How Does the Productivity and Economic Growth Performance of China and India Compare in the Post-Reform Era, 1981-2011?

Harry X. Wu
Hitotsubashi University, Tokyo

K. L. Krishna
Delhi School of Economics, Delhi

Deb Kusum Das
Ramjas College, Delhi

Pilu Chandra Das[1]
Kidderpore College, Kolkata

ABSTRACT

Applying an aggregate production possibility frontier (APPF) framework for growth accounting à la Jorgenson *et al.* to 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 per cent-faster than India in value added (9.4 versus 6.1 per cent per annum) but about 25 per cent-slower than India in TFP (0.83 versus 1.13 per cent 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 both countries appeared to enjoy their best performances in the 2002-2007 period following China's WTO entry, China faltered much more in terms of total factor productivity growth in the wake of the global financial crisis.

Benefiting from their market-oriented reforms, the world's two most populous countries, China and India, with of population of 1.39 and 1.34 billions 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

1 Harry X. Wu is Professor of Economics at the Institute of Economic Research, Hitotsubashi University in Japan; K.L. Krishna and Deb Kusum Das are Professors of Economics at the Delhi School of Economics and Ramjas College in Delhi, India, respectively; Pilu Chandra Das is a Lecturer of Economics at Kidderpore College in Kolkata, India. We would like to thank two referees for their helpful comments and suggestions. Earlier versions of the paper were presented at the 4th World KLEMS Conference (Madrid), the 2nd World Congress of Comparative Economics (St. Petersburg), Groningen Growth and Development Center 25th Anniversary Conference, STI seminar at the OECD (Paris) and the 4th Asian KLEMS Conference (Tokyo). We would also like to thank the participants of these events. This study is part of the India KLEMS project at the Centre for Development Economics, Delhi School of Economics, sponsored by the Reserve Bank of India, and part of the China CIP/KLEMS project jointly supported by RIETI and IER of Hitotsubashi University. We gratefully acknowledge the respective sponsors for their financial supports. Finally, we give our special appreciation for excellent research assistance by David T. Liang and Zhan Li. The usual disclaimers apply. Contact harry.wu@ier.hit-u.ac.jp for the case of China and dkd_ramjas@yahoo.com for the case of India.

uses alternative (non-official) GDP estimates for China following Maddison and Wu (2008), China grew by 7.5 per cent per annum over the period 1990-2015 whereas India grew by 6.4 per cent per annum.[2] 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-per cent annual growth rate, whereas China decelerated somewhat to 5.8 per cent per annum. Meanwhile, the rest of the world grew by 2.7 per cent per annum.

As a consequence of such rapid growth, by a 1990 G-K PPP yardstick following Maddison (2001), China and India overtook Japan in terms of GDP size in 1995 and 2006, respectively. While the world is paying serious attention to their fast pace of catching up with an enormous size effect on the world economy, 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, China achieved only 10.6 per cent of Japan's level of per capita GDP and 10.1 per cent of Japan's level of labour productivity. In the case of India, these ratios are similar, 11.8 and 14.2 correspondingly.[3] In sharp contrast, when Japan surpassed Germany in 1967 it had already attained 82.2 per cent of Germany's level of per capita GDP and 75.5 per cent of Germany's level of labour productivity (TCB, 2016).

Even if considering that 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 labour productivity. Apparently, both China and India benefitted from a huge demographic dividend, but to a large extent they were hindered by their 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 unrealistically high TFP growth in the case of China compared to that of India. For example, Bosworth and Collins (2008) find that over the period 1978-2004, China's TFP growth was 4.6 per cent per annum vis-à-vis India's 1.6 per cent per annum. Jorgenson and Vu (2005) show that during the period 1989-1995 China's TFP growth was 6.3 per cent per annum compared to India's 2.1 per cent per annum, but during the period 1995-2003 the two economies converged to the same rate of TFP growth at 2.5 per cent per annum. Some studies questioned the reliability of these TFP estimates given the likelihood of upward bias in official growth estimates (Maddison and Wu 2008; Bardhan 2010; Wu 2014).

Some researchers show that institutional deficiencies might have affected productivity growth in both China and India. Hsieh and Klenow (2009) use micro-data on manufacturing

2 Maddison and Wu proposed a volume-movement approach to adjust for the upward-bias in Chinese official statistics (Maddison and Wu 2008; see Wu, 2014 and 2016a, for further development). To have a world-wide perspective, we use the Maddison-Wu estimates in the TCB-TED data to show more plausible growth rates for China. However, as explained in the data section, to obtain industry information and maintain a necessary coherence between industries and the national accounts, which is essential in the KLEMS-type industry-level data construction, in the present study we accept Chinese official output estimates but adjust them for conceptual, coverage and classification inconsistencies (Wu, 2016b).

3 However, by 2015 the two ratios had increased to 31.8 and 28.5 per cent of the Japanese level in the case of China and 18.2 and 23.2 per cent in the case of India, reflecting China's much faster catch-up with Japan in terms of output per capita and per worker compared to India (TCB, 2016).

establishments to measure the potential extent of misallocation in China and India using the United States economy as a benchmark. When capital and labour are hypothetically reallocated to equalize the marginal products across plants to the extent observed in the United States, they find that the manufacturing TFP would be 30-50 per cent higher in the case of China and 40-60 per cent in the case of India. This suggests there are institutional barriers to factor mobility in both countries.

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 benefitted from 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 analysis.

Industry-level TFP studies require extensive data embedded in a coherent national accounts framework (e.g. Jorgenson, Gollop and Fraumeni, 1987; Jorgenson, Ho and Stiroh, 2005a and 2005b). Such research has long been obstructed by data problems. The situation began to improve in the early 2000s, thanks to the EU-KLEMS project aiming to establish industry productivity accounts coherently linked to the national accounts through input-output tables.[4]

Building in this development, 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 (Wu, 2016b) and for India from the Indian KLEMS team (Das *et al.*, 2016),[5] 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 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 literature, especially that all industries are homogenous, satisfy the same value added function, and face the same input and output prices.

This article contains five sections. The first main section outlines the process of reforms in China and India emphasizing institutional deficiencies. The methodology of productivity measurement used is presented in Section 2. The datasets for China and India are briefly described in Section 3. The empirical results on growth and productivity for the two countries are reported and compared in Section 4 with an emphasis on the effects of China's entry into the World Trade Organization (WTO) and the global financial crisis (GFC) upon both of the economies. The fifth and final section briefly concludes and proposes the way forward for future research.

4 "KLEMS" is used as an acronym for Capital, Labour, Energy, Materials and Services that are used to produce goods or services. See O'Mahony and Timmer (2009) for an introduction of the EU-KLEMS database.

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

Reforms Under Different Governance Systems and Implications for Productivity Growth

At the time of their market-oriented reforms, 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's rule, adopted a Soviet-type central planning system with omnipresent state power till the end of the 1970s. 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 the market allocation of resources, India did not outlaw private ownership and the market.

Officially, China started its agricultural reform in 1978 and industrial reform in 1984. However, if considering that China's agricultural reform through the 1980s was only a return to the pre-planning farming system, it could be compatible to that of India's private farming system by the late 1980s. At the turn of the 1990s when India began deregulating capital goods industries and trade, Deng Xiaoping, the paramount leader of the People's Repubic of China at the time, called for bolder reforms to take China out of the shadow of the Tiananmen political turmoil of 1989. Thus, we could say that by this time both countries were more or less engaged in a full-scale reform despite maintaining their pre-reform political systems, with China firmly sticking to an authoritarian regime and India following a democratic system. Compared to India, China was more open to foreign trade and direct investment, but it had also used more administrative power to intervene in resource allocation to promote growth, which negatively affected the development of a healthy legal framework and an efficient financial system (Xu, 2011). 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 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. They have resulted in a transformation, particularly through labour-intensive rural industrialization, which is still largely absent in India. He explores the factors that inhibit labour-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, 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 agriculture.

While Indian economists make a very positive assessment of the Chinese system, Chinese economists have attempted to understand its deeply-rooted institutional 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 in 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). Wu (2016b) argues that 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. 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 also agree that such a Chinese model of growth is also responsible for widespread corruption.

Taking these institutional differences and areas with unfinished reforms as a background, in this article, we are interested mainly in examining and comparing the industry origin of the growth and productivity performances between the two giant economies over the same period that saw distinct policy regime shifts and macroeconomic shocks.

Accounting for the Sources of Growth with Industry Origin[6]

The widely used aggregate production function approach to TFP analysis is subject to very stringent assumptions that "value-added functions exist and are identical across (underlying) industries up to a scalar multiple" and "the aggregation of heterogeneous types of capital and labour must receive the same price in each industry" (Jorgenson, Ho and Stiroh, 2005a). This article 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 by Jorgenson, Gollop and Fraumeni (1987) to allow direct aggregation across industries to account for the role of 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 United States 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 aggregate productivity growth and input accumulation to the underlying industries. Focusing on an industry-level production function given by equation (1), each industry (j), purchases distinct intermediate inputs, capital and labour services to produce a set of products:

$$Y_j = f_j(K_j, L_j, X_j, T) \qquad (1)$$

6 This section is adopted from Wu (2016b).

where Y is output, K is an index of capital service flows, L is an index of labour service flows, X is an index of intermediate inputs, either purchased from domestic industries or imported, and T refers to time, so that change in technology can be captured. Note that all input variables and output are also 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:

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

where $\bar{\nu}_j^K$, $\bar{\nu}_j^L$, and $\bar{\nu}_j^X$ are two-period averages of nominal weights of input $\nu_j^K = P_j^K K_j / (P_j^Y Y_j)$, $\nu_j^L = P_j^L L_j / (P_j^Y Y_j)$ and $\nu_j^K = P_j^K K_j / (P_j^Y Y_j$, respectively. Note that under constant returns to scale $\bar{\nu}_j^K + \bar{\nu}_j^L + \bar{\nu}_j^X = 1$, which is based on industry production accounts in nominal terms. Each element in the right-hand side of equation (2) indicates the proportion of output growth accounted for respectively by the growth of capital services ($\bar{\nu}_j^K \Delta \ln K_j$), labour services ($\bar{\nu}_j^L \Delta \ln L_j$), intermediate materials ($\bar{\nu}_j^X \Delta \ln X_j$), and total factor productivity (ν_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 labour services provided by different types of labour 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 the employed or hours worked as a homogenous measure of labour input. The growth of total labour input is thus defined as a Törnqvist quantity index of individual labour types as follows:

$$\Delta \ln L_j = \Sigma_h \bar{\nu}_{h,j} \Delta \ln H_{h,j} \tag{3a}$$

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 $\bar{\nu}_{h,j}$ given by two-period average shares of each type in the nominal value of labour compensation controlled by the labour 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 $\bar{\nu}_{k,j}$ and $\bar{\nu}_{m,j}$, respectively:

$$\Delta \ln K_j = \Sigma_K \bar{\nu}_{K,j} \Delta \ln Z_{h,j} \tag{3b}$$

and

$$\Delta \ln X_j = \Sigma_m \bar{\nu}_{m,j} \Delta \ln X_{m,j} \tag{3c}$$

It should be noted that the equations from (2) through the whole set of (3) also explicitly express the methodological framework for the China Industry Productivity (CIP) industry-level data construction that is linked to and controlled by the national production and income accounts.[7]

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

$$\Delta \ln Y_j = \bar{\nu}_j^V \Delta \ln V_j + \bar{\nu}_j^X \Delta \ln X_j \tag{4}$$

where V_j is the real value-added in j and ν_j^V is the nominal share of value-added in industry gross output. By rearranging equations (2) and

7 The China Industrial Productivity Database Program is sponsored by the Japanese Research Institute of Economy, Trade and Industry (RIETI) and the Institute of Economic Research at Hitotsubashi University. The application of equations 2 and 3 in CIP will be discussed when we discuss the data issues in the following section.

(4), we can obtain an expression for the sources of industry value-added growth (i.e. measured in terms of input contributions):

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

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

$$\Delta \ln V = \sum_j w_j \Delta \ln V_j \tag{6}$$

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 labour growth and TFP growth:

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

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:

$$v^T \equiv \sum_j \bar{w}_j \Delta \ln V_j - \bar{v}^K \Delta \ln K - \bar{v}^L \Delta \ln L \tag{8}$$

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):

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

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

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

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 labour across industries.

This Domar weighting scheme ($w_j / \bar{v}_j^V$), 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 labour (ρ^L) across industries, respectively. Each reallocation term, is obtained by subtracting cost-weighted aggregate factor (capital or labour) 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.

Data Issues

China and India KLEMS database

The data used in this article for both China and India are reconstructed based on official statistics. In the case of China, unlike in 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 the industry level, this is expressed in equation (2). For China, the KLEMS database is part of the ongoing China Industry Productivity (CIP) Database Project.[8] For India, it is part of the ongoing India KLEMS Database Project, which is explained in Das *et al.* (2016).[9]

Note that due to various data constraints we do not have the same measures for all variables in the two countries. In particular, in the case of China, labour input is estimated based on hours worked to capture the difference in hours worked per worker, whereas in the case of India despite differences in hours worked across different employment status there is not yet estimation for hours worked for the workforce (Aggarwal and Erumban, 2013). In addition, in the China CIP/KLEMS data all volume indicators are measured in 1990 prices and in the Indian KLEMS data such indicators are measured in 2004 prices. These differences are likely major sources of potential biases in the estimates.

Industrial classification and concordance

The classification of industries follows the International Standard Industrial Classification (ISIC) principles although somewhat constrained by country-specific problems. The China CIP/KLEMS dataset adopts a classifica-

8 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 labour quantity and compensation matrices. A brief introduction to data is provided in Wu (2016b).To access the current version of the CIP/KLEMS database and Indian KLEMS database, please follow the link managed by the World KLEMS Initiative: http://www.worldklems.net/data.htm.

9 Interested readers should also consult Erumban and Das (2013) on capital input, and Aggarwal and Erumban (2013) on employment.

tion system in line with the 2002 CSIC (China Standard of Industrial Classification) which classifies the Chinese economy into 37 industries. The Indian KLEMS dataset originally adopts the 1998 NIC (National Industrial Classification) and reclassified the Indian economy into 27 industries in line with the EU KLEMS standard of industrial classification. In this study, to facilitate China/India productivity comparisons, 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

To better distinguish industries by their positions in the production chain or distance from 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 data constraints, 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 and hotels, transport and 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.[10] To help better interpret and analyze the results against major events such as important policy regime shifts and external shocks, we divide the period into four sub-periods taking into accounts such events: 1981-1991, 1991-2002, 2002-2007, and 2007-2011.[11] The first sub-period is from 1981 to 1991. This was an early reform period for both countries. China had successfully conducted agricultural reform and introduced a planning-market double track reform to the industrial sector. India began to dissolve the long-lasting planning controls over capital goods industries and trade began to dissolve through a series of deregulation of a large number of industry groups. This sub-period ended in the aftermath of China's Tiananmen unrest (1989).

We set the next period to start in 1991 largely because in India this marks the beginning of the 1991-1992 comprehensive trade policy reforms to reduce tariffs and eliminate most non-tariff barriers while in China, Xiaoping's bolder call for deepening reforms in 1992 broke the standoff of the country's ideological debate on the nature of market reforms. This sub-period ends in 2001 or just before China joined the World Trade Organization (WTO) at the end of that year. This sub-period also includes the Asian

10 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.

11 This periodization focuses on policy regime shifts rather than depending on empirically-tested structural breaks in the data. However, our sup-Wald test for unknown break points in the output data suggests that there is only one statistically significant break point in each case, that is, 2005 in the case of China and 2006 in the case of India.

Table 1: Sources of Gross Output Growth by Industry Group, 1981-2011: China Versus India (Gross output-weighted as percentage points of annual gross output 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 and ICT	20.70	0.45	2.28	13.63	*4.35*	10.45	0.50	1.11	7.16	*1.68*
6. Mach. and 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*
Sum of 3-6: Manufacturing	*13.36*	*0.29*	*2.07*	*9.27*	*1.73*	*7.63*	*0.25*	*1.12*	*5.88*	*0.40*
Sum of 9-10: Services	*9.38*	*1.39*	*4.77*	*5.10*	*-1.88*	*7.34*	*1.41*	*2.27*	*2.37*	*1.28*

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.

Financial Crisis of 1997-1998 and its three years deflationary aftermath in China.

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 labour-intensive production but also in economies of scale. Undoubtedly, the Chinese government, both central and local, played an imperative role in engineering such an expansion (Wu, 2016b). We expect this China WTO effect to have a significant bearing on its competitors like India. This sub-period is then followed by the last sub-period from 2007 to 2011 aiming to capture the Global Financial Crisis impact 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.

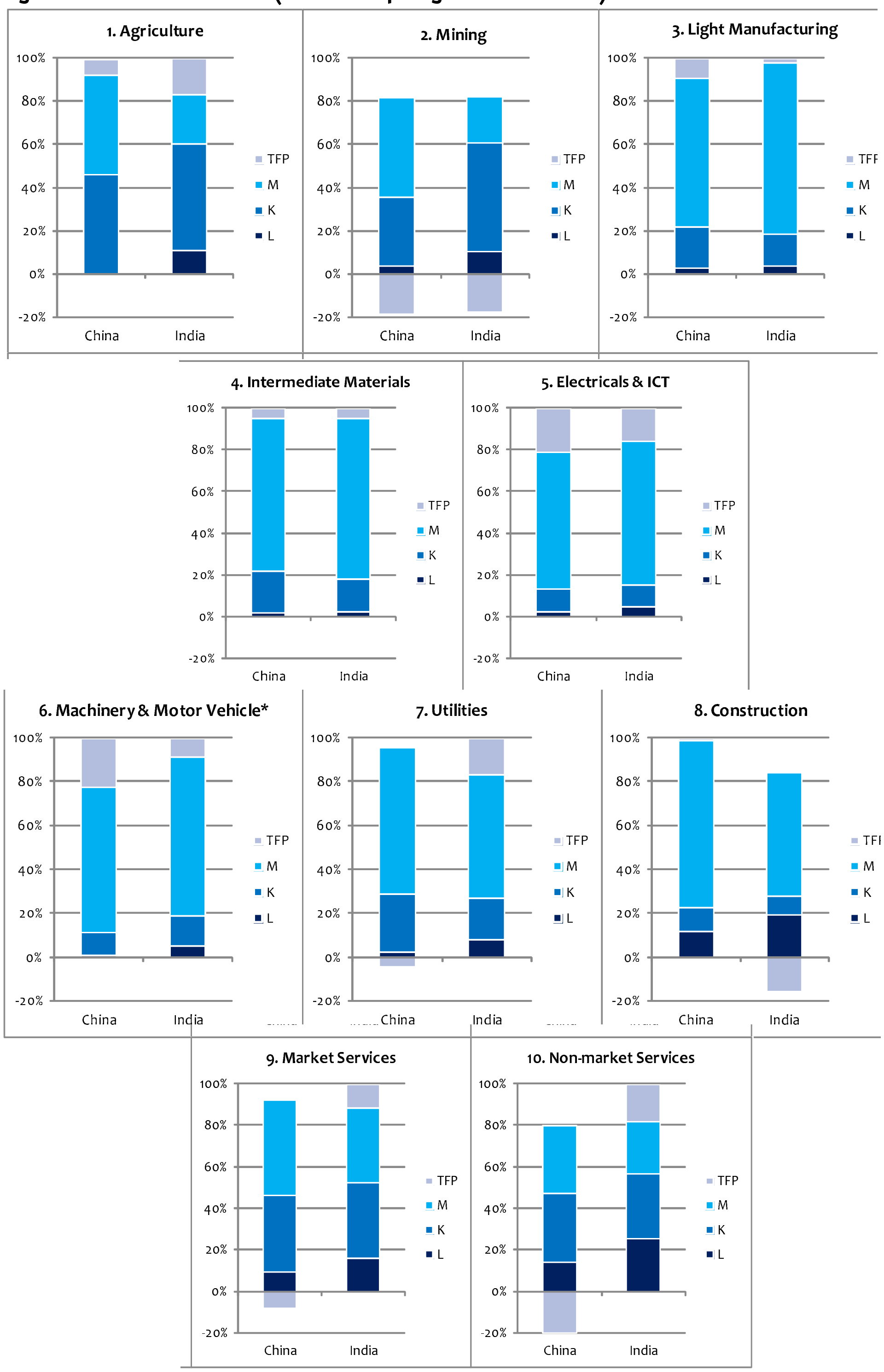
Empirical Results

In our empirical exercise, we opt for the double deflation approach to deflate gross output and intermediate inputs at the industry level. The input price change of an industry is a weighted average of the price changes of all inputs across industries used by that industry including input from the industry itself. The change of value added is hence derived based on equation (4). The measure of capital and labour inputs follows equations (3a) and (3b) although in the case of India we have to use numbers employed instead of hours worked for labour unit. In what follows, we report the empirical results by steps and compare the performances between the two countries against the macroeconomic background that is captured by our periodization.

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

Chart 1: Input Contribution to Gross Output Growth by Industry Group,1981-2011 Average: China Versus India (Gross output growth = 100%)



Note: *Including other transport equipment.
Source: Authors' estimates.

to 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 aggregate productivity growth.

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 the China and India panels respectively. To help better understand the relative contribution of each input Chart 1 depicts all the inputs as shares of a standardized gross output growth for all ten industry groups. A quick glance can tell that in general the differences between China and India for capital input are much more obvious than for labour input. Industry group comparisons however can reveal more distinctions between the two economies.

We can start from a performance comparison for the two primary groups, i.e. agriculture and mining. It may not be a big surprise to see that the Chinese agriculture grew twice faster than that of India, but to see that such growth relied little on labour contribution over the three decades (Table 1). In fact, China's labour input in agriculture declined by 0.03 per cent per annum. In the Indian agriculture sector on the contrary, labour input still grew by 0.31 per cent 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.

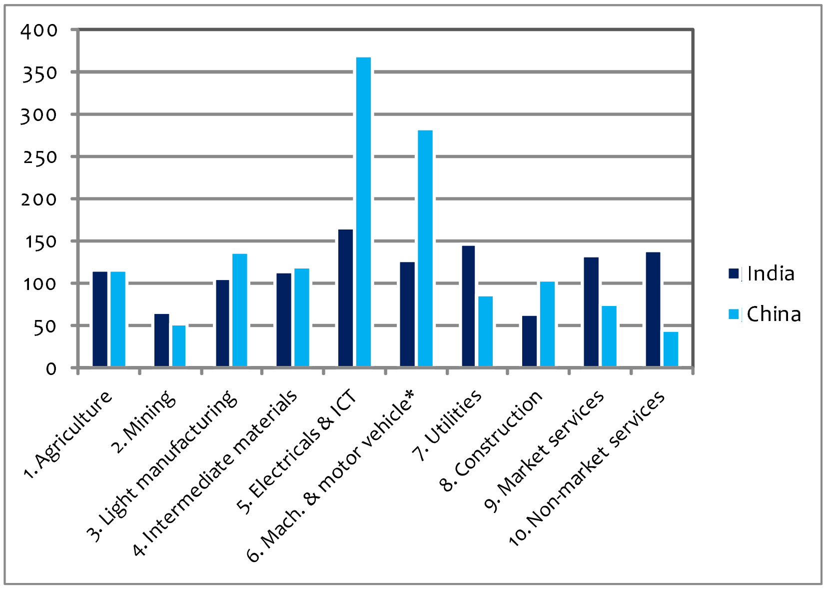
In the case of mining, China grew more than 40 per cent faster but depended much more on the growth of intermediate inputs than India. According to the estimated TFP growth for this sector, both countries appear to be inefficient in mining, but worse in the case of China. Chart 1, which is based on the numbers in Table 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 (group 4), electrical and ICT products (group 5), and machinery and motor vehicles (group 6). Noticeably, electrical-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 as fast as India.[12] Although China and India are the world's most populous countries, China relied less on the growth of labour input in these manufacturing industries than India. India was less efficient not only because its greater dependence on the growth of input materials but also due to a slower TFP growth (see standardized shares in Chart 1). Based on the industry group TFP performance, it is also interesting to see that both economies seemed to have enjoyed comparative advantage in electrical and ICT manufacturing (group 5) as well as in machinery and motor vehicle manufacturing (group 6), 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).

Since the strong growth in China and India had to be fueled by energy, how to produce energy more efficiently was an imperative challenge for both countries. It has been widely believed among Chinese observers that China is less efficient in energy production and usage than India and thus Chinese growth is much more energy-consuming than India's. We may be the first ones to provide supportive empirical evidence for China's disadvantage in energy pro-

12 In both China and India these industries substantially benefitted from deregulation of international trade and foreign direct investment (Liew and Wu, 2007; Das, 2016).

Chart 2: Total Factor Productivity by Industry Group: China Vis-A-Vis India 1981-2011(1981 = 100)



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

duction as shown by TFP growth referring to utilities with respect to India (Table 1 and Chart 1).

The Indian construction industry appears to be much more inefficient than its Chinese counterpart because it relied significantly more on the growth of input materials and experienced negative TFP growth, as shown in Table 1. Turning to services, both market and non-market, we show that China long suffered long from negative TFP growth. In the case of India, nonetheless, services appear to have been more labour-intensive, as measured by a labour-output ratio based on Table 1, less input materials-consuming, and to have experienced stronger TFP growth, especially for non-market services (Table 1 and Chart 1).

Chart 2 provides a TFP index for each industry group to show accumulated TFP growth over the entire period benchmarked on 1981 (=100). Obviously, industries above the benchmark line marked by 100 experienced TFP growth whereas industries below the line suffered from TFP decline. In general, productivity performance was much more dispersed across industry groups in China than in India. Despite the existence of productivity super stars, such as the group of electrical and ICT products and the group of machinery and motor vehicles, more industry groups experienced productivity losses in China than in India. One may reasonably conjecture that non-market forces must play a greater role influencing resource allocation, favouring some industries, hindering others, in China than in India.

Industry Contribution to Aggregate Value-Added Growth

From the examination of sources of gross output growth across industry groups in China and India, we have seen that industry groups performed very differently within each country in terms of the growth of factors and TFP. 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

Table 2: Sources of Aggregate Value-Added Growth in China and India, 1981-2011 (Contributions are share-weighted growth rate in percentage points)

China

	1981-1991	1991-2001	2001-2007	2007-2011	1981-2011
	Industry contributions to value-added growth (ppts)				
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
Sum of 3-6: Manufacturing	4.07	5.32	5.23	4.11	4.73
Sum of 9-10: Services	2.18	1.53	4.73	4.03	2.72
	Factor contributions to value-added growth (ppts)				
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

India

	1981-1991	1991-2001	2001-2007	2007-2011	1981-2011
	Industry contributions to value-added growth (ppts)				
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
Sum of 3-6: Manufacturing	1.23	1.03	1.70	1.92	1.35
Sum of 9-10: Services	2.48	3.48	4.42	4.10	3.42
	Factor contributions to value-added growth (ppts)				
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' estimates using equation (7). *Including other transport equipment.

rizes the results. In what follows we first examine the contribution of each industry group to aggregate value-added growth through each sub-period to see the role of each group in driving the growth. We then discuss the results of growth accounting in this framework in the form of both aggregate value-added and labour productivity functions.

A manufacturing sector can be formed by aggregating industry group 3 to 6 and a services sector by aggregating industry groups 9 and 10. A distinctive picture of growth emerges from looking at the aggregate. On average one half of China's value-added growth over the period 1981-2011 was driven by manufacturing (50.3 per cent, measured as 4.73 ppts of the 9.41 per cent growth, Table 2) and, in contrast, more than a half of India's growth by services (56.2 per cent, measured as 3.41 ppts of the 6.07 per cent growth, Table 2). This holds true for all sub-periods. If concentrating only on the contribution of market services to the growth, it was 22.2 per cent in the case of China (measured as 2.09 ppts of the 9.41 per cent growth) and 37.6 per cent in the case of India (2.28 ppts of the 6.07 per cent growth). Interestingly, when India underwent more comprehensive reforms in the 1990s, the growth of market services already made up nearly 40 per cent of annual value-added growth (2.32 ppts out of 5.83 per cent growth in 1991-2001). Meanwhile, in China, this was only less than 15 per cent (1.25 ppts out of 8.85 per cent annual growth in 1991-2001).

However, we also notice that a rebalancing took place in both economies following China's WTO entry. In India, while the growth in market services continued and was more rapid (3.58 per cent per annum in 2001-2007 compared to 2.32 per cent in 1991-2001), the growth of intermediate materials and machinery manufacturing groups, accelerated by a speed that was more than double the previous rate. In China, while the growth of some manufacturing industries decelerated, the growth of market services increased dramatically.

The contribution of agriculture to aggregate value-added growth declined inevitably in the two countries, but in China it was much faster than in India. When China experienced a sharp drop from about 20 per cent in 1981-1991(1.73 ppts of aggregate value-added growth of 8.81 per cent) to almost one per cent in 2007-2011 (0.11 ppts of aggregate value-added growth of 9.37 per cent), India underwent a process in which the contribution declined from 16 per cent to less than 10 per cent. We also find that in both cases, the contribution of mining was trivial (0.4 per cent for China and 2.0 per cent for India taking annual growth over the entire period as 100) and the contribution of utilities and construction also appears to be small and similar between the two countries (3.2 per cent and 5.5 per cent for China and 3.1 per cent and 4.1 per cent for India, calculated based on Table 2).

Factor Contribution to Aggregate Value-added Growth

In Table 2, 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 per cent per annum for India and 0.83 per cent per annum for China. That Indian TFP growth was over one-third faster than that of China comes as a rather big surprise. Both countries 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

Table 3: Decomposition of Aggregate Labour Productivity Growth in China and India, 1981-2011 (Contributions are weighted growth in per cent)

China

	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

India

	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

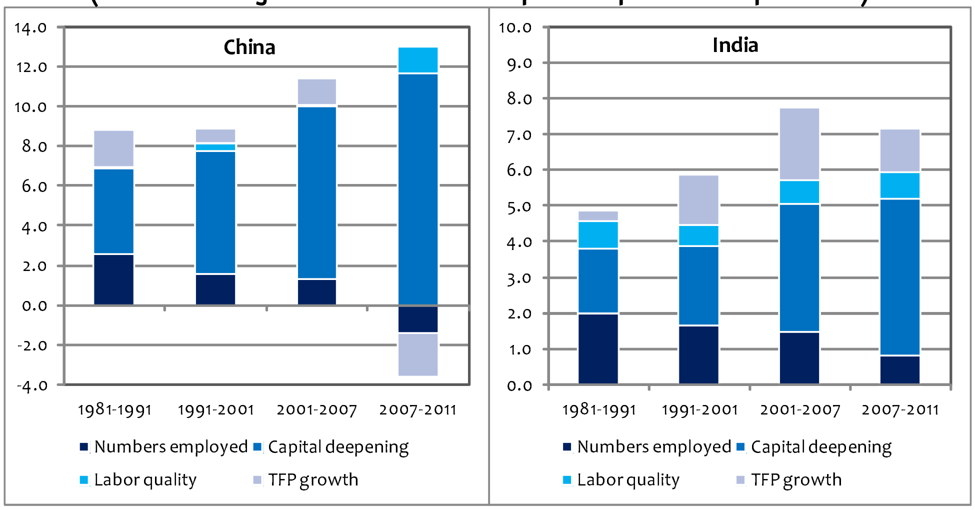
Source: Authors' estimates using labour productivity version of equation (7). *This can be compared to "numbers in homogenous unit" in Table 2.

and even maintained positive following the Global Financial Crisis shock and its recessionary aftermath. In the case of China, we find that after strong TFP growth in the first decade of reforms (1.86 per cent per annum in 1981-1991), the gain in TFP was not that dramatic over the 1990s and the post-WTO period, and turned negative in the 2007-2011 sub-period.

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 per cent of the 9.41 per cent real growth per annum was attributable to physical capital input, 10.3 to labour input and merely 8.8 to TFP calculated. In India, the corresponding figures are 56.5 per cent, 24.9 per cent and 18.6 per cent with respect to the 6.07 per cent real growth per annum. This suggests that China has been much more dependent on physical capital input than India.

As an usual and insightful analysis, in Table 3 and Chart 3 we also introduce growth accounting in the form of labour productivity, which to a large extent captures the effect of the so-call "demographic dividend" by separating the growth of numbers employed from the growth of output per employed person. As shown in Chart 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

Chart 3: Sources of Aggregate Value-Added Growth Over Sub-Periods in China and India, 1981-2011(Value-added growth = Sum of all input components in per cent)



Source: Table 3.

growth, China is slowing down to rebalance its economy from export-driven to less-volatile domestic consumption driven (Das Krishna and Bhardwaj, 2016; Bloom *et al.*, 2010). Another explanation could be that China has long been relied on government-engineered growth and hence suffered increasingly from misallocation of resources (Wu, 2016b).

To examine and compare the TFP dynamics of the two economies over time, in Chart 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 growth 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 resulted in TFP growth but not as strong as that in the 1980s. The Chinese economy returned to its productivity trend following its WTO entry. This ended in the wake of the Global Financial Crisis.

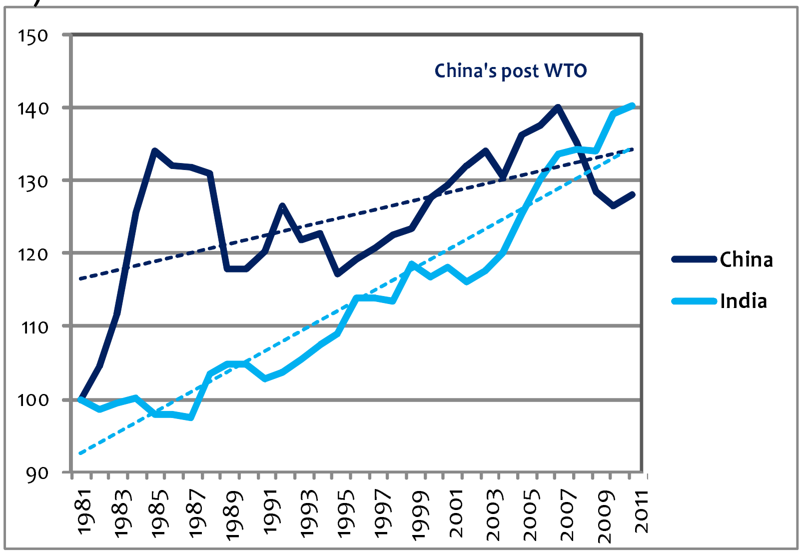
In contrast, India's TFP performance over time does not look as dramatic as that of China. However, it seems that Indian reforms indeed promoted a steady TFP improvement that remarkably converged with the Chinese productivity trend (Chart 4). Although we find that India's TFP also began to accelerate following China's WTO entry, we do not attempt to investigate the existence of a causal relationship in this study.

The post-GFC period saw a very different story to that of 2001-2007. While India seemed to have managed to continue its TFP growth, China, after a tremendous negative shock from the global financial crisis, appeared to be following a two year deteriorating productivity downturn until 2010. With the available data, it is perhaps too early to speculate on likely productivity developments in the two economies after 2011.

The Industry Origin of Aggregate TFP Growth and the Reallocation Effect

As expressed in equation (9), using the Domar aggregation approach the aggregate TFP

Chart 4: Index of Aggregate Total Factor Productivity in China and India, 1981-2011 (1981 = 100)



Source: Table 2.

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 labour reallocation across industries. The results are reported in Table 4, respectively for China and India.

When estimated with the Domar weights, we find that over the period 1981-2011, India's TFP growth (0.87 per cent per year) was still faster than China's TFP growth rate (0.61 per cent). We also find that contributions of the industry groups 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 per cent each, or 53.1 per cent in total, to the aggregate TFP growth of 1.13 per cent per annum, including both Domar and reallocation effects (Table 4). Also for the same period, the contribution of the "manufacturing" group (made up of item 3 to 6) was 29.2 per cent. These findings appear to be fairly in line with their contributions to the aggregate value-added growth (6.07 per cent per annum, Table 2), i.e. 56.2 and 22.4 per cent.

The case of China, nonetheless, seems to tell a very different story. The Chinese "manufacturing" and "services" groups contributed respectively 50.3 per cent and 29.0 per cent, respectively, to the aggregate value-added growth of 9.41 per cent per annum (Table 2), but their corresponding contributions to the aggregate TFP growth of 0.83 per cent per annum (Table 4) were 202.4 and -130.1 per cent, 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 introduced an institutional correction to the Chinese economy. If these estimates are acceptable, we may need to consider accepting Wu (2016b)'s institutional hypothesis that the growth-motivated government uses a kind of "cross subsidization" to promote the growth of labour-intensive manufacturing to timely harvest China's demographic dividend while supporting

Table 4: Domar-Weighted TFP Growth and Reallocation Effects in China and India, 1981-2011(Growth in per cent per annum and contribution in percentage points)

China

	1981-1991	1991-2001	2001-2007	2007-2011	1981-2011
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
Sum of 3-6: Manufacturing	1.02	3.07	1.74	-0.16	1.69
Sum of 9-10: Services	-0.16	-2.52	0.24	-1.73	-1.07
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

India

	1981-1991	1991-2001	2001-2007	2007-2011	1981-2011
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
Sum of 3-6: Manufacturing	0.23	-0.01	0.67	0.87	0.32
Sum of 9-10: Services	0.48	0.81	0.74	0.14	0.60
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: Authors' estimates following equation (9). *Including other transport equipment.

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.

The considerable factor reallocation effects on TFP growth in both economies, as presented in the last two rows of Table 4, suggest that industries indeed face different factor costs. This implies that 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 labour contributed to the 1.13 per cent aggregate TFP growth by 0.16 and 0.09 percentage points, 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 per cent aggregate TFP growth), thanks to a significant gain of 0.71 ppts from labour reallocation that could be attributable to substantial improvements of China's labour market. This may also lend 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.

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 China grew over 50 per cent faster than India in value added (9.4 per cent versus 6.1 per cent per annum) but about 25 per cent slower than India in TFP (0.83 versus 1.13 per cent 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 per cent and 29.0 per cent respectively in China, whereas in India their contributions nearly reversed to 22.4 and 56.2 per cent, respectively. In terms of the TFP growth, in India the contributions of the two sectors largely mirrored their role in the GDP growth, but this is not the case of China where a seemingly implausible high contribution by manufacturing (about 200 per cent) co-existed with a huge loss by services (about -130 per cent). We argue that such an imbalance in China may be to a large extent explained 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.

However, we would like to make it clear that our empirical findings and implications drawn from them are confined to the data 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 an accurate measurement of variables. Specifically, we are working together to develop more comparable datasets for the two economies in terms of classification, prices and hour-based quantitative measure of employment. Such data improvements may allow productivity comparisons in terms of levels as well as growth rates. Lastly, among various contrasts between the two economies that could motivate interesting comparative studies, comparisons in institutional effects on productivity performance should be prioritized.

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Appendix Table 1: Concordance Table for China and India Industry 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 vehicles.
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 vehicles.
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	