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How Do China and India Compare on Growth and Productivity Performance in the Post-Reform Era?*

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Abstract

Applying an aggregate production possibility frontier (APPF) framework for growth accounting *à la* Jorgenson *et al*. to an economy-wide Chinese and Indian industry productivity accounts, constructed in the spirit of the KLEMS principle, we estimate and compare growth and productivity performance in China and India over their post-reform period from 1981 to 2011. We show that during this period China grew over 50 percent-faster than India in value added (9.4 versus 6.1 percent per annum) but about 25 percent-slower than India in TFP (0.83 versus 1.13 percent per annum). The two economies also experienced very different growth and productivity performances over sub-periods distinguished by special policy regimes and governing systems. While they both appeared to enjoy their best performances following China's WTO entry, China suffered much more in productivity growth in particular in the wake of the global financial crisis. We also find that manufacturing and services indeed played distinctly different roles in the two economies. In China they accounted for 50.3 and 29.0 percent of GDP growth, whereas in India their contributions nearly reversed to 22.4 and 56.2 percent, respectively. In terms of TFP growth, in India the contributions of the two sectors largely mirrored their roles in GDP growth, but this are not the case of China where an implausibly high contribution by manufacturing co-existed with a negative contribution by services.

JEL Codes: E10, E24, C82, O47

Key Words: Aggregate production possibility frontier; Domar aggregation; reallocation, total factor productivity

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1. Introduction

Benefitted by their market-oriented reforms, the world's two most populous countries, China and India, with 1.39 and 1.34 billions of population respectively, have changed, and are still changing, the landscape of the world economy at a high speed. According to the Total Economy Database (TED) constructed by The Conference Board (TCB) that uses alternative GDP estimates for China following Maddison and Wu (2008), measured in the compound growth rate of total GDP in 1990 G-K PPPs,[1] over the period 1990-2015 China grew by 7.5 percent per annum whereas India grew by 6.4 percent per annum. The two economies also appeared to be most resilient to the global financial crisis and its long recessional aftermath. Based on the same TED data (TCB 2016), over the period 2008-2015 India performed even better than China by maintaining its previous 6.4-percent annual growth rate, whereas China somewhat decelerated to 5.8 percent per annum. Meanwhile, the rest of the world grew by 2.7 percent per annum.

As a consequence of such a rapid growth, by the same 1990 G-K PPP yardstick following Maddison (2001), China and India overtook Japan in the size of GDP in 1995 and 2006, respectively. While the world is paying a serious attention to their fast speed of catching up with an enormous size effect, their true productivity performances have been somewhat ignored. In this regard, the most important teaching of the TCB/TED data is that by the time of overtaking Japan, nonetheless, China achieved only 10.6 percent of Japan's level of per capita GDP and 10.1 percent of Japan's level of labor productivity. In the case of India, the ratios are similar or slightly better, 11.8 and 14.2 correspondingly. In sharp contrast, when Japan surpassed Germany in 1967 it achieved 82.2 percent of Germany's level of per capita GDP and 75.5 percent of Germany's level of labor productivity (TCB 2016).

Even if considering that the pre-war Japan had already reached the same level of development as that of the mid-1950s, China and India are still not yet in the same league with other East Asian counterparts such as South Korea and Taiwan in terms of productivity. Apparently, both China and India are benefitted by a huge demographic dividend as well as long working hours but to some extent hauled by less satisfactory total factor productivity (TFP) growth. However, TFP studies focusing on the total economy have not reached a consensus about the productivity performance of the two economies (for the case of China, see Wu, 2011). There is a tendency in literature to show an unrealistically high TFP growth in the case of China compared to that in the case of India. For example, Bosworth and Collins (2008) find that over the period 1978-2004, China's TFP growth was 4.6 percent per annum vis-à-vis India's 1.6 percent per annum. Jorgenson and Vu (2005) show that during the period 1989-1995 China's TFP growth was 6.3 percent per annum compared to India's 2.1 percent per annum, but during the period 1995-2003 the two economies converged to the same rate of TFP growth at 2.5 percent per annum.

While some researchers questioning the quality of the official data especially the likelihood of exaggerating growth (Maddison and Wu 2008; Bardhan 2010), some show institutional obstructs to productivity growth. Hsieh and Klenow (2009) use micro data on manufacturing establishments to measure the potential extent of misallocation in China and India using the US economy as a benchmark. When capital and labour are hypothetically reallocated to equalize the

[1] Maddison and Wu (2008; also see Wu's further development in 2014) proposed a volume-movement approach to adjust for the upward-bias in Chinese official statistics. Here in order to have a big picture world-wide, we opt to use the Maddison-Wu estimates-based TED data to show more plausible growth rate for China. However, as explained in the data section, to maintain the coherence between the industries and national accounts, which is essential in the KLEMS-type industry-level data construction, in the present study we accept Chinese official estimates with necessary adjustments for conceptual, coverage and classification consistencies (Wu 2016a).

marginal products across plants to the extent observed in US, they find that manufacturing TFP would gain by 30-50 percent in the case of China and 40-60 percent in the case of India. This suggests there are institutional barriers to factor mobility in a competitive market.

The institutional effect calls for an industry level analysis of productivity performance. It is essential to have an industry perspective because government interventions are often made through industry-specific policies. Industries that are more prone to state controls may affect other industries through the input-output linkages of the economy. There is also a strong consensus among economic observers that China's growth has been mainly benefitted by a strong, export-oriented manufacturing sector, whereas India's growth has largely been attributed to the rapid expansion of ICT (information and telecommunication technology)-related services although the post-reform development of Indian manufacturing industries is by no means insignificant (Bardhan, 2010). This also requires industry level TFP studies.

Industry level TFP studies, especially under a coherent national accounts framework (e.g. Jorgenson, Gollop and Fraumeni, 1987; Jorgenson, Ho and Stiroh, 2005a and 2005b), were for a long time obstructed by data problems. The situation began to improve from the early 2000s, thanks to the endeavor of the EU-KLEMS project aiming to establish industry productivity accounts that can be coherently linked to the national accounts through input-output tables (see O'Mahony and Timmer, 2009, for an introduction of the EU-KLEMS database).[2]

Following this trend, Chinese and Indian researchers have also made efforts to solve their industry-level data problems in the spirit of the KLEMS principles. Such KLEMS-type data have become available for China from Wu and his associates (Wu, 2016a) and for India from the Indian KLEMS team (Das et al., 2016),[3] hence facilitating the current study. Methodology-wise this study adopts the Jorgensonian aggregate production possibility frontier (APPF) framework incorporating the Domar aggregation scheme to account for the contributions of individual industries to the growth of the aggregate inputs and output, as well as the reallocation effects of factors on TFP growth (Jorgenson, Ho and Stiroh 2005a). This approach relaxes most of the restrictive assumptions adopted by the widely used aggregate production function approach in the growth accounting especially that all industries are homogenous satisfying the same value added function and facing the same input and output prices.

The plan of the paper is as follows. Section 2 outlines the process of reforms in the two countries emphasizing institutional deficiencies. The methodology of productivity measurement applied in the paper is presented in Section 3. The datasets for China and India are briefly described in Section 4. The empirical results on growth and productivity for the two countries are reported and compared in Section 5 with an emphasis on the effects of China's entry to WTO and GFC upon both of the economies. The final section briefly concludes the study and provides the way forward for future research.

2. Reforms Under Different Governance Systems and Implications for Productivity Growth

By the time of their market-oriented reforms, both China and India were among the most protected and heavily regulated economies of the world. Strictly following the Marxist dogma that prohibited the market system and private ownership, China under Mao in principle adopted a Soviet-type central planning system with omnipresent state power till the end of the 1970s.

[2] "KLEMS" is used as an acronym for Capital, Labor, Energy, Materials and Services that are used to produce any product in goods or services.

[3] The data work in both countries is on-going and closely integrated with the World KLEMS initiative based in the Harvard University.

Almost during the same period, pursuing Gandhi's ideology in the Indian independence movement, India also practiced a similar central planning system with strong state controls over commerce and inward-looking import substitution policies (Kotwal *et al*, 2011). However, despite the policies that discouraged the development of private enterprises and restricted market allocation of resources, India did not outlaw private ownership and market.

Officially, China started its current reform process in 1978 and India in 1991. However, if considering that China's agricultural reform over most of the 1980s was to return to a pre-planning system, which was similar to that of India, and in the late 1980s India began deregulating capital goods industries and trade, the two economies in fact started a full scale industrial reform more or less at the turn of the 1990s. Both have maintained their pre-reform political system with China firmly sticking to a totalitarian regime and India following a democratic system. Although China has opened up much more to foreign trade and direct investment, it has relied more on complicated administrative controls to regulate the market and inter-governmental competition to promote growth, which has obstructed the development of a healthy legal framework and an efficient financial system. In contrast, India has inherited a better financial sector and a more functional market system that has nurtured a dynamic entrepreneur class (Eichengreen *et al*, 2010).

After a comprehensive and comparative assessment of the economic rise of China and India in the post reform era, Bardhan (2010) concludes that reforms in China have been deeper and have resulted in a transformation particularly through labor intensive rural industrialization, which is still largely absent in India. He explores the factors that inhibit labor-intensive industrialization in India and draws attention to the special institutional features of Chinese reforms in terms of decentralization and career incentives for officials which uniquely facilitated economic growth.

Indeed, in recent decades, India has benefitted from the growing outsourcing of business services and has generated considerable export revenues in the telecommunication sector. Yet, as Sachs (2015) comments, after two decades of impressive economic growth, India has still over a third of its population living in extreme poverty. There are virtually two Indias with one of educated managers and engineers who have been able to take advantage of opportunities made available through globalization and the other of a huge mass of uneducated people who make a living in low productivity jobs in the informal sector, the largest of which is still in agriculture.

While Indian economists are giving a high appraisal to the Chinese system, Chinese economists have attempted to understand its deeply-rooted problems. Xu (2011) explains the "China puzzle" of a rapid growth without a healthy legal system. He attributes the growth-promoting role of local governments to a hybrid system in which a decentralized economic authoritarian regime is established coherently with a highly centralized political regime. In an empirical study, Li and Zhou (2005) show that since all efforts made by local governments are indexed by the rate of local GDP growth and assessed by upper authorities as political performance, officials are highly motivated to engage in "growth tournament" with their peers of other localities.

Consequently, their restless search for new growth engines has resulted in increasing government interventions in resource allocation and business decisions (Huang 2012; Wu and Shea 2008). In Wu's view, the government's heavy involvement has (so far) successfully solved China's growth problem, but this has taken its toll on the economy's efficiency and productivity growth, hence raising a question of growth sustainability (Wu 2016b). Indeed, Wu, Shea and Shiu (2015) using a DEA approach, show that the government-engineered growth tends to promote investment in technology but at the expenses of efficiency. The majority of China observers appear to agree that such a China model of growth is also responsible for the widespread of corruption.

In the interest of this study, we are keen to examine and compare the industry origin of the growth and productivity performances between the two giant economies over periods with distinct policy regime shifts, given institutional differences, problems and unfinished reforms.

3. Accounting for the Sources of Growth with Industry Origin[4]

The widely used aggregate production function (APF) approach to TFP analysis is implicitly subject to very stringent assumptions that for "value-added functions exist and are identical across (underlying) industries up to a scalar multiple" and "the aggregation of heterogeneous types of capital and labor must receive the same price in each industry" (Jorgenson, Ho and Stiroh 2005a). This study adopts Jorgenson's aggregate production possibility frontier (APPF) framework instead, incorporating Domar weights to account for contributions of individual industries to the growth of aggregate inputs and output through input-output links (Domar, 1961). The empirical differences between the two approaches deliver interesting insights about the role of factor reallocations in promoting TFP growth.

The APPF approach in growth accounting relaxes the strong assumption that all industries are subject to the same value-added production function to account for the industry origin of aggregate growth (Jorgenson 1966). The Domar-weighted aggregation was introduced into the APPF framework in Jorgenson, Gollop and Fraumeni (1987) to exercise direct aggregation across industries to account for the role of American industries in the changes of aggregate inputs. It has been used in Jorgenson and Stiroh (2000), Jorgenson (2001) and Jorgenson, Ho and Stiroh (2005a, 2005b) to quantify the role of information technology (IT)-producing and IT-using industries in the US economy.

To illustrate this methodology, we begin with a production function where industry gross output is a function of capital, labour, intermediate inputs and technology indexed by time. We use individual industries as building blocks which allow us to explicitly trace the sources of the aggregate productivity growth and input accumulation to the underlying industries. Focusing on an industry-level production function given by equation (1), each industry, indexed by *j*, purchases distinct intermediate inputs, capital and labour services to produce a set of products:

$$Y_j = f_j(K_j, L_j, X_j, T) \tag{1}$$

where *Y* is output, *K* is an index of capital service flows, *L* is an index of labour service flows and *X* is an index of intermediate inputs, either purchased from domestic industries or imported. Note that all input variables and output are indexed by time but this is suppressed for notational convenience.

Under the assumptions of competitive factor markets, full input utilization and constant returns to scale, the growth of output can be expressed as the cost-weighted growth of inputs and technological change, using the translog functional form:

$$\Delta \ln Y_j = \bar{v}_j^K \Delta \ln K_j + \bar{v}_{jt}^L \Delta \ln L_j + \bar{v}_j^X \Delta \ln X_j + v_j^T \tag{2}$$

where $\bar{v}_j^K$, $\bar{v}_j^L$ and $\bar{v}_j^M$ are two-period averages of nominal weights of input $v_j^K = \frac{P_j^K K_j}{P_j^Y Y_j}$, $v_j^L = \frac{P_j^L L_j}{P_j^Y Y_j}$ and $v_j^X = \frac{P_j^X X_j}{P_j^Y Y_j}$, respectively. Note that under constant returns to scale $v_j^K + v_j^L + v_j^X = 1$, which is controlled by industry production accounts in nominal terms. Each

[4] This section is basically adopted from Wu (2016).

element in the right-hand side of equation (2) indicates the proportion of output growth accounted for respectively by the growth of capital services ($\bar{v}_j^K \Delta \ln K_j$), labor services ($\bar{v}_j^L \Delta \ln L_j$), intermediate materials ($\bar{v}_j^X \Delta \ln X_j$) and total factor productivity (v_j^T).

One of the advantages of equation (2) is that it can better account for each input services by different types. For example, it can account for labor services provided by different types of labor with specific demographic, educational and industrial attributes, as shown in pioneering studies by Griliches (1960), Denison (1962) and Jorgenson and Griliches (1967). It has relaxed the usual strong assumption that treats numbers employed or hours worked as a homogenous measure of labor input. The growth of total labor input is thus defined as a Törnqvist quantity index of individual labour types as follows:

(3a) $$\Delta \ln L_j = \sum\nolimits_h \bar{v}_{h,j} \Delta \ln H_{h,j}$$

where $\Delta \ln H_{h,j}$ indicates the growth of hours worked by each labour type *h* (with specific gender, age and educational attainment) and its cost weights $\bar{v}_{h,j}$ given by two-period average shares of each type in the nominal value of labour compensation controlled by the labor income of industry production accounts.

The same user-cost approach is also applied to *K* and *M* to account for the contribution of different types of capital asset (Z_k) and intermediate input (X_m) in production with type-specific, two-period average cost weight defined as $\bar{v}_{k,j}$ and $\bar{v}_{m,j}$, respectively:

(3b) $$\Delta \ln K_j = \sum\nolimits_k \bar{v}_{k,j} \Delta \ln Z_{k,j}$$, and

(3c) $$\Delta \ln X_j = \sum\nolimits_m \bar{v}_{m,j} \Delta \ln X_{m,j}$$

It should be noted that the equations from (2) through the whole set of (3) also explicitly express the methodological framework for the CIP industry-level data construction that is linked to and controlled by the national production and income accounts. This point will be discussed again when we discuss the data issues in the following section.

Using the value-added concept, equation (2) can be rewritten as:

(4) $$\Delta \ln Y_j = \bar{v}_j^V \Delta \ln V_j + \bar{v}_j^X \Delta \ln X_j$$

where V_j is the real value-added in *j* and v_j^V is the nominal share of value-added in industry gross output. By rearranging equations (2) and (4), we can obtain an expression for the sources of industry value-added growth (i.e. measured in terms of input contributions):

(5) $$\Delta \ln V_j = \frac{\bar{v}_j^K}{\bar{v}_j^V} \Delta \ln K_j + \frac{\bar{v}_j^L}{\bar{v}_j^V} \Delta \ln L_j + \frac{1}{\bar{v}_j^V} v_j^T$$

Growth of aggregate value-added by the APPF approach is expressed as weighted industry value-added in a Törnqvist index:

(6) $$\Delta \ln V = \sum_j \overline{w}_j \Delta \ln V_j$$

where w_j is the share of industry value-added in aggregate value-added. By combining equations (5) and (6), we can have a new expression of aggregate value-added growth by weighted contribution of industry capital growth, industry labor growth and TFP growth:

(7) $$\Delta \ln V \equiv \sum_j \overline{w}_j \Delta \ln V_j = \sum_j \left(\overline{w}_j \frac{\overline{v}_j^K}{\overline{v}_j^V} \Delta \ln K_j + \overline{w}_j \frac{\overline{v}_j^L}{\overline{v}_j^V} \Delta \ln L_j + \overline{w}_j \frac{1}{\overline{v}_j^V} v_j^T \right)$$

Through this new expression, we have introduced the well-known Domar weights in our aggregation (Domar 1961), i.e. a ratio of each industry's share in total value-added (w_j) to the proportion of the industry's value-added in its gross output (v_j^V).

If we maintain the stringent assumption that capital and labour inputs have the same marginal productivity in all industries we can define aggregate TFP growth as:

(8) $$v^T \equiv \sum_j \overline{w}_j \Delta \ln V_j - \overline{v}^K \Delta \ln K - \overline{v}^L \Delta \ln L$$

However, this assumption is not likely to hold, in particular in China and India, as argued above. It is therefore interesting to look at the difference of the two measurement approaches. By subtracting equation (7) from equation (8) and rearranging, we can show how the aggregate TFP growth relates to the sources of TFP growth at the industry level and to the effect of factor mobility across industries (Jorgenson, Ho and Stiroh 2005a):

(9) $$\begin{aligned} v^T = & \left(\sum_j \frac{\overline{w}_j}{\overline{v}_j^V} v_j^T \right) \\ & + \left(\sum_j \overline{w}_j \frac{\overline{v}_j^K}{\overline{v}_j^V} \Delta \ln K_j - \overline{v}_K \Delta \ln K \right) \\ & + \left(\sum_j \overline{w}_j \frac{\overline{v}_j^L}{\overline{v}_j^V} \Delta \ln L_j - \overline{v}_L \Delta \ln L \right) \end{aligned}$$

in which the *reallocation* terms in the second and third brackets can be simplified as:

(9') $$v^T = \sum_j \frac{\overline{w}_j}{\overline{v}_j^V} v_j^T + \rho^K + \rho^L$$

Equation (9) expresses the aggregate TFP growth in terms of three sources: Domar-weighted industry TFP growth, effects of reallocation of capital and reallocation of labor across industries.

This Domar weighting scheme ($\overline{w}_j / \overline{v}_j^V$), originated by Domar (1961), plays a key role in the direct aggregation across industries under the Jorgensonian growth accounting framework. A direct consequence of the Domar-aggregation is that the weights do not sum to unity, implying that aggregate productivity growth amounts to more than the weighted average of industry-level productivity growth (or less, if negative). This reflects the fact that productivity change in the production of *intermediate inputs* do not only have an "own" effect but in addition they lead to reduced or increased prices in downstream industries, and that effect accumulates through vertical links. As elaborated by Hulten (1978), the Domar aggregation establishes a consistent link between the industry level productivity growth and the aggregate productivity growth.

Productivity gains of the aggregate economy may exceed the average productivity gains across industries because flows of intermediate inputs between industries contribute to aggregate productivity by allowing productivity gains in successive industries to augment one another. The same logic can explain productivity losses.

The next two terms reflect the impact on aggregate TFP growth of the reallocation of capital (ρ^K) and labor (ρ^L) across industries, respectively. Each reallocation term, is obtained by subtracting cost-weighted aggregate factor (capital or labor) input growth from the Domar-weighted input growth across industries. It should be noted that theoretically, when these terms are not negligible it indicates that industries do not face the same factor costs, which suggests a violation of the assumption of the widely used aggregate approach. However, one should not expect a significant reallocation effect in an economy where there is a well developed market system.

4. Data Issues

China and India KLEMS database

The data used in this study for both China and India are reconstructed based on official statistics. In the case of China, unlike Maddison and Wu (2008) the official data are not challenged because there are no alternative data that can be used to reconstruct industry accounts (Wu and Ito 2015). The data reconstruction follows the KLEMS principles. This means that for output measures, the gross output of an industry equals the total costs of "KLEMS" and the gross output of an economy equals the sum of the costs of KLEMS of all industries (O'Mahony and Timmer, 2009). At industry level, this expressed in equation (2). For China, the KLEMS database is part of the on-going China Industry Productivity (CIP) Database Project. It is beyond the scope of this study to go through a long history of the data research. We thus refer interested readers for details to three working papers by Wu (2015) on capital input, Wu and Ito (2015) on output and prices, and Wu, Yue and Zhang (2015) on labor quantity and compensation matrices. A brief introduction to data is provided in Wu (2016a). For India, it is part of the on-going India KLEMS Database Project, which is explained in details in Das et al. (2016). Interested readers should see studies on capital input in Erumban and Das (2013), and work on employment in Aggarwal and Erumban (2013).[5]

Industrial classification and concordance

The classification of industries in this study follows the ISIC principles although somewhat constrained by country specific problems. The China CIP/KLEMS dataset adopts a classification system that in line with the 2002 CSIC (China Standard of Industrial Classification) classifies the Chinese economy into 37 industries. The Indian KLEMS dataset originally adopts the 1998 NIC (National Industrial classification) and reclassifies the Indian economy into 27 industries in line with the EU KLEMS standard of industrial classification. In this study, to facilitate China/India productivity comparison the 37 Chinese industries are reclassified to match the 27 Indian industries. See Table A1 in appendix for the country-specific classification concordance between China and India.

Industry grouping

[5] Due to some data constraints for the time being, the nature unit of employment is measured in hours worked in the case of China and in numbers employed in the case of India. Besides, the constant price measured values are in 1990 prices in the China CIP/KLEMS data and in 2004 prices in the Indian KLEMS data, which may introduce some biases.

To better distinguish industries by their positions in the production chain or distance from the final demand in productivity analysis, we further categorize the 27 industries into ten groups (Table A1). In this grouping, we first allow agriculture (group 1) mining (2), utilities (7) and construction (8) to stand alone as they are. Then we divide the manufacturing sector into four groups, namely , and "light manufacturing (largely consumer goods)" (3), "intermediate materials" (4), "electricals and ICT (information-communication technology)" (5) and "machinery and motor vehicles (including all other transport equipment)" (6). Given the data constraint, especially limited classification in the Indian data, unfortunately we cannot clearly distinguish investment goods from consumer goods, but noticeably, most investment goods are produced by groups 4 and 5. We finally categorize all services into two groups, that is, one market services group including trade & Hotels, transport & storage, post and telecommunication, business services and financial services, and another non-market services group including public administration, health and education social services.

Periodization

The dataset used in this study covers the period 1981-2011.[6] To help better interpret and analyze the results against major events such as important policy regime shifts and external shocks, we divide the entire period into four sub-periods taking into accounts such events. The first one is from 1981 to 1991 as an early reform period for both China and India during which China had successfully conducted agricultural reform and introduced a planning-market double track reform to the industrial sector and in India the long-lasting planning controls over capital goods industries and trade also began to dissolve following a series of deregulations of a large number of industry groups. This sub-period ended with China's Tiananmen unrest.

We set the next period to break off in 1991 largely because in India this marks the sweep of 1991-1992 comprehensive trade policy reforms to reduce tariffs and eliminate most non-tariff barriers and in China this marks Deng's bolder call in 1992 for deepening reforms in his Southern China trip aiming to break the standoff of the country's ideological debate on the nature of the market reforms. This sub-period is ended in 2001 or just before China participated in the World Trade Organization (WTO) in the end of that year. Therefore, this sub-period also includes the shock of Asian Financial Crisis in 1997-1998 and its long-lasting deflationary aftermath in China for three years.

We set the next sub-period from 2002 to 2007 to capture the effect of China's WTO entry. This is an important period that saw China's unprecedented expansion in export-oriented manufacturing, taking its comparative advantage not only in labor-intensive production but also in size that enhances China's competitiveness. Undoubtedly, the Chinese government, both central and local, played an imperative role in engineering such an expansion (Wu, 2016a). We expect this China WTO effect, enhanced by China's size of labor-intensive manufacturing, to have a significant bearing on its competitors like India. This sub-period is then followed by the last sub-period in our compatible data from 2008 to 2011 aiming to capture the impact of the global financial crisis and its recessionary aftermath. It is of great interest to see how differently the two giant economies responded to the crisis in terms of both output growth and productivity performance.

5. Empirical Results

In our empirical exercise, we opt for the double deflation approach to deflate gross output and intermediate inputs at industry level in which the input price change of an industry is a weighted average of the price changes of all inputs across industries including input from itself.

[6] Note that the annual Chinese data throughout the paper refer to a standard calendar year, whereas the annual Indian data refer to a fiscal year ended in March of the following year.

The change of value added is hence derived based on equation (4). The measure of capital and labor inputs follows equations (3a) and (3b) although in the case of India we have to use numbers employed instead of hours worked as the nature quantitative unit. In what follows, we report the empirical results by steps and compare the performances between the two countries against the macroeconomic background that may be captured by our periodization above discussed.

Sources of gross output growth by industry group

We start with an examination of industry group-level sources of gross output growth as reported in Table 1 for the entire period in question for both China and India. The results are group-specific and methodologically based on equation (2). They provide industry group-level sketches on the contribution of each input growth to the gross output (GO) growth. Estimation as such is by no means accurate because it includes double counting. However, examining these building blocks is a necessary starting point because industries are building blocks of the national economy and the originators of the aggregate productivity growth.

TABLE 1

SOURCES OF GROSS OUTPUT GROWTH BY INDUSTRY GROUP IN 1981-2011: CHINA VIS-À-VIS INDIA

(Gross output-weighted as percentage points of annual GO growth)

	GO	L	K	X	*TFP*	GO	L	K	X	*TFP*
	China					India				
1. Agriculture	5.88	-0.03	2.73	2.74	*0.44*	2.87	0.31	1.43	0.65	*0.49*
2. Mining	7.53	0.45	3.82	5.46	*-2.21*	5.21	0.86	4.03	1.74	*-1.42*
3. Light manufacturing	11.27	0.31	2.15	7.77	*1.04*	6.72	0.27	0.99	5.33	*0.14*
4. Intermediate materials	11.48	0.24	2.25	8.43	*0.56*	7.83	0.19	1.21	6.04	*0.39*
5. Electricals & ICT	20.70	0.45	2.28	13.63	*4.35*	10.45	0.50	1.11	7.16	*1.68*
6. Mach. & motor vehicle*	15.23	0.15	1.56	10.06	*3.45*	8.85	0.44	1.22	6.42	*0.77*
7. Utilities	10.02	0.23	2.94	7.33	*-0.49*	7.30	0.57	1.38	4.11	*1.23*
8. Construction	10.86	1.28	1.20	8.24	*0.14*	6.73	1.89	0.83	5.56	*-1.55*
9. Market services	9.97	1.14	4.35	5.43	*-0.95*	8.07	1.30	2.92	2.92	*0.93*
10. Non-market services	8.20	1.93	4.53	4.47	*-2.73*	5.91	1.50	1.85	1.47	*1.09*

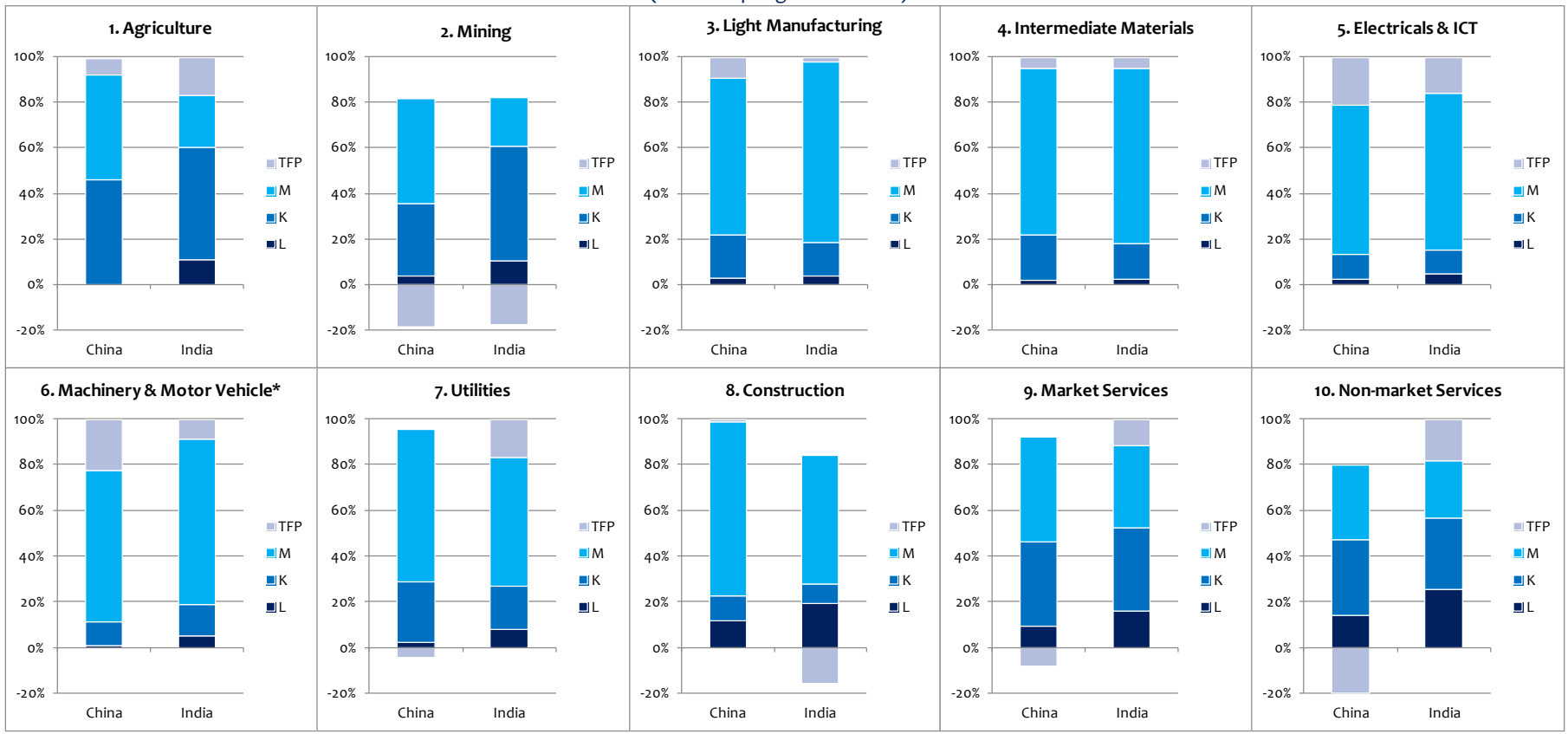
Source: Authors' estimates using equation (2). The measures of L, K and X (the growth of X is E, M and S weighted) follow equations 3a, 3b and 3c. *Including other transport equipment.

Table 1 presents (nominal) gross output-weighted input growth as percentage points of the real annual GO growth rate presented in the first column of China and India panel respectively. To help better understand the relative contribution of each input Figure 1 further depicts all the inputs as shares of a standardized GO growth. We can start from a performance comparison for the two primary groups, i.e. agriculture and mining. It is astonishing not to see that the Chinese agriculture grew twice faster than that of India, but to see that such growth strength relied little on labor contribution over the three decades. In fact, China's labor input in agriculture declined by 0.03 percent per annum, which explained the source of the current stock of about 250 million migrant workers economy-wide. In the Indian agriculture sector on the contrary, labor input still grew by 0.31 percent per annum. Both countries show similar and positive TFP growth, yet India appears to be slightly better. And the Chinese agriculture seemed to rely more on the growth of intermediate inputs.

FIGURE 1

INPUT CONTRIBUTION TO GROSS OUTPUT GROWTH BY INDUSTRY GROUP, PERIOD AVERAGE OF 1981-2011: CHINA VIS-À-VIS INDIA

(Gross output growth = 100%)



Source: see Table 1. *Including other transport equipment.

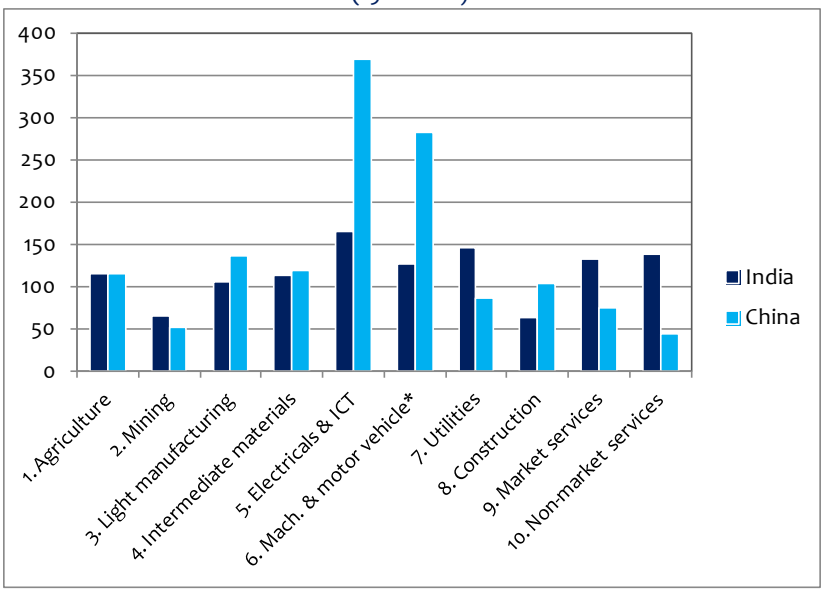
In the case of mining, China grew more than 40 percent faster but depended much more on the growth of intermediate inputs than India. According to the estimated TFP growth for this sector, both countries appear to be inefficient in mining, but worse in the case of China. Figure 1 presents distinctive illustrations for these observations.

Next, we examine and compare the four manufacturing groups between the two economies, namely light manufacturing goods (group 3), intermediate materials (4), electricals and ICT products (5), and machinery and motor vehicles (6). Noticeably, electricals-ICT products and machinery-motor vehicles were the most rapidly growing groups in both economies in which consumer electronics and automobiles manufacturing played a very important role, but China grew twice faster than India.[7] Although both are the world most populous countries, it seems that China relied less on the growth of labor input in these manufacturing industries than India. India was less efficient because of not only more depending on the growth of input materials but also a slower TFP growth (see standardized shares in Figure 1). Based on the group TFP performance, it is also interesting to see that both economies seemed to have enjoyed comparative advantage in electricals and ICT manufacturing as well as in machinery and motor vehicle manufacturing, albeit China is still evidently more productive than India. Of course, we have to wait for the more strict assessment later in a cross industry analysis as expressed in equation (9).

FIGURE 2

CHANGE IN TOTAL FACTOR PRODUCTIVITY FROM 1981 TO 2011 BY INDUSTRY GROUP: CHINA VIS-À-VIS INDIA

(1981 = 100)



Source: See Table 1. *Including other transport equipment.

The strong growth in China and India had to be fueled by energy and hence how to more efficiently produce energy is an imperative challenge to the both. It has been widely believed among Chinese observers that China is less efficient in energy producing than India and thus the Chinese growth is much more energy-consuming than India. We may be the first one to provide a supportive empirical evidence for this view (Table 1 and Figure 1).

[7] In both China and India these industries were substantially benefitted by deregulations over foreign trade and direct investment (see e.g. Liew and Wu, 2007; Das, 2016).

Besides, a quick glance can tell that the Indian construction industry appears to be much more inefficient than its Chinese counterpart although the growth of the latter relied much more on the growth of input materials and enjoyed almost no TFP growth at all over the three decades. Turning to services, both market and non-market, it shows that China long suffered from a negative TFP growth. In the case of India, nonetheless, it appears to be more labor-intensive, less input materials-consuming and stronger TFP growth, especially for non-market services (Table 1 and Figure 1).

To zoom in the differences in productivity performance between the two economies, in Figure 2 we provide a TFP index for each industry group to show accumulated productivity effect over the entire period benchmarked on 1981 (=100).

Industry contribution to aggregate value-added growth

From the above examination of sources of gross output growth across industry groups in China and India, we have seen that groups performed very distinctively within each country in terms of the growth of factors and productivity. The comparison between the two countries reveals a sharp contrast. In this sub-section we scrutinize the sources of value added growth in the two countries in the APPF framework taking into account that industries (groups) may have very different value-added functions.

Tables 2a (China) and 2b (India) summarize the results. In what follows we first examine the contribution of each industry group to the aggregate value-added growth through each sub-period to see the role of each group in driving the growth, and then we discuss the results of growth accounting in this framework in the form of both aggregate value-added and labor productivity functions.

If one puts the four groups from item 3 to 6 as the "manufacturing" sector and put all services (industry 9 and 10) as the "services" sector, and make a comparison between the two economies, a distinctively different picture would emerge. It shows that on average a half of China's value-added growth over the period 1981-2011 was driven by manufacturing (50.3 percent, measured as 4.73 ppts of the 9.41 percent growth, Table 2a) and to the contrary more than a half of India's growth by services (56.2 percent, measured as 3.41 ppts of the 6.07 percent growth, Table 2b). This holds true for all sub periods. If more meaningfully concentrating only on the contribution of market services to the growth, it was 22.2 percent in the case of China (measured as 2.09 ppts of the 9.41-percent growth, Table 2a) and 37.6 in the case of India (measured as 2.28 ppts of the 6.07-percent growth, Table 2b). Interestingly, when India underwent more comprehensive reforms in the 1990s, the growth of market services already made up nearly 40 percent of annual value-added growth (2.32 ppts out of 5.83-percent growth in 1991-2001, Table 2b), meanwhile in China this was only less than 15 percent (1.25 ppts out of 8.85-percent annual growth in 1991-2001, Table 2a).

However, we also notice that a somewhat rebalancing took place in both economies following China's WTO entry. In India, while the growth market services continued and more rapidly (3.58 percent per annum in 2001-2007 compared to 2.32 in 1991-2001, Table 2b), the growth of all manufacturing groups, except for light manufacturing goods, accelerated by a speed that was more than doubling the previous rate. In China, while the growth of some manufacturing industries decelerated, the growth of market services increased dramatically.

Besides, throughout this stage of development, the contribution of agriculture to the aggregate value-added growth declined inevitably in the two countries, but in China it was much faster than in India. Astonishingly enough, when China experienced a drop from about 20 to almost one percent, India underwent a process in which the contribution declined from 16 to less than 10 percent. We also find that in both cases, the contribution of mining was trivial (0.4 percent for China and 2.0 percent for India taking annual growth over the entire period as 100)

and the contribution of utilities and construction also appears to be similar (3.2 and 5.5 for China and 3.1 and 4.1 for India, calculated based on Tables 2a and 2b).

TABLE 2A

CHINA: SOURCES OF AGGREGATE VALUE-ADDED GROWTH, 1981-2011

(Contributions are share-weighted growth rate in percent)

	1981-1991	1991-2001	2001-2007	2007-2011	*1981-2011*
		Industry contributions to value-added growth			
Value-added growth (%)	8.81	8.85	11.37	9.37	*9.41*
1. Agriculture	*1.73*	*1.31*	*0.37*	*0.11*	*1.10*
2. Mining	*-0.04*	*0.17*	*-0.14*	*0.19*	*0.04*
3. Light manufacturing	*1.19*	*1.79*	*1.66*	*1.23*	*1.49*
4. Intermediate materials	*0.97*	*1.90*	*1.41*	*1.40*	*1.42*
5. Electricals & ICT	*0.82*	*0.87*	*1.02*	*0.75*	*0.87*
*6. Machinery & motor vehicles**	*1.10*	*0.77*	*1.15*	*0.73*	*0.95*
7. Utilities	*0.33*	*0.01*	*0.62*	*0.43*	*0.30*
8. Construction	*0.52*	*0.49*	*0.56*	*0.50*	*0.52*
9. Market services	*1.61*	*1.25*	*3.56*	*3.17*	*2.09*
10. Non-market services	*0.58*	*0.29*	*1.17*	*0.85*	*0.64*
		Factor contributions to value-added growth			
Value-added growth (%)	8.81	8.85	11.37	9.37	*9.41*
- Capital input:	*5.83*	*7.01*	*9.45*	*10.83*	*7.61*
- Stock	5.83	7.08	9.54	10.82	7.65
- Capital quality (composition)	-0.00	-0.07	-0.08	0.01	-0.04
- Labor input:	*1.12*	*1.12*	*0.59*	*0.77*	*0.97*
- Number (homogenous)	1.07	0.69	0.54	-0.60	0.61
- Labor quality (composition)	0.06	0.43	0.05	1.37	0.36
- Aggregate TFP	*1.86*	*0.72*	*1.32*	*-2.22*	*0.83*

Source: Authors' using equation (7). *Including other transport equipment.

TABLE 2B

INDIA: AGGREGATE VALUE-ADDED GROWTH AND SOURCES OF GROWTH, 1981-2011

(Contributions are share-weighted growth rate in percent)

	1981-1991	1991-2001	2001-2007	2007-2011	*1981-2011*
		Industry contributions to value-added growth			
Value-added growth due to (%)	4.87	5.83	7.75	7.16	*6.07*
1. Agriculture	*0.78*	*0.89*	*0.51*	*0.64*	*0.75*
2. Mining	*0.20*	*0.08*	*0.08*	*0.08*	*0.12*
3. Light manufacturing	*0.38*	*0.38*	*0.34*	*0.65*	*0.41*
4. Intermediate materials	*0.59*	*0.36*	*0.81*	*0.74*	*0.58*
5. Electricals & ICT	*0.12*	*0.09*	*0.14*	*0.19*	*0.13*
*6. Machinery & motor vehicles**	*0.13*	*0.20*	*0.40*	*0.35*	*0.24*
7. Utilities	*0.18*	*0.22*	*0.22*	*0.09*	*0.19*
8. Construction	*-0.00*	*0.13*	*0.81*	*0.33*	*0.25*
9. Market services	*1.24*	*2.32*	*3.58*	*2.88*	*2.28*
10. Non-market services	*1.25*	*1.16*	*0.84*	*1.22*	*1.13*
		Factor contributions to value-added growth			
Value-added growth due to (%)	4.87	5.83	7.75	7.16	*6.07*
- Capital input:	*2.75*	*3.03*	*4.34*	*4.79*	*3.43*
- Stock	2.30	2.74	4.02	4.50	3.09
- Capital quality (composition)	0.45	0.29	0.32	0.29	0.35
- Labor input:	*1.83*	*1.42*	*1.35*	*1.15*	*1.51*
- Number (homogenous)	1.04	0.83	0.72	0.39	0.82
- Labor quality (composition)	0.79	0.60	0.63	0.75	0.69
- Aggregate TFP	*0.28*	*1.38*	*2.05*	*1.22*	*1.13*

Source: Authors' using equation (7). *Including other transport equipment.

Factor contribution to aggregate value-added growth

In the lower panel of Tables 2a and 2b, we show our estimates of factor contribution to the aggregate value-added growth including the contribution of TFP growth in the same APPF framework. On an average, the estimated TFP growth for the entire period 1981-2011 is 1.13 percent per annum for India (Table 2b) and 0.83 percent per annum for China (Table 2a). That Indian TFP growth was over one-third faster than that of China comes as a rather big surprise, though both did not perform as well as the post-war East Asia forerunners such as Japan, South Korea and Taiwan (Felipe, 1999). Throughout the sub-periods, China's TFP growth was more volatile than that of India. It can be seen that from the 1980s, India's TFP was on an upward march, reflecting that domestic reforms in manufacturing and trade liberalization had gradually improved efficiency and even maintained positive following the GFC shock and its recessionary aftermath. In case of China, we find that after the most significant productivity growth in the first decade of reforms (1.86 percent per annum in 1981-1991), the gain in TFP was not that dramatic over the 1990s and the post-WTO period, and it turned into negative following GFC.

Our estimates of the sources of value-added growth also put the two economies in sharp contrast. In China, on the average of the period 1981-2011, 80.9 percent of the 9.41-percent real growth per annum was attributable to physical capital input, 10.3 to labor input and merely 8.8 to TFP calculated based on Table 2a). In India, the corresponding figures are 56.5, 24.9 and 18.6 with respect to the 6.07-perent real growth per annum (based on Table 2b). This suggests that China has been much more dependent on physical capital input than India.

TABLE 3A

CHINA: DECOMPOSITION OF AGGREGATE LABOR PRODUCTIVITY GROWTH, 1981-2011

(Contributions are weighted growth in percent)

	1981-1991	1991-2001	2001-2007	2007-2011	*1981-2011*
			Growth Rates		
Value-Added Growth (APPF)	8.81	8.85	11.37	9.37	*9.41*
-Value added per number employed	*6.26*	*7.26*	*10.08*	*10.78*	*7.96*
*- Number employed (natural unit)**	*2.55*	*1.59*	*1.28*	*-1.41*	*1.45*
			Factor Contributions		
Value-Added per employed person	6.26	7.26	10.08	10.78	*7.96*
- Capital deepening	*4.35*	*6.11*	*8.71*	*11.63*	*6.78*
- Labor quality	*0.06*	*0.43*	*0.05*	*1.37*	*0.36*
- TFP growth	*1.86*	*0.72*	*1.32*	*-2.22*	*0.83*

Source: Authors' estimates using labor productivity version of equation (7). *This can be compared to "homogenous unit" in Table 2a.

TABLE 3B

INDIA: DECOMPOSITION OF AGGREGATE LABOR PRODUCTIVITY GROWTH, 1981-2011

(Contributions are weighted growth in percent)

	1981-1991	1991-2001	2001-2007	2007-2011	*1981-2011*
			Growth Rates		
Value-Added Growth (APPF)	4.87	5.83	7.75	7.16	*6.07*
-Value added per number employed	*2.89*	*4.19*	*6.26*	*6.35*	*4.46*
*- Number employed (natural unit)**	*1.97*	*1.64*	*1.48*	*0.80*	*1.61*
			Factor Contributions		
Value-Added per employed person	2.89	4.19	6.26	6.35	*4.46*
- Capital deepening	*1.82*	*2.22*	*3.58*	*4.39*	*2.65*
- Labor quality	*0.79*	*0.60*	*0.63*	*0.75*	*0.69*
- TFP growth	*0.28*	*1.38*	*2.05*	*1.22*	*1.13*

Source: Author's estimates using labor productivity version of equation (7). *This can be compared to "homogenous unit" in Table 2b.

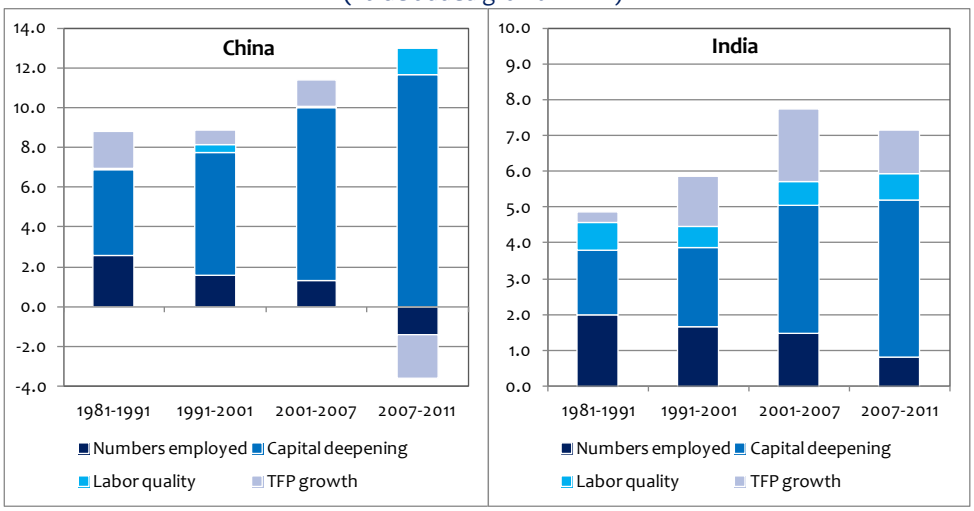
As a usual and insightful analysis, in Table 3a and 3b we also introduce a growth accounting in the form of labor productivity, which to a large extent captures the effect of so-call

"demographic dividend" by separating the growth of numbers employed from the growth of output per employed person. Helped with an intuitive presentation in Figure 3, it is clear that both economies have been increasingly driven by capital deepening but the Indian economy looks healthier than the Chinese economy as suggested by their different TFP performances relative to their different capital-deepening processes. One explanation could be that India was relatively more insulated from the world economy than China, hence less volatile. Also, after three decades of rapid growth, China is slowing down to rebalance its economy from export-driven to less-volatile domestic consumption driven economy (Das Krishna and Bhardwaj, 2016; Bloom et al., 2006). Another explanation could be that China has long been relying on government engineered growth and hence suffered increasingly from misallocation of resources (Wu, 2016a).

FIGURE 3

CONTRIBUTION TO AGGREGATE VALUE-ADDED GROWTH OVER SUB-PERIODS, 1981-2011: CHINA VIS-À-VIS INDIA

(Value-added growth = 100)

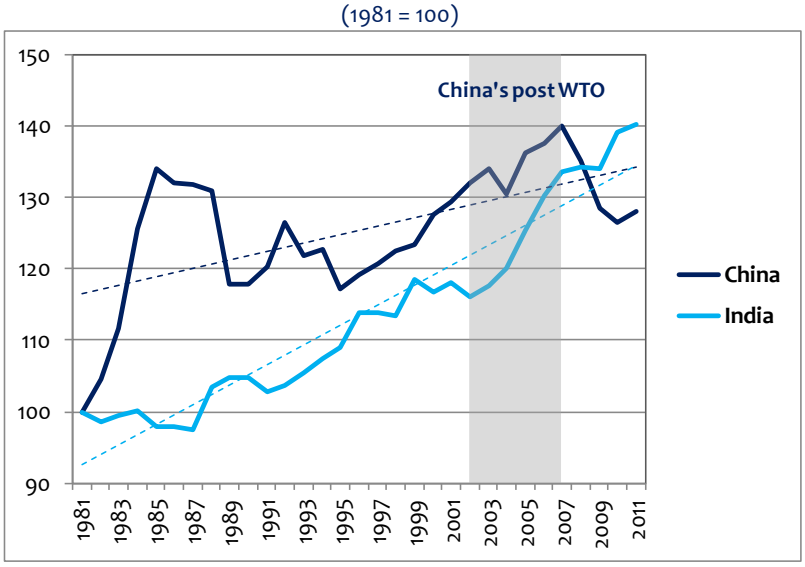


Source: Table 3a and 3b.

To examine and compare the TFP dynamics of the two economies over time, in Figure 4 we translate the annual aggregate TFP growth rates into a level index with 1981 as the base year. We also add a regression line to each country's index as its underlying productivity trend to benchmark its actual TFP movement. It is apparent that China's first TFP drive was associated with the early agricultural and industrial reforms in the early 1980s, but it ended at the time of the Tiananmen political crisis in 1989. Deng's call for bolder reforms in the early 1990s was responded by a TFP rise but not as significant as that in the 1980s. The Chinese economy returned to its productivity trend following its WTO entry (shaded area in Figure 4), yet ended in the wake of the global financial crisis.

In contrast, India's TFP performance over time does not look as dramatic as that of China. But it seems that Indian reforms indeed promoted a steady TFP improvement that remarkably converged with the Chinese productivity trend (Figure 4). We find that India's TFP began to accelerate also following China's WTO entry. However, the post-GFC period saw a very different story. While India seemed to have managed to continue its productivity growth, China, after a tremendous negative shock of the GFC, appeared to be following a deteriorating productivity downturn for two years till 2010. With the available data, it is perhaps too early to speculate the likely productivity changes in the two economies after 2011.

FIGURE 4
INDEX OF AGGREGATE TOTAL FACTOR PRODUCTIVITY GROWTH IN 1981-2011:
CHINA VIS-À-VIS INDIA
(1981 = 100)



Source: See Table 2a and 2b.

The industry origin of aggregate TFP growth and the reallocation effect

As expressed in equation (9), using the Domar aggregation approach the aggregate TFP growth rate can be decomposed into three additive components, that is, the change of the Domar-weighted aggregate TFP, the effect of capital reallocation across industries and the effect of labor reallocation across industries. The results are reported in Tables 4a and 4b, respectively for China and India. We now first examine and compare the contribution of each industry group to the aggregate TFP growth between the two countries.

When estimated with the Domar weights, we find that on an average of the period 1981-2011, India's TFP growth (0.87) is still faster than China's TFP growth rate (0.61). We also find that industry groups' contributions to the Domar-weighted annual TFP growth vary but to a much greater extent in the case of China compared to the case of India. For India, the major contributors to the TFP growth rate were services, in which market and non-market services made an equal contribution of 26.5 percent each, or 53.1 percent in total, to the aggregate TFP growth of 1.13 percent per annum, including both Domar and reallocation effects (Table 4b). Also for the same period, the contribution of the "manufacturing" group (made up of item 3 to 6) was 29.2 percent. These readings appear to be fairly in line with their contributions to the aggregate value-added growth (6.07 percent per annum, Table 2b), i.e. 56.2 and 22.4 percent (see the discussion of Table 2b).

The case of China, nonetheless, seems to tell a very different story. The Chinese "manufacturing" and "services" groups contributed respectively 50.3 and 29.0 percent, respectively, to the aggregate value-added growth of 9.41 percent per annum (Table 2a), but their corresponding contributions to the aggregate TFP growth of 0.83 percent per annum (Table 4a) were 202.4 and -130.1 percent, respectively. Such an unreasonable mismatch of growth and productivity performances is observed throughout all sub-periods with the worst case in the period 1991-2001. It may be reasonable to argue that entering WTO introduces an institutional correction to the Chinese economy. If these estimates are acceptable, we may need to consider accepting Wu (2016a)'s institutional hypothesis that the growth-motivated government uses a

kind of "cross subsidization" to promote the growth of labor-intensive manufacturing to timely harvest China's demographic dividend while supporting strategic industries that are capital-intensive and may not be in line with China's comparative advantage. The government-favored or selected industries enjoy the benefit of various underpaid costs (Huang and Tao, 2010), which in turn as a negative externality takes the toll on the costs of other industries.

TABLE 4A

CHINA: DOMAR-WEIGHTED TFP GROWTH AND REALLOCATION EFFECTS, 1981-2011

(Growth in percent per annum and contribution in percentage points)

	1981-91	1991-01	2001-07	2007-11	*1981-11*
Aggregate TFP growth	1.86	0.72	1.32	-2.22	0.83
1) Domar-weighted TFP growth	1.47	0.63	1.47	-2.90	0.61
1. Agriculture	*0.89*	*0.46*	*-0.18*	*-0.68*	*0.33*
2. Mining	*-0.43*	*-0.00*	*-0.71*	*-0.36*	*-0.33*
3. Light manufacturing	*-0.17*	*0.92*	*0.67*	*0.13*	*0.40*
4. Intermediate materials	*-0.22*	*1.02*	*0.10*	*-0.40*	*0.23*
5. Electricals & ICT	*0.57*	*0.56*	*0.40*	*0.14*	*0.47*
*6. Machinery & motor vehicles**	*0.84*	*0.58*	*0.56*	*-0.03*	*0.58*
7. Utilities	*0.07*	*-0.32*	*0.21*	*0.18*	*-0.01*
8. Construction	*0.07*	*-0.06*	*0.17*	*-0.17*	*0.02*
9. Market services	*0.19*	*-1.27*	*1.22*	*-0.32*	*-0.16*
10. Non-market services	*-0.34*	*-1.25*	*-0.98*	*-1.41*	*-0.92*
2) Reallocation of K (ρ^K)	-0.26	-0.36	-1.34	-0.15	-0.49
3) Reallocation of L (ρ^L)	0.65	0.44	1.19	0.83	0.71

Source: Authors' estimates following equation (9). *Including other transport equipment.

TABLE 4B

INDIA: DOMAR-WEIGHTED TFP GROWTH AND REALLOCATION EFFECTS, 1981-2011

(Growth in percent per annum and contribution in percentage points)

	1981-91	1991-01	2001-07	2007-11	*1981-11*
Aggregate TFP growth	0.28	1.38	2.05	1.22	*1.13*
1) Domar-weighted TFP growth	0.52	1.02	1.34	0.67	*0.87*
1. Agriculture	*0.12*	*0.30*	*-0.00*	*0.27*	*0.18*
2. Mining	*-0.05*	*0.03*	*-0.16*	*-0.11*	*-0.05*
3. Light manufacturing	*0.01*	*-0.01*	*-0.00*	*0.43*	*0.06*
4. Intermediate materials	*0.18*	*-0.10*	*0.39*	*0.15*	*0.13*
5. Electricals & ICT	*0.06*	*0.04*	*0.09*	*0.10*	*0.06*
*6. Machinery & motor vehicles**	*-0.03*	*0.07*	*0.20*	*0.18*	*0.08*
7. Utilities	*0.04*	*0.14*	*0.14*	*-0.04*	*0.08*
8. Construction	*-0.30*	*-0.26*	*-0.05*	*-0.47*	*-0.26*
9. Market services	*-0.01*	*0.42*	*1.01*	*-0.29*	*0.30*
10. Non-market services	*0.49*	*0.39*	*-0.27*	*0.43*	*0.30*
2) Reallocation of K (ρ^K)	-0.27	0.37	0.37	0.42	*0.16*
3) Reallocation of L (ρ^L)	0.03	-0.01	0.35	0.13	*0.09*

Source: Author's estimates following equation (9). *Including other transport equipment.

The considerable factor reallocation effects on the TFP growth in both economies, as presented in the last two rows of Tables 4a and 4b, suggest that industries indeed face different factor costs, thus the traditional aggregate production function approach is inappropriate as discussed in Jorgenson et al. (2005a and 2005b). In theory, along with market-oriented reforms such reallocation is expected to be TFP promoting. This is largely reflected by the case of India that over the period 1981-2011 the reallocation of capital and labor contributed to the 1.13-percent aggregate TFP growth by 0.16 and 0.09 ppts, respectively. In the case of China, nevertheless, the reallocation of capital resulted in a big loss of -0.49 ppts. However, China's net reallocation effect was still positive (0.22 ppts out of the 0.83-percent aggregate TFP growth), thanks to a significant gain of 0.71 ppts from labor reallocation that could be attributable to substantial improvements of China's labor market. This may also lend a strong support to our conjecture that institutional

defects including government interferences are mainly responsible for the productivity loss due to the misallocation of capital in China. In our view, institutional effects on both growth and productivity performances between the two countries remain a very challenging and exciting topic of research.

6. Concluding Remarks

In this study we apply the same aggregate production possibility frontier (APPF) framework for growth accounting à la Jorgenson et al. (2005a and 2005b) to an economy-wide Chinese and Indian industry-level dataset, separately constructed in the spirit of the KLEMS principle using official statistics, to estimate growth and productivity performance in China and India over the post-reform period from 1981 to 2011. This is the first attempt made to compare the two countries in a consistent and rigorous empirical assessment for growth and productivity performance.

We show that over the three decades in comparison China grew over 50 percent-faster than India in value added (9.4 versus 6.1 percent per annum) but about 25 percent-slower than India in TFP (0.83 versus 1.13 percent per annum). The two economies also experienced very different growth and productivity performances over various sub-periods distinguished by special policy regimes and governing systems. While they both appeared to enjoy their best performances following China's WTO entry, China suffered much more in productivity growth in particular in the wake of the global financial crisis.

We find that manufacturing and services indeed played distinctly different roles in the two economies. In terms of the GDP growth, they accounted for 50.3 and 29.0 percent in China, whereas in India their contributions nearly reversed to 22.4 and 56.2 percent, respectively. In terms of the TFP growth, in India the contributions of the two sectors largely mirrored their roles in the GDP growth, but this are not the case of China where an implausibly high contribution by manufacturing (about 200 percent) co-existed sharply with a negative contribution by services (about -130 percent). We argue that this apparent imbalance may be to a large extent explainable by the negative effect of capital reallocation on TFP growth that reflects serious institutional barriers to factor mobility and government intervention-induced misallocation of resources.

While both China and India are increasingly regarded as successful reform stories, both are confronting serious challenges to sustaining economic growth. China's challenges include the need for comprehensive financial sector reform, greater exchange rate flexibility, more environment friendly growth, and a better balance between consumption and investment. India for its part needs growth of its manufacturing sector, reform its labor laws, invest in infrastructure and further liberalize its foreign trade. While some of these challenges overlap, the two economies are likely to remain a study in contrasts. Comparisons in institutional effects on productivity performance should be prioritized, and productivity comparisons should not only be made in growth rates but also in levels.

It should be made clear that our empirical findings and implications drawn from them are confined to the current data we used. Both the Chinese CIP/KLEMS dataset and India KLEMs dataset are still evolving over time with new source data and more methodological sophistication towards the measurement accuracy of variables. Specifically, we are working together to develop more consistent datasets for the two economies in terms of classification, prices and hour-based quantitative measure of employment.

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TABLE A1

CONCORDANCE TABLE FOR CHINA AND INDIA DATA AND GROUPING

CHINA CIP/KLEMS		INDIA KLEMS		Grouping
1	Agriculture	1	Agriculture	1. Agriculture
2	Coal mining	2	Mining and quarrying	2. Mining
3	Oil and gas extraction			
4	Metal mining			
5	Non-metallic minerals mining			
6	Food and kindred products	3	Food products, beverages	3. Light manufacturing
7	Tobacco products		and tobacco	
8	Textile mill products	4	Textiles, textile products,	
9	Apparel and other textile products		Leather and footwear	
10	Leather and leather products			
11	Saw mill products, furniture, fixtures	5	Wood and products of wood	
12	Paper products, printing & publishing	6	Paper products, printing & publishing	
13	Petroleum and coal products	7	Petroleum & products; nuclear fuel	4. Intermediate materials
14	Chemicals and allied products	8	Chemicals and chemical products	
15	Rubber and plastics products	9	Rubber and plastic products	
16	Stone, clay, and glass products	10	Other non-metallic mineral products	
17	Primary & fabricated metal industries	11	Basic and fabricated metal products	
18	Metal products (excl. rolling products)			
19	Industrial machinery and equipment	12	Machinery, nec.	6. Machinery & motor v.
20	Electric equipment	13	Electrical and optical equipment	5. Electricals & ICT
21	Electronic and telecommunication eq.			
22	Instruments and office equipment			
23	Motor vehicles & other transport eq.	14	Transport equipment	6. Machinery & motor v.
24	Miscellaneous manufacturing	15	Manufacturing, nec; recycling	3. Light manufacturing
25	Utilities	16	Utilities	7. Utilities
26	Construction	17	Construction	8. Construction
27	Wholesale and retail trades	18	Trade	9. Market services
28	Hotels and restaurants	19	Hotels and restaurants	
29	Transport, storage & post	20	Transport and storage	
30	Information & computer services	21	Post and telecommunications	
31	Financial Intermediation	22	Financial services	
32	Real estate activities	27	Other services	10. Non-market services
33	Technical, science & business Services	23	Business service	9. Market services
34	Public administration and defense	24	Public administration and defense	10. Non-market services
35	Education	25	Education	
36	Health and social security	26	Health and social work	
37	Other services	27	Other services	