Analysing convergence with a multi-country computable general equilibrium model: PPP versus MER

by

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Abstract

In studies of the greenhouse gas implications of convergence by developing countries to the per-capita GNPs of developed countries, considerable discussion has centred on whether purchasing power parity (PPP) or market exchange rates (MER) should be used in measuring per-capita GNPs. We suggest that technology gaps between developing and developed countries should be the starting point for convergence analysis rather than per-capita GNP gaps. We estimate two sets of initial technology gaps, using PPP or MER price assumptions combined with input-output data. In simulating the effects of closing technology gaps (convergence) using a dynamic, multi-country CGE model, we find:

(1) the MER/PPP distinction matters. MER-based estimates of initial technology gaps lead to higher estimates of convergence-induced growth in greenhouse-gas-emitting industries in developing countries than do PPP-based estimates.
(2) the industry detail in CGE models is valuable. Our simulations show a wide range of convergence-induced changes in output across industries.

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1. AIM AND MOTIVATION

Convergence is often interpreted as meaning that GNP per capita in developing countries catches up to GNP per capita in developed countries. The aim of this paper is to show how convergence between developing and developed countries can be analysed in a computable general equilibrium (CGE) model.

Our motivation is provided by the Castles/Henderson critique [1 & 2] of the Special Report on Emissions Scenarios (SRES) by the Intergovernmental Panel on Climate Change (IPCC) [3]. The SRES is concerned with the greenhouse-gas implications of convergence. Castles and Henderson argue that the SRES may have overestimated the increase in greenhouse gas emissions associated with convergence by using inappropriate measures of current GNP for developing countries.

Estimates of GNP per capita are readily available for most countries in national currencies. When these estimates are converted by market exchange rates (MERs) into a common currency, they imply very large differences between developing and developed countries. This gives the impression that convergence will mean enormous growth in output in developing countries, which in turn leads to fears that convergence will generate huge increases in the world volume of greenhouse gas emissions.

Against this, Castles and Henderson [1 & 2] argue that comparisons of GNP at MERs strongly understate output in developing countries relative to that in developed countries. They suggest that comparisons should be made in terms of purchasing power parity (PPP). Where the U.S. is the reference country, a PPP of *x* for China, for example, means that $US1 buys *x* times as much goods and services in China as it does in the U.S. Because *x* tends to be greater than 1 for developing countries, the use of PPPs rather than MERs leads to smaller gaps between developing and developed countries in estimated GNPs. At first glance, this seems to mean that convergence projections made with PPP estimates of initial GNPs will show smaller increases in greenhouse-gas emissions than projections made with MER estimates.

However, the first-glance conclusion is not necessarily right. Holtsmark and Alfsen [4] point out that we need to consider not only growth in GNP in converging countries but also movements in their emissions per unit of GNP. Underestimation of current values of GNP in developing countries through the use of MER rather than PPP may be offset by overestimation of current values of their emissions per unit of GNP. Analysis by Nordhaus [5] even suggests that use of MER estimates of initial GNP levels may lead to under-projection of energy use and emissions in a partially converged world economy.[1]

In our view, the conflicts in the PPP-MER debate can be avoided by treating technology differences between developing and developed countries as the starting point for convergence analysis rather than GNP differences. In this paper we assume that countries have different GNP per capita mainly because they have different technologies (processes by which inputs are turned into outputs). We interpret convergence as meaning that technologies in developing countries become as efficient as those in developed countries.

We develop this idea in the context of a multi-country CGE model. A CGE model is potentially an attractive vehicle for analysing the effects of technological change. Thus, a CGE model is potentially an attractive vehicle for analysing the effects of convergence. With technology differences as the starting point for an analysis in a CGE framework, controversies concerning inter-country comparisons of GNP are largely avoided.

The remainder of this paper is organised as follows. In the next section we show how technology variables for different countries can be derived from the input-output database of a multi-country CGE model. We illustrate our method in a three-country model: Rest of world (ROW), China and Australia. ROW is set up to be a wealthy country: we are thinking of North America, Japan and Europe. The differences between our estimated technology variables for China and ROW are illustrative of the differences between technology variables for developing and developed countries that we would expect to find in a more detailed study. The

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[1] Figure 4 in Nordhaus [5] shows that use of MER estimates of GNP can lead to underestimation of the derivative of energy use with respect to GNP.

inclusion of Australia in the model reflects the interests of the model builders, but has little significance for the present application.[2] To save space, we omit references to Australia in the rest of this paper.

Our method for deriving technology variables depends on assumptions about prices of goods and factors in different countries. We derive two sets of technology variables. For the first set, we assume that prices are broadly consistent with estimates of PPP. For the second, we assume that prices reflect MERs.

In section 3, we present two simulations of the effects of partial convergence by China over the next twenty-five years, that is the effects of extra technical progress in China that partially closes the gap between Chinese technology variables and the corresponding variables in ROW. Comparison of simulation results reveals the implications of PPP versus MER assumptions in the estimation of technology gaps.

It should be emphasised that the numbers in this paper, including the technology-gap estimates and the two sets of simulation results, are purely illustrative. We aim to demonstrate the feasibility and potential value of a detailed CGE analysis of convergence. More empirical effort than was possible for this paper will be required to get beyond the illustrative stage.

Section 4 contains concluding remarks.

2. ESTIMATION OF TECHNOLOGY VARIABLES IN DIFFERENT COUNTRIES FOR A GIVEN YEAR

2.1 Defining technology variables and convergence

Assume that there are two varieties of commodity i produced in country z. The first variety, (1,i), is sold domestically. The second variety, (2,i), is exported. The production function in industry i (the producer of both varieties of commodity i) in year t is specified as

$$Y_{iz}(t) = F_i\left(\frac{X_{1iz}(t)}{A_{1iz}(t)}, ..., \frac{X_{niz}(t)}{A_{niz}(t)}\right) \qquad \text{and} \tag{2.1}$$

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[2] The model was designed by Mai and Horridge [6] to investigate a potential free-trade agreement between Australia and China.

$$Y_{iz}(t) = G_i\left(B_{1iz}(t)Y_{1iz}(t), B_{2iz}(t)Y_{2iz}(t)\right) \tag{2.2}$$

where

$Y_{iz}(t)$ is the overall level of output in industry i in country z in year t;

$Y_{kiz}(t)$ is the output of variety k produced by industry i in country z in year t;

$X_{hiz}(t)$ is the input of h to production of i in country z in year t, with h = 1, …, n covering the inputs of n-1 commodities and a primary factor (a composite of labour and capital);

$A_{hiz}(t)$ is a technology variable allowing for changes in requirements of h per unit of overall output in industry i in country z; and

$B_{kiz}(t)$ is a technology variable allowing for changes in the output of variety k per unit of overall output in industry i in country z.

Under specification (2.1)-(2.2), industry i buys inputs to achieve a level of overall output, with more inputs being required for more output. With a given level of overall output, the industry can produce different combinations of (1,i) and (2,i) along a concave (from below) transformation frontier. With a higher level of overall output (requiring more inputs), the transformation frontier moves out allowing expansions in the output of both varieties.

The same functions F_i and G_i apply in all countries z. Technological differences across countries are captured by differences in the technology variables A_{hiz} and B_{kiz}. Decreases in technology variables can be used to simulate technological improvements. A reduction in $A_{hiz}(t)$ of 10 per cent is a technological change that allows industry i in country z to maintain given levels of outputs of both varieties of goods while reducing inputs of h by 10 per cent with all other inputs held constant. A reduction in $B_{kiz}(t)$ of 10 per cent is a technological change that allows industry i in country z to increase its output of variety k by 10 per cent with no change in the output of the other variety and no change in inputs. Without loss of generality, we assume that all improvements in multi-factor productivity (reductions in inputs per unit of overall output) are carried by movements in the A_{hiz}s. Movements in the B_{kiz}s will be used to simulate the effects of productivity-neutral changes in the shape of transformation frontiers.

We interpret convergence as being an hypothesis about relative movements between countries in A_{hiz}s and B_{kiz}s. Convergence occurs at time τ if

$$A_{hiz}(\tau) = A_{hi\,L}(\tau) \text{ and } B_{kiz}(\tau) = B_{ki\,L}(\tau) \text{ for all h, k, i, and z} \quad , \tag{2.3}$$

where L is the benchmark or technologically leading economy. Because they can be used to simulate the effects of movements in A_{hiz}s and B_{kiz}s away from their initial (year 0) values, CGE models can be used to investigate the effects of convergence.

The main problem in applying a multi-country CGE model to simulate the effects of convergence is to decide the starting values for the technology variables, the $A_{hiz}(0)$s and the $B_{kiz}(0)$s. To do this we need data on *quantities* of outputs and inputs. What is readily available from national input-output tables is *values* of outputs and inputs in national currencies. These values can be converted easily to a common currency, e.g. dollar U.S., by using MERs. This is done for example in creating the input-output database for GTAP (Hertel *et al.*, [7]), a widely used multi-country CGE model. However, for many commodities conversion via MERs doesn’t tell us anything about quantities. The problem is that non-traded goods in relatively poor countries are cheap in terms of U.S. dollars. As hypothesised by Balassa [8], this is explained by developing countries having higher ratios of non-traded/traded productivity than developed countries. Thus, comparable haircuts in China and the U.S. might cost $US1 and $US15. To work out quantities we should divide the Chinese value by 1 and the U.S. value by 15. More generally, to get from values in national input-output tables (and databases for multi-country models such as GTAP) to quantities and then to $A_{hiz}(0)$s and $B_{kiz}(0)$s, what we need is information on input and output prices in each country.

McKibbin *et al.* [9 & 10] have already applied a multi-country CGE model, G-cubed, in an analysis of the effects of convergence. Like us, they view convergence as an hypothesis about relative movements between countries in technology variables.[3] However, they avoid the use of explicit price information. They start by looking at differences across countries in GNP per capita with GNP calculated in PPP terms. If GNP per capita in country z is *x* per cent less than that in the U.S., the leading country, then they assume that labour productivity in every industry in country z is *x* per cent less than that in the U.S. As they recognize, the assumption that the productivity gap between country z and country L is uniform across industries is not ideal.[4] Following the Balassa explanation of PPP differences between developing and developed countries, we would expect productivity gaps in industries producing traded goods to exceed those in industries producing non-traded goods. In addition, we would expect technology differences to encompass not only the labour variables $A_{\ell iz}(t)$ and $A_{\ell iL}(t)$ but also variables concerned with the use of capital and materials.

In the next subsection, we show how input-output data can be combined with price data to obtain a comprehensive picture of cross-country differences in technology variables. Such a picture can then provide a more appropriate starting point and more appropriate shocks for a CGE convergence simulation than those used by McKibbin *et al.*

2.2 Deducing starting values of technology variables from multi-country input-output data

The three-country model that we use to illustrate the CGE approach to the convergence hypothesis is dynamic and distinguishes 57 commodities/industries. The input-output and trade data and most parameter values are taken from the GTAP database (Dimaranan and McDougall, [12]).

Table 2.1 is a simplified version of the model's input-output data for country z for year 0, with C and I referring to the number of commodities and industries. Because we assume that each commodity is produced by just one industry and each

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[3] Another multi-country CGE study concerned with environmental effects of convergence is that by Manne and Richels [11]. However, in their analysis they exogenize movements in per-capita GNP rather than letting these movements emerge from explicit hypotheses about technology variables.

[4] McKibbin *et al.* [9, p.32] mention that "If we then have evidence that a particular sector is likely to be closer to or further away from the US sectors than the average numbers suggest, we adjust the initial sectoral gaps …". However, they don't mention whether any such adjustments were made.

industry produces just one commodity, C = I (= 57). O refers to the number of occupations, which equals two, skilled and unskilled.

The first I columns in Table 2.1, labelled Industries, show inputs to the I industries in country z. V1BAS(c,dom,i,z) is the value in basic prices (prices to producers) of domestically produced commodity c used as an input to current production in industry i in country z. V1BAS(c,imp,i,z) is the value in basic prices (landed duty-paid) of imported commodity c used as an input to current production in industry i in country z. V1TAX(c,dom,i,z) and V1TAX(c,imp,i,z) are the collections of sales taxes on flows of domestic and imported commodity c to industry i in country z. V1CAP(i,z) is the return to capital used by industry i in country z. V1LAB(i,o,z) is the return to labour of occupation o used by industry i in country z. The sum of the input entries down the i-th industry column is the value of output in industry i, VOUTPUT(i,z). This can also be obtained by adding MAKEDOM(i,z) and MAKEEXP(i,z) which are the values of i produced in country z for the domestic market (variety 1 of i) and for export (variety 2 of i).

The basic values of domestic and imported commodities used in investment, household consumption and government consumption are given by the V2BAS, V3BAS and V5BAS vectors in the columns of Table 2.1 labelled Investors, Households and Government. The associated sales taxes are given by the V2TAX, V3TAX and V5TAX vectors. The column labelled Exports shows the basic values of exports and associated export taxes.

Our task now is to move from data of the type illustrated in Table 2.1 to estimates of starting values for technology variables, $A_{hiz}(0)$s and $B_{kiz}(0)$s. To do this we need to convert commodity and factor values to quantities. This requires data on prices for commodities and factors.

Price data and assumptions

After conducting an internet search and receiving advice from colleagues in the GTAP network[5], we concluded that the International Comparison Project (ICP)

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[5] This is a network of about 2,000 researchers around the world grouped loosely around the GTAP model (Hertel, [7]). We would like to thank Joe Francois and John Reilly for particularly useful advice.

conducted between the University of Pennsylvania and the World Bank is the only potential source of detailed price data that can be meaningfully compared across a large number of countries. Unfortunately, these data are not publicly available in disaggregated form. Obtaining them would require resources well beyond those available to us.

Given that it was impractical to obtain international price data, we resorted to using various sets of assumptions, two of which are set out in Table 2.2.[6] Without loss of generality we assume that the basic prices of goods produced in ROW are 1. In both sets of assumptions, the initial basic prices of Chinese exports (variety 2 goods) are also 1. With the input-output data being presented in a common currency ($US), this amounts to assuming that a shipment of plastics, for example, that is exported from China and has a value of $US1 at a Chinese factory door represents the same quantity of plastics as a shipment from ROW that has a value of $US1 at a ROW factory door.[7] The initial basic price of a unit of imports is calculated as the initial basic price of a unit of exports (that is, 1) *plus* export taxes per unit charged by the exporting country *plus* tariffs per unit charged by the importing country *plus* transport costs per unit between the two countries.

In making our first set of assumptions (labelled PPP) about the initial basic prices of domestically used goods (variety 1 goods) in China, we imagined that we have data showing that the PPP for China relative to ROW is 2. We assume that a high PPP value for China is consistent with the Balassa [8] hypothesis. Reflecting this, we set prices of variety 1 non-traded goods (mainly services) in China at 0.25 and the prices of variety 1 traded goods (mainly agricultural, manufacturing and mineral products) at 0.75. Under these assumptions the China/ROW PPP is at our imagined observed value of 2.

In our second set of assumptions (labelled MER), we ignore the PPP idea and set the initial basic prices of all domestically produced goods at 1 in all countries. By

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[6] A further set of price assumptions is analysed in the longer version of this paper, Dixon and Rimmer [13].

[7] Ideally, common price assumptions should apply to shipments at a notional world central point.

comparing results from simulations performed under the second set of assumptions with those performed under the first, we can illustrate the implications of using MER in convergence analysis rather than PPP.

In both sets of assumptions we fix the wage of skilled labour at twice that of unskilled labour in all countries. We assume that wage rates for both types of labour are much lower in China (the developing country) than in ROW (the developed country). While we are confident that our wage assumptions are qualitatively realistic, we recognise that with additional effort these assumptions could be fine tuned via empirical research.

With the commodity-price assumptions in place, we can compute quantities of intermediate inputs and quantities of outputs from the input-output flows [V1BAS, MAKEDOM and MAKEEXP] in Table 2.1. To measure quantities of primary-factor inputs, we use unskilled labour equivalents. The unskilled labour equivalent of the primary factor input to industry i in country z is the total returns to primary factors in (i,z) divided by the unskilled wage rate in z. Thus we assume that if the unskilled equivalent of primary-factor inputs to industry i in country z is twice that to industry j in country y, then (i,z) uses twice as much primary factors as (j,y).

Deducing the starting values for the technology variables

We define quantity units so that the quantity of output in industry i in country z in year zero is the sum of the quantities of variety 1 and variety 2 of i produced by the industry:

$$Y_{iz}(0) = Y_{1iz}(0) + Y_{2iz}(0) \quad \text{for all i, z} \quad . \tag{2.4}$$

Equation (2.4) is a natural definition of output for industry i in ROW: a unit of the two varieties of goods produced by industry i in ROW has the same price. By adopting (2.4) for China, we are ensuring that if industry i in China produces the same number of units of good i variety 1 and good i variety 2 as are produced in ROW, then we record the output of industry i in China as being the same as the output of industry i in ROW. Similarly, we define the year-zero quantity [$X_{ciz}(0)$] of input of commodity c into industry i in country z as a sum of the quantities of domestically produced and imported c.

Having determined the initial quantities of industry outputs, $Y_{iz}(0)$, and industry inputs, $X_{1iz}(0)$, …, $X_{niz}(0)$, we now move to the determination of the initial values of the technology variables, $A_{hiz}(0)$ and $B_{kiz}(0)$. In our CGE model, the F_i functions in (2.1) have the Leontief form. Thus, the $A_{hiz}(0)$s are simply the initial levels of inputs per unit of output:

$$A_{hiz}(0) = X_{hiz}(0) / Y_{iz}(0) \quad \text{for all h, i, z} \quad . \tag{2.5}$$

The G_i functions in (2.2) have the CET form:

$$Y_{iz}(0) = \left[\sum_{k=1}^{2} \{B_{kiz}(0) * Y_{kiz}(0)\}^{-\rho_{iz}} \right]^{-1/\rho_{iz}} \quad \text{for all i, z} \quad , \tag{2.6}$$

where ρ_{iz} is a parameter with value less than -1, that controls the degree of transformability between the two varieties of good i in the production process of industry i in country z. We set ρ_{iz} at -1.333 for all i and z. This gives transformation elasticities of 3, implying that producers can readily switch their production between domestic and export varieties. With values already in place for $Y_{iz}(0)$ and $Y_{kiz}(0)$, we can use (2.6) together with the tangency condition[8] on the transformation frontiers to deduce $B_{kiz}(0)$ for all k,i,z.

3. RESULTS

We report results from two simulations. For the first, we estimated initial values for technology variables [$A_{hiz}(0)$s and $B_{kiz}(0)$s] using PPP prices while for the second we used MER prices. Each simulation consists of two runs: a basecase and a “policy”. The basecases for the two simulations depict bland situations in which technology variables move at the same rates in China and ROW, thus preserving initial technology gaps. In the policy runs, we assume that over the next 100 years multi-factor productivity in Chinese industries catches up to that in ROW: the A_{hiz} variables for China converge to those of ROW. In the first simulation (with the PPP prices) the initial ratios of export to domestic prices in China differ from those in ROW. This implies that at the initial production points, China and ROW’s export/domestic transformation frontiers have different slopes (Figure 3.1). With its full integration into the world economy, we assume that over the next 25 years China will improve its ability to service export markets relative to domestic markets. We introduce this idea in the first simulation by allowing the B variables for China to converge to those for ROW. As mentioned already, the B movements do not impart any further multi-factor-productivity change to Chinese industries. In simulation 2, there are no B movements because at the initial production points, China and ROW's transformation frontiers have the same slopes.

It is not informative to use our model for projections over a period as long as 100 years. Consequently, for both simulations, we report deviations in variables (differences between the basecase and policy results) caused by convergence 25 years into the process.

3.1. Multi-factor productivity gaps

Equation (2.5) generates initial values for 58 input-technology variables [the A(0)s, 57 intermediate inputs and 1 composite primary-factor input] in each industry in each country. Columns (1) and (2) of Table 3.1 give summary measures of the A(0)s. For each industry they show the ratio of multi-factor productivity in China to that in ROW. For example, the first entry in column (1) indicates that in 1998 multi-factor productivity in the Chinese paddy rice industry was 21 per cent of that in ROW, where the quantities of inputs and outputs used in Paddy rice are estimated for the two countries by applying PPP price assumptions (Table 2.2) to input-output data. In our convergence simulations we move all 58 variables for each industry i in China smoothly towards the values of these variables in ROW. However, it is reasonable to think of the simulations as generating the effects of movements in the numbers in columns (1) and (2) about 25 per cent of the way towards one.

The multi-factor-productivity ratios in column (1) of Table 3.1, estimated under PPP assumptions, lie between 0.09 (for Wool & silk worms, industry 12) and 1.02 (for Construction, industry 46), with the average ratio being 0.47. The ratios in column (2), estimated under MER, average 0.35 and range between 0.07 (for Wool & silk worms) to 0.56 (for Vegetables, oils and fats, industry 21).

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[8] Under optimising behaviour $(\partial G_i / Y_{1iz})/(\partial G_i / Y_{2iz}) = P_{1iz}/P_{2iz}$. Also see Figure 3.1.

As can be seen from Figure 3.2, the higher average multi-factor-productivity ratio in column (1) relative to column (2) reflects the ratio estimates for the service industries (industries 43 to 57). For the non-service industries (1 to 42) the estimates in the two columns are quite similar. For the non-service industries, the movement from PPP to MER: (a) decreases the estimated quantity of domestic goods of variety 1 produced in China by 25 per cent; (b) decreases the estimated quantity of domestically produced material (non-service) inputs by 25 per cent; and (c) decreases the estimated quantity of domestically produced service inputs by 75 per cent. These reductions in estimated outputs and inputs are approximately balanced. For service industries (43 to 57), the dominant effect on the estimated multi-factor-productivity ratios in the move from PPP to MER is the decrease in estimated output of variety 1 goods in China of 75 per cent.

3.2 Macro results

Table 3.2 shows, for our two simulations, percentage deviations in macro variables caused by Chinese convergence. The figure 96.25 in the first row of the first column, for example, shows for the PPP case that 25 years into a 100 year convergence process, Chinese GDP is 96.25 per cent higher than it would have been in the absence of a convergence process.

In a journal-length paper it is not possible to write down the equations of a CGE model of the type used in this paper or to describe in any detail the underlying database. Nevertheless, it is possible to explain particular sets of results, such as those in Table 3.2, in terms of key theoretical mechanisms and features of the database. We do this via back-of-the-envelope (bote) models and calculations. Rather than set out an exhaustive list of assumptions, we let the key assumptions emerge from the bote explanations of the results.

Simulation 1: Initial technology estimates for China reflect PPP assumptions

The GDP deviation for China in the first simulation, 96.25 per cent, arises mainly from the direct effect of increased technical progress that allows more output from given levels of inputs. In this simulation, the typical Chinese industry in the 25th year experiences a 21 per cent gain in multi-factor productivity.[9] Because GDP in China is only about 37 per cent of total inputs to industries (intermediate inputs plus primary factors), a multi-factor-productivity gain of 21 per cent across all Chinese industries translates into a GDP gain of about 57 per cent (= 21/0.37). We assume that extra technical progress in China does not affect long-run employment. Thus, the rest of the Chinese GDP gain is contributed by increased capital. The capital share of GDP in China is about 36 per cent, implying that the 103.03 per cent increase in capital shown for China in column (1) of Table 3.2 contributes about 37 per cent to GDP. Together, these back-of-the-envelope calculations of technology and capital contributions to GDP sum to 94 per cent (57 plus 39), closely matching the simulation result.

For understanding why China’s capital stock increases, a useful starting point is the marginal productivity condition for capital in a one-sector model:

$$\frac{Q}{P_g} = \frac{1}{A} * F_k(K/L) \quad , \tag{3.1}$$

where K and L are inputs of capital and labour;

Q is the rental per unit of capital;

P_g is the price of a unit of output (unit of GDP);

(1/A)*F(K,L) is the production function;

A is a technology term with decreases in A representing technological progress; and

F_k is the partial derivative of F with respect to K. We assume that F_k is a monotonically decreasing function of K/L.

The LHS of (3.1) is a measure of the rate of return on capital: the rental price of capital divided by the asset price where we assume that units of capital are made out of units of GDP. Under the assumption that rates of return in China are determined by world interest rates, independently of China’s technical progress, we see that

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[9] If the average multi-factor-productivity ratio grows smoothly from 0.47 to 1 over 100 years, then it reaches 0.57 in the 25th year. Thus, with convergence, China’s multi-factor productivity is 21 per cent higher [=100*(0.57/0.47-1)] in the 25th year than it is without convergence.

decreases in A cause decreases in F_k and consequently increases in K/L. With L fixed, K must increase.

In simulations under the fixed rate-of-return assumption, we found that the increase in K is not sufficient to keep pace with the increase in GDP. A reduction in K/GDP is at odds with the experience described by Young (e.g. [14]), Krugman [15] and others of convergence by emerging Asian nations. On the basis of this experience, we would expect capital in China to grow at least as fast as GDP during the convergence period. Consequently, in the simulations reported in Table 3.2, we assumed that as the Chinese economy develops, it will be viewed as a safer place for investment. This will reduce required rates of return. In our simulations, we assumed that required rates of return [the LHS of (3.1)] will fall sufficiently to allow the convergence-induced percentage increases in K to approximately match those in GDP.

In addition to an unrealistic decline in K/GDP, our initial attempts to simulate Chinese convergence produced results suggesting that there would be a fall in Chinese trade relative to GDP. Again, this seems at odds with experience. Since 1990, there have been increases in the trade/GDP ratios of converging countries such as Korea, Taiwan and Hong Kong. Expansion of Chinese exports (and hence imports) was checked in our initial simulation experiments by reductions in prices for Chinese exports (movements down the demand curves of trading partners). In both simulations reported in Table 3.2, we assumed that as part of the convergence scenario, China achieves favourable twists in the preferences of ROW. These twists generate outward movements in the demand curves of ROW for Chinese products. Such twists could be explained if, in the convergence process, China improved its marketing efforts, improved the quality of its products and improved its reliability as a source of supply. The twists we imposed were sufficient to prevent convergence from causing a reduction in China’s terms of trade. With the twists in place, simulation 1 shows convergence-induced expansions in exports and imports (107.70 and 99.03 per cent) approximately in line with that in GDP (96.25 per cent).

Extra technical change in China produces a sharp increase in real wages (103.28 per cent, simulation 1, Table 3.2). This can be understood via the labour-market equilibrium condition:

$$\frac{W}{P_g} = \frac{1}{A} * F_\ell(K/L) \quad , \tag{3.2}$$

where W is the wage rate; and F_ℓ is the partial derivative of F with respect to L.

W/P_g must increase because A decreases and F_ℓ increases via the increase in K/L.

The final macro result for China in simulation 1 is a 40.19 per cent reduction in the China/ROW PPP (from 2 to about 1.2). With our assumed movements in China's B coefficients, convergence largely eliminates the Balassa effect.

The deviations shown for simulation 1 for ROW are negligible. This reflects the smallness of the Chinese economy in relation to the world economy: in our database for 1998, Chinese GDP (converted at MER) is only about 3 per cent of world GDP.

Simulation 2: Initial technology estimates for China reflect MER assumptions

In simulation 2 we adopt the same assumptions as in simulation 1 except that we use the MER estimates as the starting point for Chinese technology. In terms of Table 3.1, the initial multi-factor-productivity ratios are those in column (2) rather than those in column (1).

The MER estimates imply that Chinese technology has considerably further to go to catch up to ROW technology than do the PPP estimates. Under the MER estimates, the average technology ratio for Chinese industries is 0.35 compared with 0.47 under PPP. Consequently, deviation results for simulation 2 in Table 3.2 show greater stimulation of the Chinese economy than those for simulation 1. For example, the percentage increase in GDP for China is 54.5 per cent higher in simulation 2 than in simulation 1 [54.5 = 100*(148.68/96.25 – 1)]. If PPP is the right basis for estimating the initial Chinese/ROW technology ratios, then 54.5 per cent is an indicator of the extent to which adoption of MER leads to overestimation of the effect of convergence on Chinese GDP after 25 years of a 100 year process.

Two aspects of the MER results for China in Table 3.2 are unrealistic. First, they imply that convergence would be accompanied by reductions in the ratios of exports and imports to GDP. Growth in Chinese trade is restricted in the move from simulation 1 to simulation 2 because we are biasing technological change in favour of the production of non-tradeable goods. To understand this, recall Figure 3.2 which shows that the Chinese technology ratios for non-tradeables (industries 43 to 57) under MER are lower than those for tradeables (industries 1 to 42). The second unrealistic aspect of the MER results is that they imply that convergence would have little effect (-4.33 per cent) on the China/ROW PPP. Unlike the PPP simulation, in the MER simulation there is no tendency for China to change the shape of its transformation frontiers (Figure 3.1) in favour of production for export markets.

As with simulation 1, the ROW deviations for simulation 2 are negligible.

3.3. Industry results

Column (5) of Table 3.1 shows convergence-induced deviations in the outputs of Chinese industries in simulation 1 (PPP). These vary from a maximum of 139 per cent for Air transport (industry 50) to a minimum of -21 per cent for Wool and silk worms (industry 12).

Air transport is a major winner in simulation 1 for two reasons. First, it is highly capital intensive and will benefit in China's convergence process from reduction in the cost of using capital relative to the cost of using labour. Second, Air transport is highly trade exposed: exports account for 56.58 per cent of its sales and imports account for 37.97 per cent of Chinese purchases [columns (3) and (4) of Table 3.1]. High trade exposure means that the elasticity of demand for the products of the Air transport industry is high so that favourable movements in the relative prices of capital and labour translate into a large increase in output rather than just a reduction in price.

The first step in understanding the result for Wool and silk worms in simulation 1 is to note that 98 per cent of its sales are to Textiles (industry 27). Thus, what happens to the output of Wool and silk worms depends mainly on what happens to the input of Wool and silk worms per unit of output of Textiles and what happens to the output of Textiles. The A_{hiz} shock for h = Wool and silk worms, i = Textiles and z = China is strongly negative: by year 25 in the policy run of simulation 1, the Textile industry uses 32 per cent less Wool and silk worms per unit of output than it did in the basecase. At the same time, output expansion in Textiles is subdued [only 12 per cent compared with an average over all industries of 49 per cent]. This subdued response reflects three factors. First, Textile production is quite labour intensity and will suffer in China as wages rise relative to the cost of using capital. Second, our estimates of technology ratios in column (1) of Table 3.1 imply that the Chinese textile industry is currently efficient relative to most other Chinese industries producing traded goods: the technology ratio for Textiles in column (1) is 0.44, whereas the average technology ratio over industries 1 to 42 is only 0.26. Thus, among traded goods industries, Textiles is harmed by having a relatively small multi-factor productivity improvement in the convergence process. Third, Textiles has high trade exposure, with an export share of 17.47 per cent and an import share on 20.11 per cent [columns (3) and (4) of Table 3.1]. High trade exposure and therefore a high elasticity of demand is bad for an industry if its multi-factor-productivity increase is insufficient to offset wage increases generated by productivity increases in the rest of the economy. Together, the 32 per cent reduction in the input of Wool and silk worms per unit of output in Textiles and the 12 per cent increase in the output of textiles imply a 24 per cent reduction in demand for Wool and silk worms by Textiles [-24 = 100*(1.12*(1-0.32)-1)]. This is approximately the result (-21) given by simulation 1 for the output of the Wool and silk worms industry.

The most interesting aspect of the industry results for simulation 1 is that the average output deviation is only 49 per cent, whereas the increase in GDP is 96.25 per cent. The gap between the average percentage increase in industry outputs and the percentage increase in GDP arises from intermediate-input-saving technical progress. This type of technical progress can reduce industry outputs while increasing GDP. Of relevance to the greenhouse debate is that simulation 1 shows percentage output increases for China’s main greenhouse industries, Coal (industry 15, 41 per cent increase), Electricity (industry 43, 30 per cent) and Road & rail transport (industry 48, 40 per cent) that are considerably less than the percentage increase in real GDP. An implication is that analysis based on a fixed coefficient linking energy use and GDP is likely to overstate the greenhouse-gas implications of Chinese convergence.

The industry output deviations for Chinese industries in simulation 2 (MER) are shown in column (6) of Table 3.1. On average, the output results for simulation 2 are 71 per cent larger than those for simulation 1 [71 = 100*(84/49– 1)]. For the greenhouse gas industries, Coal, Electricity and Road & rail transport, the output increases in simulation 2 are 58, 213 and 142 per cent larger than those in simulation 1 [65 cf 41, 94 cf 30 and 97 cf 40]. As with the GDP results, we conclude that if PPP is the right basis for estimating the initial Chinese/ROW multi-factor-productivity ratios, then adoption of MER leads to a considerable overestimate of the effect of convergence on the output of Chinese greenhouse gas industries with the attendant danger of a considerable overestimate of greenhouse gas emissions.

4. CONCLUDING REMARKS

We interpret convergence as meaning that technologies in developing countries will move towards those in developed countries. Under this interpretation, the analysis of convergence requires estimates of the initial technology gaps between developing and developed countries. Estimates of these gaps are not readily available. What is available through the Global Trade Analysis Project (GTAP) is input-output tables for about 50 countries, distinguishing about 60 industries and commodities. Input-output tables show *values* of commodity and factor flows. For estimating technology gaps, we need *quantities*. To get from values to quantities we need price data for comparable products in different countries.

In describing an approach to convergence analysis similar to our own, Nordhaus [5, p. 25] anticipates that suitable price data are unlikely to be available. During the research for this paper, we found that a promising source of relevant price data is the International Comparisons Project (ICP) conducted by the University of Pennsylvania and the World Bank. The ICP makes PPP estimates based on detailed price information for many countries. Their policy is not to release the detailed price data that underlies their PPP estimates to individual researchers. However, it seems possible that the data could be released to a major international organization such as the Intergovernmental Panel on Climate Change. In the meantime, our research establishes the feasibility and efficacy of combining price and input-output data in a convergence study using a multi-country CGE model.

Unable to obtain suitable price data, we moved from input-output values to our preferred estimates of quantities by assuming: (a) that the prices of an export good, after conversion into a common currency by MERs, are broadly the same across countries; and (b) that the prices of a non-traded good, after MER conversions, are considerably lower in developing countries than in developed countries. These assumptions are consistent with: (a) the law of one price applied to heavily traded goods; and (b) the often-observed phenomenon that PPP for a typical developing country is high relative to that for a typical developed country. Having obtained quantity estimates, we derived coefficients describing technology in each industry in each country. These coefficients then provided the initial technology gaps for a convergence analysis.

To work out the implications of convergence (closing of technology gaps) the best approach is simulation with a multi-country CGE model. CGE models are capable of accepting scenarios at a detailed industry level on technological change. They can also be used to simulate the effects of twists in technologies in favour or against the production of goods for export relative to goods for the home-market and in favour or against the use of imported inputs relative to domestic inputs.

In this paper, we used a three-country dynamic CGE model to illustrate the estimation of technology gaps and the simulation of partial catch up by developing countries. For each industry in each country, we estimated technology coefficients describing the use of a primary-factor composite and 57 intermediate inputs. While this level of industry-input detail seems satisfactory, the level of country detail in our model was not ideal. The countries in the model are Australia, China and Rest of world (ROW). We used China as a representative developing country and ROW and Australia as representative developed countries. Convergence analysis should be carried out in a model that identifies: several developing countries, several middle-income countries and several high income countries. Using GTAP data such an analysis is possible. However, it would be a major project. To make it worthwhile, it would probably be necessary to arrange access to detailed price data of the type held by ICP, and it would certainly be necessary to do more work on factor prices, particularly wage rates, than was undertaken for the present paper.

Despite its restricted country detail, our model suggests three interesting conclusions.

First, the MER/PPP distinction matters. When we use MERs, we obtain distinctly different estimates of initial technology gaps to those obtained when we use price assumptions broadly consistent with PPP. In simulating the effects of convergence, we found that MER-based estimates of initial technology gaps lead to considerably higher estimates of convergence-induced growth in developing countries than do PPP-based estimates. In our example, where China converges to ROW over a 100 year period, the MER-based simulation (simulation 2) shows a convergence-induced increase in the real GDP of China of 149 per cent after 25 years of the convergence process. In simulation 1, conducted under the same macro assumptions as simulation 2, but with initial technology gaps estimated with PPP-consistent prices, the increase in the real GDP of China after 25 years is only 96.25 per cent. If PPP is the right basis for estimating initial technology gaps, then the use of MER-based analysis runs the danger of significantly overestimating convergence-induced growth in developing countries and thereby overstating environmental concerns such as the emission of greenhouse gases.

Second, under convergence, the outputs of industries in developing countries will not grow as rapidly as their GDPs. This reflects intermediate-input-saving technical change. As part of the process of convergence, developing countries will use less intermediate inputs per unit of output in many industries. This means that analysis based on fixed-coefficient relationships between environmental variables and GDP is likely to overstate the environmental damage (including greenhouse-gas emissions) associated with convergence. It is possible to avoid overstatement by building trends into environment/GDP coefficients. However, CGE analysis provides an attractive alternative to such a procedure. CGE modelling can explain changes in environment/GDP relationships and make explicit the technological assumptions underlying such changes.

Third, for convergence analysis the industry detail in CGE models is valuable. Our simulations showed a wide range of convergence-induced changes in output across industries. For example, at the 25 year mark of a 100 year convergence process, we estimate the convergence-induced change in the output of the Chinese Wool and silk worm industry at -21 per cent (simulation 1). At the other extreme, our estimate of the convergence-induced change in the output of the Chinese Air transport industry after 25 years is 139 per cent (simulation 1). If we are to understand the environmental, occupational and trade implications of convergence, then results such as these suggest that the use of models with a detailed industrial structure is unavoidable.

As explained in the introduction, the motivation for this paper was provided by the ongoing discussion of the greenhouse implications of convergence. However, convergence is a broader topic. Convergence will affect patterns of trade and the occupational composition of employment in developed countries as well as in developing countries. Analysis of convergence should therefore be of interest to economic planners throughout the world. The research in this paper demonstrates that multi-country CGE models have the potential to provide detailed projections of the implications of convergence. However, to realize this potential, considerable effort may be required to obtain price data suitable for use in the estimation of initial technology ratios.

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Table2.1. Simplified representation of input-output data for country z

		Industries	*Investors*	*Households*	*Exports*	*Government*
	size	← I →	*1*	*1*	*1*	*1*
Domestic commodity used domestically (variety 1)	↑ C ↓	**V1BAS(c,dom,i,z)**	**V2BAS(c,dom,z)**	**V3BAS(c,dom,z)**		**V5BAS(c,dom,z)**
Domestic commodity exported (variety 2)	↑ C ↓				**BAS4(c,z)**	
Imported commodities	↑ C ↓	**V1BAS(c,imp,i,z)**	**V2BAS(c,imp,z)**	**V3BAS(c,imp,z)**		**V5BAS(c,imp,z)**
Tax on domestic commodity of variety 1	↑ C ↓	**V1TAX(c,dom,i,z)**	**V2TAX(c,dom,z)**	**V3TAX(c,dom,z)**		**V5TAX(c,dom,z)**
Tax on domestic commodity of variety 2	↑ C ↓				**V4TAX(c,z)**	
Tax on imports	↑ C ↓	**V1TAX(c,imp,i,z)**	**V2TAX(c,imp,z)**	**V3TAX(c,imp,z)**		**V5TAX(c,imp,z)**
Capital	*1*	**V1CAP(i,z)**				
Labour	↑ O ↓	**V1LAB(i,o,z)**				
Totals	*1*	**VOUTPUT(i,z)**				
MAKE (varieties 1&2)	↑ 2 ↓	**MAKEDOM(i,z)** **MAKEEXP(i,z)**				

Table2.2. Assumptions concerning initial prices

	China	**ROW**
First set of assumptions, PPP, used in simulation 1		
Basic prices of exports (type 2 goods)	1	1
Basic prices of domestic non-traded (type 1, services)	0.25	1
Basic prices of domestic traded(type 1, non-services)	0.75	1
Wage rates of skilled labour	0.1	1
Wage rates of unskilled labour	0.05	0.5
Purchasing power parity, China/ROW	2.0	-
Second set of assumptions, MER, used in simulation 2		
Basic prices of exports (type 2 goods)	1	1
Basic prices of domestic non-traded (type 1, services)	1	1
Basic prices of domestic traded(type 1, non-services)	1	1
Wage rates of skilled labour	0.1	1
Wage rates of unskilled labour	0.05	0.5
Purchasing power parity, China/ROW	1.0	-

Table 3.1. Ratios of multi-factor productivities, export and import shares for China and simulation results

Commodity/industry		Multi-factor-productivity ratios for 1998 China/ROW, under		Trade shares for 1998, China		Simulation results (% deviations in industry outputs)	
No.	**Name**	**PPP** (1)	**MER** (2)	**Export/output (%)** (3)	**Import/absorption (%)** (4)	**Sim 1 (PPP)** (5)	**Sim2 (MER)** (6)
1	Paddy rice	0.21	0.18	0.43	0.01	48	72
2	Wheat	0.22	0.20	0.16	6.56	41	69
3	Cereal grains nec	0.23	0.20	7.26	5.80	41	69
4	Vegetables, fruit & nuts	0.23	0.21	1.61	0.94	44	70
5	Oil seeds	0.20	0.17	3.56	19.02	25	38
6	Sugar cane & beet	0.21	0.19	0.09	0.06	62	103
7	Plant-based fibres	0.32	0.33	0.06	16.84	-12	-1
8	Crops nec	0.16	0.15	34.93	16.72	64	93
9	Cattle, sheep, goats & horses	0.23	0.20	0.96	0.13	31	57
10	Animal products nec	0.29	0.26	2.05	1.20	60	90
11	Raw milk	0.20	0.17	0.28	0.24	41	71
12	Wool & silk worms	0.09	0.07	1.55	11.48	-21	-10
13	Forestry	0.19	0.18	1.09	7.32	19	37
14	Fishing	0.19	0.17	2.61	0.53	38	61
15	Coal	0.21	0.21	10.95	0.89	41	65
16	Oil	0.16	0.14	13.00	21.61	109	157
17	Gas	0.17	0.16	31.82	0.00	126	181
18	Minerals nec	0.29	0.31	2.15	7.92	30	46
19	Meat: cattle, sheep, goats & horses	0.27	0.38	3.15	13.34	18	26
20	Meat products nec	0.49	0.51	9.67	8.66	71	105
21	Vegetable oils & fats	0.50	0.56	4.91	30.63	53	85
22	Dairy products	0.19	0.26	4.17	21.79	25	46
23	Processed rice	0.25	0.25	0.82	0.83	36	57
24	Sugar	0.35	0.37	21.75	39.44	129	187
25	Food products nec	0.28	0.28	12.16	8.02	96	140
26	Beverages & tobacco products	0.27	0.26	2.62	4.16	72	108
27	Textiles	0.44	0.46	17.47	20.11	12	27
28	Wearing apparel	0.35	0.38	48.61	9.31	47	62
29	Leather products	0.38	0.45	54.94	14.99	32	36

Table 3.1 continues …

Table 3.1 continued …

Commodity/industry		**Multi-factor-productivity ratios for 1998 China/ROW, under**		**Trade shares for 1998, China**		**Simulation results (% deviations in industry outputs)**	
No.	**Name**	**PPP** (1)	**MER** (2)	**Export/output (%)** (3)	**Import/absorption (%)** (4)	**Sim 1 (PPP)** (5)	**Sim2 (MER)** (6)
30	Wood products	0.40	0.43	19.13	8.70	74	101
31	Paper products & publishing	0.32	0.33	4.14	16.57	35	47
32	Petroleum & coal products	0.54	0.54	3.45	13.74	64	92
33	Chemical, rubber & plastic prods	0.42	0.44	10.57	20.26	41	62
34	Mineral products nec	0.36	0.39	5.01	3.78	53	68
35	Ferrous metals	0.44	0.49	5.97	13.28	45	68
36	Metals nec	0.45	0.50	8.12	19.39	43	70
37	Ferrous metal products	0.44	0.49	12.47	6.55	65	92
38	Motor vehicles & parts	0.49	0.50	3.84	12.88	36	63
39	Transport equipment nec	0.45	0.46	12.81	17.66	74	125
40	Electronic equipment	0.47	0.50	44.79	45.32	52	85
41	Machinery & equipment nec	0.43	0.45	16.45	23.22	50	85
42	Manufactures nec	0.26	0.28	39.08	7.51	55	80
43	Electricity	0.83	0.37	0.61	0.02	30	94
44	Gas manufacture & distribution	0.41	0.18	1.79	0.00	54	104
45	Water	0.61	0.24	0.23	0.66	33	96
46	Construction	1.02	0.36	0.26	0.72	67	127
47	Wholesale & retail trade	0.62	0.24	5.00	4.89	25	80
48	Road & rail transport	0.58	0.20	8.92	7.76	40	97
49	Water transport	0.43	0.23	39.11	17.52	86	109
50	Air transport	0.37	0.23	56.58	37.97	139	143
51	Communication	0.44	0.14	1.86	2.03	35	96
52	Financial services nec	0.46	0.17	0.31	1.66	41	109
53	Insurance	0.38	0.18	8.19	18.34	42	94
54	Business services	0.48	0.17	4.62	6.71	67	135
55	Recreation & other services	0.55	0.22	0.52	4.47	32	91
56	Government services	0.63	0.25	0.89	1.21	64	110
57	Ownership of dwellings	0.42	0.18	0.00	0.00	86	202
	Averages	**0.47**	**0.35**	**10.44**	**10.72**	**49**	**84**

Table 3.2. Marco effects of Chinese convergence over 100 years: Percentage deviations after 25 years

	China		ROW	
	Sim 1 (PPP)	**Sim 2 (MER)**	**Sim 1 (PPP)**	**Sim 2 (MER)**
Real GDP	96.25	148.68	-0.04	0.00
Aggregate employment	0.00	0.00	0.00	0.00
Aggregate capital	103.03	139.37	0.01	0.10
Export volumes	107.70	84.69	-0.04	-0.13
Import volumes	99.03	74.65	0.57	0.52
Real post-tax wage rate	103.28	148.27	0.10	0.16
PPP (China to ROW)	-40.19	-4.33	0.00	0.00

Figure 3.1. Transformation frontier for industry i in China

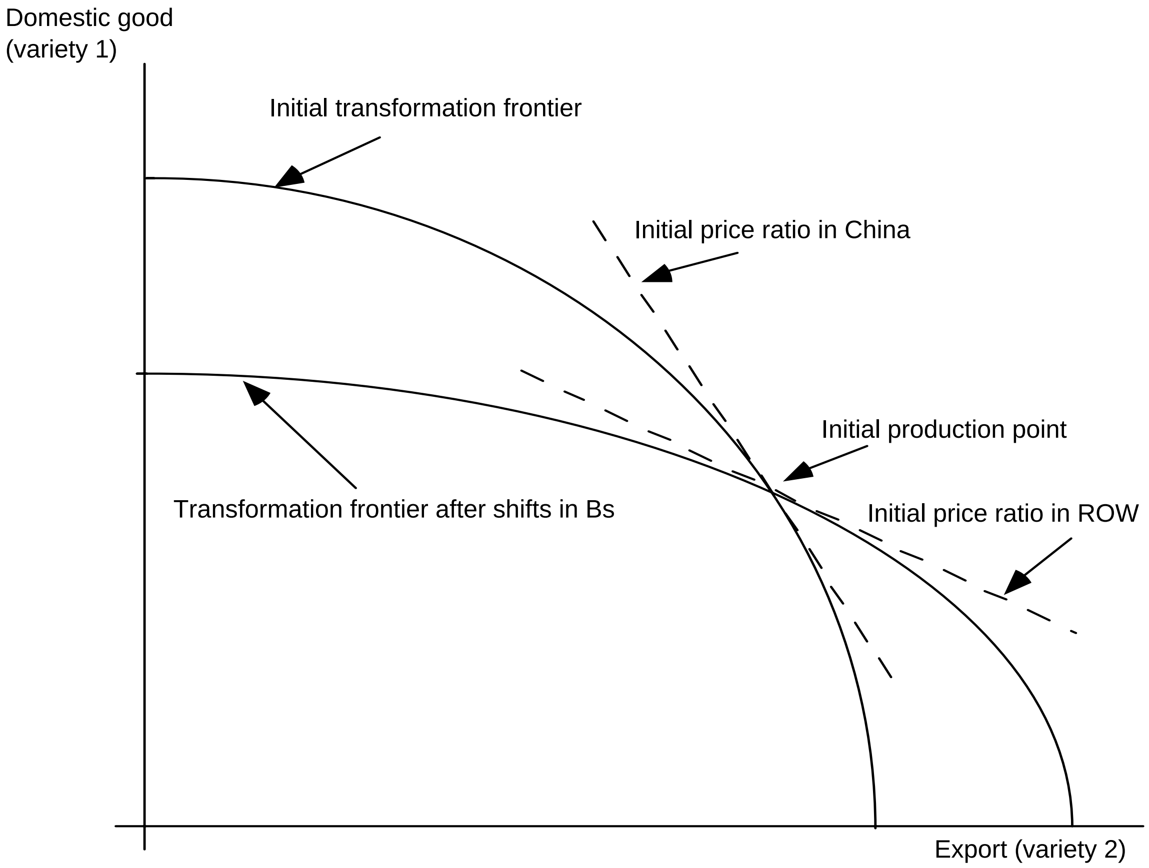

Figure 3.2. Comparison of estimates of multi-factor-productivity ratios for Chinese industries in 1998