Estimation of China’s Industry-Level TFP and Analysis of Growth Drivers

Xianchun Xu, Zhongwen Zhang, Zekun Lei, Zihao Chang

By examining how China’s total factor productivity (TFP) evolved over time on the industry level, we can help determine where China should head for in a new era featured by a shift from old to new growth drivers and promote high-quality economic development. Based on consistent and comparable data of input and output, this paper measures total factor productivity on the industry level through growth accounting method and then estimate the overall productivity of the entire economy with aggregate production possibility frontier (APPF) and cross-industry direct aggregation. On this basis, China’s growth drivers are analyzed. Results show that from 1985 to 2015, capital input was the top contributor to China’s economic growth and TFP also played an important role. Up to 70 percent of the aggregate TFP growth could be attributed to increases in industrial TFP, while the remaining 30 percent came from improved cross-industrial resource allocation.

Keywords: total factor productivity (TFP), efficiency of resource reallocation, analysis of growth drivers

1. Introduction

Forty years after the launch of the reform and opening-up policy, China has made remarkable achievements in its economic development. According to the National Bureau of Statistics, China’s nominal GDP grew from RMB367.9 billion in 1978 to RMB90030.9 billion in 2018. Based on constant prices, the latter is 36.8 times the former and the average annual growth rate is up to 9.4 percent. However, China shifted from high-speed to mid-to-high-speed growth in 2012. As President Xi Jinping said at the Central Economic Work Conference in 2013, China entered an economic new
normal featured by slowdown in economic growth, difficult structural adjustments, and absorbing the effects of the previous economic stimulus policies. It was made clear in the report delivered at the 19th National Congress of the Communist Party of China that socialism with Chinese characteristics had ushered in a new era and China’s economy had moved from the stage of high-speed growth to one of high-quality development. The key to high-quality development is the successful shift from old to new growth drivers and an increase in TFP.

From the perspective of neoclassical economics, to study the growth drivers of an economy, one must do estimations and analysis based on factors of production. This means that efforts must be made to separate the contributions of factor input and TFP to economic growth (Solow, 1957). Research has been done on China’s growth drivers from the perspective of TFP. Some considered only the aggregate TFP on the macro level or the TFP of some specific industries (Chow, 1993; Chow and Lin, 2002; Zhang, 2002), some estimated the TFP of specific sectors with microeconomic data (Brandt et al., 2012; Yang, 2015; Gai et al., 2017), and only a small amount of work has been done covering both of the two approaches. Traditionally, TFP is deemed equal to technical progress, but the truth is that resource allocation across different sectors is also a very important source of TFP increase (Chenery et al., 1986). China is an economy in transition. Many research findings show that the market-oriented development since the reform and opening-up has achieved a great deal. Major moves such as the reform towards the household contract responsibility system in rural areas, the reform of state-owned enterprises (SOEs), China’s accession to the World Trade Organization (WTO) and the resulted integration into the global competition are widely believed to have served as powerful drivers for China’s economic growth (Hsieh and Klenow, 2009; Song et al., 2011; Cai et al., 2018; Tombe and Zhu, 2019). However, it should be pointed out here that there are still institutional constraints and barriers that hamper the free flow of capital, labor, and other factors of production (Zhang, 2015). Therefore, to dig deeper into China’s growth drivers, what needs to be done is to go beyond analysis of the aggregate TFP and build a framework to align the performance of specific industries to that of the economy on the whole. This will reveal which industries exactly contributed to the increases in the aggregate TFP and offer a better understanding of the efficiency of resource reallocation across different industries.

On the basis of the framework of Massell (1961) and Jorgenson et al. (1987), this paper builds a framework to calculate the APPF based on the industrial value-added function. Then, it uses the cross-industry direct aggregation method to carry out more in-depth analysis on China’s growth drivers across the past development periods, so as to find out the industries that contributed the most to the higher efficiency and the efficiency of resource reallocation across different industries. Meanwhile, this paper adopts an APPF approach that has fewer assumptions to estimate the aggregate TFP.
of the Chinese economy with the production function. Through comparison, it points out how assumptions of dependence of the aggregate production function impacts the estimated TFP.

Existing estimations of China’s TFP differ greatly mainly because there are large discrepancies in methodology and the estimated factor inputs. Among all methods for productivity estimation, growth accounting shows clear advantages in revealing the internal mechanism or driving forces for TFP changes (Bai and Zhang, 2014) and is widely used by international organizations and the statistics authorities of many governments. Therefore, growth accounting is also used in this paper to estimate TFP on the macro and industry levels. Meanwhile, to make the TFP estimations comparable, data on capital and labor input in different industries must be homogeneous (Jorgenson et al., 1990). However, due to limited data availability, most research efforts, except those based on the KLEMS framework (Ren and Sun, 2009; Cao et al., 2009; Sun et al., 2012; Wu, 2015a; Wu, 2019), did not do anything to tackle the heterogeneity of factor input data.

This paper, based on consistent and comparable data of input and output, conducts empirical study on China’s economy over the period of 1985–2015. In constructing data of capital input, society-wide fixed asset investment is carefully distinguished from fixed capital formation. For labor input, industry-specific data of Wu (2019) is used for it is the most detailed such data available for the time being. Based on these, this paper gives more objective and better-grounded estimations of increases in aggregate TFP and industrial TFP, laying a solid foundation for accurate identification of growth drivers of the Chinese economy.

Here is an outline of the rest of this paper: The second part presents the accounting framework, the third part provides the data, the fourth part analyzes industrial productivity, and the last part is the conclusions.

2. Accounting Framework

2.1. Industrial Growth Accounting

In this paper, the economy is divided into 37 industries and the industrial value-added production function is assumed to be Hicks neutral:

\[ Y_i = F_i(A_i, K_i, L_i) \] (1)

Here, \( Y_i \) stands for industrial value-added (constant price), and \( K_i \) and \( L_i \) are respectively the capital input and labor input in the industry concerned. Capital input is the sum of input in the forms of buildings and equipment which are weighted with corresponding rental prices. Industry-specific labor input is categorized based on
gender, age and education background and inputs of different categories of labor are then added up to produce the gross labor input of a given industry. \( A_i \) stands for the TFP of industry \( i \) and the production function \( F_i \) of industry \( i \) is assumed as a translog function.

Assume the market is perfectly competitive, the production capacity is fully used, and the returns on scale is constant, the industrial TFP growth rate \( v_i \) is expressed as follows:

\[
v_i = \Delta \ln Y_i - \bar{v}_K \Delta \ln K_i - \bar{v}_L \Delta \ln L_i
\]

(2)

where \( \Delta \ln Y_i = \ln \left( \frac{Y_i}{Y_{i-1}} \right) \), standing for the change rate of constant price-based value-added between two periods. Similarly, all other difference signs in the equation indicate change rates between two periods. \( t \) indicates the period. \( \bar{v}_K \) and \( \bar{v}_L \) respectively stand for the average value of capital input and labor input over two periods. That is, \( \bar{v}_K = \frac{1}{2} (v_{ki} + v_{ki,-1}) \) and \( \bar{v}_L = \frac{1}{2} (v_{li} + v_{li,-1}) \).

The shares of capital input and labor input in gross value-added are respectively expressed by:

\[
v_{ki} = \frac{P_{ki} K_i}{P_{yi} Y_i} \quad \text{and} \quad v_{li} = \frac{P_{li} L_i}{P_{yi} Y_i}
\]

Given that China adopts the single-deflation method for GDP accounting based on constant prices, \( P_{yi} \) stands for producer price on the industry level, \( P_{ki} \) is the rental price of capital goods, and \( P_{li} \) is the price of labor input. Since returns on scale is assumed constant, \( v_{ki} + v_{li} = 1 \).

2.2. Aggregate Growth Accounting

To analyze the aggregate TFP, work needs to be done to reach from the industry level to the macroeconomic level and according to Jorgenson et al. (2005), there are three ways to do this: (1) aggregate production function (APF); (2) aggregate production possibility frontier (APPF); and (3) cross-industry direct aggregation.

Among these, APF is widely used for the estimation of aggregate TFP but it requires the most assumptions: (1) industry-level APF can be divided for value-added and intermediate input; (2) the value-added function is the same for all industries; (3) the capital input function or labor input function for the aggregation of heterogeneous data is the same for all industries; and (4) each type of capital or labor has the same price across all industries. Since different industries usually have different production
models, assumption (2) is not likely to apply in the economic reality. Thus, APPF gives up on assumption (2) and does not allow constant price-based GDP to be produced simply by adding up the constant-price value-added of all industries. Cross-industry direct aggregation is a method that produces aggregate TFP by directly adding up the weighted value-added of various industries. It imposes no constraint on value-added and factor input across industries and goes further from APPF to give up on the assumption concerning prices of homogeneous capital or labor across industries. Therefore, a comparison between the latter two methods can help tackle the issue of the efficiency of cross-industry resource allocation.

With APPF, constant-price GDP growth rate is the Tornqvist aggregation of the growth rates of constant-price value-added of all industries:

$$\Delta \ln Y = \sum_{i} \bar{w}_{i} \Delta \ln Y_{i}$$

(3)

Here, \( Y \) is constant-price GDP, \( \bar{w}_{i} \) is the two-period average share of nominal value-added in nominal GDP of industry \( i \), that is, \( \bar{w}_{i} = \frac{1}{2} \left( w_{i} + w_{i,t-1} \right) \), and the share of nominal value-added in nominal GDP of industry \( i \) is expressed as follows:

$$w_{i,t} = \frac{P_{yt}Y_{yt}}{\sum_{i} P_{yt}Y_{yt}}$$

The growth rates of aggregate capital input and aggregate labor input are respectively the Tornqvist aggregation of heterogeneous capital services and heterogeneous labor services, specifically:

$$\Delta \ln K = \sum_{k} \bar{w}_{k} \Delta \ln K_{k} \quad \Delta \ln L = \sum_{l} \bar{w}_{l} \Delta \ln L_{l}$$

(4)

Here, \( K \) is aggregate capital input, \( L \) is aggregate labor input, \( K_{k} \) is the input of capital of category \( k \), \( L_{l} \) is the input of labor of category \( l \). Subscript \( k \) is used for different categories of capital such as buildings and equipment, and subscript \( l \) is for different categories of labor based on gender, age, and education background. \( \bar{w}_{k} \) and \( \bar{w}_{l} \) respectively stand for the two-period average of the share of Category-\( k \) capital input in aggregate capital input and the two-period average of the share of Category-\( l \) labor input in aggregate labor input, i.e. \( \bar{w}_{k} = \frac{1}{2} \left( w_{k} + w_{k,t-1} \right) \), \( \bar{w}_{l} = \frac{1}{2} \left( w_{l} + w_{l,t-1} \right) \).

The share of Category-\( k \) capital input in aggregate capital input and the share of
Category-\(l\) labor input in aggregate labor input can be expressed by the following:

\[
\begin{align*}
  \omega_{kl} &= \frac{P_{kk}K_{kl}}{\sum_{k} P_{kk}K_{kl}}, \quad \omega_{ll} = \frac{P_{ll}L_{ll}}{\sum_{l} P_{ll}L_{ll}} \tag{5}
\end{align*}
\]

Where \(P_{kk,l}\) stands for the price of each category of capital input and \(P_{ll,l}\) stands for the price of each category of labor input.

Based on assumption (4), if each category of capital or labor has the same price in all industries, then the input of Category-\(k\) capital \(K_k\) and the input of Category-\(l\) labor \(L_l\) of the entire economy equal respectively the simple aggregation of Category-\(k\) capital input in all industries \(K_{k,i}\) and the simple aggregation of Category-\(l\) labor input in all industries \(L_{l,i}\).

\[
\begin{align*}
  K_k &= \sum_i K_{ki}, \forall k, \quad L_l = \sum_i L_{li}, \forall l \tag{6}
\end{align*}
\]

Therefore, within the framework of APPF, the aggregate TFP growth rate \(v_T\) can be expressed as follows:

\[
\begin{align*}
  v_T &= \Delta \ln Y - \bar{v}_K \Delta \ln K - \bar{v}_L \Delta \ln L \tag{7}
\end{align*}
\]

where \(\bar{v}_K\) and \(\bar{v}_L\) stand respectively for the two-period average of the share of aggregate capital income in GDP and the two-period average of the share of aggregate labor income in GDP, i.e.

\[
\begin{align*}
  \bar{v}_K &= \frac{1}{2}(v_{ki} + v_{k,i-1}), \quad \bar{v}_L = \frac{1}{2}(v_{li} + v_{l,i-1}).
\end{align*}
\]

Then, the share of total capital income and the share of total labor income in GDP can be expressed respectively by the following:

\[
\begin{align*}
  v_{ki} &= \frac{P_{ki}K_{i}}{P_{yi}Y_i}, \quad v_{li} = \frac{P_{li}L_{i}}{P_{yi}Y_i}
\end{align*}
\]

where \(P_{ki}\) stands for the price of aggregate capital input, \(P_{li}\) stands for the price of aggregate labor input, and \(P_{yi}\) stands for GDP deflator.

By substituting (2) and (3) into (7), we get the expression of aggregate TFP growth rate:

\[
\begin{align*}
  v_T &= \sum_i \bar{w}_i v_i + \left( \sum_i \bar{w}_i \bar{v}_K \Delta \ln K_i - \bar{v}_K \Delta \ln K \right) + \left( \sum_i \bar{w}_i \bar{v}_L \Delta \ln L_i - \bar{v}_L \Delta \ln L \right) \tag{8}
\end{align*}
\]

(8) presents the sources of TFP based on APPF and TFP increases generally come from three sources: (1) weighted average of industrial TFP growth, i.e. \(\sum \bar{w}_i v_i\); (2) efficiency
of capital reallocation \((\text{REALL}_K)\), i.e. \(\sum_i w_i \bar{v}_i \Delta \ln K_i - \bar{v}_K \Delta \ln K\); and (3) efficiency of labor reallocation \((\text{REALL}_L)\), i.e. \(\sum_i w_i \bar{v}_i \Delta \ln L_i - \bar{v}_L \Delta \ln L\). The latter two describe the impact of loosening APPF’s restrictions on factor input.

To test the applicability of APF and the impact of assumption (2) on TFP estimates, we will compare APF with APPF. Jorgenson et al. (2005) defined the efficiency of value-added reallocation as the difference between the APF-based and the APPF-based constant-price GDP growth rates:

\[
\text{REALL}_{VA} = \Delta \ln Y^{PF} - \Delta \ln Y = \Delta \ln Y^{PF} - \sum_i w_i \Delta \ln Y_i
\]

(9)

Here, \(Y^{PF}\) is constant-price GDP based on APF, which is the simple aggregation of the constant-price GDP of all industries, i.e. \(Y^{PF} = \sum_i Y_i\).

3. Data

To ensure the comparability and homogeneity of data and results, this paper collects its data based on the methodology of Jorgenson et al. (2005) and China Industrial Productivity (CIP) Database (Wu, 2015b; Wu and Ito, 2015; Wu et al., 2015). Specifically, labor input data comes from Wu (2019) and laborers are put into groups based on their gender, age, and education background, so as to tackle heterogeneity. Self-employed laborers like small household business owners and farmers are also taken into consideration. As such, our estimation of China’s industry-level labor input is in line with the KLEMS principles and covers a long time span (1978–2017). CIP definitions are used for the 37 two-digit industries that cover all of the three economic sectors. To examine how position on an industry chain and industrial heterogeneity influence industrial TFP, we put the 37 industries into eight groups, and to match the labor input data, the data on industrial value-added and capital input are also constructed according to the CIP classification of industries.

3.1. Industrial Value-Added

Within the time span covered by this paper, that is, 1985–2015, China successively had four different standards for industry classification and official value-added data are not available for some industries of the manufacturing and services sectors. Given
these, to ensure consistency, we first aligned all data to the classification standard of 2002 and then made adjustments to ensure compliance with CIP standards.\(^1\) For industries where value-added data is not available, we used official input-output tables to calculate their value-added. Generally, for different industries, the value-added based on constant prices is obtained in one of the following three ways. (1) For agriculture, construction, wholesale and retail trades, hotels and restaurants, transportation, storage & post services, and financial intermediations, data come directly from *China Statistical Yearbook*; (2) For two-digit industries within the manufacturing sector, official data on nominal value-added is not published, so we divided data on the value-added of the manufacturing sector as a whole based on the structure of the input-output table, and deflated the results with the PPI specific to each industry to produce industry-specific constant-price value-added; (3) For some industries in the service sector, the statistical definitions changed over time, so we split the data before 2004 by industry based on the input-output table and recombined them according to the *Industrial Classification for National Economic Activities* of 2002. Thus, the statistics of all years involved became fully comparable, and the data were then deflated with corresponding CPI or average wage values. See Table 1 for details.

<table>
<thead>
<tr>
<th>CIP industrial classification</th>
<th>Classification in <em>China Statistical Yearbook</em> 2004 and later</th>
<th>Classification in <em>China Statistical Yearbook</em> before 2004</th>
<th>Price index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information and computer services</td>
<td>Information transmission, computer services &amp; software</td>
<td>Computer application services + telecommunications</td>
<td>Telecommunication service price index</td>
</tr>
<tr>
<td>Leasing, technical, Leasing and business science &amp; business services</td>
<td>Leasing + tourism + information consulting services</td>
<td></td>
<td>Average wage index of the leasing and business services industry</td>
</tr>
<tr>
<td>Scientific research and technical services</td>
<td>Geological prospecting + scientific research and polytechnic services</td>
<td></td>
<td>Average wage index of the scientific research and technical services industry</td>
</tr>
<tr>
<td>Government, public administration, and political and social organizations, etc.</td>
<td>Management of water conservancy, environment, and public facilities</td>
<td>Water conservancy + environment, resources and public utilities management</td>
<td>Average wage index of the water conservancy, environment and public utilities management industry</td>
</tr>
<tr>
<td>Public management, social security and social organization</td>
<td>Government agencies, parties agencies and social organizations</td>
<td></td>
<td>Average wage index of public management and social organizations</td>
</tr>
</tbody>
</table>

\(^1\) Adjustments are made to the CIP industry classification based on *Industrial Classification for National Economic Activities* (GB/T4754–2002). See Wu and Ito (2015) for details.
3.2. Capital Input

When calculating the industry-level productivity, capital input should be defined as capital services instead of capital stock. Capital services refer to the service flow generated in the process of putting capital stock into use in production. Therefore, it measures the contribution of capital to the production process. The industry-level capital input index is built in three steps: (1) collect data on capital stock; (2) measure the rental price of capital; and (3) aggregate different types of capital input to get the overall capital input index, with items weighted with corresponding rental prices of capital (Sun et al., 2012).

3.2.1. Industry-Level Capital Stock

Capital stock is usually estimated with the perpetual inventory method (PIM) and this requires appropriate selection of investment data and depreciation rate and the calculation of investment price index and the capital stock of the base period (Ren and Sun, 2009).

Currently, two definitions coexist for investment in official statistics: total fixed asset investment used in investment statistics and the gross fixed capital formation used in GDP calculation with the expenditure approach. According to the 1993 system of national accounts (SNA) and the recommendation of OECD made in 2001, the latter should be used. However, data is available only for gross fixed capital formation on the national level, not any industry-specific data, so total fixed asset investment seemed to be our only option. Yet it will also be problematic if we use it directly here, because the statistical definitions are different from those of fixed capital formation and overestimation is highly likely. Based on these, both the statistical definition and the overestimation have been dealt with (Xu et al., 2020).
As for the investment price indices, *China Statistical Yearbook* provides values for buildings and equipment for the years 1992–2015, and for years before that, i.e. 1985–1991, we used the values provided by Bai and Zhang (2015). For depreciation, the geometric depreciation method was used and we cited the rates from Bai and Zhang (2015), i.e. 8 percent for buildings and 24 percent for equipment. As for the capital stock of the base period, we used the steady-state approach which can be described as \( S_0 = I_0 / (g + \delta) \), where \( S_0 \) stands for the capital stock of the base period, \( I_0 \) is the investment in buildings or equipment of 1985, \( g \) is the five-year average of GDP growth, and \( \delta \) is the depreciation rate of buildings or equipment.

### 3.2.2. From Capital Stock to Capital Input Index

Capital stock of different categories was converted into capital input based on the heterogeneous impact of investment on production efficiency and the corresponding rental prices were calculated. Then, capital stock was converted further into a homogeneous capital input index for each industry with due consideration given to the different marginal output generated by different categories of capital input.

Since new investment is not likely to be put into effective use in the production process immediately, there is bound to be a gap between capital services and capital stocks. According to Jorgenson *et al.* (2005), a specific category of capital services in industry \( i \) is indicated by \( K_{kit} \), and the corresponding capital stock is marked as \( S_{kit} \), thus:

\[
K_{kit} = \frac{1}{2} Q_{kki} (S_{kit} + S_{kit-1}) = Q_{kki} Z_{kit}
\]  (10)

Here, \( Z_{kit} \) stands for the average capital stock over two periods, \( Q_{kki} \), as was proposed by Jorgenson and Griliches (1967), is a factor of a fixed proportion.

Jorgenson (1963) clearly defined the rental price of capital and built a model for it, taking tax into consideration. When tax is excluded, Jorgenson’s formula for the rental price of capital goods can be expressed as follows:

\[
P_{kkit} = (r_i - \pi_{kit}) P_{kii,t-1,i-1} + \delta_k P_{kkit}
\]  (11)

where \( P_{kkit} \) is the rental price of capital good \( k \) in industry \( i \), \( P_{kki,t-1,i-1} \) and \( P_{kkit} \) are respectively the price to purchase the capital good in the year \( t-1 \) and the year \( t \), \( r_i \) is the nominal return on capital goods in industry \( i \), \( \delta_k \) is the depreciation rate of
capital goods, and $\pi_{ki}$ is the expected rate of capital gains of capital $k$ in industry $i$. The capital depreciation rate here is the same as that used in the calculation of PIM-based capital stocks, the expected rate of capital gains is obtained from changes in the purchasing prices of the capital goods between two periods, and the purchasing prices are the same as those used for PIM-based capital stock calculation. Thus, to calculate the rental price of capital, the only parameter we still need to find out now was the nominal return on capital, and for this, we used the internal rate of return proposed by Christensen and Jorgenson (1969).

After obtaining the rental price and the capital service price for each category of capital $k$, we can get the capital input index of each industry through Tornqvist aggregation:

$$
\Delta \ln K_{it} = \sum_k v_{ki} \Delta \ln K_{kit} \quad \text{and} \quad v_{ki} = \frac{P_{kki} K_{kit}}{\sum_k P_{kki} K_{kit}}
$$

(12)

Here, $v_{k,i}$ stands for the share of the value of the $k^{th}$ capital service in the total service value of industry $i$ and $\bar{v}_{k,i}$ is the corresponding two-period average. Substituting (10) for the capital service of category $k$ in (12) yields:

$$
\Delta \ln K_{it} = \sum_k \bar{v}_{ki} \Delta \ln (Q_{kii} Z_{kit}) = \sum_k \bar{v}_{ki} \Delta \ln Z_{kit}
$$

(13)

for industry-specific capital input. Here, the capital input of an industry is expressed as the Tornqvist aggregate of capital stocks of different categories, weighted by the rental price of each type of capital service.

4. Industrial TFP of China

During China’s reform and opening-up, a number of major events and policy changes had important impacts on economic development on the whole. Examples include the launch of the reform and opening-up policy in 1978, Deng Xiaoping’s speeches during his South China Tour in 1992 which kick started more ambitious reform attempts and basically set the socialist market economy as the orientation, China’s accession to WTO in 2001 which ushered in the new era of further opening-up to the outside world, and the 2008–2009 global financial crisis which dealt a blow on the largely export-oriented economy of China. With these as milestones, we divided the time span of this research into four periods: 1985–1991, 1992–2001, 2002–2007, and 2008–2015. On this basis, we will present how China’s industrial TFP evolved over time.
As can be seen from Table 2, in 1985–1991, agriculture, forestry, animal husbandry and fishery showed relatively high productivity. This can mainly be attributed to the benefits brought about by the first decade of the reform and opening-up, which fixed farm output quota for each household. In comparison, many industries in the manufacturing sector did not show high productivity and examples include the oil and gas excavation industry, the tobacco products industry, the petroleum and coal products industry, etc. In the early years of the reform and opening-up of China, restrictions were not yet lifted for these industries, so their TFP actually declined. The services sector, especially the leasing, technical, science & business services industry, healthcare and social security services, and education, delivered the highest productivity. Before the reform and opening-up, the development of the services sector was largely held back because it did not produce materials. Such misunderstanding was corrected and policies changed after the launch of the reform and opening-up policy, so at this time, this sector delivered excellent performance.

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</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>Agriculture, forestry, animal husbandry &amp; fishery</td>
<td>2.1</td>
<td>1.2</td>
<td>3.5</td>
<td>2.1</td>
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<td>Construction</td>
<td>Construction</td>
<td>2.7</td>
<td>1.6</td>
<td>7.8</td>
<td>3.3</td>
</tr>
<tr>
<td>Energy</td>
<td>Coal mining</td>
<td>0.4</td>
<td>11.4</td>
<td>–1.8</td>
<td>2.0</td>
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<tr>
<td></td>
<td>Oil &amp; gas excavation</td>
<td>–11.9</td>
<td>–5.0</td>
<td>–6.1</td>
<td>–5.2</td>
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<tr>
<td></td>
<td>Petroleum and coal products</td>
<td>–18.0</td>
<td>–10.3</td>
<td>4.8</td>
<td>2.5</td>
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<td></td>
<td>Power, steam, gas and tap water supply</td>
<td>–9.9</td>
<td>0.0</td>
<td>5.5</td>
<td>–1.7</td>
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<td>Commodities and primary input materials (C&amp;P)</td>
<td>Metal mining</td>
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<td>20.0</td>
<td>–4.9</td>
<td>0.4</td>
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<td>Non-metallic minerals mining</td>
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<td>12.6</td>
<td>0.1</td>
<td>–3.1</td>
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<td>Textile mill products</td>
<td>–4.8</td>
<td>11.4</td>
<td>–0.5</td>
<td>0.3</td>
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<td>Paper products, printing &amp; publishing</td>
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<td>7.7</td>
<td>0.0</td>
<td>2.7</td>
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<tr>
<td></td>
<td>Chemicals and allied products</td>
<td>–14.4</td>
<td>2.1</td>
<td>3.4</td>
<td>2.8</td>
</tr>
<tr>
<td></td>
<td>Stone, clay and glass products</td>
<td>0.2</td>
<td>–1.0</td>
<td>7.1</td>
<td>–0.2</td>
</tr>
<tr>
<td></td>
<td>Primary &amp; fabricated metal industries</td>
<td>–3.0</td>
<td>7.3</td>
<td>4.4</td>
<td>4.1</td>
</tr>
</tbody>
</table>
During 1992–2001, thanks to the development of the socialist market economy, and the SOE reform launched in the late 1990s that further unleashed the vitality of
enterprises, many enterprises, driven by goals set by the government, used the wealth accumulated in the 1980s to improve R&D, and the industrial TFP was the best among all periods. Best performers include metal mining, electronic and telecommunication equipment, saw mill products, furniture, fixtures, etc.

Then, in 2002–2007, accession to WTO boosted China’s economy. In the meantime, government interventions in the economy increased, capital accumulation accelerated, and the manufacturing sector, in particular, became clearly investment-driven. As can be seen from Figure 1 and Table 2, for many manufacturing industries, capital input grew much faster than value-added and the TFP dropped. Typical examples include the apparel and other textile products industry and the rubber and plastics products industry. Housing prices surged and the real estate services industry boomed. However, since the government had monopoly over land supply, the real estate services industry witnessed declines in its TFP though its profitability was on the rise (Chen et al., 2015). During this period, export-oriented enterprises in China grew rapidly as they faced competitions squarely on the global market and improved their efficiency in a learning-by-doing manner. A large quantity of surplus labor joined the workforce of the manufacturing and services sectors and the efficiency of labor allocation was thus improved, contributing to the TFP of some industries.

Figure 1. Growth Accounting by Industry, 2002–2007
Typical examples include the instruments and office equipment industry, financial intermediations, and the electronic and telecommunication equipment industry.

During 2008–2015, because of the global financial crisis, growth of all industries slowed. The four-trillion economic stimulus program and the rapid rise of local government financing that soon followed helped China maintain a strong momentum in investment activities (see Figure 2). Most of the investment went to capital-intensive industries and SOEs, pushing down the overall capital allocation efficiency. Therefore, in this period, most industries saw their TFP decline. Sharp drops were seen in real estate services, oil & natural gas excavation, and hotels and restaurants; and leasing, technical, science & business services, in particular, witnessed the largest drop as both capital input and labor input increased much more significantly than output.

Figure 2. Growth Accounting by Industry, 2008–2015

5. China’s Growth Drivers

To find out where China’s growth drivers lie, we first analyzed what were the sources of China’s GDP growth with the APPF approach.


<table>
<thead>
<tr>
<th>Source of GDP growth</th>
<th>APPF approach</th>
<th>APF approach</th>
<th>APPF VS. APF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Contribution to GDP growth (%)</td>
<td>Contribution to GDP growth (%)</td>
<td>Efficiency of value-added reallocation</td>
</tr>
<tr>
<td>- Agriculture</td>
<td>1.03</td>
<td>0.74</td>
<td>0.54</td>
</tr>
<tr>
<td>- Construction</td>
<td>0.37</td>
<td>0.59</td>
<td>0.74</td>
</tr>
<tr>
<td>- Energy</td>
<td>0.16</td>
<td>0.40</td>
<td>0.82</td>
</tr>
<tr>
<td>- C&amp;P</td>
<td>0.83</td>
<td>1.69</td>
<td>1.72</td>
</tr>
<tr>
<td>- SF&amp;F</td>
<td>1.48</td>
<td>3.04</td>
<td>3.24</td>
</tr>
<tr>
<td>- Services I</td>
<td>1.30</td>
<td>1.41</td>
<td>1.64</td>
</tr>
<tr>
<td>- Services II</td>
<td>1.22</td>
<td>1.77</td>
<td>2.29</td>
</tr>
<tr>
<td>- Services III</td>
<td>0.44</td>
<td>0.45</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Capital input</td>
<td>4.48</td>
<td>5.30</td>
<td>7.76</td>
</tr>
<tr>
<td>- Labor input</td>
<td>1.22</td>
<td>0.94</td>
<td>0.29</td>
</tr>
<tr>
<td>- TFP</td>
<td>1.12</td>
<td>3.85</td>
<td>3.80</td>
</tr>
<tr>
<td>APPF VS. APF</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP growth, APF</td>
<td>7.32</td>
<td>9.86</td>
<td>12.85</td>
</tr>
<tr>
<td>GDP growth, APPF</td>
<td>6.82</td>
<td>10.09</td>
<td>11.85</td>
</tr>
<tr>
<td>Efficiency of value-added reallocation</td>
<td>0.50</td>
<td>-0.23</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: The contribution of each industry group’s value-added is calculated through aggregation based on formula (3).
As can be seen from Table 3, during 1985–2015, China’s average annual GDP growth was up to 9.4 percent and SF&F was always a major driving force, making a contribution of 2.54 percentage points. Services II followed closely with a contribution of 1.77 percentage points, and C&P and services I, with contributions of 1.43 and 1.42 percentage points respectively, were also important growth drivers. In dynamic terms, the contribution of all groups was on the rise before the global financial crisis as economic growth gained momentum; while after the crisis hit, growth slowed and the contributions of all groups also declined more or less. Specifically, the contribution of SF&F dropped by 1.04 percentage points, that of services II was down by 0.51 percentage point, but construction maintained a relatively high contribution as China increased investment in infrastructure and real estate development in the aftermath of the crisis.

As for contributions to GDP growth by factor of production, capital was clearly the most powerful growth driver. During 1985–2015, the average annual contribution of capital input was as high as 6.27 percentage points, or 67 percent of the total growth, playing an overwhelming role. Labor input made a relatively low contribution of 0.83 percentage point, or 9 percent of the total, to GDP growth on average over the 30-year period. The contribution of TFP lay in between with an average annual contribution of 2.3 percentage points or 24 percent of the total.

Table 3 also compares the results of APF and APPF approaches. For 1985–2015, APF presents an average annual GDP growth of 9.81 percent while the APPF estimation is 9.40 percent, so the part that comes from the efficiency of value-added reallocation is 0.41 percentage point. This renders invalid the assumption that prices are the same for the value-added of all industries. The efficiency of value-added reallocation fluctuated wildly over time, and the peak contribution, which appeared for the latter two of the four periods, was 1 percentage point. This is also proof that the APF approach is not suitable for TFP estimation within a short period of time (Jorgenson et al., 1990). Comparing the APF- and APPF-based TFP growth rates, we found the APF-based result to be up by 1 percentage point. From 2002 to 2007, the average annual TFP growth was up to 4.8 percent, the highest of all periods, and the average annual growth during 2008–2015 was 1.13 percent, which was quite good for a post-crisis era. This differs vastly from the APPF-based results and can lead to misjudgments about China’s growth drivers.

To further reveal the sources of the improved efficiency of the Chinese economy and the contributions of cross-industry resource reallocation, we proceeded with the APPF approach and supplemented it with cross-industry direct aggregation to delve deeper into China’s aggregate TFP growth. Table 4 shows the findings: During 1985–2015, the average annual aggregate TFP growth was 2.3 percent and the weighted average contribution of industrial TFP growth was 1.6 percentage points, or 70 percent of the total. The remaining 0.7 percentage point, or 30 percent, came from the
efficiency of resource reallocation. Generally, industrial TFP growth played a leading role in the growth of the aggregate TFP and improved resource allocation efficiency also made important contributions.

Table 4. Contributions of Industrial TFP Growth and Cross-Industry Resource Allocation Efficiency

(Contribution is represented by share-weighted average annual growth, %)

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate TFP growth</td>
<td>1.12</td>
<td>3.85</td>
<td>3.80</td>
<td>0.12</td>
<td>2.30</td>
</tr>
<tr>
<td>Industrial TFP growth (weighted average)</td>
<td>0.34</td>
<td>3.39</td>
<td>2.90</td>
<td>–0.66</td>
<td>1.60</td>
</tr>
<tr>
<td>- Agriculture</td>
<td>0.56</td>
<td>0.25</td>
<td>0.43</td>
<td>0.20</td>
<td>0.34</td>
</tr>
<tr>
<td>- Construction</td>
<td>0.13</td>
<td>0.08</td>
<td>0.44</td>
<td>0.21</td>
<td>0.20</td>
</tr>
<tr>
<td>- Energy</td>
<td>–0.62</td>
<td>0.00</td>
<td>0.08</td>
<td>–0.07</td>
<td>–0.12</td>
</tr>
<tr>
<td>- C&amp;P</td>
<td>–0.86</td>
<td>0.81</td>
<td>0.36</td>
<td>0.24</td>
<td>0.24</td>
</tr>
<tr>
<td>- SF&amp;F</td>
<td>0.19</td>
<td>2.05</td>
<td>0.30</td>
<td>–0.01</td>
<td>0.78</td>
</tr>
<tr>
<td>- Services I</td>
<td>0.38</td>
<td>–0.02</td>
<td>0.93</td>
<td>0.15</td>
<td>0.30</td>
</tr>
<tr>
<td>- Services II</td>
<td>0.33</td>
<td>0.18</td>
<td>0.06</td>
<td>–1.24</td>
<td>–0.19</td>
</tr>
<tr>
<td>- Services III</td>
<td>0.23</td>
<td>0.03</td>
<td>0.31</td>
<td>–0.15</td>
<td>0.08</td>
</tr>
<tr>
<td>Capital reallocation efficiency</td>
<td>0.31</td>
<td>0.10</td>
<td>0.04</td>
<td>–0.06</td>
<td>0.09</td>
</tr>
<tr>
<td>Labor reallocation efficiency</td>
<td>0.47</td>
<td>0.36</td>
<td>0.87</td>
<td>0.84</td>
<td>0.61</td>
</tr>
</tbody>
</table>

Note: The TFP growth rates of industry groups are calculated by adding up the first item of formula (8) for all industries within each group.

Table 4 presents the contributions of weighted average TFP growth of each industry group. Over the entire timespan covered by this study, SF&F made the highest contribution, which was 0.78 percentage point. The second and third largest contributions, 0.34 and 0.30 percentage point respectively, came from agriculture and services I. The lowest contributions are seen in services II and the energy sector, whose contributions were respectively –0.19 and –0.12 percentage point. Such a poor performance of services II can mainly be attributed to the negative contribution of the real estate industry, which averaged –0.27 percentage point.

Based on the above, we will examine how the changes in governance systems over time had influenced TFP. In the 1980s, agriculture, forestry, animal husbandry and

1 Resource reallocation efficiency equals capital reallocation efficiency plus labor reallocation efficiency.
fishery benefited the most from the reform. In the first decade of the China’s reform, as farm output quota was set for each household instead of collectives and yields were purchased by the government at better prices, agricultural productivity improved (Lin, 1992). Then, starting from 1984, township enterprises rose rapidly and a large number of rural surplus laborers found jobs as workers because employment restrictions based on household registration were lifted for them (Yuan and Xie, 2011). As rural surplus labor gradually transferred out of agricultural production, the TFP of agriculture, forestry, animal husbandry and fishery remained high for quite some time. However, as the overall industrial structure changed, the share of this part in the total value-added declined continuously\(^1\) and its contribution to industrial TFP growth also dropped because the figure is a weighted average. Despite this drop, though, the contribution remained quite high on the whole.

During 1992–2001, industrial TFP growth, which stood at 3.85 percent, accounted for 3.39 percentage points of the growth of aggregate TFP, including 2.05 percentage points from SF&F and 0.81 percentage point from C&P. This was mainly because of the reform of SOEs and the opening-up to foreign investment, which together greatly promoted market-oriented industrial development and technical upgrading.

After China’s accession to WTO, the contribution of industrial TFP growth to GDP growth was lower than before. During 2002–2007, the weighted average contribution of industrial GDP growth was 2.9 percentage points. This was mainly because of the sharp drops in the contributions of SF&F and C&P. Driven by export demands and the race of local governments for higher GDP, industrial investment increased much faster than before, dragging down industrial productivity as a result. This is in line with the researching findings of Jiang et al. (2014) on the TFP of the manufacturing sector. In this period, services I made the highest contribution, 0.93 percentage point, and construction was another major contributor, providing 0.44 percentage point of growth as investment in infrastructure shot up in China.

After the global financial crisis, a heavy blow from the outside dragged down China’s overall economic growth and the Chinese government launched a four-trillion economic stimulus program, pushing up local government investment. Infrastructure, real estate development and SOEs where the top beneficiaries of the program. Large government-backed investment projects pushed resource allocation efficiency down and the contribution of industrial TFP growth was –0.66 percentage point. For the real estate industry, in particular, low efficiency coexisted with high profitability (Chen et al., 2015) and rocketing housing prices attracted huge investment, giving it a high weight in services II, whose contribution was pulled down to –1.24 percentage points. The energy sector, highly monopolized, suffered from overcapacity resulted from

\(^1\) Agriculture, forestry, animal husbandry and fishery accounted for 28.3 percent of the GDP in 1985, yet its share dropped to 9.1 percent in 2015.
strong fiscal stimuli, and the contribution of its TFP growth was also negative. In sum, during this period, not a single industry lent strong driving forces and the aggregate TFP did not improve much. C&P, construction, agriculture, and services I played the role of economic drivers more or less.

According to Table 4, during 1985–2015, the contribution of resource reallocation was 0.7 percentage point, or 30 percent of the aggregate TFP growth. Specifically, labor reallocation efficiency contributed 27 percent, while capital reallocation efficiency contributed only 4 percent. This shows that reforms of the household registration system, SOEs, and other aspects, which facilitated the free flow of labor, played a very important role in the efficiency improvement, unleashing the population dividend. With indirect financing was in a dominant position on the financial market, SOEs and non-SOEs were in a non-neutral competition for capital, and resources were thus seriously mismatched. This was while capital reallocation efficiency did not do much for the improvement of China’s aggregate TFP growth. (Dollar and Wei, 2007; Hsieh and Klenow, 2009; Song et al., 2011). Resource reallocation efficiency had always been positive in China throughout the process. This is impossible for any mature market economy (Jorgenson et al., 2005; Wu, 2015a). Therefore, it is fair to say that on the one hand, China’s factor market still faces institutional obstacles which hamper the free flow of resources; and on the other hand, by deepening the reform and pushing up the efficiency of resource allocation, great potential can be unleashed for further economic growth (Hsieh and Klenow, 2009; Brandt et al., 2013).

6. Conclusions

This paper built the APPF accounting framework based on industrial value-added function, collected factor input data that were homogeneous, estimated the industry-specific TFP growth for 1985–2015 while ensuring consistency between specific industries and the economy on the whole, analyzed the sources of China’s economic growth, revealed the industry-specific contributions to aggregate TFP growth and made special efforts to examine the efficiency of resource reallocation across different industries. Major findings are as follows:

First, during 1985–2015, China’s average annual GDP growth was 9.4 percent, to which capita input contributed 6.27 percentage points, or 67 percent of the total. Development, therefore, was clearly driven mainly by investment. The average annual aggregate TFP growth was 2.3 percent, making a contribution of 24 percent to GDP growth, also playing an important role in the fast economic growth of China. However, in the aftermath of the global financial crisis, capital input’s contribution to GDP growth spiked to 90 percent and TFP largely stopped growing. Then, as economic growth lowered to a medium speed, what we must do in pursuit of high-quality
development is to promote innovation-driven development, deepen the reform, and step up opening-up, so as to push up TFP.

Second, during 1985–2015, growth of China’s aggregate TFP mainly came from industrial TFP growth, which made a contribution of up to 70 percent. Meanwhile, the enhanced efficiency of resource allocation resulted from China’s reform and opening-up also played a highly important role. Labor reallocation efficiency, in particular, contributed 0.61 percentage point to the TFP growth, or 27 percent, while capital allocation was not of much help. It should be pointed out here that the household registration system and the land system are still obstacles to the further transfer of rural labor so much more can be done to enhance labor allocation efficiency further more. The division between SOEs and non-SOEs are still clear-cut in China’s capital market with SOEs enjoying more concessional credit policies and government subsidies than non-SOEs. This may squeeze highly efficient private investment projects out of the market. To better pursue innovation-driven development, we must give full play to the market in resource allocation, advance the market-oriented reforms of SOEs and the financial system and push up the efficiency of capital allocation.

Lastly, prior to the global financial crisis, the manufacturing sector, especially the manufacturing of finished and semi-finished goods, which were downstream the industry chain and more export-oriented, was a major driver of efficiency improvement in China. However, as China moved towards the forefront of technological development in the global arena of manufacturing, it became less likely for it to continue to benefit from scaling up and external technology spillover. Moreover, starting from 2003, accelerated investment growth in the manufacturing sector dragged down the efficiency of capital allocation within the sector, significantly pushing down the industrial TFP. Meanwhile, producer services centered around information technology experienced sharp increases in its efficiency. Digital technologies, with characteristics of general technologies may integrate deeply with traditional industries to promote industrial transformation and upgrading, and facilitate the shift from old to new growth drivers.

References


