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Abstract

The conventional growth-accounting approach to estimating the sources of economic growth requires unrealistically strong assumptions about the competitiveness of factor markets and the form of the underlying aggregate production function. This paper outlines a new approach utilizing nonparametric derivative estimation techniques that does not require imposing these restrictive assumptions. The results for East Asian countries show that output elasticities of capital and labor are different from the income shares of these factors, and that the growth of total factor productivity over the period 1960–95 has been an important factor in the overall growth performance of these countries.

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I. Introduction

For nearly a quarter century since the early 1970s, the countries in East Asia grew at phenomenal rates, leading observers to dub the period as the "Asian Miracle." The rapid growth came to an abrupt end when the financial crisis hit in 1997, with many of the high-performing countries in the region falling into painful recessions and facing the distinct possibility that the miracle, if indeed there had been one, was over.

Clearly the Asian financial crisis was an unprecedented event and was unforeseen by virtually everyone. But what is troubling is that a decline in growth in East Asian countries, even abstracting from the effects of the financial crisis, was already being predicted by some. Paul Krugman (1994) in particular, using the results of Young (1992), argued persuasively that the rapid growth of the East Asian economies over the past three decades had come primarily from capital accumulation, increasing labor force participation, and improving labor quality, rather than from improvements in productivity. As such, the rate of growth of these countries was bound to slow down eventually. Even though Krugman did not see the Asian financial crisis coming, he certainly saw an end to the so-called Asian miracle—presumably the crisis only made the end come faster.

The Young (1992) and Krugman (1994) papers set off a heated debate on the sources of economic growth in East Asia.[2] One group, subscribing to the "accumulation view", claimed that growth in East Asian countries was mainly driven by high rates of capital formation.[3] The second group adheres to the "assimilation view," arguing that the essential component of East Asian high growth was the acquisition and mastery of foreign technology.[4] In other words, high growth resulted largely, although not exclusively, from gains in efficiency and productivity.

Whether the accumulation or assimilation view of growth is a more accurate characterization of the East Asian miracle has important implications for growth strategies. If the accumulation view is correct and growth is mainly based on capital formation, it will not be sustainable for long because the law of diminishing returns (to capital) will eventually prevail. As Krugman (1994) puts it rather dramatically, the East Asian economies with their high rates of investment would end up looking like the

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[2] See the extremely useful surveys by Crafts (1999) and Felipe (1999); see also Rodrik (1997).

[3] This group includes Young (1992, 1995), Krugman (1994), Collins and Bosworth (1997), Sarel (1997), and Senhadji (2000), among others.

[4] This second group includes, for example, Romer (1993), Nelson and Pack (1996), Klenow and Rodriguez-Clare (1997), and Easterly and Levine (2000).

former Soviet Union! Following this logic, the future looks quite bleak for the East Asian countries even when they recover from the fallout of the financial crisis; growth rates in the future will be permanently below those experienced in earlier years. The practical implication for growth-enhancing strategies under the accumulation view is that to improve living standards requires investment, which has to be paid for in large part through foregone consumption.

On the other hand, the assimilation view would point to a more optimistic outcome. The proponents of this view would argue that, following the downturn resulting from the financial crisis, East Asian countries can get back to their pre-crisis long-run growth paths. And, if growth indeed originates from a narrowing of the "idea gap" as the assimilation view claims, no significant opportunity costs need to be incurred to incorporate ideas from abroad (Romer, 1993). Instead, ideas can be transmitted to the mutual benefit of producers and no sacrifice of current consumption for future growth is required.

Both groups can point to empirical evidence for a variety of countries that support their respective cases.[5] Most of the studies associated with the accumulation view use time-series data and follow the conventional growth-accounting method based on the Solow (1957) model. This growth-accounting method relies on the assumption of competitive factor markets, enabling one to replace output elasticities (with respect to capital and labor), with the respective income shares of these factors. While the use of income shares may well be a reasonable approximation in industrial countries,[6] this procedure is more questionable for developing countries, including the East Asian countries, where the capital and labor markets are unlikely to be perfectly competitive. The assimilation view on the other hand is generally supported by cross-country empirical growth analysis where the values of the output elasticities of capital and labor are estimated rather than imposed. These estimated elasticities are then used to calculate productivity changes. To do the cross-country regression analysis, however, requires assuming a particular form for the underlying aggregate production function, which may or may not be valid. Indeed, as Hulten (2000) points out, the original growth-accounting formulation due to Solow (1957) is completely nonparametric, and thus assuming any particular form for the production function is basically incorrect.

This paper proposes a new method of estimating the sources of economic growth and the growth of total factor productivity (TFP) using nonparametric derivative estimation techniques. This method requires no specific assumptions on the competitive state of factor markets or the form of the underlying aggregate production function. Applying this methodology to East Asian countries over the period 1960–95 yields estimates of output elasticities with respect to capital and labor, as well as TFP growth.

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[5] International comparisons of the sources of growth have been made by Dougherty and Jorgenson (1996); see also Islam (1999).

[6] See Oulton and Young (1996).

Two main results emerged from the analysis. First, the estimated output elasticities of capital and labor tend to be quite different from their respective income shares, casting some doubt on the conventional growth-accounting model assumption of competitive factor markets. Second, the growth rates of TFP turn out in many cases to be similar to those obtained in other studies, yet in certain important cases are much higher, lending support to the assimilation view of sources of economic growth.

The rest of the paper proceeds as follows: Section II discusses the basic framework used to analyze the sources of economic growth. Section III describes the nonparametric derivative estimation method, and Section IV reports the estimation results. The final section provides a brief conclusion.

II. Estimating the Sources of Economic Growth

In the context of the neoclassical growth model, we start with an aggregate production function, which typically is specified as

$$Y(t) = \underline{F}(K(t), L(t), t), \tag{1}$$

where Y is output, K and L are capital and labor inputs, and t indicates time. The aggregate production function approach is an analytical simplification that makes it possible to summarize detailed information about the complex process of economic growth within a simple unified framework (for a review of the neoclassical growth model, see, for example, Barro and Sala-i-Martin (1995)). Differentiating the logarithm of (1) with respect to t, we obtain

$$\frac{\dot{Y}}{Y} = \frac{\partial \underline{F}}{\partial K}\frac{K}{\underline{F}}\frac{\dot{K}}{K} + \frac{\partial \underline{F}}{\partial L}\frac{L}{\underline{F}}\frac{\dot{L}}{L} + \frac{\partial \underline{F}}{\partial t}\frac{1}{\underline{F}}, \tag{2}$$

where $\dot{X} = dX/dt$ is the time derivative of the respective variable.
The production function (1) is often specified more explicitly in Hicks neutral form as

$$\underline{F}(K(t), L(t), t) = A(t)F(K(t), L(t)), \tag{3}$$

where A(t) is called total factor productivity or TFP, and measures the shift in the production function $\underline{F}$ at given levels of capital and labor. In this form, taking log derivatives of (3) with respect to time yields

$$\frac{\dot{Y}}{Y} = \frac{\partial F}{\partial K}\frac{K}{F}\frac{\dot{K}}{K} + \frac{\partial F}{\partial L}\frac{L}{F}\frac{\dot{L}}{L} + \frac{\dot{A}}{A} \tag{4}$$

The last term on the right hand side of (2) is interpreted in (4) as the growth rate of TFP.[7] Since (3) is the form typically assumed in the literature, we base our discussion on this specification throughout this paper. Equation (4) can be written as

$$\begin{pmatrix}\text{growth rate}\\ \text{of GDP}\end{pmatrix} = \varepsilon_K \times \begin{pmatrix}\text{growth rate}\\ \text{of capital}\end{pmatrix} + \varepsilon_L \times \begin{pmatrix}\text{growth rate}\\ \text{of labor}\end{pmatrix} + \begin{pmatrix}\text{growth rate}\\ \text{of TFP}\end{pmatrix}$$

where ε_K and ε_L stand for the elasticity of output with respect to capital and labor, respectively. Since the growth rates of GDP, capital, and labor are available in the national income accounts data of most countries, TFP growth rates are obtained by subtracting from GDP growth the sum of the growth rates of capital and labor with appropriate weights ε_K and ε_L. An obvious problem with this procedure is that ε_K and ε_L are unknown parameters depending on the functional form of $F(\cdot,\cdot)$ and it is these parameters that are critical in calculating TFP growth.

The question then is how to estimate ε_K and ε_L. There are two approaches developed in the literature. The first approach assumes that the factor markets are perfectly competitive so that the necessary equilibrium conditions are given by equalities between the income shares of capital and labor in GDP (v_K and v_L) and the elasticities of output. The rental price of capital, *r*, and the wage rate, *w*, are then given by $r = A \cdot \partial F/\partial K$ and $w = A \cdot \partial F/\partial L$ so that $\varepsilon_K \equiv (\partial F / \partial K)(K / F) = rK/Y = v_K$ and $\varepsilon_L \equiv (\partial F / \partial L)(L / F) = wL/Y = v_L$. In other words, ε_K and ε_L are equal to the income share of each factor (v_K and v_L). Under constant to returns to scale, $v_K + v_L = \varepsilon_K + \varepsilon_L = 1$. Thus, with this replacement, the growth rate of TFP may be calculated by simple subtraction. The result is what is known as the "Solow residual."[8]

The second approach assumes a particular parametric form of (1) and estimates the production function by running a regression either in level or difference form. The output elasticities are constructed using the parameter estimates and TFP growth is again calculated as a residual.

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[7] A little caution is necessary here because the last term on the right hand side of (2) is the partial derivative of *F* with respect to time so that it depends on the values of *K* and *L*. Here it is assumed that $(\partial F / \partial t) = 0$.

[8] Hsieh (1997) calculates the dual measure of TFP growth by comparing the growth of output prices with the growth of the weighted average of capital and labor input prices. This method is very data intensive and difficult to use. For a critique of the Hsieh approach, particularly as applied to Singapore, see Young (1998).

Neither assumption, however, is particularly attractive when dealing with developing economies. For one thing, capital and labor markets in these economies are likely to be far from perfectly competitive. Furthermore, there is no guarantee that any particular functional form of the production function is appropriate for these economies (see Hulten (2000)). The simplest form used has been the Cobb-Douglas function, which involves estimating a single parameter, and then using the constant returns to scale assumption, calculating the other elasticity.[9] The parametric form that became popular in 1970s is the translog function, which essentially attempts to estimate the second-order Taylor approximation of general function (3).[10] However, a straightforward application of a translog production function often results in severe collinearity problems when using time series data. Kim and Lau (1994) apply a common translog form to all the East Asian countries they studied, with some parameter variations allowed for each country.[11] Furthermore, as pointed out by White (1980), least squares does not provide a proper approximation to the unknown function, and hence, the resulting estimates are often misleading.[12]

This paper proposes a third approach that has not been utilized in this context. For this approach, we do not need the assumption of perfectly competitive factor markets. Nor do we need to assume any particular functional form of the aggregate production function. All that is needed is only some kind of smoothness of the production function. The proposed approach is based on non-parametric kernel derivative estimation techniques developed recently in the statistics and econometrics literature (see Hardle (1990), and Pagan and Ullah (1999)). The logarithmic transformation of (1) and (3) with the addition of a stochastic term is

$$\ln Y(t) = a(t) + F^*(\ln K(t), \ln L(t)) + u(t) \tag{5}$$

where $a(t) \equiv \ln A(t)$ is an unknown function of t, $F^*(x_1, x_2) = \ln F(e^{x_1}, e^{x_2})$, and $u(t)$ is an error term satisfying $E[u(t) \mid \ln K(t), \ln L(t), t] = 0$. The idea behind the estimation procedure is as follows. Note that output elasticities ε_K and ε_L are simply the partial derivatives of the systematic part of (5) with respect to the first two arguments. Hence, application of nonparametric derivative estimation techniques yields the estimates $\hat{\varepsilon}_K$ and $\hat{\varepsilon}_L$, which can be plugged in (4) to get the estimate of TFP growth as a residual.

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[9] See Senhadji (2000) who uses this form to estimate output elasticities for a large number of countries.

[10] See Christensen et al. (1980) for a comprehensive review of the translog function.

[11] Hu and Khan (1997) substitute income shares for the elasticities of output in the translog function to calculate TFP growth in China.

[12] Barro (1998) also questions the appropriateness of the regression approach.

Alternatively, note that TFP growth is equal to the time derivative of $a(t)$ in (5), and the application of nonparametric techniques to calculate this derivative yields an estimate of TFP growth directly.

The nonparametric regression method has been usefully applied in many areas of economics.[13] Specifically, a semi-parametric regression model, in which the function is partly parametric (usually linear) and partly nonparametric, has been implemented by Engle, Granger, Rice, and Wise (1986), Stock (1989), and Iwata, Murao, and Wang (2000), among others. Another popular variant is the nonparametric estimation of derivatives of a regression function. Examples of nonparametric estimation of derivatives include Rilstone (1992), who applied the techniques to examine the properties of a production function, and Rilstone (1991), to estimate average uncompensated price elasticities. Also, Lewbel (1993) provides nonparametric estimates of average compensated price elasticities, while Lewbel (1995) nonparametrically tests demand constraints and compares them with those yielded by the standard parametric test, assuming that the demand system has the quadratic, almost ideal, form. But, as far as we are aware, the nonparametric derivatives method has not been utilized to calculate the sources of growth or TFP growth.

III. Estimation Method

In order to estimate output elasticities ε_K and ε_L, first note that the conditional expectation of $\ln Y(t)$ in (5) is given by

$$m(\ln K, \ln L, t) \equiv E[\ln Y \mid \ln K, \ln L, t] = a(t) + F^*(\ln K, \ln L), \tag{6}$$

which we call the mean function. This additive separability form imposes structure on the conditional mean, which can improve the efficiency of estimation of derivatives. Note that

$$\varepsilon_K \equiv \frac{\partial \ln F}{\partial \ln K} = \frac{\partial F^*}{\partial \ln K(t)}$$

$$\varepsilon_L \equiv \frac{\partial \ln F}{\partial \ln L} = \frac{\partial F^*}{\partial \ln L(t)}$$

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13 For a very useful survey of nonparametric methods of estimation, see Delgado and Robinson (1992).

are the partial derivatives of the mean function $m(x_1, x_2, x_3)$ with respect to the first two arguments, or the slopes of the regression curve (5).

We now introduce the nonparametric estimation approach. The idea of the nonparametric regression is simply local averaging, that is, averaging the y values of observations having predictor values $\mathbf{x} = (x_1, x_2, x_3)$ close to a target value. As you include more distant observations for averaging, the resulting curve would be smoother and smoother until all observations are included for averaging, in which case the curve would be a straight line. This is the case of a linear regression. On the other hand, if only the closest observations are averaged, the resulting curve would become less smooth. How smooth the function should be is controlled by the parameter called bandwidth (h).

To see how to estimate the derivatives, it is helpful to consider nonparametric estimation of the mean function F^* first.[14] Let $K(\mathbf{z})$ be the kernel function satisfying $\int K(\mathbf{z})d\mathbf{z} = 1$. The well-known Nadaraya-Watson kernel regression estimator of $m(\mathbf{x})$ is given by

$$\hat{m}(\mathbf{x}) = \hat{g}(\mathbf{x}) / \hat{f}(\mathbf{x})$$

where

$$\hat{g}(\mathbf{x}) = \frac{1}{nh_1h_2h_3}\sum_{i=1}^{n} K(\mathbf{z}_i)y_i\,,\ \hat{f}(\mathbf{x}) = \frac{1}{nh_1h_2h_3}\sum_{i=1}^{n} K(\mathbf{z}_i) \tag{7}$$

$\mathbf{x} = (x_1, x_2, x_3) = (\ln K, \ln L, t)$, $\mathbf{z}_i = \left((x_{1i} - x_1)/h_1, (x_{2i} - x_2)/h_2, (x_{3i} - x_3)/h_3\right)$, and h_j indicates the bandwidth for variable x_j for $j = 1,2,3$. This is a standard technique of non-parametric regression, from which our non-parametric derivative estimation method is derived. Since F^* is time invariant, we have $\frac{1}{T}\int m(x_1, x_2, t)dt = \frac{1}{T}\int a(t)dt + F^*(x_1, x_2)$. Therefore, it is natural to consider an estimator of F^* by taking a time average of $\hat{m} - a(t)$, or $\hat{F}^*(x_1, x_2) = (1/T)\sum_{t=1}^{T}[\hat{m}(x_1, x_2, t) - a(t)]$, which is a type of estimator discussed by Chen et al. (1996). Although this estimator itself is not operational because $a(t)$ is unknown, the derivatives of F^* like ε_K and ε_L are estimable in the following manner. Vinoid and Ullah (1988) show an estimate of the derivative of F^* is obtained by analytically differentiating $\hat{F}^*$. This simple estimator turns out to be free of $a(t)$ in the above context and hence, the estimation is fairly straightforward. That is,

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[14] For a comprehensive review of nonparametric regression procedures including the kernel method, see Delgado and Robinson (1992), Eubank (1988), Hardle (1990), and Pagan and Ullah (1999).

$$\hat{\varepsilon}_K(x_1,x_2)=\frac{1}{T}\sum_{t=1}^{T}\frac{\partial}{\partial x_1}\hat{m}(x_1,x_2,t) \qquad \text{and} \qquad \hat{\varepsilon}_L(x_1,x_2)=\frac{1}{T}\sum_{t=1}^{T}\frac{\partial}{\partial x_2}\hat{m}(x_1,x_2,t)$$

where

$$\frac{\partial \hat{m}(\mathbf{x})}{\partial x_j}=\left[\hat{g}_j(\mathbf{x})-\hat{f}_j(\mathbf{x})\hat{m}(\mathbf{x})\right]/\hat{f}(\mathbf{x})$$

$$\hat{g}_j(\mathbf{x})=-\frac{1}{nh_1h_2h_3h_j}\sum_{i=1}^{n}K_j(\mathbf{z}_i)y_i, \qquad \hat{f}_j(\mathbf{x})=-\frac{1}{nh_1h_2h_3h_j}\sum_{i=1}^{n}K_j(\mathbf{z}_i) \tag{8}$$

$K_j(\mathbf{z}_i)=\partial K(\mathbf{z}_i)/\partial z_{ji}$ and z_{ji} is the j-th element of $\mathbf{z}_i$ for $j=1,2$. The growth rate of TFP is then calculated as a residual after substituting $\hat{\varepsilon}_K$ and $\hat{\varepsilon}_L$ into equation (4). Finally, the probability bands for the estimated residual $(\hat{\dot{A}}(t)/A(t))$ are constructed based on the joint sampling distribution of $\hat{\varepsilon}_K$ and $\hat{\varepsilon}_L$. Appendix II gives the asymptotic α% pointwise error bands. The model (5) is substantially general and allows one to test whether the factor markets are actually competitive and whether a specific parameterization of the production function is correct.

As mentioned, there is an alternative more direct way to estimate $\dot{A}(t)/A(t)$. Rather than estimating it as the residual using equality (4), we can first estimate $a(t)$ by

$$\hat{a}(t)=\frac{1}{n}\sum_{x_1,x_2}\hat{m}(x_1,x_2,t)-F^{*}(x_1,x_2)$$

and then obtain TFP growth as

$$\tilde{\dot{A}}(t)/A(t)=(d/dt)\hat{a}(t)=(1/n)\sum_{x_1,x_2}(\partial/\partial t)\hat{m}(x_1,x_2,t)\,. \tag{9}$$

In this method, TFP growth is estimated not as a residual but directly.

The first procedure above can be referred to as the nonparametric "residual" method, and the second procedure as the nonparametric "direct" method. The two estimation methods are based on different smoothness assumptions. The residual method assumes that output elasticities are smooth over time, but does not assume any kind of smoothness of TFP growth. By contrast, the direct method assumes that TFP growth rate is smooth over time, but does not assume smoothness of output elasticities. The estimates of TFP growth using the residual method tend to be much more volatile in general than those using the direct method, while the output elasticities fluctuate substantially with the direct method.

In implementing the procedures, we need to choose a kernel function and the bandwidth. The accuracy of kernel smoothers as estimators of m (the mean function) or derivatives of m is a function of the kernel K and the bandwidth h. In practice, the accuracy depends mainly on the bandwidth h (Hardle 1990). Appendix III describes how the selection is made based on the cross validation method.

The large sample properties of the above estimators are well established. When the sample size is small, however, a large sample approximation may be misleading. To find out how reliable the estimators are in a situation like ours, we conducted a small Monte Carlo experiment with the CES production function, which is reported in Appendix IV.[15] The result indicates that even with a sample size as small as ours, the nonparametric derivative estimates look superior, in terms of bias, to the parametric estimates such as the Cobb-Douglas and Translog models. On the other hand, (as expected) the variances of the nonparametric estimators are found to be larger than the parametric ones. The standard errors reported in the tables in the next section, therefore, should be interpreted with a degree of caution.[16]

IV. Estimation Results

Using the procedures outlined in the previous section, we estimate TFP growth rates for nine East Asian countries: Hong Kong SAR, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan Province of China, Thailand, and China. We use two data sets for this study: First, the data set based on the Penn World tables covering the period 1960–1990, and second, the data set constructed by Collins and Bosworth (1996) which covers the period 1960–1995. Each of the data sets is described in Appendix I. The data for Hong Kong SAR are only available in the Penn data set.

Before presenting our nonparametric estimates of TFP growth rates, we summarize the results obtained with the conventional methods in Table 1. Because the results using two data sets are similar, only the estimates with the Collins data set are reported here. The results from the Penn data set, as well as the estimates for sub-periods—1960s, 1970s, 1980s, and 1990s—are available upon request. Table 1 reports the conventional growth accounting estimates of TFP growth rates for the nine East Asian countries. The estimates in the column labeled with "Young" are reported for Hong Kong SAR, Korea, Singapore, and Taiwan Province of China, using weighted labor

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[15] Note that Rilstone (1991, 1992) also utilized the nonparametric regression methods for sample sizes ranging between 25-44 observations.

[16] In our case, the results reported in the tables are the overall sample averages of the estimated derivatives rather than a point derivative estimate at any particular point. This increases the speed of convergence by factor of root n because the point estimates are asymptotically uncorrelated.

shares calculated by Young (1995). In the column labeled "Collins" are the TFP growth estimates based on the constant labor and capital shares equal to 0.65 and 0.35 respectively, which serve as a benchmark.[17] Figures in brackets are the percentage contributions of TFP growth to GDP growth. As can be seen from Table 1, differences between the Young and the Collins estimates are quite small in three of the countries that are common to both studies. The exception is Singapore, where the difference is substantial. This result follows directly from the relatively small income share estimate of labor used by Young.[18]

Table 2 presents the nonparametric TFP growth estimates averaged over the whole time period,[19] together with estimated output elasticities for nine East Asian countries. For TFP growth, only the results using the residual method are reported here.[20] There is no important difference between the nonparametric estimates using the different data sets (not reported in the table). However, the nonparametric estimation methods yield quite different estimates of the TFP growth rate, as compared to the conventional methods. Except for the cases of Hong Kong SAR and China, our estimates of TFP growth over the period 1960-1995 are higher than the estimates obtained using the "Young" and "Collins" methods. Table 2 also reports the estimated output elasticities of capital and labor. All the estimates are highly significant based on the values of their asymptotic standard errors.

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[17] The income shares were assumed to be the same across countries by Collins and Bosworth (1996). In an interesting paper, Sarel (1997) uses international evidence to estimate technologically-determined coefficients for each major sector of activity and then derives a weighted average for each country according to their output composition. Sarel's estimates for the capital share are between 0.28—0.35, which are close to the Collins-Bosworth value of 0.35.

[18] Young uses 0.51 as the average labor share for Singapore, compared to 0.63 for Hong Kong SAR, 0.70 for Korea, and 0.74 for Taiwan Province of China. The growth rate of capital in Singapore during 1960-90 is 12 percent, which is about the same as in Korea and Taiwan Province of China, so Young's very large income share estimate of capital makes TFP growth for Singapore less than a half percentage point. Collins and Bosworth (1998) use a labor share of 0.65 for Singapore (common across countries). Senhadji (2000) finds the output elasticity of labor for Singapore to be 0.52 (in levels) and 0.7 (in differences). Sarel (1997) uses an estimate of 0.65 for Singapore.

[19] Note that the nonparametric estimates are calculated at all points of time and then averaged over various time periods to be compared with the conventional estimates.

[20] We do not emphasize the results using the direct method for two reasons. First, the profession has long been accustomed to identify TFP growth as a Solow residual. Second, it is generally supposed that TFP growth rates are volatile over time, which contradicts the assumption of the smoothness implicit in the direct method.

Table 3 provides the comparison of the conventional estimates and the nonparametric estimates for four East Asian countries: Hong Kong SAR, Korea, Singapore, and Taiwan Province of China. We find that the nonparametric "residual" estimates and the conventional estimates using Young's weighted labor shares ("Residual" and "Young" in Table 3) are quite similar for Hong Kong SAR, Korea and Taiwan Province of China, but very different for Singapore. These results indicate that the Young and Collins-Bosworth estimates are validated, except for Singapore. TFP growth in Singapore turns out to be much higher than would be the case using the "Young" and "Collins" methods. The estimate here results from the fact that the labor elasticity (0.63) is higher than that used by Young, and in fact close to that of Collins and Bosworth (1996). However, the estimated capital elasticity (0.17) is considerably smaller than the income share (0.35) assumed by Collins and Bosworth.

A comparison of factor elasticities and factor shares reveals three interesting points. First, in most East Asian countries, the estimated capital elasticity is smaller than the capital share, while the estimated labor elasticity is larger than the labor share.[21] Second, the difference between the labor share and the estimated labor elasticity is quite large in the East Asian countries. Third, the sum of the capital and labor elasticity is not far away from unity in most East Asian countries, seemingly verifying the constant returns to scale assumption.

The above results have an intuitive appeal. The first point above implies that capital is compensated higher than its marginal product, while labor is compensated less than its marginal product. This finding is in line with the typical government policy in many East Asian countries that taxes labor and subsidizes capital in order to attract foreign investment. It is interesting to observe that this pattern is not applicable to Hong Kong SAR, which is known as a free capitalist economy, as compared to government-led capitalist economies like Korea and Singapore. The second point is consistent with the view that the equality of the factor elasticity and the factor income share is unlikely to hold in developing countries. This casts doubt on the validity of the conventional procedure of the growth accounting calculation. The third point suggests that the aggregate production functions of most East Asian economies exhibit more or less constant returns to scale.[22]

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[21] The estimated capital elasticities for Korea, Singapore, and Taiwan Province of China are respectively 0.18, 0.17, and 0.18, whereas the corresponding capital shares of those countries are 0.30, 0.49, and 0.26.

[22] For all eight countries: Hong Kong SAR, Indonesia, Korea, Malaysia, Singapore, Taiwan Province of China, Thailand, and China, the 95 percent confidence intervals of the sum of the two elasticities roughly contain unity, suggesting constant returns to scale technology. The only exception is the Philippines, whose corresponding interval is (0.40, 0.63).

It is fairly common to assume that the aggregate production function exhibits constant returns to scale. Therefore, we next estimate the elasticities by explicitly imposing this restriction. More specifically, with constant returns to scale, equation (1) together with (3) is replaced by

$$Y/L = A \cdot F(K/L,1) = A \cdot f(K/L),$$

while (5) is replaced by

$$\ln(Y/L) = a + f^{*}(\ln(K/L)) + u.$$

The elasticities are then obtained as

$$\varepsilon_K \equiv \frac{\partial \ln F}{\partial \ln K} = \frac{\partial f^{*}}{\partial \ln(K/L)} \quad \text{and} \quad \varepsilon_L = 1 - \varepsilon_K .$$

Table 4 presents the results of this constrained nonparametric derivative estimation. Comparing the results in Table 4 and Table 2, we find that the constrained estimates of TFP growth are very close to the unconstrained ones. In particular, the constrained growth estimates for Hong Kong SAR, Korea, Taiwan Province of China, and China lie within one standard error from the unconstrained estimates. The estimates for Singapore and Thailand lie within two standard errors. The constrained and unconstrained estimates are significantly different from each other only in the cases of Indonesia, Malaysia, and the Philippines.

Overall, our estimates are quite similar to the Young's modified estimates (Young (1995)) with one major exception. Our TFP growth estimate for Singapore (3.6–3.7 percent) turns out to be much larger than Young's (0.3–0.5 percent). Our results are consistent with those obtained by Hsieh (1997), who calculated the dual measure of TFP growth. Klenow and Rodriguez-Clare (1997) also report a similar number (3.3 percent) for Singapore.

V. Conclusion

This paper develops a new method of estimating the growth rate of TFP that does not require such strong assumptions that are needed for the conventional growth-accounting method. Our findings based on the new estimation procedure can be summarized as follows. First, we find that Hong Kong SAR, Korea, Singapore, and Taiwan Province of China all have very similar TFP growth of about 3.7 percent over the period 1960–1995, which represents nearly half of output growth of each country during that period. On the other hand, capital growth contributes only 27 percent of output growth in these countries. These results provide little support for the strong version of the accumulation hypothesis.

Second, we find that the output elasticities of capital and labor are quite different from the income shares of those factors in the East Asian countries. The actual capital elasticity appears to be much smaller than the measured income share of capital, resulting in a misleadingly high contribution of capital growth to output growth in conventional growth-accounting exercises.

In conclusion, our findings appear to suggest an alternative view about East Asian economic growth that is somewhat different from either the strict "accumulation" or "assimilation" views. On one hand, as the "assimilation" view suggests, economic growth in East Asian countries appears to come from productivity improvements rather than only capital accumulation. On the other hand, in order to attract foreign investment through which new technology is transferred to the country's economy, the government has to encourage a higher capital compensation and a lower labor compensation than what is economically justified. As a result, there is likely to have been excessive capital investment. Therefore, according to this scenario, unlike what the pure assimilation view would predict, there appear to be some opportunity costs associated with a narrowing of the "idea gap." All in all, on the basis of the new estimates, we would argue that East Asian growth reflects a combination of the accumulation and assimilation views of economic growth.

Table 1. Conventional Estimates of TFP Growth of East Asian Countries, 1960-95

Country	TFP growth estimate (%)				Labor share (Young)	Growth (%)		
	Young		Collins			Output	Capital	Labor
Hong Kong SAR	4.1	[53 %]	4.1	[53 %]	0.63	7.7	5.2	2.6
Indonesia	-		1.4	[24 %]	-	5.9	8.2	2.5
Korea	2.8	[34 %]	2.3	[28 %]	0.71	8.2	11.8	2.7
Malaysia	-		1.5	[22 %]	-	6.8	9.6	3.0
Philippines	-		-0.1	[-3 %]	-	3.8	5.7	2.9
Singapore	0.5	[6 %]	1.8	[23 %]	0.51	8.0	12.1	3.1
Taiwan Province of China	3.4	[41 %]	2.6	[31 %]	0.74	8.3	11.4	2.7
Thailand	-		2.1	[28 %]	-	7.5	10.3	2.7
China	-		3.1	[46 %]	-	6.8	6.9	2.0

Notes:

1. 'Young' and 'Collins' indicate, respectively, the estimates based on the income share of labor from Young (1995), and the income share set equal to 0.65 as in Collins and Bosworth (1996).
2. Figures in brackets are the contributions (%) of TFP growth to GDP growth.
3. 'Labor share' is the income share of labor used in Young (1995).
4. 'Growth (%)' is the actual growth rate of each variable.

Table 2. Nonparametric Estimates of TFP Growth of East Asian Countries, 1960-95

Country	TFP growth estimate (%)		Elasticity estimates		Growth (%)		
			Capital	Labor	Output	Capital	Labor
Hong Kong SAR	3.4	[44 %]	0.41	0.71	7.7	5.2	2.6
	(0.41)		(0.058)	(0.098)			
Indonesia	2.6	[44 %]	0.18	0.64	5.9	8.2	2.5
	(0.30)		(0.025)	(0.087)			
Korea	3.7	[46 %]	0.18	0.81	8.2	11.8	2.7
	(0.42)		(0.025)	(0.114)			
Malaysia	3.2	[49 %]	0.19	0.58	6.8	9.6	3.0
	(0.34)		(0.026)	(0.080)			
Philippines	1.7	[45 %]	0.17	0.34	3.8	5.7	2.9
	(0.21)		(0.025)	(0.053)			
Singapore	3.7	[46 %]	0.17	0.63	8.0	12.1	3.1
	(0.39)		(0.024)	(0.089)			
Taiwan Province of China	3.8	[46 %]	0.19	0.76	8.3	11.4	2.7
	(0.41)		(0.027)	(0.105)			
Thailand	3.7	[49 %]	0.19	0.67	7.5	10.3	2.7
	(0.40)		(0.029)	(0.099)			
China	2.8	[41 %]	0.28	0.95	6.8	6.9	2.0
	(0.43)		(0.043)	(0.146)			

Notes:

1. TFP growth estimates are based on the nonparametric residual method.
2. Figures in parentheses are the standard errors.
3. Figures in brackets are the contributions (%) of TFP growth to GDP growth.
4. The values of the elasticity of capital and labor are estimated by a nonparametric method.
5. 'Growth (%)' is the actual growth rate of each variable.

Table 3. Comparison of Estimates

Country	TFP growth estimate (%)			Capital		Labor	
	Conventional		Nonparametric	Elasticity	Income share	Elasticity	Income share
	Young	Collins					
Hong Kong SAR	4.1	4.1	3.4	0.41	0.37	0.71	0.63
Korea	2.8	2.3	3.7	0.18	0.29	0.81	0.71
Singapore	0.5	1.8	3.7	0.17	0.49	0.63	0.51
Taiwan Province of China	3.8	2.1	3.8	0.19	0.26	0.76	0.74

Notes:

1. 'Young' and 'Collins' indicate, respectively, the conventional estimates based on the income share of labor from Young (1995), and the income share set equal to 0.65 as in Collins and Bostworth (1996).
2. Nonparametric estimates are based on the nonparametric residual method.
3. The values of the elasticity of capital and labor are estimated by a nonparametric method.
4. The income shares of labor are the values used in Young (1995).

Table 4: Nonparametric Estimates of TFP Growth of East Asian Countries
with Constant Returns to Scale, 1960-95

Country	TFP growth estimate (%)		Elasticity estimates		Growth (%)		
			Capital	Labor	Output	Capital	Labor
Hong Kong SAR	3.5	[45 %]	0.51	0.49	7.7	5.2	2.6
	(0.125)		(0.0230)				
Indonesia	1.9	[32 %]	0.25	0.75	5.9	8.2	2.5
	(0.035)		(0.0044)				
Korea	3.3	[40 %]	0.24	0.76	8.2	11.8	2.7
	(0.054)		(0.0047)				
Malaysia	2.3	[34 %]	0.23	0.77	6.8	9.6	3.0
	(0.043)		(0.0045)				
Philippines	0.5	[13 %]	0.13	0.87	3.8	5.7	2.9
	(0.034)		(0.0061)				
Singapore	3.1	[39 %]	0.20	0.80	8.0	12.1	3.1
	(0.052)		(0.0045)				
Taiwan Province of China	3.4	[41 %]	0.25	0.75	8.3	11.4	2.7
	(0.057)		(0.0051)				
Thailand	3.0	[40 %]	0.23	0.77	7.5	10.3	2.7
	(0.058)		(0.0055)				
China	3.0	[44 %]	0.36	0.64	6.8	6.9	2.0
	(0.068)		(0.0095)				

Notes:

1. TFP growth estimates are based on the nonparametric residual method.
2. Figures in parentheses are the standard errors.
3. Figures in brackets are the contributions (%) of TFP growth to GDP growth.
4. The values of the elasticity of capital and labor are estimated by a nonparametric method.
5. 'Growth (%)' is the actual growth rate of each variable.

Data Description

Two data sets, referred to as "Penn" and "Collins", were constructed. The Penn data set is based on the Penn World Tables Mark 5.6. The Penn World Tables Mark 5.6 covers the period from 1950 to 1992. The output measure is Gross Domestic Product expressed in international prices. The labor data are extracted from the Penn World Tables. Although the capital data are available in the Penn World Tables, many East Asian countries have missing observations in the early years. We therefore obtained the capital data from Nehru and Dhareshwar (1993) (available at http://www.worldbank.org/research/growth/ddhehdha.htm), which cover the period from 1950 to 1990 for most of the East Asian countries except Hong Kong SAR. The capital data for Hong Kong SAR are extracted from the Penn World Tables.

The Collins data set is based on Collins and Bosworth (1996) (available at http://www.brookings.edu/es/research/project/develop/develop.htm), which cover the period from 1960 to 1996. The output measure is an index of Real Gross Domestic Product (GDP) based on World Bank data. The labor input measure is an index of total labor force based on OECD employment or International Labor Organization. The capital stock is an index of capital stock from Nehru and Dhareshwar (1993) data.

Two types of conventional estimates are calculated under the labels: "Collins" and "Young", depending on the source of labor share data. The "Collins" method uses the labor share set equal to 0.65 as in Collins and Bosworth (1996). The "Young" method uses the labor share estimates used in Young (1995). Young's estimates are available for Hong Kong SAR, Korea, and Singapore, and Taiwan Province of China up to 1990.

Distribution of Output Elasticities

It can be shown that the limiting distribution of $(\hat{\varepsilon}_K, \hat{\varepsilon}_L)$ in (8) is given by

$$\begin{bmatrix} (nh_1^3 h_2)^{1/2} & 0 \\ 0 & (nh_1 h_2^3)^{1/2} \end{bmatrix} \begin{bmatrix} \hat{\varepsilon}_K(\mathbf{x}) - \varepsilon_K(\mathbf{x}) \\ \hat{\varepsilon}_L(\mathbf{x}) - \varepsilon_L(\mathbf{x}) \end{bmatrix} \xrightarrow{L} N(\mathbf{0}, \mathbf{\Omega}(\mathbf{x}))$$

where

$$\mathbf{\Omega}(\mathbf{x}) = \begin{bmatrix} \omega_{11}(\mathbf{x}) & \omega_{12}(\mathbf{x}) \\ \omega_{12}(\mathbf{x}) & \omega_{22}(\mathbf{x}) \end{bmatrix}$$

$$\omega_{ii}(\mathbf{x}) = \frac{\sigma_u^2(\mathbf{x})}{f(\mathbf{x})} \int K_i(\mathbf{z})^2 d\mathbf{z} = \frac{\sigma_u^2(\mathbf{x})}{16\pi^{3/2} f(\mathbf{x})} \qquad \text{for } i = 1,2$$

$$\omega_{12}(\mathbf{x}) = \frac{\sigma_u^2(\mathbf{x})}{f(\mathbf{x})} \int K_1(\mathbf{z}) K_2(\mathbf{x}) d\mathbf{z} = 0 .$$

Therefore, the asymptotic α% point-wise error bands are given by $\Delta Y_t / Y_t - \hat{\varepsilon}_K(\Delta K_t / K_t) - \Delta\hat{\varepsilon}_L(\Delta L_t / L_t) \pm z_{(1-\alpha)/2} s$, where $z_{(1-\alpha)/2}$ stands for the upper $(1-\alpha)/2$ quantile of the standard normal distribution and s is the standard error of the estimate given by

$$s(\mathbf{x}) = \frac{1}{4\pi^{3/4}\sqrt{nh_1 h_2}} \left(\frac{\hat{\sigma}^2(\mathbf{x})}{\hat{f}(\mathbf{x})} \right)^{1/2} \sqrt{\frac{1}{h_1^2}\left(\frac{\Delta K_t}{K_t}\right)^2 + \frac{1}{h_2^2}\left(\frac{\Delta L_t}{L_t}\right)^2}$$

where $\hat{\sigma}^2(\mathbf{x}) = \sum_{i=1}^n [y_i - \hat{m}(\mathbf{x}_i)]^2 K(\mathbf{z}_i) / \sum_{i=1}^n K(\mathbf{z}_i)$ and $\hat{f}(\mathbf{x})$ is given in (7).
The above bands are not strictly the classical asymptotic α % confidence interval, since the non-parametric regression estimator is not asymptotically unbiased in general.

Kernel Function and Bandwidth Selection

To implement the procedures described in Section III, we use the second order Gaussian product kernel to reduce the bias

$$K(\mathbf{z}_i) = (1/8)\prod_{j=1}^{3}(3 - z_{ij}^2)\phi(z_{ij}),$$

the derivative of which is given by

$$K_j(\mathbf{z}_i) = -(1/8)z_{ij}(5 - z_{ij}^2)\phi(z_{ij})\prod_{k\neq j}(3 - z_{ik}^2)\phi(z_{ik})$$

for $j = 1,2,3$, where $\phi(\cdot)$ stands for the standard normal density function. The selection of bandwidth h_j is made on the basis of the cross validation method outlined below.

Noticing that

$$d\ln Y = da(t) + (\partial F^*/\partial \ln K)d\ln K + (\partial F^*/\partial \ln L)d\ln L,$$

we select the bandwidth h so as to minimize the cross validation function:

$$CV(h) = (T-1)^{-1}\sum_{t=2}^{T}[\Delta\ln Y_t - (d/dt)\hat{a}(t) - \hat{\varepsilon}_K\Delta\ln K_t - \hat{\varepsilon}_L\Delta\ln L_t]^2 .$$

In the above, the estimates $(d/dt)\hat{a}(t)$, $\hat{\varepsilon}_K$ and $\hat{\varepsilon}_L$ are the "leave-two-out" estimators, that is, they are estimated using all observations except those at time t and t-1. The CV-function validates the ability to predict $\{\Delta\ln Y_t\}$ across the subsamples $\{(\ln Y_t - \ln Y_{t-1}, \mathbf{X}_s)_{s\neq t-1, s\neq t}\}$ (Stone 1974).

A Monte Carlo Experiment

The purpose of this Monte Carlo experiment is to ascertain how well the nonparametric estimates of derivatives perform with small samples. In this experiment, the true form of the regression function is known, and the data are drawn from a known population. The model and data set is initially constructed by White (1980) and used by Byron and Bera (1983) and Rilstone (1989) (the latter result is reproduced in Table 4.1 of Pagan and Ullah (1999)).

The true model is a stochastic CES production function

$$y_i = (x_{i1}^{-5} + 2x_{i2}^{-5})^{-1/5} e^{u_i}$$

or $$\ln y_i = -(1/5)\log\left(e^{-5\ln x_{i1}} + 2e^{-5\ln x_{i2}}\right) + u_i \qquad \text{for } i = 1,2,3,\ldots,n,$$

where y_i, x_{i1}, and x_{i2} stand for the values of output, capital, and labor, respectively. Further $\ln x_{i1}$ and $\ln x_{i2}$ are generated from the independent uniform distribution with mean 0.5 and variance 1/12, while u_i are generated independently from a normal distribution with mean zero and variance 0.01.

Our goal is to estimate derivatives or elasticities $\partial \ln y / \partial \ln x_j$. In the literature on production economics, the parametric approximations often used for this purpose are

(1) CD: Cobb-Douglas function

$$\ln y_i = \beta_0 + \beta_1 \ln x_{i1} + \beta_2 \ln x_{i2} + u_i$$

(2) TL: Translog function

$$\ln y_i = \beta_0 + \beta_1 \ln x_{i1} + \beta_2 \ln x_{i2} + \beta_3 (\ln x_{i1})^2 + \beta_4 \ln x_{i1} \ln x_{i2} + \beta_5 (\ln x_{i2})^2 + u_i$$

Table A1 presents three sets of estimates of the output elasticities $b_j(x_1, x_2) = \partial \ln y / \partial \ln x_j$ for $j = 1,2$ at the mean point $(\ln x_1, \ln x_2) = (.5,.5)$, using OLS estimation assuming (i) the Cobb-Douglas (CD) and (ii) Translog (TL) forms of production function as well as (iii) nonparametric estimation (NP). The sample size is 200. A similar result is reported in Rilstone (1989). It is clear that in terms of bias, the nonparametric estimates are much superior to the parametric counterparts. The standard errors for the Cobb-Douglas and Translog estimates are somewhat smaller compared to the nonparametric standard errors. This may reflect the slow speed of convergence of nonparametric estimates.

Table A2 presents the same comparison using only 35 observations, which is equal to the sample size in our study. The result is strikingly similar to Table A1, except the standard errors are larger. The nonparametric estimates remain less biased.

Table A1: Monte Carlo Experiment (sample size 200)

$b(x)$	CD	TL	NP	True value
$\hat{b}_1$	0.3926 (0.0346)	0.3920 (0.0239)	0.3518 (0.0880)	0.3333
$\hat{b}_2$	0.6072 (0.0337)	0.6070 (0.0241)	0.6599 (0.1002)	0.6667

Notes:

1. The estimates are mean values of $b_1(x_1, x_2)$ and $b_2(x_1, x_2)$ based on 300 samples of size 200.
2. Standard errors are in parentheses.

Table A2: Monte Carlo Experiment (sample size 35)

$b(x)$	CD	TL	NP	True value
$\hat{b}_1$	0.3997 (0.0874)	0.3956 (0.0659)	0.3531 (0.1567)	0.3333
$\hat{b}_2$	0.6136 (0.0866)	0.6119 (0.0645)	0.6593 (0.1749)	0.6667

Notes:

1. The estimates are mean values of $b_1(x_1, x_2)$ and $b_2(x_1, x_2)$ based on 300 samples of size 35.
2. Standard errors are in parentheses.

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