# Technology Assimilation and Aggregate Productivity

Ping Wang, Washington University in St. Louis and NBER Tsz-Nga Wong, Bank of Canada Chong K. Yip, Chinese University of Hong Kong

December 2015

<u>Abstract</u>: This paper develops a technology assimilation framework to explain how domestic firms uncover global technologies under limited technique availability and production flexibility. We construct a micro-founded measure of endogenous total factor productivity (TFP) based on the interaction of stage-dependent local knowledge of a country with advanced foreign technologies. We then perform development and growth accounting exercises to better understand the large and widening TFP gaps across countries and over time. By comparing our results with other popular models, we find that the success of assimilation of frontier technologies can be instrumental in differentiating miracle economies from trapped economies. About half of the rapid growth experienced in miracle economies can be attributed to successful assimilation, whereas about one third of the negative growth outcome in trapped economies is due to the lack of it or backward assimilation. This finding suggests that an adequate provision of correct incentives and institutional settings is crucial for domestic firms to assimilate relevant frontier technologies in a way that is suitable for their development stages.

### JEL Classification: O41, O47, D90, E23.

Keywords: Assimilation of Global Technology, Flexible Production, Local Knowledge of Limited Techniques, Development and Growth Accounting.

Acknowledgment: We are grateful for the valuable comments and suggestions of Fernando Alvarez, Costas Arkolakis, Paul Beaudry, Bob Becker, Rick Bond, Anton Braun, Tom Cooley, Peter Howitt, Boyan Jovanovic, Sam Kortum, Finn Kydland, Zheng Liu, Serdar Ozkan, Steve Parente, Ed Prescott, B. Ravikumar, Ray Riezman, Victor Rios-Rull, Peter Ruppert, Rob Tamura, Yin-Chi Wang, and Jianpo Xue, as well as those of the participants at the North America Summer Meeting of the Econometric Society, the Asian Meeting of the Econometric Society, the Conference on Dynamics, Economic Growth, and International Trade, the Midwest Macroeconomic Conference, the Society for Advanced Economic Theory Meeting, Academia Sinica, and the National Taiwan University. We gratefully acknowledge the financial support of Academia Sinica, Talent Strategy of the Bank of Canada, the Chinese University of Hong Kong, and the Center for Economic Dynamics, that made this international collaboration possible. We would like to thank Terry Cheung and Ting-Wei Lai for helpful research assistance. The usual disclaimers apply.

Correspondence: Ping Wang, Department of Economics, Washington University in St. Louis, <u>Campus Box 1208</u>, One Brookings Drive, St. Louis, MO 63130, U.S.A.; 314-935-4236 (Phone); 314-935-4156 (Fax); pingwang@wustl.edu (E-mail). "The sixteenth-century Dutch, on the verge of becoming economic leaders of the world, borrowed heavily from the techniques of the Italians, the outgoing leaders. By then, the English were already learning not only from the Low Countries but also from other parts of the continent. The Americans borrowed heavily from the English and from other European sources, particularly from the time they achieved independence up until the middle of the nineteenth century." (Baumol et al. 1991 pp. 271-272)

## 1 Introduction

Why, in the past half-century, have many countries successfully taken off, catching up with world leaders, while some have experienced growth stagnation? The world income distribution has widened over the last 50 years. From 1970 to 2011, the U.S. real GDP per capita relative to that of poor nations in the bottom 10 percentile was about 5.4 times on average, with the gap rising over time. Macroeconomists attempt to account for the income differences using a neoclassical aggregate production function. They find that, even when controlling for the accumulation of physical and (education-based) human capital per worker, an unusually large total factor productivity (TFP) gap is still required to account for the income disparities (e.g., Lucas 2000). However, why would technology not flow from the rich to the poor? Are there "missing inputs" in standard aggregate production? Are there "barriers to rich" in less-developed countries? Over the past two decades, the field of development accounting has emerged; it is devoted to understanding the underlying causes of the persistent and widening world income disparities. These studies focus primarily on correcting the mismeasurements of factors inputs and identifying missing inputs in the neoclassical production framework. In this paper, we depart from neoclassical production theory to quantify endogenous TFP gaps by examining country-specific processes of technology assimilation.

To illustrate our idea of technology assimilation in a nontechnical fashion, let us consider a product (e.g., smartphones) with different product blueprints (such as Apple iPhone, Samsung Galaxy Note, HTC One, etc.). In contrast to standard neoclassical production theory, we generalize the concept of "production techniques" developed by Houthakker (1956-57), Kortum (1997), and Jones (2005) to capture "mini-blueprints" that specify ways to organize factor inputs so that they fit a given product blueprint. In our framework, availability of such production techniques is limited due to imperfect knowledge about product orders ex ante and about the most effective mini-blueprints that are suitable for a particular firm (e.g., Foxconn Technology Group). As a result, mismatches may arise and output can fall below the potential level. In this circumstance, "production flexibility" can make firms less vulnerable to their limitations in available techniques. In a global economy, a domestic firm can "assimilate" a relevant global leader and thus expand its set of available techniques; these assimilated techniques help to re-organize factor inputs in the continually changing process of production. The endogenous choice of such techniques yields a dynamic process of technology assimilation and generates endogenous TFP; however, this process depends on "local knowledge" that summaries a country's limitations related to the available techniques and production flexibility. Which particular leader should be assimilated can also be different across countries and over time. Assimilation under the condition of limited production techniques and restricted flexibility can prohibit the flow of technologies from developed to developing countries, leading to endogenous TFP gaps and the flying geese paradigm (FGP) of economic development documented by Akamatsu (1962) and Baumol et al. (1991).

Numerous well-documented case studies show that successful assimilation of technology is the common denominator in Asian economic development [Wan (2004)]. Geographical proximity in technology assimilation generates the FGP, with some early birds taking off sequentially, followed by various late comers. Conversely, failure to assimilate technology has caused the backwardness seen in African economic development. In 1970, per capita incomes of the Sub-Saharan countries were almost comparable with those of the Asian Tigers and were even ahead of some of their ASEAN counterparts.<sup>1</sup> Subsequently the Asian economies took off and continued to advance along sustained growth paths, whereas Africa's post-independence industrialization remains isolated from world markets and frontier technologies, even in their main sectors of production, such as cash crops (e.g., cocoa and coffee in Cote d'Ivoire and Kenya).

As elaborated below, technology assimilation differs from the standard concepts of technology adoption, imitation, or spillover. In general, the ability of technology assimilation are related to entrepreneurs' understanding of foreign techniques, their learning from experimenting, the flexibility of institutions and organizations, the human capital that is responsive to the frontier techniques, and the infrastructure and taxation schemes that enhance the adap-

<sup>&</sup>lt;sup>1</sup>For instance, the 1970 per capita GDP of Korea and Taiwan was 16.1% and 15.6% that of the United States, and Thailand's and Vietnam's were only 9.2% and 3.9%, whereas there of Cote d'Ivoire and Kenya were 12.6% and 8.4%, respectively.

tation. Thus, we can study how diverse growth experiences across countries can be explained by this assimilation measure over time. To investigate the relationship between technological advancement and flexible production, we need a systematic comparison between technologies with different elasticities of substitution. We therefore adopt a constant elasticity of substitution (CES) production function normalized to a particular country at a given stage of technology assimilation. We then decompose the real GDP per capita relative to the U.S. (the income ratio) into a relative technology component (the TFP ratio), a relative factor endowment component (the capital-labor ratio), and a time-varying, country-specific measure of technology assimilation with respect to an advanced foreign technology, which depends on the interaction of limited technique availability and production flexibility.

Our technology assimilation framework contributes to production theory and development economics in several significant aspects. In contrast to the neoclassical production approach, our framework disentangles the designed usages of production factors (production techniques) for a given level of technology from the physical inputs of production factors. Because the mini-blueprints governing factor use are specific to each production input, our framework is also different from organizational capital theory. Accordingly, we are able to establish a clearcut relationship between technological advancement and production flexibility. Moreover, by comparing local performance and global technology, we can extract more information from the data and can obtain measures of production flexibility and technology assimilation that are specific to a country over time. This allows us to generate new measures of TFP. We thus gain further insights into the role of assimilation in the dynamic process of economic advancement for various countries, and obtain new measures of aggregate productivity that are sharply different than comparable figures computed under the conventional neoclassical production framework. As our model is related to the literature of appropriate technology, we perform income accounting exercises and systematically compare them with other popular models such as those given in Lucas (2000), Basu and Weil (1998), and Acemoglu (2009). We shall refer to the Basu-Weil-Acemoglu framework of inappropriate technology as BWA because of its high relevance. We also generalize the Cobb-Douglas benchmark of Lucas (2000) with the CES formulation, referred to this generalization as the CES model.

The main findings of this paper are as follows. Theoretically, when local information about the available techniques suitable for domestic use is limited, the technologies will not flow from more advanced to less advanced countries. Poor assimilation is the barrier to growth and leaves nations in poverty traps. Using the normalized CES specification for the assimilation process, we decompose the aggregate production function into two components: a conventional Cobb-Douglas production term and a CES-type assimilation term. We show that country-specific assimilation of a global technology can serve as an effective vehicle for development accounting and can help to reduce the unexplained component in the large TFP differences.

Quantitatively, our development accounting results suggest that our model of the assimilation of global technology, the CES and the BWA models fit the data far better than the Lucas benchmark. Moreover, our model, on average, outperforms both the CES and the BWA models in most economic and geographic groups (classified by initial stage of development, development speed, and current state of development). These advantages are particularly noticeable for countries that are either in development traps or are experiencing development miracles. Furthermore, we select a group of representative countries and separate them into the following economic/geographic clusters: OECD, Asian Miracles, late-coming miracles, trapped, and laggards. By conducting growth accounting exercises, we find that the Lucas benchmark performs well for OECD countries, but noticeable differences exist between our model and the CES and the BWA models for trapped and miracle countries. Specifically, more than half of the relative income growth in all of the miracle countries can be attributed to successful assimilation. Moreover, the lack of or backward assimilation accounts for about one third of the negative growth performance of all of the trapped countries. By backward assimilation, we refer to the situation where assimilating a foreign frontier leads to lower production performance. Most of the development miracles have exhibited successful assimilation over the past four decades, whereas many of the trapped economies are found to suffer from the lack of or backward assimilation. Therefore, we can conclude that the *effective* assimilation of frontier global technology is an important factor for explaining many of the Asian Miracle cases, and the lack of assimilation of frontier global technology is crucial for explaining why most Sub-Saharan African countries suffer the poverty trap. Moreover, we identify successful assimilation with the flexibility of production over time, and find that the two larger Asian Tigers (i.e., South Korea and Taiwan) are more flexible in (techniquesaugmented) factor substitution than the two smaller Tigers and that India (software-led) is more flexible than China (assembly-based). Such flexibility has important implications for a country's production efficiency and development success.

Finally, based on country-specific growth data, we find that the fitness of our assimilation model significantly improves when we allow for delayed assimilation in several Latin American countries and an early stop of assimilation in Hong Kong and Singapore. Allowing Taiwan to first assimilate the techniques from Japan and then from the U.S. yields a much better fit; a similar assimilation switching does not change the results for Korea. For several ASEAN economies and China, geographical or FDI-based assimilation gives much better model fitness outcomes. In contrast, no alternative assimilation schemes improve the fitness outcomes for most of the trapped economies where technology assimilation is found lacking or backward.

#### <u>Related Literature</u>

Our paper is related to two strands of research: the study of appropriate technology and the study of development accounting.

To formalize the concepts of technology assimilation, we refer to the now-classic pieces by Atkinson and Stiglitz (1969) and Houthakker (1956-57) and more recent studies by Kortum (1997) and Jones (2005). Atkinson and Stiglitz specify that a country's local production features localized learning by doing. Houthakker, Kortum, and Jones obtain a Cobb-Douglas production function as an envelope of Leontief local productions in which firms are free to choose any production techniques drawn from independent Pareto distributions. Based on the idea of local production, Basu and Weil (1998) construct a Solow-type growth model of technological progress that emphasizes that technological advances will benefit certain types of technologies, but not others. Therefore, even if all technologies are freely available and instantly transferred, a country may refrain from using a new but "inappropriate" technology. Parente and Prescott (1994) examine how barriers to technology adoption affect the process of development. With the exogenous growth of world knowledge, the amount of investment required for technological advances decreases, and this enhances long-term growth. Recent studies have focused on costly technology acquisition, including Caselli's (1999) study of costly learning. Caselli and Coleman (2006) show that given different economic conditions and factor endowments, some countries may optimally choose not to adopt a frontier technology. Acemoglu (2009) provides a heuristic Leontief specification of the Basu-Weil appropriate technology so that the production function is Cobb-Douglas and the appropriateness can be summarized by a single parameter defined on the unit interval. Depending on the magnitude of this parameter, the latter study shows that the inappropriateness of some technologies has the potential to explain cross-country income differences. Building on the Houthakker-Kortum-Jones foundation, Wong and Yip (2014) construct a model of technology assimilation to study how adopting a frontier technology may lead to a development trap instead.

Since the pivotal works of Lucas (1990, 2000), Chari, Kehoe, and McGrattan (1996), and Prescott (1998), there has been a growing interest in development accounting. Many contributions have attempted to reduce the required TFP gap by improving the measurements of the quality of physical and human capital and the associated barriers and distortions. To name a few, Caselli and Wilson (2004) introduce "quality" of physical capital in the accounting exercise. Erosa, Koreshkova, and Restuccia (2010) and Schoellman (2012) improve the measurement of human capital beyond the typical Mincerian 'years of schooling' estimate. Aghion, Howitt, and Mayer-Foulkes (2005), and Buera and Shin (2012) study the role of financial markets distortions on capital investment to account for world income disparities.

# 2 The Aggregate Production Function: A Prelude

In order to understand the cross-country variation of the aggregate production function, the existing literature adopt the prototypical model

$$y_j = \frac{Y_j}{N_j} = \frac{z_j F(K_j, N_j)}{N_j} = z_j f(k_j).$$
(1)

According to (1), a representative firm in country j employs capital K and labor N to manufacture a final product Y using a constant-returns-to-scale technology with total factor productivity (TFP) z. In per capital term, we have k = K/N and f(k) = F(k, 1). The standard practice is to allow the TFP (z) to vary across countries so that z is higher in high-income countries. Lucas (2000) focuses on the Cobb-Douglas specification of F:

$$y_j^{\text{Lucas}} = z_j^{\text{Lucas}} k_j^{\alpha},\tag{2}$$

where  $\alpha \in (0, 1)$  is the common output elasticity of capital for all countries. Based on (2), the common conclusion is that about 40% of the variation in world income can be attributed to differences in z. However, TFP is a residual component which measures our ignorance of the production relation specified in f. So recent research attempts to study extensions to the aggregate production function in order to reduce the resulting z.<sup>2</sup> Our model of technology assimilation follows this line of research. In the assimilation framework studied in the next section, we extend the aggregate production function by allowing a country to adopt an advanced (more capital intensive) foreign technology for its domestic production along the line proposed by Houthakker (1955-56) and Jones (2005). The assimilation between the

 $<sup>^{2}</sup>$ The literature on TFP is huge and we refer the readers to Caselli (2005) for a partial survey.

foreign technology and the domestic factor endowment in the adoption process is shown to be captured by an elasticity of substitution to reflect the flexibility of the aggregate production function. Specifically, we can establish the resulting micro-founded per worker aggregate production function of the form:

$$y_j^{\text{Assim}} = \tau_j^{\text{Assim}} z_s k_{s_j}^{\alpha} \left[ \alpha \left( \frac{k_j}{k_{s_j}} \right)^{\frac{\sigma_j - 1}{\sigma_j}} + (1 - \alpha) \right]^{\frac{\sigma_j}{\sigma_j - 1}}, \tag{3}$$

where  $\tau_j^{\text{Assim}}$  is the relative TFP of country j to the assimilation target country s, and  $\sigma_j \in [0, 1]$  measures the country j's ability of assimilating country s's technology. The fact that the target technology being assimilated is  $k_{s_j}$ , implying that the targeting choice depends on the local information of country j.

Since our production function given by (3) is more general than the Lucas benchmark (2), we can expect that the resulting TFP z to be smaller.<sup>3</sup> However, there are other alternatives that can achieve the same objective. According to (3), our assimilation approach generalizes the Lucas aggregate production function in two ways. On the one hand, production flexibility in technology substitution captured by  $\sigma_j$  matters; on the other hand, the technologically advanced source country being adopted, captured by the ratio  $k_j/k_{s_j}$ , also matters. In reference to the Lucas case (2), our former generalization can alternatively be studied with a CES aggregate production:

$$y_j^{\text{CES}} = z_j^{\text{CES}} \left[ \alpha \left( k_j \right)^{\frac{\epsilon_j - 1}{\epsilon_j}} + (1 - \alpha) \right]^{\frac{\epsilon_j}{\epsilon_j - 1}}, \tag{4}$$

where  $\epsilon_j > 0$  is country j's elasticity of factor substitution in production. When  $\epsilon_j = 1$ , (4) coincides with (2). For the latter generalization, we can allow for adoption barriers following BWA where a country j adopts production technology from an advanced source country s:

$$y_j^{\text{BWA}} = \tau_j^{\text{BWA}} z_s \min\left[1, (k_j/k_s)^{\zeta_j}\right] k_j^{\alpha}.$$
 (5)

In (5),  $\tau_j^{\text{BWA}}$  measures the relative TFP of country j to country s, and  $\zeta_j \in [0, 1]$  captures the degree of inappropriateness of the foreign technology that may be referred to as country j's barriers to adoption. When  $\zeta_j = 0$ , (5) coincides with (2). It is clear that both the CES and the BWA setups are more general than the Lucas benchmark.

<sup>&</sup>lt;sup>3</sup>The two obvious exception cases are given by either  $k_j = k_{s_j}$  (same technologies) or  $\sigma_j = 1$  (perfect assimilation).

While our framework is more general than the Lucas benchmark, the comparison with the CES and the BWA setups is not straightforward. On the one hand, production flexibility in factor substitution matters, similar to the CES setup but in contrast to the BWA setup. On the other hand, the advanced source country matters, similar to the BWA approach but in contrast to the CES setup. Moreover, in contrast to both setups, how to assimilate the target country s's technology captured by both the ratio  $k_j/k_{s_j}$  and  $\sigma_j$  is crucial. Specifically, the target country for assimilation depends on the "local" conditions of country j, as highlighed by the notation  $k_{s_j}$  instead of  $k_s$ , which does not necessarily have to be the world technology frontier. In order to provide a better understanding on these issues, we now turn to study the microfoundation of the underlying assimilation mechanism.

# 3 The Model

Consider a production environment in which a firm specializes in a particular product that has a range of product blueprints, that vary between orders. Departing from the neoclassical production framework, we introduce the concept of "production technique," which is a miniblueprint that specifies how to organize factor inputs to fit a given blueprint. Before a particular order specifies a blueprint, the factor inputs have already been employed by the firm. Together with imperfect knowledge about the potentially most effective component design, these 'pre-determined' inputs may limit the available choices of techniques. If the available techniques are limited, the firm's optimization problem can produce an outcome that differs sharply from the neoclassical one.<sup>4</sup> In particular, not only does the set of available techniques matter, but the "flexibility" of production under limited alternatives is also crucial.

Given a limited set of available techniques, which may not be perfectly suited to the factor endowment of the firm, output can fall below the potential level. Flexibility of production is the ability to relieve the tension between limited alternatives and a pre-set factor endowment so as to reduce the output loss from its potential level. In other words, a more flexible production makes the firm less vulnerable to its limitations in available techniques. We describe the firm's flexible organization of production inputs as "technology assimilation," which can be understood as a process of alternating a mini-blueprint under its factor endowment. Notably, assimilation differs from Lucas' (1978) span-of-control theory of production, which augments neoclassical production with an additional managerial input. Instead, assimilation

<sup>&</sup>lt;sup>4</sup>This captures the spirit of the local production function described in Atkinson and Stiglitz (1969).

re-organizes factor inputs in the process of production, generating flexible mini-blueprints that we refer to as "assimilated techniques." The firm then chooses and implements the most suitable assimilated technique for production, aiming to reduce efficiency losses caused by limitations in available techniques.

Limitations in available techniques and production flexibility under assimilation are important components of a firm's "local knowledge." In a global economy, domestic firms are given opportunities to assimilate relevant techniques from global leaders. This advanced technique expands the set of available techniques and the local knowledge of domestic firms, initiating an assimilation process. We can then account for the output gap between a country and the global leader, the so-called TFP difference, based on the dynamic interaction of a country's local knowledge with advanced foreign techniques. As a result, we have a theory of endogenous TFP based on technology assimilation.

Using the concepts of modified production under assimilation and cross-country variations in local knowledge, we establish a new development accounting framework for generating insights into the large and widening TFP gaps across countries and over time.

#### 3.1 Production Technique

A production technique is a mini-blueprint that specifies the organization of factor inputs, capital (K), and labor (N), for an output level  $Y_i$ , defined by two parameters of factor-augmented productivity,  $a_i$  and  $b_i$ .<sup>5</sup> Thus,

$$Y_i = \min(a_i K, b_i N) = N b_i \min(\frac{k}{\kappa_i}, 1), \tag{6}$$

where  $k \equiv K/N$  and  $\kappa_i \equiv b_i/a_i$ . That is, technique *i* is indexed by  $(b_i, \kappa_i) \in \mathcal{P}$ , where the menu  $\mathcal{P}$  is the set of techniques. The capital-labor ratio *k* is what matters to the output per capita because of constant return to scale. We want to emphasize that  $\kappa_i$  is the input required by the technique *i*, and  $k/\kappa_i$  measures the mismatch between the factor endowment ratio and technique requirement. This mismatch is due to the limitation in available techniques, which prevents choosing  $\kappa_i = k$ . When  $\kappa_i > k$ , capital is insufficient to achieve the potential output  $\kappa_i = k$ ; when  $\kappa_i < k$ , some capital is wasted.

For choosing a technique, k is given and  $\kappa_i$  is the subject of selection. Given k, the firm would like to match the technique perfectly to the capital-labor ratio such that  $\kappa_i = k$ .

 $<sup>{}^{5}</sup>$ See Houthakker (1956-57), Kortum (1997), and Jones (2005) for further details of this Leontief formulation of the so-called local production.

But it may not be feasible, as the menu  $\mathcal{P}$  only consists of a limited number of techniques. The concept of production techniques can be best illustrated using a two-sided matching terminology, as outlined in Chen, Mo, and Wang (2012). Technique *i'* is called *latent* if  $b_{i'} < b_i$  for  $\kappa_{i'} = \kappa_i$  or  $\kappa_{i'} > \kappa_i$  for  $b_{i'} = b_i$ . A latent technique yields a lower output per worker given the same input requirement or requires more input to yield the same output per worker. We shall call a technique *manifest* if it is not latent. Then we denote the set of manifest techniques as  $\mathcal{B}$ , and define the manifest technique associated with  $\kappa$  as  $B(\kappa) \equiv \left\{ b_i | b_i = \max_{(b_j,\kappa) \in \mathcal{P}} b_j \right\} \in \mathcal{B}$ , which is the best technique for a given  $\kappa$  in a country. It is important to note that  $\mathcal{P}$ , and hence  $\mathcal{B}$ , can be different across countries and time.

#### 3.2 Assimilated Technique and Production

We are now prepared to introduce the concept of *technology assimilation*. Recall that the menu  $\mathcal{P}$  may consist of a limited number of techniques. As a result, we may have a mismatch, and output may fall below the potential level. Technology assimilation is a means to mitigate the detrimental consequence of a mismatch by allowing for alternative ways of organizing techniques with respect to the factor endowment. To capture this, we propose the following *production function under assimilation*, which specifies the output with the technique  $(a_i, b_i)$ , given the factor endowment (K, N) such that

$$\widetilde{F}(K,N;a_i,b_i) = \tau \left[ \alpha \left( a_i K \right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha) \left( b_i N \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}.$$
(7)

It is clear that when  $(a_i, b_i) = (z, z)$ ,  $\tilde{F}(K, N; z, z)$  becomes a standard neoclassical CES production function with TFP captured by  $\tau z$ . When  $(a_i, b_i) = (a, b)$ , i.e., the set of techniques is a singleton,  $\tilde{F}(K, N; a, b)$  capture the production technology with factor-biased technical progress as in Acemoglu (2003).

Our production function under assimilation is not a simple extension of neoclassical production. As in the neoclassical framework,  $\tau$  is an efficiency measure, though it is now specific to the implementation of a particular technique for production. In sharp contrast to the neoclassical framework, we consider the endogenous choice of production technique, and introduce technology assimilation that depends crucially on the limited menu of available techniques and the flexibility parameter  $\sigma \in [0, 1]$ . In particular, although limitations in available techniques can result in mismatches, assimilation under greater flexibility (higher  $\sigma$ ) can help to mitigate the output loss caused by these mismatches. As analyzed below, the endogenous choice of a manifest technique under a limited menu of techniques will generate new measures of TFP, that depend jointly on technique limitation and flexibility. It is convenient to rewrite the production function in terms of an assimilated technique  $(b_i, \kappa_i) \in \mathcal{P}$  such that

$$F(K,N;b_i,\kappa_i) = \tau b_i \left[ \alpha \left(\frac{K}{\kappa_i}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha) N^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\nu}{\sigma-1}}.$$
(8)

This turns out to be the normalized CES production function proposed by Klump and de la Grandville (2000), where the normalization point is specified at the input requirement of a technique target,  $\kappa_i$ . A graphical representation of the assimilation concept is given in Chart 1. Consider a menu consisting of two available techniques,  $\kappa_1$  and  $\kappa_2$ . In the case where  $\sigma \to 1$ , we have perfect assimilation and F becomes Cobb-Douglas, and the potential output  $y_3$  is achieved. In the case where  $\sigma \to 0$ , it is impossible to assimilate the technique and F is Leontief. The output under technique  $\kappa_1$  is then given by  $y_1 < y_3$ . With  $\sigma \in (0, 1)$ , we have partial assimilation. Under technique  $\kappa_1$ , output becomes  $y_2 \in (y_1, y_3)$ ; under  $\kappa_2$ , the potential output  $y_3$  can be achieved, but some capital is wasted.

Given the capital rental rate r and the wage rate w, the profit maximization problem of a representative firm can be conveniently specified in two steps. In the first step, for any manifest technique  $\kappa$ , the associated output is  $F(K, N; B(\kappa), \kappa)$  and the resulting profit is

$$\pi\left(\kappa; r, w\right) = \max_{K, N} \left\{ F(K, N; B(\kappa), \kappa) - rK - wN \right\},\tag{9}$$

which is the standard neoclassical firm's optimization problem. In the second step, for  $(B(\kappa), \kappa) \in \mathcal{P}$ , the optimization problem becomes

$$\Pi(r,w) = \max_{\kappa} \left\{ \pi(\kappa; r, w) \right\}.$$
(10)

The solution to the two-step optimization problem then gives the *global* production function of Jones (2005). It can be shown that it is given by (see Appendix A)

$$F(K,N) = zK^{\alpha}N^{1-\alpha},\tag{11}$$

where z is a positive constant. In summary, the global frontier of a country with a universe menu  $\mathcal{U} \equiv \{(b,\kappa) | b \leq \overline{z}\kappa^{\alpha}\}$  has the Cobb-Douglas functional form given in (11).

Chart 2 provides a graphical representation of  $\pi(\kappa; r, w)$ . It is clear that  $\pi(\kappa; r, w)$  is peaked at  $\kappa = k$ . When factor prices are high and production efficiency is low,  $\pi(\kappa; r, w)$  can be negative for a  $\kappa$  far away from k. Chat 1 depicts the local and global production under only two available techniques,  $\kappa_1$  and  $\kappa_2$ , both are different from k. As shown in Chart 2, both techniques are inferior to k. Although  $\kappa_2$  is able to achieve the potential output  $y_3$ , it is not necessarily more profitable than  $\kappa_1$ . This is because if capital is very expensive (high r), the wasted capital can be costly enough to outweigh the extra output produced.

For a given production technique  $\kappa$ , we have  $\sigma = -d \ln (k/\kappa) / d \ln (r/w)$ . In the limit case  $\sigma \to 0$ , the mismatch  $k/\kappa$  is not responsive to changes in the relative factor price, r/w. In the case of  $\sigma \to 1$ , the assimilation is so flexible that the unit cost always remains constant no matter how r/w changes. A country's *local knowledge* consists of a triple  $\{\mathcal{P}, \sigma, \tau\}$ . If either  $\mathcal{P}$  is the universe menu  $\mathcal{U}$ , or  $\sigma = 1$ , we have the Cobb-Douglas global production function. In this case,  $\tau$  is just the conventional TFP measure. In general, the other two components of local knowledge  $\mathcal{P}$  and  $\sigma$  will change the TFP measure.

To apply the assimilation model for understanding world income differences, we suppose that firms can assimilate the manifest technique  $(b, \kappa)$  of an advanced foreign global frontier, where  $b = \bar{z}\kappa^{\alpha}$ . As a result, the menu  $\mathcal{P} \subset \mathcal{U}$  is augmented by additional techniques from the global frontier aboard. Specifically, the assimilation process simply recovers one point of the foreign global production function, represented by the technique associated with  $\kappa$ . If the assimilation is perfect so that the domestic country recovers the whole global frontier production function, then we have  $\sigma \to 1$  and  $\tau = 1$ . Therefore, the TFP wedge parameter  $\tau$ measures the productivity difference *after* the assimilation process, with a higher  $\tau$  indicating less productivity loss after the assimilation.

#### 3.2.1 Production Flexibility: A Remark

Just how production flexibility from assimilation may affect production efficiency? We would like to refer to a recent work by Uras and Wang (2014), who show that, given the techniques constraint  $a_i^{\psi} b_i^{1-\psi} = z$ , techniques ratio and factor inputs ratio are inversely related:

$$\frac{a_i}{b_i} = \left(\frac{\alpha}{1-\alpha}\right)^{\frac{\sigma}{1-\sigma}} \left(\frac{w}{r}\right)^{\frac{\sigma}{1-\sigma}} \left(\frac{K}{N}\right)^{-\frac{1}{1-\sigma}}$$

Moreover, the unit cost of production can be solved as:

$$c(w,r) = \frac{1}{z} \left( \left(\frac{\psi}{\alpha}\right)^{\frac{\sigma}{\sigma-1}} \frac{r}{\psi} \right)^{\psi} \left( \left(\frac{1-\psi}{1-\alpha}\right)^{\frac{\sigma}{\sigma-1}} \frac{w}{1-\psi} \right)^{1-\psi}$$

In the limit cases with extreme flexibility measures, the unit cost of production converges to: (i)  $\sigma \to 0$ :  $c(w,r) = \frac{1}{z} \left(\frac{r}{\psi}\right)^{\psi} \left(\frac{w}{1-\psi}\right)^{1-\psi}$ ; (ii)  $\sigma \to \infty$ :  $c(w,r) = \frac{1}{z} \left(\frac{r}{\alpha}\right)^{\psi} \left(\frac{w}{1-\alpha}\right)^{1-\psi}$ . Thus,

while factor prices are always weighted by the technique usage share  $(\psi)$ , how much they affect the unit cost depend crucially on production flexibility. When flexibility is shut down  $(\sigma \rightarrow 0)$ , the production technology (the CES aggregator) precludes technique-augmented factor inputs from substituting by each other. So factor prices are deflated only by their technique usage shares. With a greater technique usage share, a factor price would not raise the unit cost of production as much. When flexibility is perfect, on the contrary, factor prices are deflated only by their income shares. In this case, an increase in the price of a factor with a greater income share would become less damaging to the unit cost of production.

Using the expressions above, one may obtain:

$$y_j^{\text{Assim}} = (1 - \alpha)^{\frac{\sigma_j}{\sigma_j - 1}} \tau_j^{\text{Assim}} b_i \left( 1 + \frac{r}{w} k_j \right)^{\frac{\sigma_j}{\sigma_j - 1}}$$
(12)

where r and w are capital rental and labor wage,  $\tau_j^{\text{Assim}}$  measuring the relative TFP of country j to the assimilation target country s, and  $b_i$  is a specific labor-augmented technique used by country j. Thus, from (12), the variance of output per worker of country j ( $y_j^{\text{Assim}}$ ) can be decomposed into three sub-components: the variance of the factor income ratio ( $rk_j/w$ ), the variance of labor-augmented technique ( $b_i$ ) and the variance of TFP ( $\tau_j^{\text{Assim}}$ ).

Importantly, following the logics underlying Chart 1 and the optimization specified in  $\Pi(r, w) = \max_{\kappa} \{\pi(\kappa; r, w)\}$ , assimilation of a global technology is now embedded in the parameter  $\sigma_j$  that entails the extent to which such an assimilation can be done effectively. More specifically, by applying Uras and Wang (2014) with  $\sigma \in (0, 1)$ , production flexibility  $(\sigma_j)$  can be shown to monotonically reduce the unit cost of production for any given pair of factor prices (w, r). This implies a positive impact of production flexibility on production outcomes. That is, greater flexibility in a country is, other things being equal, expected to be associated with a smaller TFP gap from the frontier economy.

### 3.3 Assimilation of a Global Frontier

We define the global frontier as the country with a universe menu  $\mathcal{U}$ , where the production function has the Cobb-Douglas functional form, as shown in the previous section. Suppose that firms can assimilate the manifest technique  $(b, \kappa)$  of the global frontier, where  $b = \overline{z}\kappa^{\alpha}$ . As a result, the menu  $\mathcal{P} \subset \mathcal{U}$  is augmented by additional techniques from the global frontier. Specifically, the assimilation process of global technology simply recovers one point of the global frontier production function, represented by the technique associated with  $\kappa$ . If the assimilation is perfect so that the domestic country recovers the whole global frontier production function, then we have  $\sigma \to 1$  and  $\tau = 1$ . Therefore, the TFP wedge parameter  $\tau$  measures the productivity difference *after* the assimilation process, with a higher  $\tau$  indicating less productivity loss after the assimilation.

From (8), we can formulate an endogenous TFP using the global frontier technique:

$$z\left(\frac{k}{\kappa},\sigma,\tau\right) \equiv \frac{F_{\kappa}(k,1)}{k^{\alpha}} = \underbrace{\tau\overline{z}}_{\text{TFP effect}} \times \underbrace{\left(\frac{\kappa}{k}\right)^{\alpha} \left[\alpha\left(\frac{k}{\kappa}\right)^{\frac{\sigma-1}{\sigma}} + 1 - \alpha\right]^{\frac{\sigma}{\sigma-1}}}_{\text{assimilation effect}}.$$
 (13)

When a country assimilates the frontier technique  $(b, \kappa)$ , its TFP measure,  $z\left(\frac{k}{\kappa}, \sigma, \tau\right)$ , becomes endogenous and contains two effects: (i) a conventional TFP effect, captured by  $\tau$ ; and (ii) an assimilation effect, jointly captured by the assimilation parameter  $\sigma$  and the mismatch or capital waste  $k/\kappa$  depending on the limitation on  $\mathcal{P}$ . Clearly, adopting and assimilating the frontier technique may not always lead to a higher TFP than autarky. As the assimilation ability of a country decreases (thus  $\sigma$  decreases), the endogenous TFP measured by z also decreases. Moreover, the endogenous TFP is lower when the factor endowment is further away from the input required by the advanced foreign technique (i.e.,  $|k - \kappa|$  increases).<sup>6</sup>

Interestingly, in the case of perfect assimilation,  $\sigma \to 1$  and  $z = \tau \overline{z}$ ; this is the example used by Lucas (2000) for development accounting. In contrast, the extreme case of no assimilation, i.e.,  $\sigma \to 0$  and  $z = \tau \overline{z} (k/\kappa)^{1-\alpha}$ , becomes a special case of BWA.

It is noteworthy that, throughout our analysis, we have used the country-specific representativeproducer setup that is typically used in development accounting, including in our main reference points, in Lucas and in BWA. For completeness, however, we would like to provide a brief discussion on what happens if firms within a country are heterogeneous. Let us maintain the assumption that the share parameter  $\alpha$  is global and the elasticity parameter  $\sigma$  is country-specific but common to all domestic firms. However, firms may have different menus of techniques and different endowment ratios, that is,  $k/\kappa$  may be firm-specific. From (13), the term capturing the assimilation effect is hump-shaped in  $k/\kappa$ , reaching the maximum of one at  $k/\kappa = 1$ . It is strictly concave for  $k/\kappa < 1$  and turns from strictly concave to strictly convex when  $k/\kappa$  becomes sufficiently larger than one. Suppose that all firms have a menu with  $k/\kappa < 1$ , and therefore suffer mismatch losses. Then, by Jensen's inequality, the average of the assimilation effects associated with all of the different firms is smaller than the assimilation effect associated with the average (representative) firm. In this case, the

<sup>&</sup>lt;sup>6</sup>It is straightforward to show that  $\partial z/\partial \sigma > 0$  and  $\partial z/\partial (k/\kappa) > 0$  iff  $k < \kappa$ .

assimilation effects become weaker when they are aggregated over heterogeneous firms. In contrast, suppose that all of the firms have values of  $k/\kappa$  that far exceed one, with severe capital waste. Then the average of the assimilation effects associated with all of the firms is larger than the assimilation effect associated with the average firm, implying stronger assimilation effects in the presence of firm heterogeneous and representative firms tends to narrow as  $\sigma$  increases. That is, the distributional effects from firm heterogeneity become smaller under greater production flexibility. When heterogeneous firms are free to choose any production techniques drawn from independent Pareto distributions, we have the Cobb-Douglas production function as in Houthakker (1956-57), Kortum (1997), and Jones (2005) and the accounting exercise reduces to Lucas (2000).

## 4 Development Accounting

Suppose that the reference country, the U.S., is on the frontier of technology (i.e., having the collection of the highest *a* and *b*). So the U.S. uses its own domestic technology and does not adopt any foreign technique. The US output is  $y_{US,t} = z_{US,t} k_{US,t}^{\alpha}$ . We allow the US productivity and per capital to change over time, as denoted by the time subscript *t*.

Beside Lucas (2000), our specification of technology assimilation is also related to the concept of localized technological changes proposed by Atkinson and Stiglitz (1969). Recently, Basu and Weil (1998) elaborate on this idea of inappropriate technology in the Solow growth model, where appropriateness is defined in terms of capital intensity: a technology is appropriate for one and only one capital-labor ratio. The intuition is that frontier technologies are generally designed in reference to a specific capital intensity. For instance, if the technology is developed for high-capital-intensive production in advanced economies, then adopting it is not appropriate for developing countries because the production taking place in developing countries is usually high-labor intensive. We compare our assimilation model with Lucas (2000) and Basu and Weil (1998). Finally, given that our production function under assimilation takes a CES specification, we also study a version of Lucas (2000) where output are produced with standard CES technologies in all countries.

The Assimilation Model. If the US technique is assimilated, the relative income  $q_{j,t}$  of

country j to the frontier captured by the U.S. in year t is

$$q_{j,t} \equiv \frac{f_j(k_{j,t}; k_{US,t}, z_{US,t}, \tau_j^{Assim}, \sigma_j)}{y_{US,t}} = \tau_j^{Assim} \left[ \alpha \left( \frac{k_{j,t}}{k_{US,t}} \right)^{\frac{\sigma_j - 1}{\sigma_j}} + (1 - \alpha) \right]^{\frac{\sigma_j}{\sigma_j - 1}}.$$
 (14)

Note that we now allow the TFP distortion parameter  $\tau_j$  and the assimilation parameter  $\sigma_j$  to be country specific, and they will be investigated by the development accounting exercise.

The relative capital-labor ratio  $k_{j,t}/k_{US,t}$  in the relative income expression above must be recognized as a *techniques-augmented factor proportion*: the effective factor of the country j in terms of the input required by the US technique. The decisions on assimilated foreign techniques and optimized factor demands are made jointly. This techniques-augmented factor proportion and the elasticity of substitution between the two techniques-augmented factor inputs capture the process of technology assimilation. One should not view our techniquesaugmented factor proportion as one that simply measures the capital accumulation effect relative to the frontier because of its different meaning from the conventional literature.

The Lucas Model. In this case, countries produce output according to their domestic production functions so that the income ratio becomes

$$q_{j,t} \equiv \frac{f_j(k_{j,t}; k_{US,t}, z_{US,t}, \tau_j^{Lucas}, 1)}{y_{US,t}} = \tau_j^{Lucas} \left(\frac{k_{j,t}}{k_{US,t}}\right)^{\alpha}.$$
(15)

Note that the calibration exercise based on (14) has Lucas (2000) as a special case of  $\sigma = 1$ . We denote  $\tau_j^{Lucas}$  as the corresponding TFP distortion parameter in the Lucas model. **The CES Model.** To allow for more flexibility into the Lucas benchmark, suppose that all countries' output are given by the standard CES production functions:

$$y_{j,t} = z_{j,t} \left[ \alpha \left( k_{j,t} \right)^{\frac{\epsilon_j - 1}{\epsilon_j}} + 1 - \alpha \right]^{\frac{\epsilon_j}{\epsilon_j - 1}}.$$

In order to compare with the BWA and assimilation models, we apply the idea of normalized CES technique to the US economy so that  $\epsilon_{US} = 1$  and hence  $y_{US} = z_{US} (k_{US})^{\alpha}$ . Since normalization per se does not have any implications on technology adoption, we do not impose any restriction on the parameterization of  $\epsilon_j$ . Thus, the resulting  $\epsilon_j$  can take on values that are either greater or less than unity. The relative income is given by

$$q_{j,t} \equiv \frac{f_j(k_{j,t}; k_{US,t}, z_{US,t}, \tau_j^{CES}, \epsilon_j)}{y_{US,t}} = \tau_j^{CES} \left(k_{US,t}\right)^{-\alpha} \left[\alpha \left(k_{j,t}\right)^{\frac{\epsilon_j - 1}{\epsilon_j}} + 1 - \alpha\right]^{\frac{\epsilon_j}{\epsilon_j - 1}}.$$
 (16)

Again, note that the Lucas case is a special case of the CES model, where  $\epsilon_j = 0$ .

The BWA Model. To compare the concept of inappropriate technology with our assimilated technology, we follow the specification of Acemoglu (2009) to have the following intensive production function of country j:

$$f(k_j, k_s) = \tau_j^{BWA} z_s \min\left[1, (k_j/k_s)^{\zeta_j}\right] (k_j/k_s) k_j^{\alpha},$$
(17)

where  $k_s$  is the level of foreign capital designed for the technology with TFP  $z_s$  in the source country s, and  $\zeta_j \in [0, 1]$  captures the degree of inappropriateness of the foreign technology. As  $\zeta_j$  increases, the inappropriateness increases so that the productivity of the adopted technology and thus the domestic production is reduced. Again the TFP wedge parameter  $\tau_j^{BWA}$  captures the net efficiency in overall production after the adoption of the inappropriate technology. Setting the U.S. as the source country implies that the per capita income ratio of country j relative to that of the U.S. is

$$q_{j,t} \equiv \frac{f_j(k_{j,t}; k_{US,t}, z_{US,t}, \tau_j^{BWA}, \zeta_j)}{y_{US,t}} = \tau_j^{BWA} \left(\frac{k_{j,t}}{k_{US,t}}\right)^{\alpha+\zeta_j}.$$
(18)

We will compare the calibration and development accounting results between the BWA model and our assimilation model. Again, note that the Lucas case is a special case of the BWA model, where  $\zeta_j = 0$ .

#### 4.1 Data, Parameterization, and Methodology

We use the Penn World Table 8.0 (PWT) over the period of 1970 to 2011.<sup>7</sup> The first 10 years of the data (1960 to 1969) are discarded to calculate the initial level of capital as in standard real business cycle exercises. We exclude former USSR countries (data do not start in 1970) and all OPEC countries (due to nonstandard economic responses similar to the concern with the financial tsunami). For China, we use the Version 2 data. In the end, we have a panel of 151 countries over a time span of 38 years.

Following Hall and Jones (1999), we set  $\alpha = 1/3$  and 6% as the depreciation rate of capital to calculate the level of capital from the investment data in PWT. Bearing in mind the potential endogeneity problem when recovering parameters from the data of output and capital, we calibrate the TFP wedge parameter  $\tau_i$  and the assimilation parameter  $\sigma_i$  to match the average level of log  $(q_{i,t})$  and the average lag difference of log  $q_{i,t}$  (thus matching the long-

 $<sup>^{7}</sup>$ We use PWT 6.3 for the sake of robustness. See Johnson et al. (2013) for concerns about the reliability of the versions of PWT after 6.3.

run income gap with respect to the US and the long-run growth rate of the income gap). Similarly, we calibrate the productivity ratio  $\tau_i$  and the inappropriateness parameter  $\zeta_i$  of the BWA model to match the average level of  $\log(q_{i,t})$  and the average lag difference of  $\log q_{i,t}$ . The Lucas model only has one free parameter, and we calibrate the productivity ratio  $\tau_i$  to match the average level of  $\log(q_{i,t})$ . (See Appendix B for detailed calibration steps)

Conventionally, for development accounting, fitness is measured by the success rate:

$$S = \frac{var(\text{explained component of log(income ratio}))}{var(\log(\text{income ratio}))}.$$

Note that this measure crucially depends on the magnitude of the variance of the explained component of log(income ratio), which cannot reflect any bias in the explained component. For example, consider  $\log \hat{y} = \beta + \log y$ , where  $\beta \neq 0$ . Then, we have  $S(\hat{y}) = 1 = S(y)$ ; i.e.,  $\hat{y}$  and y are equivalently good fit to y. To rectify this problem, we propose a mean squared error (*MSE*) measure over the period of interest t = 1, ..., T:

$$MSE \equiv \sqrt{\frac{1}{T} \sum_{t=1}^{T} [\operatorname{error}_t]^2}.$$
(19)

Specifically, MSE captures the income ratio that cannot be captured by the explained component. Although MSE is not a normalized measure and can be greater than one, it is a measure that will not suffer the bias problem mentioned above. Therefore, we shall use the MSE measure as the criterion to judge the fitness of the model.<sup>8</sup>

### 4.2 Results

The average of our calibrated values of the productivity ratio  $\tau_j$  and the assimilation parameter  $\sigma_j$  are reported in Table 1. The average values are based on various groupings of countries: (i) initial stage of development measured by the income ratio (real GDP per capita relative to that of the U.S.) in 1970 (< 10%, 10% - 20%, 20% - 50%, and > 50%); (ii) speed of development measured by the average growth rate from 1970 to 2011 (< 0%, 0% - 1%, 1% - 2%, 2% - 4%, and > 4%); (iii) current state of development measured by the income ratio in 2011 (< 20%, 20% - 40%, 40% - 60%, 60% - 80%, and > 80%). As an illustration, Figure 1a (1b) plots the MSEs of the BWA (CES) model and our assimilation model based on different country groupings of their average growth rates. We have adjusted the number of categories from five to four by combining the first two groupings (< 0% and 0% - 1%) for

<sup>&</sup>lt;sup>8</sup>For a comparison between S and MSE of the models, see Figure A1 in the appendix.

better graphical display.<sup>9</sup>

The results suggest that the fitness of our assimilation model based on our constructed MSE measure is very good: the averaged value of our MSE measure in all different groups ranges from 0.09 to 0.21. Interestingly, the best fitness is obtained for countries experiencing moderate to fastest growth (MSE = 0.09 for those growing at a rate between 2% and 4% annually) or for those in the upper-middle income group (MSE = 0.09 and 0.08, respectively, for those reaching more than 50% of the US real GDP per capita in 1970 and 60% to 80% in 2011). For the countries experiencing non-positive growth, the performance of our model is the least (MSE = 0.21), although the other approaches behave the same.

Next, we examine the assimilation parameter  $\sigma_j$  that measures the flexibility of production in (techniques-augmented) factor substitution. Three observations are noticeable. First, the best-fitting countries in income levels (those with the least MSE), either initially (1970) or currently (2011), have the highest assimilation measures (with average  $\sigma_j$  of 0.78 and 0.73 respectively). Our finding suggests that these economies enjoy high per capita income levels due to their successful assimilation. Second, the average speed of growth (1% to 2%) have the highest assimilation measures (average value of  $\sigma_j$  is 0.85). This finding is intuitive: overall, the development success of these countries hinges heavily on whether or not they can assimilate and move toward the world frontier. Third, the growth miracles (countries growing more than 4% annually) have the lowest measure in assimilation (average values of  $\sigma_j$  is only about 0.38). At the first glance, the result is puzzling and thus deserves further country-by-country studies.

Let us look at our calibrated TFP ratio. Note that the calibrated  $\tau_j$  is a good measure of relative technology only if the fit is good; otherwise, a significant part of this measure captures information contained in unexplained error terms. Many of such cases with poor fit generates extreme values of  $\tau_j$ . Keeping in mind this measurement issue, we must neglect the groups with large standard deviations (particularly those with standard deviations exceeding 1). We can then draw two inferences. First, not surprisingly, countries with higher income ratios either initially or currently have higher TFP ratios. Second, the slowest growing (< 0%, and 0% to 1%) economies exhibit the highest TFP ratios.

<sup>&</sup>lt;sup>9</sup>Similar plots that based on groupings of income levels, either initially (1970) or currently (2011), are demonstrated in Figures A2-A5 of the Appendix.

#### 4.2.1 A Comparison

By comparing the MSE measures across the four models in Table 1, we can see that although it is not surprising that both our assimilation model and the BWA model fit far better than the Lucas benchmark, our model, on average, outperforms the BWA model in essentially all economic and geographic groups (i.e., initial stage of development, development speed, and current state of development). The advantage of using our assimilation model is the greatest for two groups of countries in terms of the average growth rate. Figure 1a highlights the fact that trapped countries with average growth below 1% (or even negative growth) as well as those experiencing development miracles, with an average growth that exceeds 4%, work very well with our model. Specifically, as shown in the upper left and lower right panels, almost all the data lie above the 45° line.<sup>10</sup>

Next, for the CES model, the results suggest that the overall fitness of our assimilation model based on our constructed MSE measure, on average, outperforms it in essentially all economic groups (i.e., initial stage of development, development speed, and current state of development).<sup>11</sup> For instance, for the groups of countries based on different growth rates, the averaged value of our MSE measure in all different growth-rate groups ranges from 0.09 to 0.21, comapred with the CES case of 0.10 to 0.31. In particular, for trapped countries, the performance of our model is the least (MSE = 0.21), but still out-performed the Lucas case of 0.31. The same comparative result applies to the case of fastest-growing countries: we have MSE = 0.12 whereas the Lucas case yields MSE = 0.24. Finally, for the moderate growing economies, i.e., with growth rates averaging 1% - 2% and 2% - 4%, the fitness results of MSE in the CES case improve a lot: the MSE are 0.12 and 0.10 respectively. Our MSE for these groups are given by 0.13 and 0.09 respectively. It seems that assimilation may not be the main story for growth of these countries.<sup>12</sup>

In terms of different stages of development, the advantage of using our assimilation model is the greatest for the low income country groups, both in terms of the initial level of income and the current level of income. For the former group, our assimilation model provides the best fit for countries falling in development traps with less than 10% of the US real GDP

 $<sup>^{10}</sup>$ For the group of different initial income levels, as shown in the upper left panel of Figures A2 and A4, our assimilation model provides the best fit for countries falling in development traps with less than 10% of the US real GDP per capita in 1970 as most of the data lie above the 45° line.

<sup>&</sup>lt;sup>11</sup>There are two exceptions. The first one is the group of initial income (in 1970) that are above 50% of the US income. The second group is those countries whose average growth rates are between 1% and 2%.

 $<sup>^{12}</sup>$ But BWA performs worse for these countries where the MSE are 0.15 and 0.12 respectively.

per capita in 1970 (MSE = 0.14 compare to 0.18 - 0.21 in the other three cases). Similarly, for the latter group, trapped countries with at least 40% of the US real GDP per capita in 2011 work very well with our model (MSE = 0.14 compare to 0.17 - 0.19 in the other three cases for countries with relative income of 20% and less in 2011, and 0.11 compare to 0.16 for countries with relative income between 20% and 40%). As a matter of fact, our assimilation model also fits at least as good as the other three models for countries in other stages of development, except for those initially rich countries whose real GDP per capita in 1970 were above 50% of the US (our MSE = 0.09 compare to 0.08 in the CES case).

# 5 Assimilation Dynamics

In this section, we conduct growth accounting and country-specific studies and examine the assimilation dynamics facing each country over its development process. Upon studying each country's development experiences and institutions, we then modify the assimilating target most relevant to each country. We also provide country-by-country case studies for understanding why in some occasions a country's relative performance is difficult to explain based on our development and growth accounting exercise in Appendix E.

To elaborate on this without overkill using the entire sample, we select several representative countries from each of the following five geographic clusters: (i) major OECD countries: the three leading European countries, namely, France, Germany, and the U.K., plus one in North America, Canada;<sup>13</sup> (ii) development miracle countries - Early Birds (all countries from Asia that are relatively more advanced than others): Japan and the newly industrial economies (NIEs) that are known as the four Asian Tigers, namely, Hong Kong, Singapore, South Korea, and Taiwan; (iii) development miracle countries - Late Comers (two from Africa and five from Asia; all relatively less advanced compared with miracle countries Set 1): two African miracles, namely, Botswana and Mauritius, three ASEAN miracles, namely, Malaysia, Thailand, and Vietnam, and two Asian giants, namely, China and India; (iv) trapped countries (five from sub-Saharan Africa): Comoros, Cote d'Ivoire, Ghana, Kenya, and Uganda; (v) laggard countries: the major four latin American economies, namely, Argentina, Brazil, Chile, and Mexico, plus two countries outside Latin America, namely, Greece and Philippines.

Table 2 summarizes the results. By comparing the calibrated TFP ratios, we can see that for OECD countries (especially for the leading ones), the Lucas model performs relatively

<sup>&</sup>lt;sup>13</sup>We have removed the benchmark country (the U.S.) and several countries falling into other categories (for example, Japan in the early birds and Greece in the laggards groups).

well. In general, no significant differences exist between our assimilation model and the Lucas-CES and BWA models. This finding is intuitive: these countries are arguably on or close to the frontier with few barriers or distortions; the same explanation applies to Japan under miracle Early Birds). In particular, the assimilation dynamics for the leading OECD countries are basically all zero, indicating further that these countries are producing using global technology. Therefore, neither assimilation nor appropriate technology could change the calibrated TFP much from the Lucas benchmark.<sup>14</sup> For laggard economies, the findings are mixed, some with large differences (e.g., Argentina, Brazil, and Philippines) and others with small differences. In terms of the four countries in Latin America, all three models perform closely in MSE. Yet, it is noted that this group is very different than the OECD group, namely, the laggard countries are definitely not on the technology frontier. This finding explains why it is useful to study the assimilation dynamics associated with country-specific growing experience (e.g., the inflationary environment and the external problem for the Latin American group). For all other groups, our model in general has significant improvements over the two alternatives for most countries.

**Remark:** We can further examine  $\sigma_i$  to obtain better insight on assimilation dynamics, which depends on the substitutability of production inputs in a complicated manner. Table 2 does not exhibit any stable pattern over economic/geographic clusters. Of particular interest are the patterns of production flexibility among miracle countries. Most of the miracle countries exhibit a relatively flexible production, with  $\sigma \geq 4.9$  (except Hong Kong, Singapore, China and Botswana). Among the miraculous early birds, the two larger Asian Tigers (i.e., Korea and Taiwan) are more flexible in (techniques-augmented) factor substitution than the two smaller Tigers (i.e., Hong Kong and Singapore). Likewise, for the two developing giants, the software-led Indian industry is more flexible than the assembly-based Chinese economy. On the contrary, among the OECDs and the laggards, only one laggard country, Brazil, illustrates production flexibiliy with  $\sigma = 0.5$ . However, for Brazil, the fitness of the assimilation model given by the MSE is dominated by the others sligitly.

### 5.1 Growth Accounting

To gain insight into the role played by assimilation, we decompose relative income growth into three underlying driving forces, namely, neoclassical capital accumulation, technology assimilation, and residual TFP. Recall the income of country j relative to the US frontier in

<sup>&</sup>lt;sup>14</sup>See Figure A6 in the Appendix.

year t:

$$q_{j,t} = \tau_{j,t} \left[ \alpha \left( \frac{k_{j,t}}{k_{US,t}} \right)^{\frac{\sigma_j - 1}{\sigma_j}} + (1 - \alpha) \right]^{\frac{\sigma_j}{\sigma_j - 1}}$$

By defining  $k_{j/US,t} \equiv k_{j,t}/k_{US,t}$ , log-linearization then produces

$$\hat{q}_{j,t} = \hat{\tau}_{j,t} + \pi_{j/US,t-1} k_{j/US,t}, \tag{20}$$

where  $\hat{x}_t \equiv \log x_t - \log x_{t-1}$  and  $\pi_{j/US,t} \equiv \alpha \left( k_{j/US,t} \right)^{\frac{\sigma_j - 1}{\sigma_j}} / \left[ \alpha \left( k_{j/US,t} \right)^{\frac{\sigma_j - 1}{\sigma_j}} + (1 - \alpha) \right]$  is the relative capital share of country j under CES assimilated technology. From a growth accounting perspective, we take the annual variation and average the contributions of each component of (20) to obtain the growth accounting results. For the purpose of comparison, we conduct similar exercises, decomposing the relative income growth rate based on the BWA into neoclassical capital accumulation, adoption inappropriateness, and residual TFP. The results are reported in Table 3.

Overall, technology assimilation plays an important role by contributing to growth in many countries. In all countries that have experienced faster growth (over 4%), the contribution of assimilation is substantial. In countries that have experienced negative growth, the lack of or backward assimilation is the key. Specifically, in miracle countries, approximately half of income growth relative to the U.S. can be attributed to technology assimilation. In trapped economies, the lack of or backward assimilation accounts for more than 40% of their negative growth outcomes.

Relative to the BWA model, our assimilation framework reduces the contribution of the unexplained residual TFP component to relative income growth, especially for the miracle and the trapped countries; compared to the CES model, the reduction in the unexplained residual TFP is substantial.<sup>15</sup>

A Remark on the CES Specification. The growth accounting decomposition of the CES case based on (16) is given by

$$\hat{q}_{j,t} \cong \hat{\tau}_{j,t} + \tilde{\pi}_{j,t-1}\hat{k}_{j,t} - \alpha \hat{k}_{US,t}$$
$$= \hat{\tau}_{j,t} + \alpha \hat{k}_{j/US,t} + (\tilde{\pi}_{j,t-1} - \alpha) \hat{k}_{j,t}.$$
(21)

<sup>&</sup>lt;sup>15</sup>To determine the importance of technology assimilation in driving the variation of relative income growth, we also decompose the variance of the relative income growth rate into the same three underlying driving forces: neoclassical capital accumulation, technology assimilation, and residual TFP. To save space, all the details are presented in the Appendix C.

where

$$\tilde{\pi}_{j,t} \equiv \frac{\alpha \left(k_{j,t}\right)^{\frac{\epsilon_j - 1}{\epsilon_j}}}{\alpha \left(k_{j,t}\right)^{\frac{\epsilon_j - 1}{\epsilon_j}} + 1 - \alpha}.$$

It is noted that the growth-accounting frameworks of the two CES specifications, captured by the RHS terms of (20) and (21), are very different.

### 5.2 Country-Specific Assimilation Dynamics

We now examine assimilation dynamics linked to country-specific environment and development process. By assimilating the world frontier technology (the U.S.), we study how a country can move up according to a growth ladder.<sup>16</sup>

We restrict our attention to the episodes of the miracle countries and the trapped economies. For the OECD countries, our assimilation model does not provide any significant value added to the calibrated TFP of the Lucas model. For the Latin American countries among the laggards, many of them have experienced, at some stages, high or hyper-inflation over the past half century. Although both the BWA and our benchmark assimilation models significantly outperform the Lucas model, the fitness is not applicable to miracle and trapped economies. We therefore omit their detailed analysis.

In what follows, we document key economic conditions and institutions relevant to our study for each individual country and focus on two miracle groups and the trapped countries (with the country-specific details given in Appendix D). We summarize the results in each of the three selected clusters.

#### 5.2.1 Miracle Countries: Early Birds

Japan led the group of rapidly growing economies, creating an interesting class of "Asian Economic Miracles" that have been intensively studied in development economics. In terms of MSE, the assimilation model provides the best fit, although the corresponding calibrated TFP is not significantly different from the alternatives. The calibrated assimilation parameter

<sup>&</sup>lt;sup>16</sup>In Appendix E, rather than simply assimilating the world frontier technology (the U.S.), we study how a country can move up according to a growth ladder. Moving up is done by adopting the technology of the country in the next upper-tier in geographical proximity and with strong international interrelationships. Such an assimilation is a result of learning by observing the success of earlier adopters at similar innovation stages in the region (see Rogers (1983)) and/or of spatially dependent costs of adoption (see Comin, Dimitriev and Rossi-Hansberg (2012)). By considering geographical proximity and international interrelationships, we propose an alternative assimilation (to an alternative country) to replace the US frontier technology in the benchmark case. Based on our MSE criterion, we explore whether the proposed assimilation can perform better than the benchmark one in terms of accounting for the upturns and downturns in the growth dynamics.

 $\sigma$  is 0.49, which implies that factor accumulation may matter more in growth performance. This finding is caused by the lost decade of the country since 1990s, as technology adoption was no longer the main contributor to growth.

As thoroughly documented by Uchida (1991) and Wan (2007), Japan assimilated the U.S. to advance its technologies in many of its major industries (e.g. electronics) since the late 19th century. In the 1960s and the 1970s, Japanese FDI went to Taiwan first and then to South Korea and Hong Kong for "efficiency seeking" and "market seeking." In the late 1970s, Japanese firms have expanded production facilities to Singapore, where American semiconductors operated at that time and suppliers were concentrated. Learning from the success of neighboring economic giant, Japan, the Asian Tigers followed Japanese footsteps, realizing that export expansion is the main momentum to growth. Particularly, Weiss (2005) notes a wave of Asian countries after Japan that illustrates the successful application of ELG: (i) first tier of Asian Miracle countries, namely, Taiwan, South Korea, Hong Kong, and Singapore, whose takeoff began in the 1960s, (ii) second tier, namely, Thailand, Malaysia, Philippines, and Indonesia, whose takeoff began in the 1980s, and (iii) the 1990s wave, featuring China and, to a lesser extent, Vietnam. These Asian growth experiences exhibit the "Flying Geese" Pattern (FGP) of economic development, as documented by Akamatsu (1962). Therefore, we shall refer to Japan and Asian Tigers as the "Early Birds" of development miracles.

As shown in Table 2, the assimilation story best fits the growth experience of Asian Tigers according to MSE measures. In terms of calibrated  $\sigma$ , South Korea and Taiwan have a higher assimilation ability than Hong Kong and Singapore, which is consistent with the fact that the former group is manufacturing based and the latter is service oriented.

Figure 2 reports the assimilation dynamics based on the world technology frontier (the U.S.). Our model fits well for each country's development process. In the case of Japan, the Lucas benchmark, the CES and BWA model fit well already (MSE = 0.15). Our model is even better on the margin (MSE = 0.09). In the case of Hong Kong, the performance of the Lucas benchmark and the CES model are almost the same (MSE = 0.17); the BWA model fits better (MSE = 0.14); our model is even better (MSE = 0.12). The structural transformation can account for the downward bias of the assimilation model since the 1980s as well as the low calibrated  $\sigma$ . As shown in Figure 2, Hong Kong has suffered three noticeable downturns. The first is the Sino-British Joint Declaration in 1984 of the return of Hong Kong to China that triggered sizable capital flights and skilled labor emigration. The second is the Asian financial crisis that hit Hong Kong in the summer of 1998, causing both currency

and housing market crises. Third is the severe epidemic (i.e., SARS) that broke out in 2003, damaging the operation of Hong Kong businesses across the board and specifically hurting the tourism industry. In the cases of Singapore, South Korea, and Taiwan, the BWA framework fails to improve on the baseline Lucas model. For Singapore, the assimilation model perform well in terms of the dynamics until the 1985 recession. Since the new millennium, the development of the high-tech industries has pushed out the technology frontier of the country far enough so that it may even be ahead of those of the U.S. As a result, assuming the U.S. as the frontier economy can become a misspecification for the sample period since the first half of the 2000s. The dynamics of the assimilation model has outperformed the alternatives for the sampling period for both Korea and Taiwan. The only drawback of Korea is the 1997 crisis. However, the strong influence of Japan on its initial economic development until the 1980s may be worth taking into consideration in optimizing the assimilation model for its application to the Korean and Taiwan experience.

#### 5.2.2 Miracle Countries: Latecomers

Aside from geographical proximity, international interrelationships are essential in determining the technology assimilation pattern of LDCs. FDI from more advanced countries is a good indicator to measure how enterprises of developing countries can benefit from more advanced source countries, not only in the financial but also in the technological aspects.

For the ASEAN countries, Singapore was the largest FDI source country. Within the ASEAN, 63.7% of source FDI is from Singapore and more than 34% of outward FDI from Singapore was directed to Malaysia. However, as these ASEAN countries further developed, especially over the past decade or two, they became more globalized and less dependent on its regional leader. For China, the introduction of the open door policy led to a huge relocation of Hong Kong's labor-intensive industries to Guangdong province in the late 1970s. An overwhelming 90% of FDI in Guangdong was invested by entrepreneurs from Hong Kong. Under the export-oriented growth strategy of China, other East Asian early-starters, especially Taiwan, also began to relocate and diversify their costly production bases. As regards India, between 1950 and 1990, the government implemented restrictive trade, financial, and industrial policies and took control of major heavy industries. However, the well-known 1991 balance-of-payment crisis finally ended the protectionist policies and started the liberalization of the economy that resulted in its takeoff in the mid-1990s.

So far, the assimilation story seems to be all about Asian growth miracles. However, we

believe that this should not be the case as the international interrelationships involved in the assimilation model, such as FDI and ELG, are universal.<sup>17</sup> To address this issue, we apply our assimilation analysis to two African miracle countries, Botswana and Mauritius. Interestingly, to a large extent, our assimilation model also fits better because of its growing experience than the two alternatives.

As shown in Table 2, our assimilation model has the lowest MSE compared with the alternatives. It also provides reasonable improvement over the Lucas model in calibrated TFPs. In terms of the calibrated  $\sigma$ , only China and Mauritius yield extremely low values. The latter is a very small open economy that survives mainly on tourism. For China, the low calibrated  $\sigma$  suggests that its growth performance depends heavily on factor accumulation, which we will study in more detail below.

In Figure 3, we report the benchmark assimilation dynamics of these late comers, based on the world technology frontier (the U.S.). Our model fits best for the development processes of all six countries over the sample period, compared with the BWA and Lucas alternatives. In the cases of the ASEAN countries Thailand, Malaysia, and Vietnam, our outperforming is obvious in terms of both MSE and the calibrated  $\tau$ . For Malaysia, the assimilation model misses two episodes: 1) the scale-back adjustment and the economic transformation from agriculture and resource to manufacturing in the 1980s after the triple-digit growth in the 1970s, and 2) the Asian Financial Crisis era. In the case of Thailand, we are also unable to capture the dynamics associated with the Asian Financial Crisis. For China and Botswana, the performances of the BWA model and ours are close, and both are far better than the Lucas benchmark. For the Orient giant that is China, our assimilation model captures the dynamics well except for initial period of the 1960s. This finding may be due to the events of the Great Leap Forward and the Cultural Revolution. Nonetheless, our model still outperforms the alternatives in terms of MSE. We interpret our low calibrated  $\sigma$  to be consistent with the conventional view that the China growth is not technology based but investment based. The calibrated  $\tau$ , which is larger than unity, may indicate that, as the "World Factory," China is subsidizing its technology adoption in production. For the African miracle that is Botswana, the assimilation model shows a downward bias in the 1990s because of the economic transformation caused by the diversification of the economy. Then, the overshoot

<sup>&</sup>lt;sup>17</sup>Nevertheless, the fact that the Asian miracle growth can be well accounted by the assimilation model supports the conclusion of Nelson and Pack (1999) that "the absorption or assimilation of increasingly modern technology and the change in industrial structure has been the critical component of this (miracle) process" (p.416).

of the assimilation dynamics followed is mainly caused by the major recession of the industrial sector that took place afterwards. Finally, in the case of India, the Lucas benchmark and the BWA model are similar, and both dominated by ours. Before the 1990s, all three models overshoot the assimilation dynamics. However, the assimilation model begins to have an increasing trend in 1990, outperforming the alternatives in terms of MSE and calibrated  $\tau$ .

#### 5.2.3 Trapped Countries

Even with many emerging economies advancing their development statuses, many countries remain in the poverty trap, including many Sub-Saharan economies, which are our focus. In the Appendix D, we report the details of the assimilation dynamics based on either the world frontier or geographical proximity/international interrelationships. The results in Table 2 suggest that our assimilation model always yields better fitness outcomes than the BWA and Lucas models. We further conduct an alternative calibration for each country by assimilating the country of their colonial origin.<sup>18</sup> Except for Comoros and Uganda, the alternative calibrations do not yield better fit.

### 5.3 Summary

After examining the country-specific assimilation dynamics, we can conclude that most of the development miracles generally exhibit assimilation with flexible production over the past four decades (see Table 2). On the contrary, many of the trapped economies suffer backward assimilation with low production flexibility; that is, the assimilation of frontier technology is at least partly responsible for these countries to remain in poverty traps.

Based on growth rate decomposition exercises, we conclude that countries that experiencing faster growth have more substantial assimilation contributions; for miracle countries, about half can be attributed to assimilation. For trapped countries, except Ghana, the lack of or backward assimilation accounts for about 40% of the negative growth performance.

Moreover, we characterize the calibrated elasticities of factor substitution (techniqueaugmented). Our main findings are summarized as follows: (i) no clear pattern of the magnitude of factor substitution over economic/geographic clusters exist; (ii) Korea and Taiwan are more flexible in techniques-augmented factor substitution than Hong Kong and Singapore; and (iii) India is more flexible than China.

 $<sup>^{18}{\</sup>rm See}$  Figure A7 in the appendix for the details.

In terms of assimilation dynamics, we further conclude that for developing economies (especially those in Asia) where assimilation is successful, the  $\sigma$ 's are reasonably high and the fitting is much better than the other two alternative models in terms of MSE. However, in the lack of or backward assimilation, we cannot provide a clean characterization for  $\sigma$  in terms of magnitude with good fitting.

# 6 Concluding Remarks

In this paper, we have developed a technology assimilation framework in which technological advancement needs be accompanied by flexibility in production. By applying this technology assimilation approach to studying global technology and development accounting, we have shown that our assimilation model performs very well. It is not only much better than the Lucas benchmark but significantly dominates the BWA model especially, for trapped countries with consistently low income ratios throughout the sample period and for miracle countries with fast economic growth. Thus, we have identified the success of assimilation of the frontier technology as the key to differentiating between fast-growing miracle and povertytrapped economies. The main implication is clear: to pull a poor country out of the trap, we need an adequate provision of correct incentives and institutional settings that is crucial for domestic firms to assimilate relevant frontier technologies in a way that is suitable for their development stages. In particular, the establishment of science parks can be rewarding. This is because that with high tech firms clustering, local learning to the specific need can greatly enhance the effectiveness of technology assimilation. Additionally, the establishment of incentives to encourage know-how and tacit knowledge that are essential for technology assimilation can further ensure technology advancement and sustained economic growth.

Along these lines are several interesting avenues for future studies, but for brevity we shall discuss only two. The first is to evaluate various human capital, industrial, and trade policies for their effectiveness to promote growth through the channel of technology assimilation. Specifically, our framework of techniques and technology assimilation may be incorporated with Jovanovic (2009) to explain the interdependence of vintage technology and human capital distribution. As a consequence, directional human capital policies may possibly affect cross-industry human distribution as well as manifest techniques, industry-specific assimilation, and vintage technology. Moreover, the promotion of key industries in some developing countries may possibly be harmful for growth because of the lack of proper and efficient assimilation.

Furthermore, the reluctance to a further reduce in tariffs associated with imported technology may have differential effects on the development processes, depending on the flexibility in production and ability to assimilate world technologies. The second is to apply our framework to country-by-country analysis across sub-industries. As firms in different industries can be foreseen to have different frontier technologies and different assimilation process, the results obtained can be readily compared with those in the misallocation literature pioneered by Hsieh and Klenow (2009) and Restuccia and Rogerson (2008).

## References

- [1] Acemoglu, D., 2009. Introduction to Modern Economic Growth. The Princeton University Press.
- [2] Aghion, P., Howitt, P., Mayer-Foulkes, D., 2005. The effect of financial development on convergence: Theory and evidence. The Quarterly Journal of Economics 120, 173-222
- [3] Akamatsu, K., 1962. Historical pattern of economic growth in developing countries. The Developing Economies 1, 3-25.
- [4] Atkinson, A., Stiglitz, J., 1969. A new view of technological change. *Economic Journal* 79, 573-578.
- [5] Basu, S., Weil, D., 1998. Appropriate technology and growth. Quarterly Journal of Economics 113, 1025-1054.
- [6] Baumol, W.J., Blackman, S. A. B., Wolff, E. N., 1991, Productivity and American leadership: the long view. The MIT Press, Cambridge, MA.
- [7] Buera, F.J., Shin, Y., 2012. Financial frictions and the persistence of history: a quantitative exploration. *Journal of Political Economy* (forthcoming).
- [8] Caselli, F., 1999. Technological revolutions. American Economic Review 89, 78-102.
- [9] Caselli, F., Coleman, W., 2006. The world technology frontier. American Economic Review 96, 499-522.
- [10] Caselli, F., Wilson, D., 2004. Importing technology. Journal of Monetary Economics 51, 1-32.
- [11] Chari, V.V., Kehoe, P.J., McGrattan, E.R., 1996. The poverty of nations: a quantitative exploration," NBER WP# 5414.
- [12] Chen, B., Mo, J., Wang, P., 2012. A micro-matching foundation of neutral technical progress. *Economic Theory* 50, 445-462.
- [13] Comin, D., Dimitriev, M., Rossi-Hansberg, E., 2012. The spatial diffusion of technology. NBER WP# 18534.
- [14] Erosa, A., Koreshkova, T., Restuccia, D., 2010. How important is human capital? a quantitative theory assessment of world income inequality. *Review of Economic Studies* 77, 1421-1449.

- [15] Hall, R., Jones, C., 1999. Why do some countries produce so much more output per worker than others? *Quarterly Journal of Economics* 114, 83-116.
- [16] Houthakker, H.S., 1955-56. The Pareto distribution and the Cobb-Douglas production function in activity analysis. *Review of Economic Studies* 23, 27-31.
- [17] Hsieh, C.T., 2002. What explains the industrial revolution in East Asia? evidence from the factor markets. *American Economic Review* 92, 502-526.
- [18] Hsieh, C.T., Klenow, P.J., 2009. Misallocation and manufacturing TFP in China and India. Quarterly Journal of Economics 124, 1403-1448.
- [19] Johnson, S., Larson, W., Papageorgiou, C., Subramanian, A., 2013. Is newer better? Penn World Table revisions and their impact on growth estimates. *Journal of Monetary Economics* 60, 255-274.
- [20] Jones, C., 2005. The shape of production functions and the direction of technical change. Quarterly Journal of Economics 120, 517-549.
- [21] Jovanovic, B., 2009. The technology cycle and inequality. *Review of Economic Studies* 76, 707-729.
- [22] Klump, R., de la Grandville, O., 2000. Economic growth and the elasticity of substitution: two theorems and some suggestions. *American Economic Review* 90, 282-291.
- [23] Kortum, S.S., 1997. Research, patenting, and technological change. *Econometrica* 65, 1389-1420.
- [24] Kuo, S. W.-Y., 1983, The Taiwan Economy in Transition, Westview Press.
- [25] Lucas, R.E. Jr., 1978. On the size distribution of business firms. Bell Journal of Economics 9, 508–23.
- [26] Lucas, R.E. Jr., 1990. Why doesn't capital flow from rich to poor countries? American Economic Review 80, 92-96.
- [27] Lucas, R.E. Jr., 2000. Some macroeconomics for the 21st century. Journal of Economic Perspectives 14, 159-168.
- [28] Nelson, R., Pack, H., 1999. The Asian miracle and modern growth theory. *Economic Journal* 109, 416-436.
- [29] Parente, S., Prescott, E., 1994. Barriers to technology adoption and development. Journal of Political Economy 102, 298-321.
- [30] Parente, S., Prescott, E., 2002. Barriers to Riches. The MIT Press, Cambridge, MA.
- [31] Prescott, E., 1998. Needed: a theory of total factor productivity. International Economic Review 39, 525-553.
- [32] Restuccia, D., Rogerson, R., 2008. Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics* 11, 707-720.
- [33] Rogers, E. M., 1983. Diffusion of innovations. Free Press, New York.
- [34] Schoellman, T., 2012. Education quality and development accounting. Review of Economic Studies 79, 388-417.

- [35] Uchida, H., 1991. The Transfer of the Electrical Technology from America and Europe to Japan: 1869-1914, in Jeremy, D. ed., *International Technology Transfer: Europe, Japan* and the U.S.A.: 1700-1914, Edward Elgar, Aldershot, England.
- [36] Wan, H., 2004. Economic Development in a Globalized Environment: East Asian Evidence, Kluwer Academic Publishers (chapters 4, 7 and 8).
- [37] Wan, H., 2007. Globalization and Economic Development in East Asian: Lecture Notes, RIEB, Kobe University.
- [38] Weiss, J., 2005. Export growth and industrial policy: lessons from the East Asian miracle experience. Discussion paper 26. Tokyo: Asian Development Bank Institute.
- [39] Wong, T.N., Yip, C.K., 2014. A model of technology assimilation. the Chinese University of Hong Kong. Mimeo.
- [40] Young, A., 1995. The tyranny of numbers: confronting the statistical realities of the East Asian growth experience. *Quarterly Journal of Economics* 110, 641-680.

|                      | Assimilation Model |           |      |         | Lucas Model |           |               | BWA Model |         | ļ           | Lucas-CES Model |         |             |         |
|----------------------|--------------------|-----------|------|---------|-------------|-----------|---------------|-----------|---------|-------------|-----------------|---------|-------------|---------|
| Country Group        | sigma              | sd(sigma) | tau  | sd(tau) | MSE         | Lucas tau | sd(Lucas tau) | Lucas MSE | BWA tau | sd(BWA tau) | BWA MSE         | CES tau | sd(CES tau) | CES MSE |
| 1 0 1070             |                    |           |      |         |             |           |               |           |         |             |                 |         |             |         |
| 1. By 1970 income    |                    |           |      |         |             |           |               |           |         |             |                 |         |             |         |
| <10%                 | 0.56               | 0.40      | 0.55 | 0.59    | 0.14        | 0.14      | 0.08          | 0.21      | 0.64    | 1.01        | 0.18            | 0.59    | 0.90        | 0.20    |
| 10% - 20%            | 0.66               | 0.35      | 0.54 | 0.28    | 0.12        | 0.35      | 0.12          | 0.16      | 0.90    | 0.73        | 0.16            | 1.51    | 1.85        | 0.15    |
| 20% - 50%            | 0.44               | 0.43      | 0.84 | 0.40    | 0.14        | 0.52      | 0.19          | 0.17      | 0.93    | 0.55        | 0.15            | 2.69    | 4.10        | 0.16    |
| >50%                 | 0.78               | 0.36      | 0.94 | 0.25    | 0.09        | 0.92      | 0.25          | 0.10      | 1.20    | 0.80        | 0.11            | 9.21    | 16.88       | 0.08    |
| 2. By average growth |                    |           |      |         |             |           |               |           |         |             |                 |         |             |         |
| <1%                  | 0.41               | 0.40      | 0.82 | 0.61    | 0.17        | 0.28      | 0.37          | 0.25      | 0.90    | 0.92        | 0.20            | 6.62    | 14.72       | 0.23    |
| 1-2%                 | 0.85               | 0.32      | 0.49 | 0.50    | 0.13        | 0.35      | 0.31          | 0.15      | 0.72    | 0.70        | 0.15            | 4.60    | 8.18        | 0.12    |
| 2-4%                 | 0.67               | 0.36      | 0.69 | 0.37    | 0.09        | 0.54      | 0.32          | 0.10      | 0.85    | 0.59        | 0.12            | 0.63    | 0.46        | 0.10    |
| >4%                  | 0.38               | 0.34      | 0.68 | 0.35    | 0.12        | 0.39      | 0.26          | 0.24      | 1.06    | 1.54        | 0.20            | 0.39    | 0.26        | 0.24    |
| 3. By 2007 income    |                    |           |      |         |             |           |               |           |         |             |                 |         |             |         |
| <20%                 | 0.58               | 0.41      | 0.55 | 0.55    | 0.14        | 0.18      | 0.11          | 0.19      | 0.60    | 0.62        | 0.17            | 1.24    | 1.98        | 0.18    |
| 20-40%               | 0.64               | 0.41      | 0.63 | 0.37    | 0.11        | 0.40      | 0.11          | 0.16      | 0.94    | 0.67        | 0.16            | 1.62    | 3.60        | 0.16    |
| 40-60%               | 0.58               | 0.44      | 0.83 | 0.22    | 0.15        | 0.71      | 0.26          | 0.17      | 1.26    | 1.23        | 0.17            | 12.43   | 15.34       | 0.15    |
| 60-80%               | 0.73               | 0.30      | 0.86 | 0.14    | 0.08        | 0.77      | 0.16          | 0.12      | 1.41    | 1.68        | 0.13            | 3.18    | 8.58        | 0.11    |
| >80%                 | 0.60               | 0.44      | 1.08 | 0.23    | 0.10        | 1.00      | 0.25          | 0.12      | 1.18    | 0.39        | 0.12            | 6.58    | 18.24       | 0.10    |

Table 1: Comparison between Lucas, BWA and Our Assimilation Models (by various groups)

|                          | Data                       |                                | Assimilati | Assimilation Model |      |            | ess       |            | Lucas and BWA Models |            |         |             |
|--------------------------|----------------------------|--------------------------------|------------|--------------------|------|------------|-----------|------------|----------------------|------------|---------|-------------|
|                          | 1970<br>Relative<br>Income | Average<br>Growth<br>1970-2007 | tau        | sigma              | MSE  | BWA<br>MSE | CD<br>MSE | CES<br>MSE | CD<br>tau            | CES<br>tau | BWA tau | BWA<br>zeta |
| 1. OECD                  |                            |                                |            |                    |      |            |           |            |                      |            |         |             |
| Canada                   | 85.53%                     |                                |            | 1.00               | 0.09 | 0.09       | 0.09      | 0.04       | 1.06                 | 2.31       |         | 0.00        |
| France                   | 69.16%                     |                                |            | 1.00               | 0.05 | 0.12       | 0.05      | 0.05       | 0.81                 | 1.01       |         | 0.67        |
| Germany                  | 71.50%                     | 1.99%                          |            | 1.00               | 0.05 | 0.05       | 0.05      | 0.04       | 0.91                 | 1.30       |         | 0.00        |
| United Kingdom           | 68.03%                     | 2.19%                          | 0.91       | 1.00               | 0.04 | 0.04       | 0.04      | 0.03       | 0.91                 | 1.59       | 0.91    | 0.00        |
| 2. Miracles: Early Birds |                            |                                |            |                    |      |            |           |            |                      |            |         |             |
| Hong Kong                | 38.82%                     | 4.58%                          | 1.03       | 0.06               | 0.12 | 0.14       | 0.17      | 0.17       | 0.81                 | 0.82       | 1.09    | 0.67        |
| Japan                    | 63.57%                     |                                |            | 0.49               | 0.09 | 0.15       | 0.15      | 0.15       | 0.77                 | 0.77       | 0.77    | 0.00        |
| Korea, Republic of       | 16.10%                     | 5.43%                          | 0.71       | 0.50               | 0.06 | 0.10       | 0.31      | 0.31       | 0.48                 | 0.48       | 0.90    | 0.39        |
| Singapore                | 28.89%                     |                                |            | 0.13               | 0.11 | 0.14       | 0.19      | 0.19       | 0.68                 | 0.68       |         | 0.10        |
| Taiwan                   | 15.57%                     |                                | 0.87       | 0.57               | 0.08 | 0.26       | 0.24      | 0.24       | 0.62                 | 0.63       |         | 0.53        |
| 3. Miracles: Late Comers |                            |                                |            |                    |      |            |           |            |                      |            |         |             |
| Botswana                 | 5.25%                      | 5.94%                          | 0.88       | 0.02               | 0.14 | 0.35       | 0.35      | 0.35       | 0.24                 | 0.24       | 0.24    | 0.00        |
| China                    | 3.72%                      | 6.43%                          | 0.92       | 0.01               | 0.08 | 0.24       | 0.51      | 0.51       | 0.13                 | 0.13       | 0.41    | 0.39        |
| India                    | 5.83%                      | 3.16%                          | 0.32       | 0.65               | 0.04 | 0.05       | 0.12      | 0.12       | 0.15                 | 0.15       | 1.54    | 0.67        |
| Malaysia                 | 14.42%                     | 4.91%                          |            | 0.57               | 0.10 | 0.27       | 0.13      | 0.13       | 0.33                 | 0.33       |         | 0.67        |
| Mauritius                | 21.04%                     | 4.13%                          | 0.38       | 0.49               | 0.07 | 0.10       | 0.26      | 0.26       | 0.22                 | 0.22       | 0.40    | 0.30        |
| Vietnam                  | 3.87%                      | 4.23%                          |            | 0.73               | 0.07 | 0.27       | 0.12      | 0.12       | 0.13                 | 0.13       |         | 0.67        |
| Thailand                 | 9.23%                      |                                |            | 0.49               | 0.07 | 0.10       | 0.26      | 0.26       | 0.22                 | 0.22       |         | 0.30        |
| 4. Trapped Countries     |                            |                                |            |                    |      |            |           |            |                      |            |         |             |
| Comoros                  | 9.23%                      | -0.32%                         | 0.56       | 0.05               | 0.08 | 0.08       | 0.20      | 0.20       | 0.09                 | 0.09       | 0.60    | 0.67        |
| Cote d`Ivoire            | 12.56%                     | -0.43%                         | 0.41       | 0.57               | 0.15 | 0.17       | 0.25      | 0.25       | 0.16                 | 0.16       | 1.42    | 0.67        |
| Ghana                    | 6.58%                      | 0.51%                          | 0.13       | 1.00               | 0.13 | 0.23       | 0.13      | 0.14       | 0.13                 | 0.15       | 0.51    | 0.51        |
| Kenya                    | 8.43%                      | 0.48%                          | 0.29       | 0.66               | 0.05 | 0.15       | 0.15      | 0.15       | 0.13                 | 0.13       | 0.13    | 0.00        |
| Uganda                   | 4.98%                      | 0.42%                          | 2.17       | 0.05               | 0.13 | 0.20       | 0.26      | 0.26       | 0.12                 | 1.14       | 0.43    | 0.28        |
| 5. Laggards              |                            |                                |            |                    |      |            |           |            |                      |            |         |             |
| Argentina                | 51.84%                     | 0.92%                          | 0.60       | 0.16               | 0.13 | 0.13       | 0.19      | 0.16       | 0.41                 | 2.60       | 0.73    | 0.67        |
| Brazil                   | 22.93%                     |                                |            | 0.50               | 0.13 | 0.12       | 0.12      | 0.12       | 0.33                 | 0.33       | 0.33    | 0.00        |
| Chile                    | 33.72%                     |                                |            | 1.00               | 0.13 | 0.18       | 0.13      | 0.14       | 0.41                 | 0.56       |         | 0.67        |
| Greece                   | 55.52%                     | 2.34%                          | -          | 1.00               | 0.10 | 0.18       | 0.10      | 0.10       | 0.68                 | 0.74       |         | 0.67        |
| Philippines              | 10.51%                     | 1.42%                          |            | 1.00               | 0.21 | 0.25       | 0.21      | 0.12       | 0.21                 | 1.78       |         | 0.48        |
| Mexico                   | 29.26%                     | 1.63%                          |            | 1.00               | 0.11 | 0.12       | 0.11      | 0.09       | 0.53                 | 1.18       |         | 0.34        |

Table 2: Comparison between Lucas, BWA and Our Assimilation Models (by selected countries)

|                               |                    |          |              | assimilatio |          | inappropriat |          | Lucas-CES |           |
|-------------------------------|--------------------|----------|--------------|-------------|----------|--------------|----------|-----------|-----------|
|                               | average relative   |          |              | n           | Lucas    | е            | BWA      | factor    | Lucas-CES |
|                               | income growth rate | capital  | assimilation | residual    | residual | technology   | residual | share     | residual  |
| 1970 income                   |                    |          |              |             |          |              |          |           |           |
| <=10%                         | -0.10%             | -77.49%  | 34.03%       | 143.46%     | 177.49%  | 25.29%       | 152.20%  | 97.37%    | 80.12%    |
| (10%, 20%]                    | 0.67%              | 144.79%  | 28.96%       | -73.75%     | -44.79%  | 43.41%       | -88.21%  | -135.61%  | 90.82%    |
| (20%, 50%]                    | 0.25%              | 33.78%   | 31.93%       | 34.29%      | 66.22%   | 28.17%       | 38.05%   | 28.43%    | 37.79%    |
| >50%                          | 0.00%              | 297.84%  | 7.78%        | -209.07%    | -201.29% | 40.34%       | -241.63% | -233.66%  | 32.37%    |
| growth rate                   |                    |          |              |             |          |              |          |           |           |
| (<=1%]                        | -1.93%             | 22.28%   | 32.98%       | 44.75%      | 77.72%   | 29.54%       | 48.18%   | 21.14%    | 56.59%    |
| (1%, 2%]                      | -0.40%             | -132.16% | 8.05%        | 224.11%     | 232.16%  | -24.38%      | 256.54%  | 105.98%   | 126.18%   |
| (2%, 4%]                      | 0.67%              | 209.23%  | 25.37%       | -136.48%    | -111.11% | 61.07%       | -172.19% | -149.39%  | 38.27%    |
| >4%                           | 3.27%              | 39.69%   | 51.19%       | 9.12%       | 60.31%   | 45.88%       | 14.43%   | -0.04%    | 60.35%    |
| 2011 income                   |                    |          |              |             |          |              |          |           |           |
| <=20%                         | -0.47%             | -63.36%  | 29.65%       | 133.71%     | 163.36%  | 18.51%       | 144.85%  | 92.51%    | 70.85%    |
| (20%, 40%]                    | 0.98%              | 189.48%  | 29.27%       | -118.75%    | -89.48%  | 58.77%       | -148.25% | -184.59%  | 95.11%    |
| (40%, 60%]                    | 0.27%              | 24.19%   | 22.42%       | 53.39%      | 75.81%   | 35.55%       | 40.26%   | 28.86%    | 46.95%    |
| (60%, 80%]                    | 1.10%              | 29.42%   | 23.33%       | 47.25%      | 70.58%   | 54.22%       | 16.36%   | 50.43%    | 20.15%    |
| >80%                          | 0.72%              | 529.25%  | 18.19%       | -453.69%    | -435.50% | 38.72%       | -474.22% | -482.54%  | 47.04%    |
|                               |                    |          |              |             |          |              |          |           |           |
| trap                          |                    |          |              |             |          |              |          |           |           |
| (<=1% growth<br>& <=10% U.S.  |                    |          |              |             |          |              |          |           |           |
| income in 1970)               | -2.07%             | 30.22%   | 40.76%       | 29.02%      | 69.78%   | 37.11%       | 32.68%   | 14.02%    | 55.76%    |
| earlybird                     |                    | 0012270  |              |             |          | 07.122.00    | 0_100/0  |           |           |
| (>=4% growth                  |                    |          |              |             |          |              |          |           |           |
| & >= 20% U.S. income in 1980) | 2.97%              | 36.87%   | 52.02%       | 11.11%      | 63.13%   | 44.85%       | 18.28%   | -0.04%    | 63.17%    |
| latecomer                     | 2.97%              | 30.07%   | 52.02%       | 11.11%      | 03.13%   | 44.05%       | 10.20%   | -0.04%    | 03.17%    |
| (>=4% growth                  |                    |          |              |             |          |              |          |           |           |
| & < 20% U.S.                  |                    |          |              |             |          |              |          |           |           |
| income in 1980)               | 3.47%              | 41.48%   | 50.67%       | 7.85%       | 58.52%   | 46.54%       | 11.98%   | -0.03%    | 58.55%    |

# Table 3: Contribution to Growth according to Lucas, BWA and Our Assimilation Models

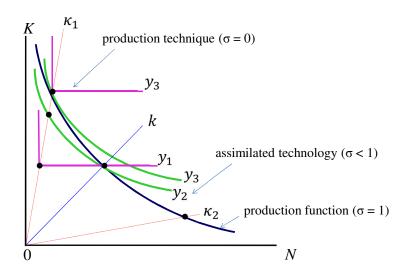


Chart 1: The Production Concepts

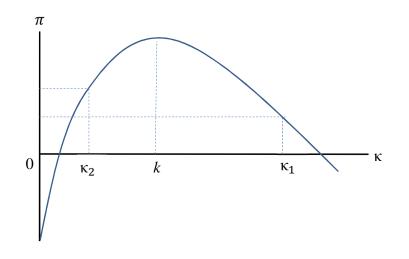


Chart 2: The Profit Function of Technique

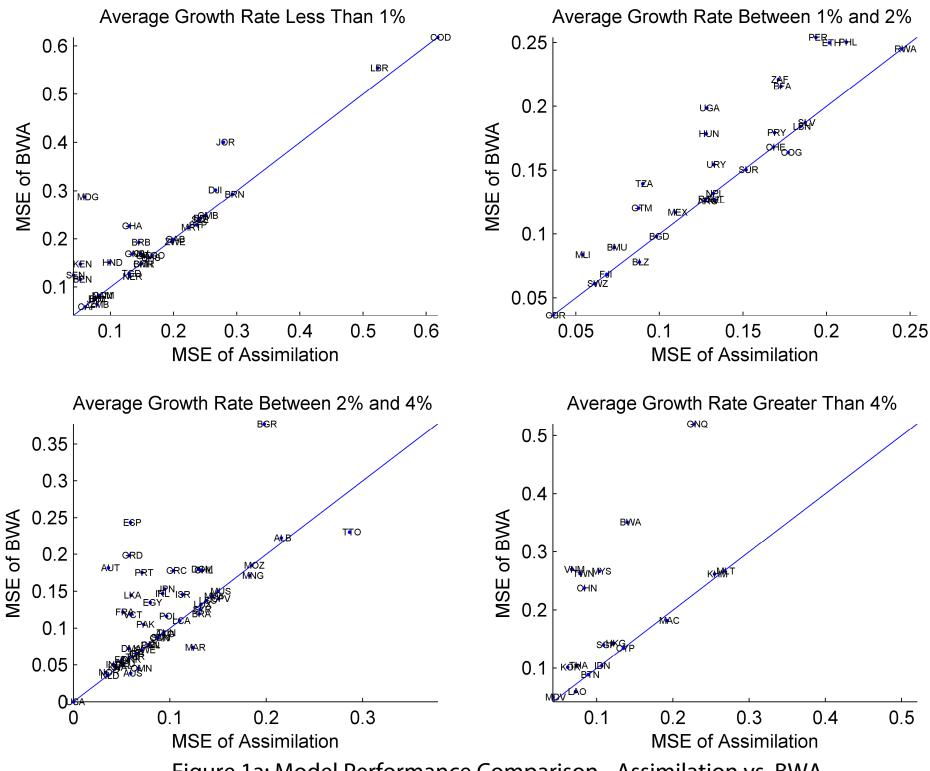


Figure 1a: Model Performance Comparison - Assimilation vs. BWA

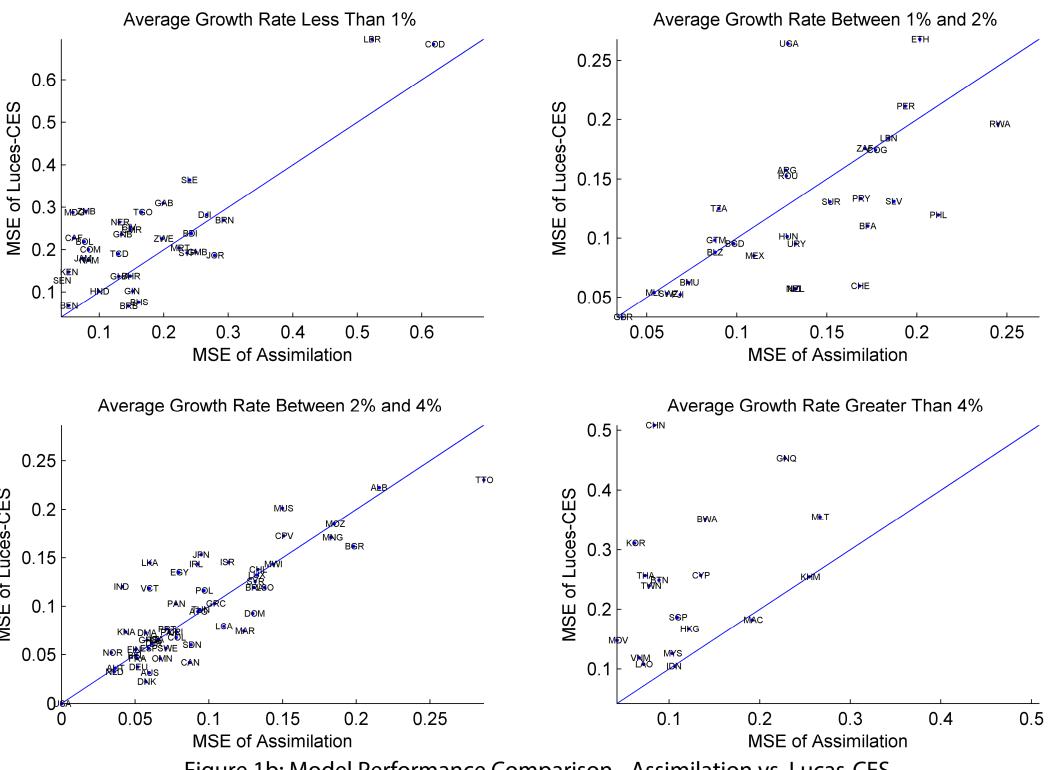


Figure 1b: Model Performance Comparison - Assimilation vs. Lucas-CES

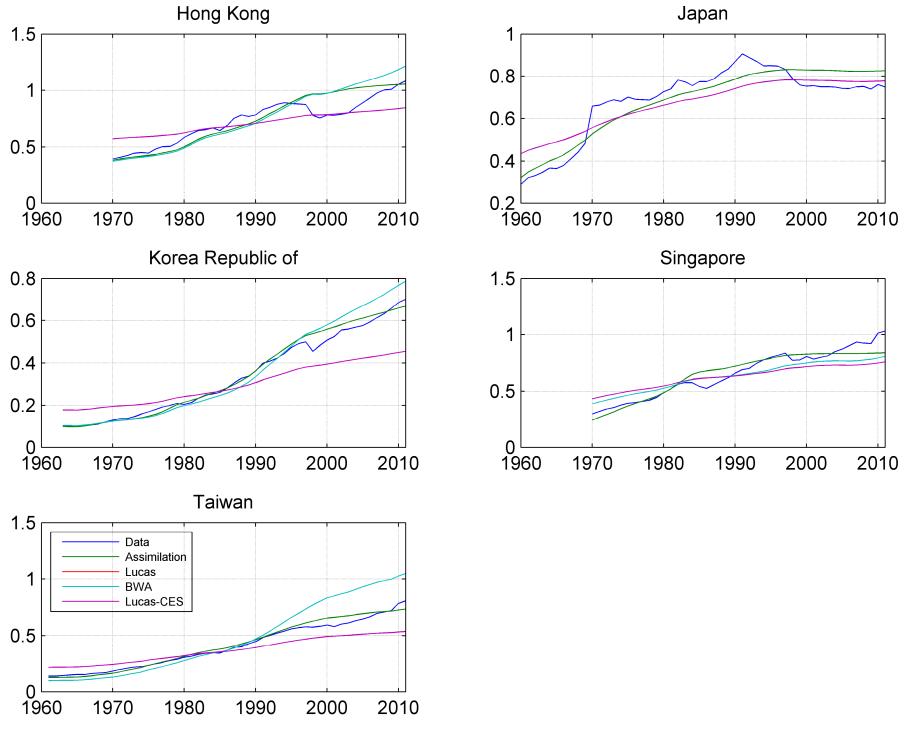


Figure 2: Assimilation Dynamics - Early Birds

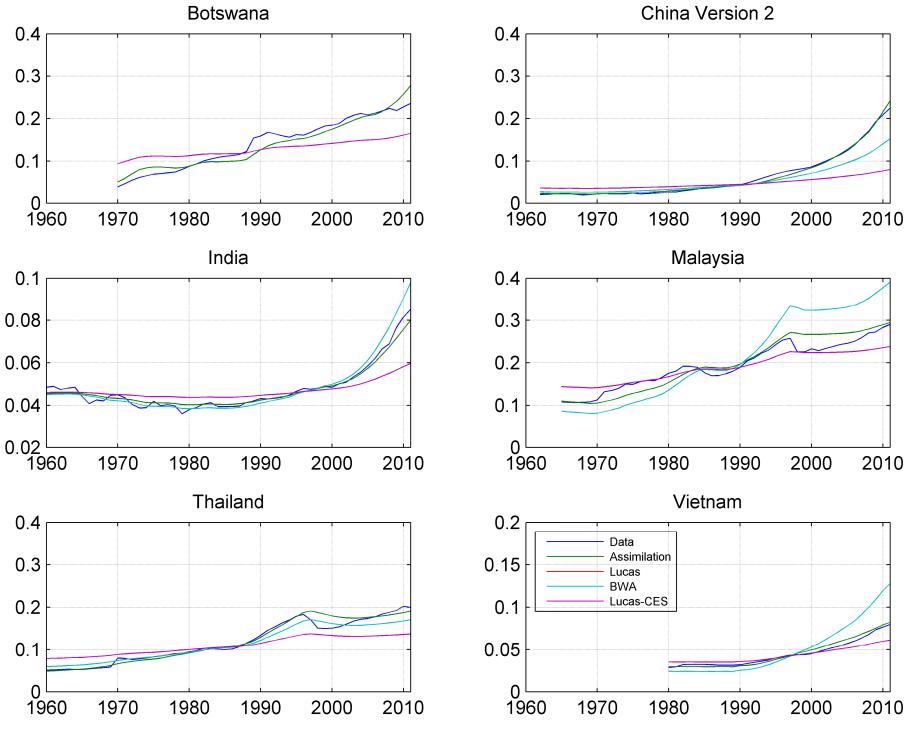


Figure 3: Assimilation Dynamics - Latecomers