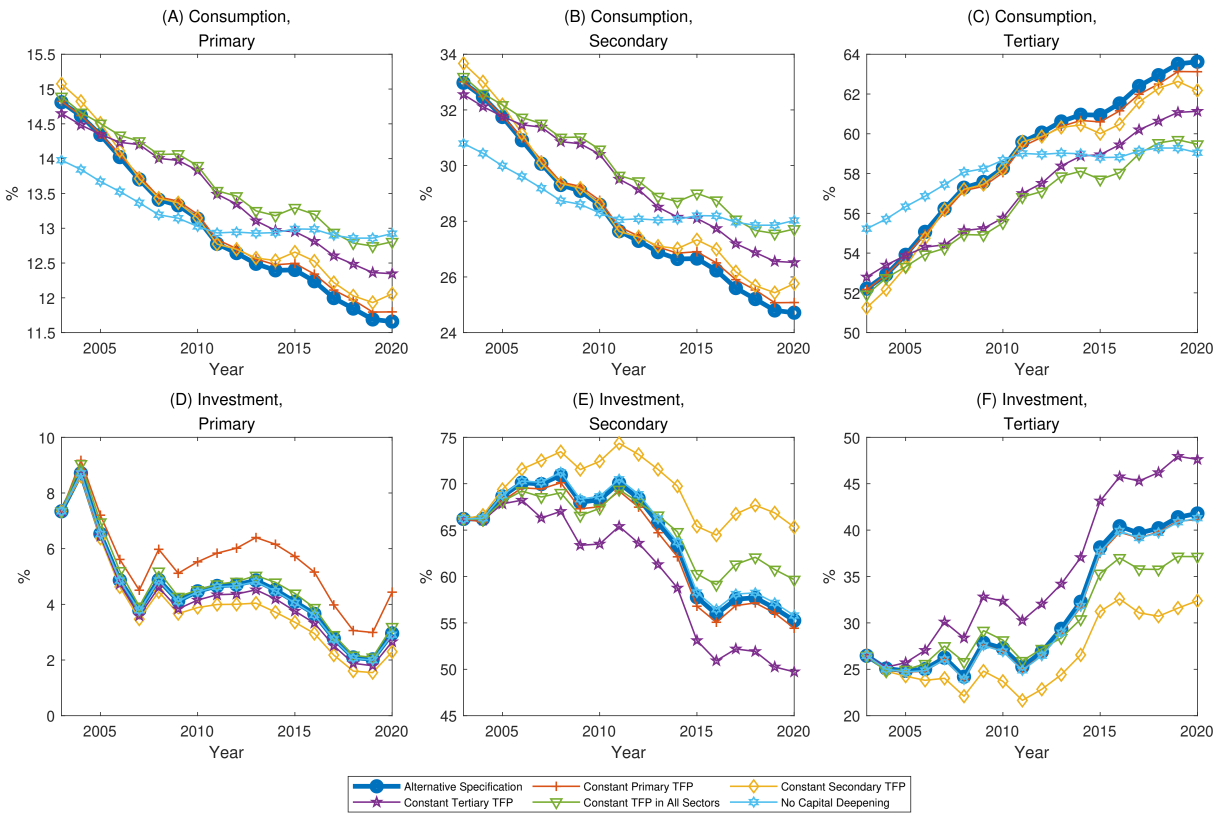

Figure A33: Effects of Broad Sector TFP Improvements on Sectoral Shares in Consumption and Investment

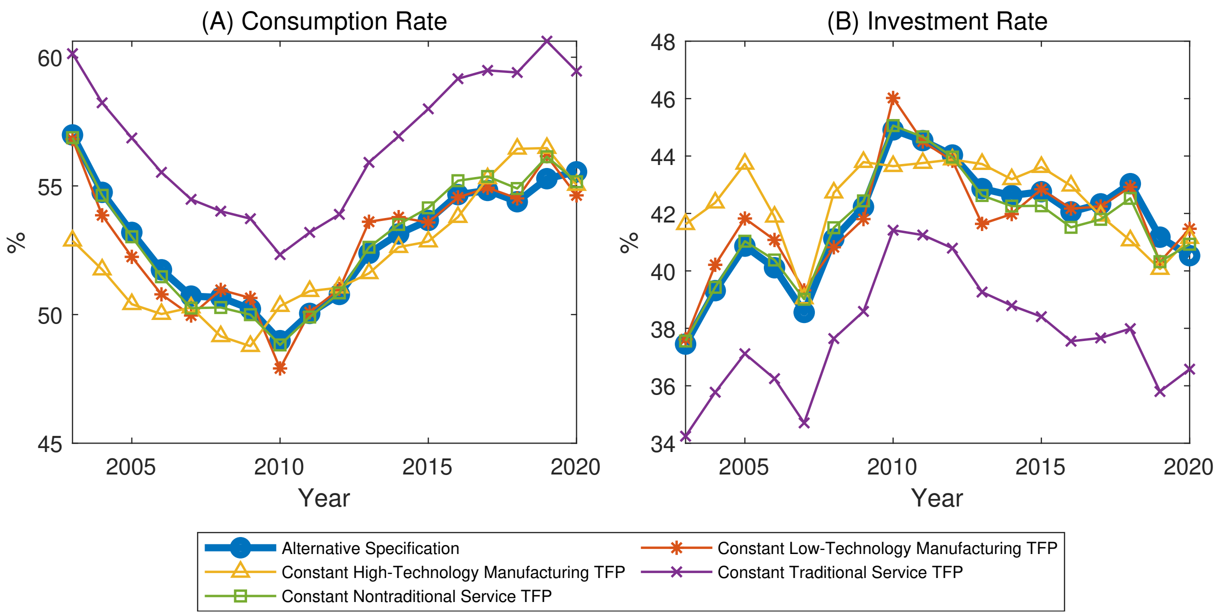

Figure A34: Effects of Subsector TFP Improvements on Consumption and Investment Rates

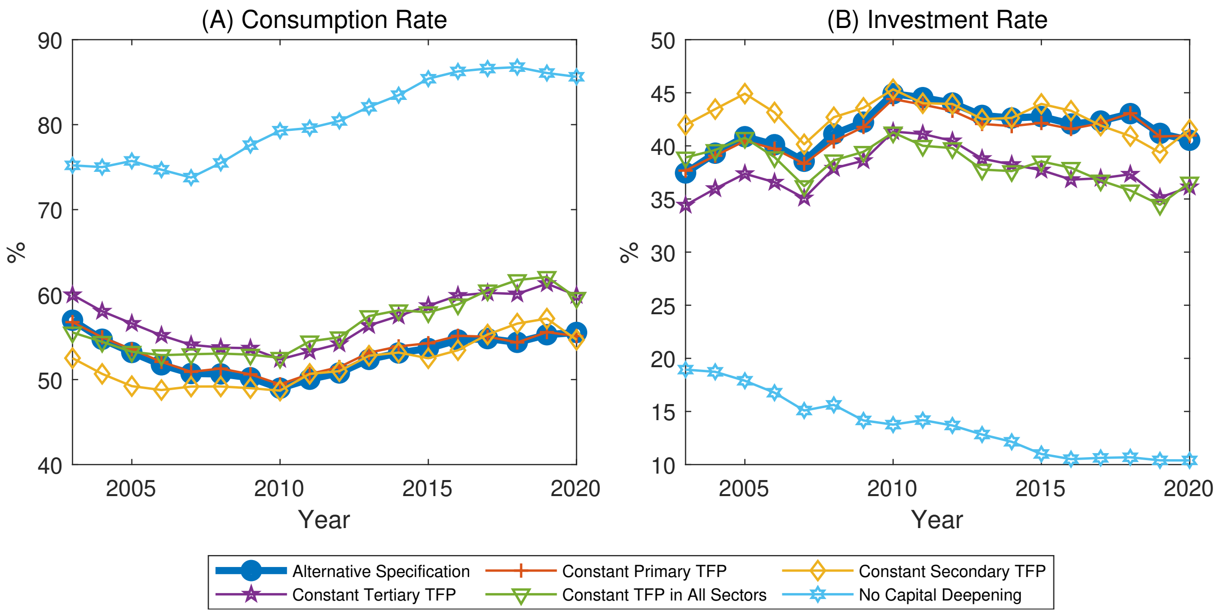

Figure A35: Effects of Broad Sector TFP Improvements on Consumption and Investment Rates

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