NBER WORKING PAPER SERIES

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Working Paper 21657
http://www.nber.org/papers/w21657

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2015

We are grateful to the Ontario Research Fund (ORF) for financial support and to seminar participants at UWO for comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. O41,O47,O57,P5

ABSTRACT

Popular literature suggests a rapid narrowing of the technology gap between China and the U.S. based on large percentage increases in Chinese patent applications, and equally large increases in college registrants and completed PhDs (especially in sciences) in China in recent years. Little literature attempts to measure the technology gap directly using estimates of country aggregate technologies. This gap is usually thought to be smaller than differences in GDP per capita since the later reflect both differing factor endowments and technology parameters. This paper assesses changes in China's technology gaps both with the U.S. and India between 1979 and 2008, comparing the technology level of these economies using a CES production framework in which the technology gap is reflected in the change of technology parameters. Our measure is related to but differs from the Malmquist index. We determine the parameter values for country technology by using calibration procedures. Our calculations suggest that the technology gap between China and the U.S. is significantly larger than that between India and the U.S. for the period before 2008. The pairwise gaps between the U.S. and China, and the U.S. and India remain large while narrowing at a slower rate than GDP per worker. Although China has a higher growth rate of total factor productivity than India over the period, the bilateral technology gap between China and India is still in India's favor. India had higher income per worker than China in the 1970's, and China's much more rapid physical and human capital accumulation has allowed China to move ahead, but a bilateral technology gap remains.

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1. Introduction

In this paper, we report calculations of the technology gaps between China and the U.S. as well as China and India between 1979 and 2008 using a CES production framework. A technology gap is defined as the difference in output using foreign technology and domestic (or foreign) factors relative to output using domestic technology and domestic (or foreign) factors. Our measure is related to but differs from the Malmquist productivity index discussed by Caves, Christensen and Diewert (1982a, 1982b). An advantage of using the technology gap measure instead of the Malmquist productivity index is that our concept is flexible to the structure of the aggregate production function, and can be conveniently generalized to include technological improvements embodied in the production function besides the multiplicative productivity factor (for example, technological improvements due to a change in the substitution elasticity or factor-augmenting technological change in a CES production function, or increasing returns to scale).

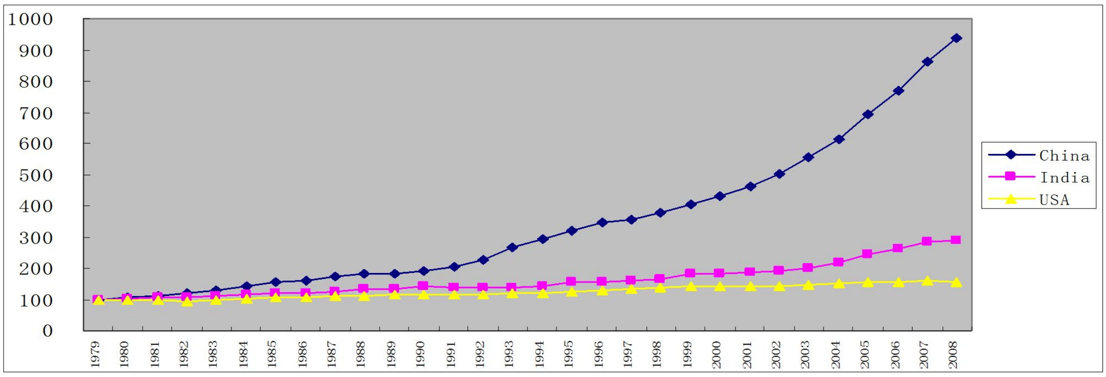
Our results suggest that although China has a higher growth rate of total factor productivity than India over the period, the bilateral technology gap between China and India is still in India's favor. India had higher income per worker than China in the 1970's, and China's much more rapid physical and human capital accumulation has allowed China to move ahead, but a bilateral technology gap remains. Also, we find that the technology gap between China and the U.S. is significantly larger than that between India and the U.S. for the period before 2008. The pairwise gaps between China and the U.S., and India and the U.S. remain large while narrowing at a slower rate than GDP per worker.

The paper is organized as follows. We provide a brief background related to our analysis in Section 2, and discuss the technology gap concept and the methodology we apply in Section 3. We describe the data sets we use in Section 4, and present our empirical results in Section 5. As a comparison, and also for robustness purposes, we report technology gap calculations for the widely used Cobb-Douglas case in Section 6. We offer concluding remarks in Section 7.

2. Background

A major development in the world economy over the last quarter of the 20th century has been strong economic growth and poverty reduction in both China and India. The Penn World Tables show that the real GDP (or real GDP per worker) in 2008 was almost 14.6 (or 9.4) and 5.3 (or 2.9) times that in 1979 for China and India respectively, while the same number for the U.S. was 2.3 (or 1.6). Figure 1 reports indices of real GDP per worker for these three countries between 1979 and 2008 (year of 1979=100). All of these data are in constant 2005 purchasing power parity dollars.

Figure 1. Indices of Real GDP/Worker for China, India and the U.S. 1979-2008



Note: Year of 1979=100.
Source: Authors' calculations using Extended Penn World Tables v.4.0, Marquetti & Foley (2011).

China and India's large economic size combined with rapid growth has meant that their economic rise has had large impacts on the global economy, although their absolute income levels are still quite low (the real GDP per worker of China and India in 2008 were about 12.9 and 9.2 percent of that of the U.S., respectively). Recent literature analyzes China and India's growing presence in the world economy (see Wang, Medianu & Whalley (2011) for related discussion), and also conducts comparative growth accounting studies for these two countries (see Herd &

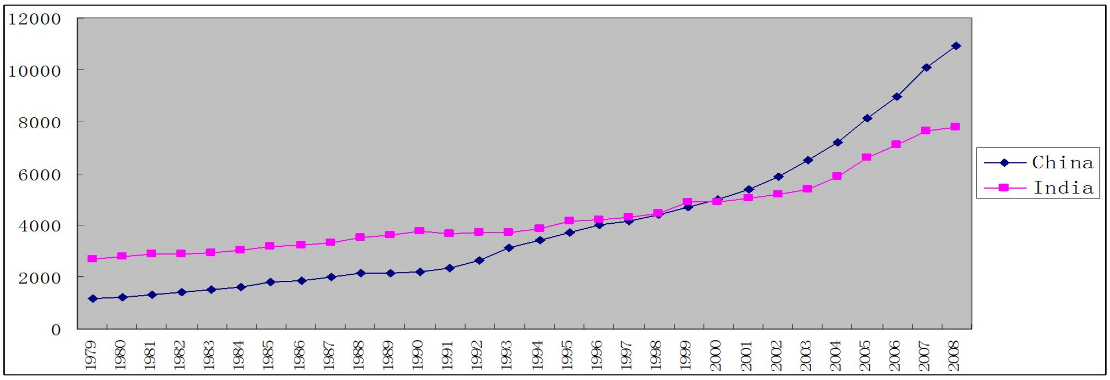
Dougherty (2007) and Bosworth & Collins (2008), for example).

It is widely recognized that technology or efficiency is at least as important as physical and human capital accumulation in explaining income differences across different countries (Hall & Jones, 1999; Caselli, 2005). Since the Cobb-Douglas specification is the most widely used for the aggregate production function, differences in technology or efficiency across countries can be simplified as TFP (Total Factor Productivity) differences, or in other words, can be summarized by the multiplicative factor A. Howitt (2000) and Klenow & Rodríguez-Clare (2005) show how large TFP differences can emerge in a world with slow technology diffusion from advanced countries to other countries, while Hsieh & Klenow (2009) estimate the effects of resource misallocation on China and India's manufacturing TFP and find that if capital and labor are hypothetically reallocated to equalize marginal products to the extent observed in the U.S., the TFP could be boosted by 30%–50% in China and by 40%–60% in India.

But as Caselli (2005) emphasizes, the Cobb-Douglas specification is key to the literature explaining income differences across countries, and a generalization of the TFP assumption from Cobb-Douglas to CES (constant elasticity of substitution) specification can lead to major changes in results. Notably, there has been increasing recent empirical evidence that rejects the (unitary-elasticity) Cobb-Douglas specification in favor of CES (generally below unity substitution elasticity) aggregate production functions (see Chirinko et al. (1999), Duffy & Papageorgiou (2000), Chirinko (2008), and Klump et al. (2007, 2011), for example).

It is also noteworthy that China's real GDP per worker did not surpass that of India until the year 1998 to 2000 (as shown in Figure 2). We can conjecture naturally that the more rapid accumulation of physical capital in China (as shown in Figure 3) may suggest a lower technology level for China compared to that of India at least before the middle of the 1990s.

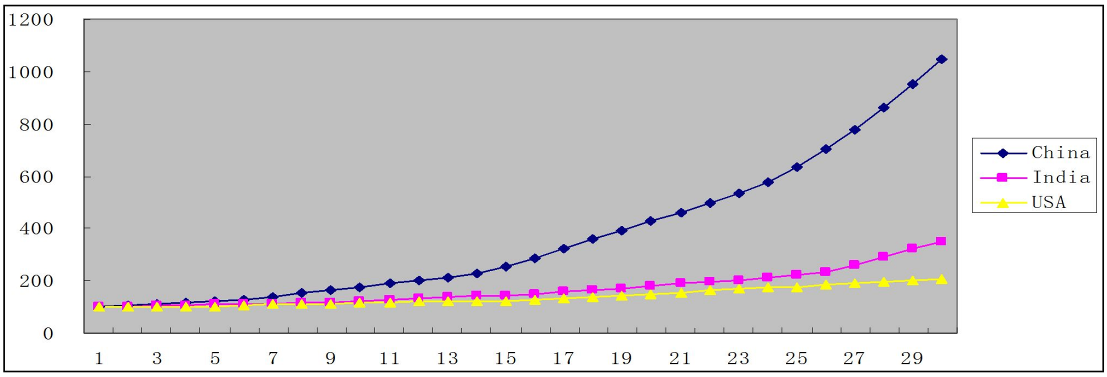
Figure 2. Real GDP per Worker for China and India 1979-2008



Note: In Chain indexed constant 2005 purchasing power parity dollars.

Source: Data from Extended Penn World Tables v.4.0, Marquetti and Foley (2011).

Figure 3. Indices of Capital Labor Ratio for China, India and the U.S. 1979-2008



Note: Year of 1979=100.

Source: Authors' calculations using Extended Penn World Tables v.4.0, Marquetti & Foley (2011).

3. Methodology

In this section we set out the methodology we use to measure the pairwise technology gaps between China, India and the U.S. over time. We measure the technology gap between two economies 1 and 2 in terms of the ratio between actual output in economy 1 using economy 1's technology and inputs, and hypothetical output using economy 2's technology with economy 1's inputs. The roles of economies 1 and 2 in such a comparison can be reversed to yield an alternative pairwise measure. We assume that each of the two economies produce a single final good Y with two factors, capital and labor. However, the two economies can have different technologies in production, i.e., they may have different parameters in (or even have different structures of) production function. They can also have different factor endowments.

Specifically, we can write the production function as follows:

$$Y_i = F_i(K_i, L_i) \qquad i = 1,2 \tag{1}$$

Here, $i = 1,2$ refer to the two different economies, and F_i represents different technologies for production.

We denote $\hat{Y}_1$ as the actual output of economy 1, i.e., $\hat{Y}_1$ is realized with endowments K_1 and L_1 using its own technology of production F_1. $\hat{Y}_2$ is defined as the hypothetical output of economy 1 that it could produce with endowments K_1 and L_1 using the technology of economy 2, F_2. Thus we have:

$$\hat{Y}_1 = F_1(K_1, L_1) \tag{2}$$

$$\hat{Y}_2 = F_2(K_1, L_1) \tag{3}$$

We can then define the technology gap between economies 1 and 2 as the ratio of hypothetical to actual output in economy 1:

$$G_{12} = \hat{Y}_2 \big/ \hat{Y}_1 \tag{4}$$

Correspondingly, we can also define $\overline{\overline{Y}}_1$ as the hypothetical output of economy 2 that it produces with endowments K_2 and L_2 using the technology in production F_1, while $\overline{\overline{Y}}_2$ is the actual output of economy 2 with endowments K_2 and L_2 using its own technology, F_2. Thus we have:

$$\overline{\overline{Y}}_1 = F_1(K_2, L_2) \tag{5}$$

$$\overline{\overline{Y}}_2 = F_2(K_2, L_2) \tag{6}$$

And we can define the reverse technology gap as:

$$G_{21} = \overline{\overline{Y}}_2 \big/ \overline{\overline{Y}}_1 \tag{7}$$

If we use a CES production function with Hicks-neutral technological change

$$Y_{it} = \gamma_i e^{\lambda_i \cdot t} \left(\delta_i K_{it}^{\ \rho_i} + (1-\delta_i) L_{it}^{\ \rho_i} \right)^{\frac{1}{\rho_i}} \tag{8}$$

Here $i = 1,2$ refers to the two different economies, t is a time variable, γ_i is an efficiency parameter, λ_i is the rate of disembodied (or Hicks-neutral) technological change, δ_i is the distribution parameter, and ρ_i is the substitution parameter. Then from equations (2)-(3) and (5)-(6), we have:

$$\hat{Y}_{1t} = \gamma_1 e^{\lambda_1 \cdot t} \left(\delta_1 K_{1t}^{\ \rho_1} + (1-\delta_1) L_{1t}^{\ \rho_1} \right)^{\frac{1}{\rho_1}} \tag{9}$$

$$\hat{Y}_{2t} = \gamma_2 e^{\lambda_2 \cdot t} \left(\delta_2 K_{1t}^{\ \rho_2} + (1-\delta_2) L_{1t}^{\ \rho_2} \right)^{\frac{1}{\rho_2}} \tag{10}$$

$$\overline{\overline{Y}}_{1t} = \gamma_1 e^{\lambda_1 \cdot t} \left(\delta_1 K_{2t}^{\ \rho_1} + (1-\delta_1) L_{2t}^{\ \rho_1} \right)^{\frac{1}{\rho_1}} \tag{11}$$

$$\overline{\overline{Y}}_{2t} = \gamma_2 e^{\lambda_2 \cdot t} \left(\delta_2 K_{2t}^{\ \rho_2} + (1-\delta_2) L_{2t}^{\ \rho_2} \right)^{\frac{1}{\rho_2}} \tag{12}$$

We can thus calculate the technology gaps G_{12} and G_{21} as in equations (4) and (7).

Similarly, for the CES production function with factor-augmenting technological change

$$Y_{it} = \left(\delta_i \left(\gamma_{Ki} e^{\lambda_{Ki} \cdot t} K_{it}\right)^{\rho_i} + \left(1-\delta_i\right)\left(\gamma_{Li} e^{\lambda_{Li} \cdot t} L_{it}\right)^{\rho_i}\right)^{\frac{1}{\rho_i}} \tag{13}$$

and the Cobb-Douglas production function

$$Y_{it} = \gamma_i e^{\lambda_i \cdot t} K_{it}{}^{\alpha} L_{it}{}^{1-\alpha} \tag{14}$$

we can also calculate the technology gaps G_{12} and G_{21} using equations (2)-(7).

Our definition of technology gaps is related to but differs from the Malmquist productivity index, a widely used productivity measure developed by Caves, Christensen and Diewert (CCD) (1982a, 1982b). An advantage of using the technology gap measures G_{12} and G_{21} set out above rather than a Malmquist productivity index is that our concept is flexible in the structure of the aggregate production function, and can be conveniently generalized to include technological improvements embodied in other parts of the production function besides the multiplicative productivity factor $A_{it} = \gamma_i e^{\lambda_i \cdot t}$ (for example, improvements due to a change in the elasticity of substitution or factor-augmenting technological change in a CES production function, or increasing returns to scale). It is also worthy of note that if the aggregate production functions of the two economies [as equations (9)-(10) or (11)-(12)] have the same values for parameters δ_i and ρ_i, and only differ from each other on the multiplicative productivity factor $A_{it} = \gamma_i e^{\lambda_i \cdot t}$, then both the technology gaps G_{12_t} and G_{21_t} can be simplified to A_{2_t} / A_{1_t}. As Bjurek (1996) mentions, to establish a relationship between the productivity indices and the corresponding Malmquist indices, CCD made the assumption that the underlying technologies were translog with equal second-order parameters. Although CCD (1982b) showed that their superlative index numbers could also be used to make multilateral output, input and productivity comparisons, if we allow for different assumptions on the production technologies, the productivity index might not be expressed easily in terms of a quantity index.

For a CES production function with Hicks-neutral technological change as in equation (8), or a CES function with factor-augmenting technological change as in equation (13), the key issues in calculating the technology gap measures G_{12} and G_{21} are how to parameterize the corresponding production functions by the observed data of the two economies, and specifically, for the production function equation (8) how to parameterize the two equations (9) and (12). Parameterization of the production function and calculation of the technology gap measures G_{12} and G_{21} can be made using a variety of techniques. Earlier literature uses the Kmenta approximation (Kmenta, 1967) or estimates a restricted translog function with traditional econometric methods. Klump et al. (2007) estimate a supply-side system for the U.S. economy using a normalized CES function with factor-augmenting technological change. Henningsen & Henningsen (2011) offer an R-package to estimate the CES function directly using different nonlinear optimization algorithms. Luoma & Luoto (2010) estimate a normalized CES production function with factor-augmenting technological change of the Finnish economy directly with

Bayesian approach.

However, estimation of restricted translog functions or utilization of the Kmenta approximation has been proved unsuitable when the underlying CES function differs from the Cobb-Douglas form (Thursby & Lovell, 1978; Henningsen & Henningsen, 2011). Results based on using nonlinear optimization techniques in many cases seem not to be stable; while the estimation of the supply-side system presented by Klump et al. (2007) encounters problems of data availability. As a result, the calibration approach is now the more commonly used method in recent literature (Caselli, 2005). Since we also compare results from different forms of production function (a Cobb-Douglas function and a CES function with Hicks-neutral or factor-augmenting technological change) or different values of the elasticity of substitution, considering the number of experiments we report on in this paper, we adopt the calibration approach.

We specify as our benchmark a CES production function with Hicks-neutral technological change that also incorporates human capital. As in Caselli (2005), we use a Hall and Jones' (1999) formulation for human capital

$$Y_{it} = \gamma_i e^{\lambda_i \cdot t}\left(\delta_i K_{it}{}^{\rho_i} + (1-\delta_i)(h_{it} L_{it})^{\rho_i}\right)^{\frac{1}{\rho_i}} \tag{15}$$

where K_{it} is the aggregate capital stock of economy i at time t, L_{it} is the corresponding number of workers, h_{it} is their average human capital, and $h_{it}L_{it}$ can be interpreted as the "quality adjusted" workforce.

In per-worker terms the production function (15) can be rewritten as

$$y_{it} = \gamma_i e^{\lambda_i \cdot t}\left(\delta_i k_{it}{}^{\rho_i} + (1-\delta_i) h_{it}{}^{\rho_i}\right)^{\frac{1}{\rho_i}} \tag{16}$$

where y_{it} is the output per worker of economy i at time t, and $k_{it} = K_{it} / L_{it}$ is the corresponding capital-labor ratio.

Accordingly, the technology gaps at time t, G_{12_t} and G_{21_t}, can also be rewritten as

$$G_{12_t} = \hat{y}_{2_t} / \hat{y}_{1_t} \tag{17}$$

$$G_{21_t} = \bar{\bar{y}}_{2_t} / \bar{\bar{y}}_{1_t} \tag{18}$$

Here $\hat{y}_{1_t}$ and $\hat{y}_{2_t}$ are actual and hypothetical output per worker of economy 1 at time t, respectively; while $\bar{\bar{y}}_{1_t}$ and $\bar{\bar{y}}_{2_t}$ are hypothetical and actual output per worker of economy 2 at time t, respectively [corresponding to equations (4) and (7)].

In order to calculate the technology gaps of interest here using a CES production function with Hicks-neutral technological change as in equation (16), we need the data sets for y_{it}, k_{it} and h_{it}, and the value of the efficiency parameter γ_i, the rate of technological change λ_i, the distribution parameter δ_i, and the substitution parameter ρ_i.

4. Data Sets for China, India and the U.S.

The data sets used in this paper combine variables from two different sources. The first is Version 4.0 of the Extended Penn World Tables (EPWT version 4.0, Marquetti & Foley, 2011). We extract from the EPWT Version 4.0 data set for the countries we study data on labor productivity (output per worker y_{it}, expressed in real GDP per worker in chain indexed 2005 purchasing power parity dollars), and capital-labor ratio (physical capital per worker k_{it}, expressed in 2005 purchasing power parity dollars). The EPWT Version 4.0 data set include time series for China from 1965 to 2008, time series for India from 1963 to 2008, and those for the U.S. from 1963 to 2009. We extract data from these sources for the period 1979 to 2008.

To construct data on human capital, we use Barro & Lee (2011) estimates of the average years of schooling in the population over 15 years old (Barro & Lee v.1.2). Data on the average years of schooling of China, India and the U.S. used here are available online (at http:/www.barrolee.com/, Last Updated: 2011.09.04). Barro and Lee's (2011) data set has both the average years of schooling in the population over 15 and 25 years old. However, as Caselli (2005) suggests, the average years of schooling in the population over 25 years old may be more appropriate for rich countries with a large share of college graduates, but it may be less appropriate for developing countries.

Following Caselli (2005), we turn these data into a measure of human capital using the formula of Hall and Jones (1999):

$$h = e^{\varphi(s)} \tag{19}$$

Where s is the average years of schooling, and $\varphi(s)$ is a piecewise linear function with slope 0.134 for $s \le 4$, 0.101 for $4 < s \le 8$, and 0.068 for $s > 8$. The Hall and Jones's (1999) measure involving the parameter values 0.134, 0.101, and 0.068 is used here to accommodate the log-linearity in the wage-schooling relationship at the country level consistent with the convexity of returns to education across countries. Specifically, the function $\varphi(s)$ can be written as:

$$\varphi(s) = \begin{cases} 0.134 \cdot s & for \quad s \le 4 \\ 0.134 \cdot 4 + 0.101 \cdot s & for \quad 4 < s \le 8 \\ 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068 \cdot s & for \quad s > 8 \end{cases} \tag{20}$$

Barro and Lee's (2011) data set of average years of schooling s is available for every five year period between 1950 and 2010. Since s changes slowly over time, we treat s as invariant before new data is available, i.e., we apply the 1980 data of s to the period 1980-1984, the 1985 data to the period 1985-1989, and so forth.

As is common in calibration exercises, besides data on y_{it}, k_{it} and h_{it}, we also need to determine the values of key technology parameters (the substitution parameter ρ_i, the distribution parameter δ_i, the efficiency parameter γ_i, and the rate of technological change λ_i).

Recent empirical evidence suggests that the U.S. and other developed economies should be better represented by a CES aggregate production function with an elasticity of substitution below unity rather than the unitary-elasticity Cobb-Douglas specification (Chirinko, 2008; Klump et al., 2007, 2011). While according to Duffy & Papageorgiou's (2000) estimates, elasticity of substitution with human capital adjusted labor could be lower than estimates without human capital. As a result, we set as a benchmark the elasticity of substitution between capital and labor $\sigma_i = 0.8$, which gives a substitution parameter $\rho_i = -0.25$ (also giving $\rho_i = \frac{\sigma_i - 1}{\sigma_i}$).

The distribution parameter δ_i in a CES aggregate production function [in per-worker terms as in equation (16)] can be written as a function of the capital-labor ratio k_{it}, the average human capital index h_{it}, the substitution parameter ρ_i, and the capital share θ_i. As in Caselli (2005), we assume that factor markets are competitive, and for the aggregate CES function in equations (15) or (16) we have

$$\delta_i = \frac{\theta_i k_{it}^{-\rho_i}}{\theta_i k_{it}^{-\rho_i} + (1-\theta_i) h_{it}^{-\rho_i}} \tag{21}$$

Since the distribution parameter δ_i is a function of the two time series k_{it} (capital-labor ratio) and h_{it} (the average human capital), in the calibration procedure we can firstly calculate a series of δ_{it}, and then take δ_i as the geometric mean of the series δ_{it}. Before calculating the country distribution parameters δ_i, we also need the value of the capital share θ_i. For our benchmark situation, as elsewhere in the literature (Caselli (2005) and Hsieh and Klenow (2009), for example), we use U.S. data on the capital share for all the three country parameters θ_i. The long-run average value is around 1/3, and we adopt this setting. Due to problems of data quality and availability, we have not adopted the actual capital shares for China and India. We will vary these parameters later in robustness analyses.

Given the values of the substitution parameters ρ_i and the distribution parameters δ_i, we can then estimate the efficiency parameters γ_i and the rates of technological change λ_i. Following Caselli (2005), we define $y_{it}^{kh} = \left(\delta_i k_{it}^{\rho_i} + (1-\delta_i) h_{it}^{\rho_i}\right)^{\frac{1}{\rho_i}}$, and rewrite equation (16) as

$$y_{it} = \gamma_i e^{\lambda_i \cdot t} \cdot y_{it}^{kh} \tag{22}$$

or

$$\gamma_i e^{\lambda_i \cdot t} = \frac{y_{it}}{y_{it}^{kh}} \tag{23}$$

It is noteworthy, however, that the values of the series y_{it}^{kh} and the distribution parameters δ_i, and consequently the estimates of parameters γ_i and λ_i are sensitive to the measurement (or unit) of time series k_{it} (capital-labor ratio), h_{it} (the average human capital) and y_{it} (output per worker). For consistency and reliability, we normalize all the time series of y_{it}, k_{it} and h_{it} by the corresponding U.S. data in 1979.[2] We also choose different years or different countries as reference points. Both different reference points for the normalized CES function and different measurements (or units) of time series for un-normalized CES function will change the estimates of the parameters γ_i and λ_i. Results are, however, comparatively more consistent with a normalized CES production function.

Following Klump & Saam (2008), for a reference point with y_0 as output per capita at k_0 and h_0, we assume

$$\delta_i = \frac{\theta_0 k_0^{-\rho_i}}{\theta_0 k_0^{-\rho_i} + (1-\theta_0) h_0^{-\rho_i}} \tag{24}$$

$$\gamma = y_0 \left(\theta_0 k_0^{-\rho_i} + (1-\theta_0) h_0^{-\rho_i}\right)^{\frac{1}{\rho_i}} \tag{25}$$

Where θ_0 is the capital share at the reference point, and γ is a efficiency parameter. With equations (24) and (25), we can then express equation (16) as

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2 The normalized CES production function was introduced by La Grandville (1989) and advanced by Klump & de La Grandville (2000), Klump & Preissler (2000) and Klump & Saam (2008), see Klump et al. (2011) for a recent survey of the related literature.

$$\frac{y_{it}}{y_0} = \gamma_i^* e^{\lambda_i \cdot t} \left(\theta_0 \left(\frac{k_{it}}{k_0} \right)^{\rho_i} + (1-\theta_0) \left(\frac{h_{it}}{h_0} \right)^{\rho_i} \right)^{\frac{1}{\rho_i}} \tag{26}$$

Here $\gamma_i^* = \frac{\gamma_i}{\gamma}$. By defining $y_{it}^{kh*} = \left(\theta_0 \left(\frac{k_{it}}{k_0} \right)^{\rho_i} + (1-\theta_0) \left(\frac{h_{it}}{h_0} \right)^{\rho_i} \right)^{\frac{1}{\rho_i}}$, the equations (22) and (23) now become

$$\frac{y_{it}}{y_0} = \gamma_i^* e^{\lambda_i \cdot t} \cdot y_{it}^{kh*} \tag{27}$$

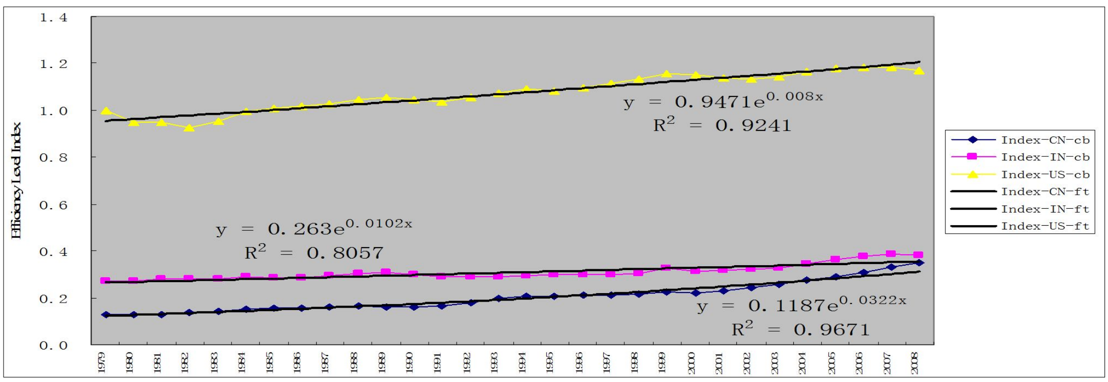
$$\gamma_i^* e^{\lambda_i \cdot t} = \frac{y_{it}/y_0}{y_{it}^{kh*}} \tag{28}$$

The series y_{it}/y_0, k_{it}/k_0 and h_{it}/h_0 used in equations (26)-(28) are data normalized with the reference point (U.S. data in 1979 in the benchmark situation). The key to the normalization procedures used here is to normalize all the data y_{it}, k_{it} and h_{it} of the three countries using a common reference point. Otherwise, all the efficiency parameters γ_i^* of these countries will become 1, and the differences in efficiency or technology level will disappear.

5. Empirical Results

Figure 4 presents the indices of technology or efficiency level $A_{it} = \gamma_i^* e^{\lambda_i \cdot t}$ between 1979 and 2008 for China, India and the U.S. calculated using equation (28), and also the estimated parameters γ_i^* and λ_i derived from a standard curve fitting procedure. The technology level index for the U.S. in 1979 is 1, as all the time series of y_{it}, k_{it} and h_{it} are normalized by the corresponding U.S. data in 1979. We can see from Figure 4 that the rate of technological change in China is much higher than India (as emphasized in literature on TFP growth rates), while the latter is still higher than that of the U.S. However, while both the efficiency or technology levels of China and India are much lower than that of the U.S., at least before the year 2008, the technology level of India is higher than that of China. Although factor accumulation rates in China exceed those of India, and economic growth rates in China also exceed those of India, the technology gap is in favor of India before 2008 since the initial gap is in India's favor and closing more slowly than relative GDP growth rates.

Figure 4. Technology Levels with CES Function for China, India and the U.S. 1979-2008



Notes: Index of "CN", "IN" and "US" denote China, India and the U.S.; and Index of "cb" and "ft" denote calibrated and fitted data, respectively.

Source: Authors' calculations.

Using the data presented in Figure 4, we can also parameterize equation (26) for China, India and the U.S., respectively. Results are shown in Table 1. Since different reference points or reference countries may have substantial impacts on the estimates, for comparative purposes, we also give results using time series normalized by China and India's data in 1979. As shown in Table 1, estimated growth rates of technological change λ_i in China and India are close to the results of Herd & Dougherty (2007) and Bosworth & Collins (2008). The estimated efficiency parameters γ_i^* of the U.S. are about 3.6, 4.5 or 4.9 times of India, and 8.0, 11.1 or 12.3 times of China, and those of India are about 2.2, 2.4 or 2.5 times of China, when we use time series normalized by the U.S., India or China's data in 1979 respectively. It is also noteworthy that by comparing estimates with different reference points, the results show that rates of technological change λ_i seem lower with a decrease in the efficiency parameters γ_i^*. Nevertheless, trends are similar as shown in Figure 4.

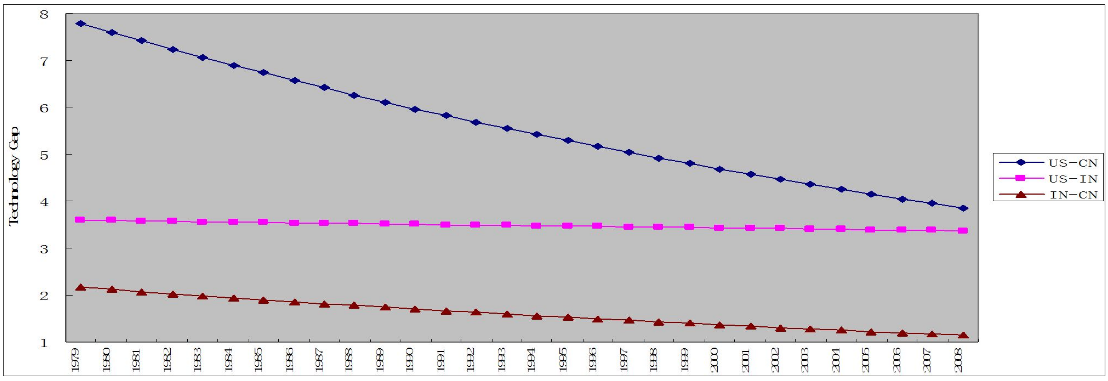
Table 1. Parameters of CES Production Functions for China, India and the U.S.

Parameter		γ_i^*	λ_i	θ_0	σ_i	ρ_i
Normalized with 1979 data of U.S.	U.S.	0.9471	0.008	1/3	0.8	-0.25
	India	0.263	0.0102			
	China	0.1187	0.0322			
Normalized with 1979 data of India	U.S.	4.2904	0.0103	1/3	0.8	-0.25
	India	0.9461	0.0134			
	China	0.3882	0.0406			
Normalized with 1979 data of China	U.S.	10.984	0.011	1/3	0.8	-0.25
	India	2.2537	0.0145			
	China	0.8965	0.0433			

Source: Authors' calculations.

The technology gaps of China and India both with the U.S. and with each other calculated using equations (17) and (18) are shown in Figure 5 [$\hat{y}_{it}$ and $\bar{\bar{y}}_{it}$ are calculated from equation (26); the reference point is U.S. data in 1979]. These calculations suggest that if China and India's input factors were hypothetically used with U.S. technology, the hypothetical output would be much larger; and if China's input factors were hypothetically used with India's technology, the hypothetical output would also be higher. Conversely, if U.S. inputs were hypothetically used with China or India's technology, the hypothetical output would be much lower; and if India's input factors were hypothetically used with China's technology, the hypothetical output would also be lower. Note that since we assume the aggregate production functions of all the three economies [as equation (26)] have the same values for parameters δ_i and ρ_i , and only differ from each other on the multiplicative productivity factor $A_{it} = \gamma_i e^{\lambda_i \cdot t}$, as mentioned earlier in Section 3, both the technology gaps G_{12_t} and G_{21_t} are simplified to A_{2_t} / A_{1_t} .

Figure 5. Pairwise Technology Gaps with CES Function between China, India and the U.S.



Notes: Technology gaps denote "US-CN" and "US-IN" are China and India's hypothetical output/worker with U.S. technology divided by their estimated output/worker with own technology, and technology gap "IN-CN" is China's hypothetical output/worker with India's technology divided by its estimated output/worker with own technology.

Source: Authors' calculations.

Figure 5 also indicates that between 1979 and 2008, the technology gaps of China and India relative to the U.S. decrease from about 7.79 and 3.59 to 3.86 and 3.37, respectively. These results confirm that the technology gap between China and the U.S. is larger than that between India and the U.S., while both the gaps of China and India narrow at a slower rate than GDP per worker (also consistent to the pattern shown in Figure 4). The technology gap of China between 1979 and 2008 relative to India decreases from 2.17 to 1.15. Since all the measures of the technology gap of China relative to India over the period are greater than 1, the technology gap is in favor of India before 2008 since the initial gap is in India's favor. These trends of the pairwise measures of technology gaps between China, India and the U.S. as shown in Figure 5 are consistent with different estimated values for parameters of γ_i^* and λ_i shown in Table 1, i.e., different reference points or reference countries do not change the trends described here.

These findings are noteworthy, since recent literature emphasizes the much higher growth rate of total factor productivity in China than in India, and misses China's comparatively lower technology level compared to India.

6. Robustness Checks

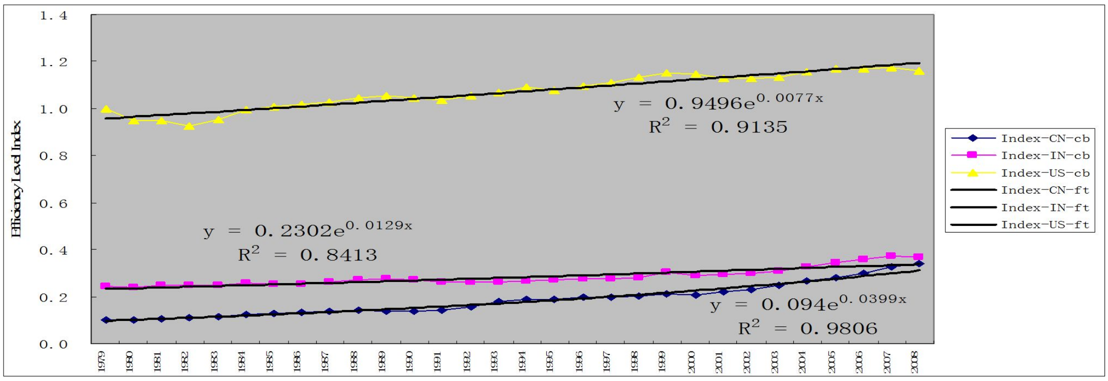
For comparative purposes, we also present results calculated using an aggregate Cobb-Douglas production function

$$\frac{y_{it}}{y_0} = \gamma_i^* e^{\lambda_i \cdot t} \left(\frac{k_{it}}{k_0}\right)^{\alpha_i} \left(\frac{h_{it}}{h_0}\right)^{1-\alpha_i} \tag{29}$$

We use U.S. data on the capital share for α_i again, i.e., we again use its long-run average value $\alpha_i = 1/3$ (capital share α_i is θ_0 in Table 1 at Section 5). Thus the only difference between the Cobb-Douglas production function used here and equation (26) used in Section 5 is the elasticity of substitution σ_i (or equivalently the substitution parameter ρ_i).

Figure 6 presents the indices of technology level $A_{it} = \gamma_i^* e^{\lambda_i \cdot t}$ for China, India and the U.S. between 1979 and 2008 calculated using equation (29), and also the estimated parameters γ_i^* and λ_i derived from a standard curve fitting procedure, with U.S. data of 1979 as the reference point (the efficiency level index of the U.S. in 1979 is 1). Comparing Figures 4 and 6, we can see that these two figures give similar trends: the growth rate of technological change in China is higher than India, and the latter is still higher than that of the U.S; while both the technology levels (measured by the efficiency level indices in the figures) of China and India are much lower than that of the U.S., the technology level of India is higher than that of China. Our previous conclusion that the technology gap is in favor of India before 2008 since the initial gap is in India's favor still holds. The major difference between Figures 4 and 6 is that with a Cobb-Douglas production function, efficiency level indices are slightly lower, and the rates of technological change are slightly higher for China and India than that for the CES case in Section 5; while for the U.S., the contrary is true.

Figure 6. Technology Levels for China, India and the U.S. Using C-D Function 1979-2008



Notes: Indices of "CN", "IN" and "US" denote China, India and the U.S.; and Indices of "cb" and "ft" denote calibrated and fitted data, respectively.

Source: Authors' calculations.

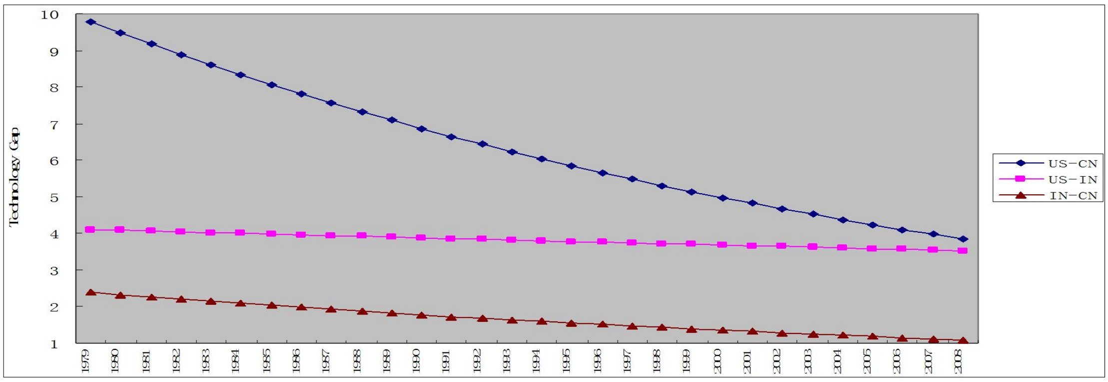
Table 2. Parameters of C-D Production Functions for China, India and the U.S.

Parameter		γ_i^*	λ_i	θ_0	σ_i
Normalized with 1979 data of U.S.	U.S.	0.9496	0.0077	1/3	1
	India	0.2302	0.0129		
	China	0.094	0.0399		
Normalized with 1979 data of India	U.S.	3.9203	0.0077	1/3	1
	India	0.9503	0.0129		
	China	0.3879	0.0399		
Normalized with 1979 data of China	U.S.	9.2667	0.0077	1/3	1
	India	2.2462	0.0129		
	China	0.9168	0.0399		

Source: Authors' calculations.

For comparative purposes, we also present results with different reference points (China, India and U.S. data in 1979) in Table 2. As shown in Table 2, the estimated growth rates of technological change λ_i in China and India are still close to the results of Herd & Dougherty (2007) and Bosworth & Collins (2008). The estimated values of efficiency parameters γ_i^* of the U.S. are about 4.1 times of India and 10.1 times of China, and those of India are about 2.4 times of China. Data in Table 2 also confirm that when the aggregate production function is Cobb-Douglas, different reference points (for ${y_{it}}/{y_0}$, ${k_{it}}/{k_0}$ and ${h_{it}}/{h_0}$) or different measures (or units) of the times series (such as y_{it}, k_{it} and h_{it}) only change the levels of the efficiency parameters γ_i^*, while having no effects on both the ratios of γ_i^* and the values of λ_i.

Figure 7. Pairwise Technology Gaps between China, India and the U.S. Using C-D Function



Notes: Technology gaps denoted by "US-CN" and "US-IN" are China and India's hypothetical output/worker with U.S. technology divided by their estimated output/worker with own technology, and technology gap denoted by "IN-CN" is China's hypothetical output/worker with India's technology divided by its estimated output/worker with own technology.
Source: Authors' calculations.

The technology gaps of China and India both with the U.S. and with each other calculated with a Cobb-Douglas aggregate production function are shown in Figure 7 [$\hat{y}_{it}$ and $\bar{\bar{y}}_{it}$ in equations (17) and (18) are calculated from equation (29); the reference point is U.S. data in 1979]. Since we assume the Cobb-Douglas aggregate production functions of all the three economies have the same values of capital share α_i, and only differ from each other in the multiplicative productivity factor $A_{it} = \gamma_i e^{\lambda_i \cdot t}$, both the technology gaps G_{12_t} and G_{21_t} are simplified to ${A_{2_t}}/{A_{1_t}}$. We can see from Figure 7 that between 1979 and 2008, the technology gaps of China and India relative to the U.S. decrease from about 9.78 and 4.10 to 3.84 and 3.53, respectively. While the technology gap of China relative to India during the period decreases from 2.38 to 1.09. Although the measures of the pairwise technology gaps in Figure 7 change slightly compare to Figure 5, and the initial gaps in the Cobb-Douglas scenario become larger, our previous conclusion still holds.

For robustness purposes, we now consider relaxing further the assumptions on the elasticity of substitution σ_i and the capital share θ_0 (or α_i), and investigate the variation of the estimated efficiency parameters γ_i^* and the estimated rates of technological change λ_i (hence the variation of the technology gaps) when the elasticity of substitution σ_i increases by a step of 0.1 from 0.3 to 1.2. Due to problems of data quality or availability in China and India, we previously set the capital share θ_0 (or α_i) of all the three countries at the U.S. long-run average value 1/3. Based on recent Chinese literature (see Zhang & Zhang (2010), for example), we set the capital share θ_0 for China in an interval from 1/3 to 3/5. For comparative purposes, we set the same interval for the capital share for India as well.

Table 3. Sensitivity Analysis of Calibrated Technology Parameters γ_i^* and λ_i to Elasticities of Substitution and Capital Share

Parameter	γ_i^*			λ_i		
	China	India	U.S.	China	India	U.S.
$\sigma_i = 0.3;\theta_0 = 1/3$	0.4174	0.6146	0.9301	-0.0044	-0.0045	0.0104
$\sigma_i = 0.4;\theta_0 = 1/3$	0.316	0.4901	0.936	0.0019	-0.0017	0.0096
$\sigma_i = 0.5;\theta_0 = 1/3$	0.2338	0.3957	0.9401	0.0104	0.002	0.009
$\sigma_i = 0.6;\theta_0 = 1/3$	0.1773	0.3321	0.9431	0.019	0.0054	0.0086
$\sigma_i = 0.7;\theta_0 = 1/3$	0.1414	0.2906	0.9453	0.0264	0.0081	0.0083
$\sigma_i = 0.8;\theta_0 = 1/3$	0.1187	0.263	0.9471	0.0322	0.0102	0.008

$\sigma_i = 0.9\,; \theta_0 = \frac{1}{3}$	0.1039	0.2439	0.9485	0.0366	0.0117	0.0078
$\sigma_i = 1.0\,; \theta_0 = \frac{1}{3}$	0.094	0.2302	0.9496	0.0399	0.0129	0.0077
$\sigma_i = 1.1\,; \theta_0 = \frac{1}{3}$	0.0869	0.22	0.9506	0.0425	0.0138	0.0075
$\sigma_i = 1.2\,; \theta_0 = \frac{1}{3}$	0.0817	0.2122	0.9514	0.0445	0.0146	0.0074
$\sigma_i = 0.8\,; \theta_0' = \frac{1}{3}$	0.1187	0.263	0.9471	0.0322	0.0102	0.008
$\sigma_i = 0.8\,; \theta_0' = 0.4$	0.1464	0.3064	0.9471	0.0271	0.0082	0.008
$\sigma_i = 0.8\,; \theta_0' = 0.5$	0.1971	0.3814	0.9471	0.02	0.0054	0.008
$\sigma_i = 0.8\,; \theta_0' = 0.6$	0.2604	0.4697	0.9471	0.0136	0.0028	0.008
$\sigma_i = 1.0\,; \theta_0' = \frac{1}{3}$	0.094	0.2302	0.9496	0.0399	0.0129	0.0077
$\sigma_i = 1.0\,; \theta_0' = 0.4$	0.1146	0.2662	0.9496	0.0352	0.011	0.0077
$\sigma_i = 1.0\,; \theta_0' = 0.5$	0.1544	0.3311	0.9496	0.0281	0.0082	0.0077
$\sigma_i = 1.0\,; \theta_0' = 0.6$	0.2079	0.4119	0.9496	0.0209	0.0054	0.0077

Notes: Changes in θ_0' *only applies to China and India,* θ_0 *for the U.S. does not change.*

Source: Authors' calculations.

Results of sensitivity analysis on the parameters γ_i^* and λ_i to changes of the elasticity of substitution σ_i and capital share θ_0 (or α_i) are shown in Table 3. Results in Table 3 show that, for China and India, the efficiency parameters γ_i^* decrease, but the growth rates of technological change λ_i increase with the elasticity of substitution σ_i from 0.3 to 1.2. For the U.S., the contrary is true. Further experiments show that the reason the U.S. has a different relationship between γ_i^* and λ_i is because it is set as a reference country. The capital share θ_0 (or α_i) presents quite different effects to the parameters γ_i^* and λ_i. We can see from Table 3 that independent of whether $\sigma_i = 0.8$ or $\sigma_i = 1$, both for China and India, γ_i^* increases and λ_i decreases when θ_0 (or α_i) increases from 1/3 to 3/5. Considering differences in the initial gaps and the growth rates of technological change as shown in Table 3, our previous inference on changes in the technology gaps of China and

India both with the U.S. and with each other seems robust.

Results of the technology gaps G_{12t} and G_{21t} for China relative to India using different key parameters are shown in Table 4. Note that if the two economies have different capital share θ_0, then the technology gaps G_{12_t} and G_{21_t} may differ, and can no longer be simplified to A_{2_t}/A_{1_t}. We can see from Table 4 that, with any non-extreme values of key parameters elasticity of substitution σ_i and capital share θ_0 (or α_i), at least before the year 2008, the technology gap of China relative to India still remains in India's favor.

Table 4. Sensitivity Analysis on Technology Gaps G_{12t} and G_{21t} for China Relative to India

Parameter	G_{12t}		G_{21t}	
	1979	2008	1979	2008
$\sigma_i = 0.3; \theta_0 = 1/3$	1.472	1.468	1.472	1.468
$\sigma_i = 0.4; \theta_0 = 1/3$	1.545	1.392	1.545	1.392
$\sigma_i = 0.5; \theta_0 = 1/3$	1.678	1.315	1.678	1.315
$\sigma_i = 0.6; \theta_0 = 1/3$	1.848	1.246	1.848	1.246
$\sigma_i = 0.7; \theta_0 = 1/3$	2.018	1.187	2.018	1.187
$\sigma_i = 0.8; \theta_0 = 1/3$	2.167	1.145	2.167	1.145
$\sigma_i = 0.9; \theta_0 = 1/3$	2.290	1.112	2.290	1.112
$\sigma_i = 1.0; \theta_0 = 1/3$	2.384	1.089	2.384	1.089
$\sigma_i = 1.1; \theta_0 = 1/3$	2.460	1.070	2.460	1.070
$\sigma_i = 1.2; \theta_0 = 1/3$	2.521	1.059	2.521	1.059
$\sigma_i = 0.8; \theta_0^i = 1/3; \theta_0^c = 0.4$	2.140	1.139	2.033	1.167
$\sigma_i = 0.8; \theta_0^i = 1/3; \theta_0^c = 0.5$	2.101	1.129	1.861	1.199
$\sigma_i = 0.8; \theta_0^i = 1/3; \theta_0^c = 0.6$	2.064	1.114	1.719	1.225
$\sigma_i = 0.8; \theta_0^i = 3/5; \theta_0^c = 1/3$	1.874	1.341	2.250	1.220

$\sigma_i = 0.8; \theta_0^i = 3/5; \theta_0^c = 0.4$	1.850	1.333	2.111	1.243
$\sigma_i = 0.8; \theta_0^i = 3/5; \theta_0^c = 0.5$	1.816	1.321	1.933	1.277
$\sigma_i = 0.8; \theta_0^i = 3/5; \theta_0^c = 0.6$	1.784	1.305	1.784	1.305
$\sigma_i = 1.0; \theta_0^i = 1/3; \theta_0^c = 0.4$	2.347	1.076	2.195	1.099
$\sigma_i = 1.0; \theta_0^i = 1/3; \theta_0^c = 0.5$	2.290	1.056	2.004	1.104
$\sigma_i = 1.0; \theta_0^i = 1/3; \theta_0^c = 0.6$	2.237	1.040	1.872	1.163
$\sigma_i = 1.0; \theta_0^i = 3/5; \theta_0^c = 1/3$	2.079	1.303	2.483	1.166
$\sigma_i = 1.0; \theta_0^i = 3/5; \theta_0^c = 0.4$	2.047	1.287	2.287	1.177
$\sigma_i = 1.0; \theta_0^i = 3/5; \theta_0^c = 0.5$	1.997	1.263	2.088	1.182
$\sigma_i = 1.0; \theta_0^i = 3/5; \theta_0^c = 0.6$	1.951	1.244	1.951	1.244

Notes: Technology gap G_{12t} denotes China's hypothetical output/worker with India's technology divided by its estimated output/worker with its own technology. G_{21t} denotes India's estimated output/worker with its own technology divided by its hypothetical output/worker with China's technology. θ_0^c and θ_0^i denote China and India's capital share, respectively.

Source: Authors' calculations.

7. Conclusion

Our paper reports calculations of the technology gaps for China and India compared both to the U.S. and to each other between 1979 and 2008 using a CES framework. These gaps reflect differences between actual output per worker and hypothetical output using other countries' technology with domestic inputs. By comparing with the U.S., we investigate changes in the technology gaps between China and India through time, and also make comparisons of the efficiency or technology level of the two countries.

We find that the pairwise gaps between China and the U.S., and India and the U.S. remain large while narrowing at a slower rate than GDP per worker. The technology gap between China and the U.S. is significantly larger than that between India and the U.S. for the period before 2008. Notably, the variations of China and India's technology gaps relative to the U.S. present different behavior. The technology gap for China relative to the U.S. is narrowing much more rapidly than India. The calculations we report here also suggest that although China has a much higher growth rate of total factor productivity than India over the period, the bilateral technology gap between China and India is still in India's favor. India had higher initial income per worker than China in the 1970's, and China's much more rapid physical and human capital accumulation has allowed China to move ahead, but a bilateral technology gap remains.

These findings are noteworthy, since it seems that in the existing literature little attention is paid to the technology gap between China and India. Recent literature seems more inclined to emphasize the much higher growth rate of total factor productivity (or technological change) in China than that in India, and thus misses China's comparatively lower aggregate efficiency or technology level compared to India.

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