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"Panel Data and Productivity"

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PANEL DATA AND PRODUCTIVITY MEASUREMENT

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17.1 INTRODUCTION
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THE chapter first discusses how productivity growth typically has been measured in classical productivity studies. We then briefly discuss how innovation and catch-up can be distinguished empirically. We next outline methods that have been proposed to measure productivity growth and its two main factors, innovation and catch-up. These approaches can be represented by a canonical form of the linear panel data model. A number of competing specifications are presented and model averaging is used to combine estimates from these competing specifications in order to ascertain the contributions of technical change and catch-up in world productivity growth. The chapter ends with concluding remarks and suggestions for the direction of future analysis.

The literature on productivity and its sources is vast in terms of empirical and theoretical contributions at the aggregate, industry, and firm level. The pioneering work of Dale Jorgenson and his associates[1] and Zvi Griliches and his associates,[2] the National Bureau of Economic Research,[3] the many research contributions made in U.S universities and research institutions, the World Bank and research institutes in Europe and other countries are not discussed here as our goal is by necessity rather narrow. We focus on work directly related to panel data methods that have been developed to address specific issues in specifying the production process and in measuring the sources of productivity growth in terms of its two main components of innovation (technical progress) and catch-up (efficiency growth), with emphasis given to one of the more important measures of the latter component and that is technical efficiency.

17.2 PRODUCTIVITY GROWTH AND ITS MEASUREMENT

17.2.1 Classical Residual based Partial and Total Factor Productivity Measurement

Total factor productivity (TFP) is measured by a ratio of a weighted average of outputs (Y_i) to a weighted average of inputs (X_i). For a single output the ratio is:

$$TFP = \frac{Y}{\sum a_i X_i}. \tag{1}$$

Historically, there are two common ways of assigning weights for this index. They are to use either an arithmetic or geometric weighted average of inputs. The *arithmetic weighted average*, due to Kendrick (1961), uses input prices as the weights while the *geometric weighted average* of the inputs, attributable to Solow (1957), uses input expenditure shares as the weights. The predominant *TFP* measure currently in use by the central governments in most countries is a variant of Solow's measure based on the Cobb-Douglas production function with constant returns to scale, $Y = AX_L^{\alpha} X_K^{1-\alpha}$, and leads to the *TFP* measure:

$$TFP = \frac{Y}{X_L^{\alpha} X_K^{1-\alpha}}. \tag{2}$$

At cost minimizing levels of inputs, the parameter α describes the input expenditure share for labor. The *TFP* growth rate is the simple time derivative of *TFP* and is given by:

$$T\dot{F}P = \frac{dY}{Y} - \left[\alpha \frac{dX_L}{X_L} + (1-\alpha) \frac{dX_K}{X_K} \right].$$

TFP is simply a ratio of index numbers. Fisher (1927) discussed the optimal properties for index numbers and these are also explored in depth by Good, Nadiri, and Sickles (1997). Jorgenson and Griliches (1972) pointed out that the TFP index could be expressed as the difference between the log output and log input indices.

17.2.2 Modifications of the Neoclassical Model: The New Growth Theory

Endogenous growth models (Romer, 1986) were proposed to address the inflexibility and simplicity of exogenously driven ("manna from heaven") technical change (Scherer, 1971). This was of course not new as Griliches (1957) and Edwin Mansfield (1961), among others, addressed these issues using endogenous rates of penetration

and endogenous rates of imitation to explain technical change. In the endogenous growth theory capital was allowed to have non-diminishing rates of return due to external effects that spillover for a variety of reasons. The level of technology A can vary depending on the stock of some privately provided input R (such as knowledge) and the production function is formulated as

$$Y = A(R)f(K, L, R)$$

As for potential sources of spillovers that could shift the production function there are many explanations. Learning-by-doing was Arrow's (1962) explanation, while for Romer (1986) it was the stock of research and development, for Lucas (1988) it was human capital, for Coe and Helpman (1995) and Coe, Helpman, and Hoffmaister (1997) it was trade spillovers, and for Diao, Rattsø, and Stokke (2005) it was trade openness. However, efficiency is another explanation if one simply attaches another reason for the spillover, such as a loosening of constraints on the utilization of the technology.

Another comment about endogenous growth models and the need to address endogeneity issues in productivity analyses needs to be made here. The literature on structural modeling of productivity models is quite dense and, again, it is not within the scope of this chapter to discuss this very important literature. However, there is a particular literature within the broader structural modeling of static and dynamic productivity model (see, e.g., Olley and Pakes 1996) that speaks to the focused issues addressed in this chapter and that is the role of errors-in-variables, weak instrument bias, and stability in panel data modeling of production processes. These issues have been taken up by a number of researchers, especially those from the NBER and include studies by Griliches and Hausman (1986), Stoker et al. (2005), Griliches and Mairesse (1990, 1998), and Griliches and Pakes (1984), to name but a few.

17.2.3 Technical Efficiency in Production

Nontransitory production inefficiencies can be attributed to a number of factors, such as random mistakes, the existence of market power (Kutlu and Sickles 2012), and historical precedent (Alam and Sickles, 2000). Technical inefficiency concepts were developed by Debreu (1951), Farrell (1957), Shephard (1970), and Afriat (1972). Measuring the intrinsically unobservable phenomena of efficiency has proven to be quite challenging. Aigner, Lovell, and Schmidt (1977), Battese and Corra (1977), and Meeusen and Van den Broeck (1977) developed the econometric methods to measure efficiency in production, while linear programming methods were initially made feasible to utilize in the classic study by Charnes, Cooper, and Rhodes (1978). As relative efficiency is usually constructed from a normalized residual and such a residual is generated from an econometric model, theoretical consideration from the economic theory of the firm and assumptions of weak exogeneity are needed in order to identify

it as a factor that is distinct from innovation. Both efficiency and technology change are the main drivers of productivity growth, along with scale economies. Scale effects may have an important role at the firm level but not necessarily at the aggregate economy level we will consider in the empirical analysis we summarize towards the end of this Chapter. As efficiency estimators differ on which identifying restrictions are imposed, it should surprise no one that results from alternative estimators differ as well. Kumbhakar and Lovell (2000) and Fried, Lovell, and Schmidt (2008) provide excellent treatments of this literature and how various modeling assumptions utilized in the early panel productivity literature by Pitt and Lee (1981), Schmidt and Sickles (1984), and others provide substantial leverage in determining measured levels of efficiency.

17.2.4 The Panel Stochastic Frontier Model

Introducing efficiency into the dynamic of productivity growth requires that we introduce a frontier production process relative to which efficiency can be measured. In order for cross-sectional methods to be useful in such a setting, identification of the efficiency term often requires a parametric assumption about its distribution, an assumption not needed when using panel data. Panel data methods for time invariant efficiency measurement introduced by Pitt and Lee (1981) and Schmidt and Sickles (1984) were soon followed up by Cornwell, Schmidt, and Sickles (1990) and Kumbhakar (1990), Battese and Coelli (1992), and Lee and Schmidt (1993) who introduced methods that allowed the efficiency effects to vary over time and between cross-sectional units. Kim and Lee (2006) generalized the Lee and Schmidt (1993) model by considering different patterns for different groups, while Hultberg, Nadiri, and Sickles (1999, 2004) modified the neoclassical country growth convergence model to allow for heterogeneities in the efficiency catch-up rates. The Hultberg, Nadiri, and Sickles (1999, 2004) studies also are instructive as they relate a set of environmental factors, such as a country's political and social institutions, to the rate of catch-up, a factor which they found to determine up to 60% of the variation in efficiency. The firm level study by Bloom and Van Reeden (2007) found that productivity differences among firms (efficiency differences) were best explained by such arcane factors as shop floor operations, monitoring, targets, and incentives, factors typically overseen by management and also typically viewed as related to managerial efficiency.

17.2.5 Index Number Approaches to Calculate Innovation and Efficiency Change

Identifying the sources of *TFP* growth while imposing minimal parametric structure has obvious appeal on grounds of robustness. Sharpness of inferences may, however,

be comprised vis-à-vis parametric structural econometric models. There has been a long-standing tradition to utilize index number procedures as well as reduced form or structural econometric estimation to quantify *TFP* growth and its determinants. Space limits the coverage that this chapter can provide to such important index number approaches. The interested reader is directed to the panel data literature on productivity index numbers and to surveys (e.g., Good, Nadiri, and Sickles 1997; Fried, Lovell, and Schmidt 2008), particular advances in decomposing productivity change into technical and efficiency growth via the Malmquist index introduced into the literature by Caves, Christensen, and Diewert (1982) (Färe et al. 1994; Grifell-Tatjé and Lovell 1995; Färe et al. 1997), problems with such index number approaches and decompositions (Førsund and Hjalmarsson 2008), and numerical approaches via bootstrapping to construct inferential procedures to assess such measures (Simar and Wilson 2000; Jeon and Sickles 2004).

17.3 DECOMPOSITION OF ECONOMIC GROWTH-INNOVATION AND EFFICIENCY CHANGE IDENTIFIED BY REGRESSION

A relatively transparent way to see how a linear regression can be used to estimate technical change and efficiency change is based on the following derivation. Let the multiple output/multiple input technology be represented by a parametric output distance function (Caves, Christensen and Diewert 1982; Coelli and Perelman 1996). Consider an output distance function or single output production function that is linear in parameters. Standard parametric functional forms widely used in empirical work that are linear in parameters are the Cobb-Douglas, translog, generalized-Leontief and quadratic. The many different specifications we consider here and the way in which various forms of unobserved heterogeneity can be modeled can be motivated using the following model for a single output technology estimated with panel data assuming unobserved country (firm) effects:

$$y_{it} = x_{it}\beta + \eta_i(t) + v_{it} \tag{3}$$

where $\eta_i(t)$ represents the country-specific fixed effect that may be time varying, x_{it} is a vector of regressors, some of which may be endogenous and correlated with the error v_{it} or the effects $\eta_i(t)$.

The regression model (3) can be derived by a relatively straightforward transformation and re-parameterization of the output distance function. A parsimonious representation of the *m*-output, *n*-input deterministic distance function $D_o(Y, X)$ is given by the Young index (Balk 2008):

$$D_o(Y, X) = \frac{\prod_{j=1}^{m} Y_{it}^{\gamma_j}}{\prod_{k=1}^{n} X_{it}^{\delta_k}} \leq 1.$$

The output-distance function $D_o(Y, X)$ is non-decreasing, linear homogeneous in outputs, and concave in Y and non-increasing and quasi-concave in X. If we take the natural logarithm of the inequality, add a symmetric disturbance term v_{it} to address the standard random error in a regression and a technical efficiency term $\eta_i(t)$ to represent inefficiency then the observed value of the distance function for country i at time t can be written as:

$$-y_{1,it} = \sum_{j=2}^{m} \gamma_j y_{jit}^* + \sum_{k=1}^{n} \delta_k x_{kit}^* + \eta_i(t) + u_{it},$$

where $y_{jit, j=2,...,m}^* = ln(Y_{jit}/Y_{1it})$ and $x_{kit}^* = \ln(X_{kit})$. After redefining a few variables the distance function can be written as

$$y_{it} = x_{it}\beta + \eta_i(t) + v_{it}.$$

The Cobb-Douglas distance function introduced by Klein (1953) not only assumes strong separability of outputs and inputs but also has a production possibility frontier that is convex instead of concave. This last drawback may not be as important as it seems, as pointed out by Coelli (2000), and the Cobb-Douglas remains a reasonable and parsimonious first-order local approximation to the true function. The Cobb-Douglas can be extended to the translog output distance function by adding second order terms to provide for flexibility in curvature possibilities and by allowing interactions among the output and inputs, thus avoiding the strong separability implied by the Cobb-Douglas output distance function. This functional form also can be transformed and re-parameterized to fit into the form of the linear panel data model given in equation (3). The translog output distance function is given by:

$$-y_{1it} = \sum_{j=2}^{m} \gamma_j y_{jit}^* + \frac{1}{2} \sum_{j=2}^{m} \sum_{l=1}^{m} \gamma_{jl} y_{jit}^* y_{lit}^* + \sum_{k=1}^{n} \delta_k x_{kit}^* + \frac{1}{2} \sum_{k=1}^{n} \sum_{p=1}^{n} \delta_{kp} x_{kit}^* x_{pit}^*$$
$$+ \sum_{j=2}^{m} \sum_{k=1}^{n} \theta_{jk} y_{jit}^* x_{lit}^* + \eta_{it} + u_{it}.$$

Since the model is linear in parameters, then after redefining a few variables the translog distance function also can be written as

$$y_{it} = x_{it}\beta + \eta_i(t) + v_{it}.$$

Transformations and re-parameterizations such as these can be used to put any output distance function that is linear in parameters into the canonical form of equation (3).

When there are multiple outputs then those that appear on the right hand side must be instrumented.

We will use this equation as the generic model for estimating efficiency change using frontier methods we will detail below. We will assume that technical innovations are available to all countries and interpret any country-specific error left over when we control for factor inputs as inefficiency. In so doing we can then decompose *TFP* growth into its two main components, innovation and catch-up. Innovation could be directly measured, for example using a distributed lag of R&D expenditures, patents, or any other direct measure of innovation. Baltagi and Griffin (1988) use time dummies to construct an innovation index. Exogenous or stochastic linear time trends have also been used (Bai, Kao, and Ng, 2009).

Below we examine a number of regression-based methods introduced into the literature to measure productivity growth and its decomposition into innovation and efficiency change using,

$$y_{it} = x_{it}\beta + \eta_i(t) + v_i,$$

which nests all multi-output/multi-input panel models that are linear in parameters and can be used to estimate productivity growth and decompose it into innovation and efficiency change. We will also assume that we have a balanced panel although this is done more for notational convenience than for substantive reasons. The methods we discuss also are appropriate when technical efficiency effects are not changing over time. After discussing the methods and how they are implemented we will discuss model averaging and how it can be used to evaluate world productivity growth from 1970 to 2000.

17.3.1 The Cornwell, Schmidt, and Sickles (1990) Panel Stochastic Frontier Model

Extensions of the panel data model to allow for heterogeneity in slopes as well as intercepts by Cornwell, Schmidt, and Sickles (CSS) (1990) allowed researchers to estimate productivity change that was specific to the cross-sectional unit (firms, industries, countries) that could change over time. A special parameterization of the CSS model that accomplishes this objective is:

$$y_{it} = x_{it}\beta + \eta_i(t) + v_{it},$$

where

$$\eta_i(t) = W_{it}\delta_i + v_{it}.$$

The L coefficients of W, δ_i, depend on different units i, representing heterogeneity in slopes. In their application to the US commercial airline industry, CSS specified $W_{it} = (1, t, t^2)$, although this was just a parsimonious parameterization useful for their application. It does not in general limit the effects to be quadratic in time.

A common construction can relate this model to standard panel data model. Let $\delta_0 = E[\delta_i]$, and $\delta_i = \delta_0 + u_i$. Then the model can be written as:

$$y_{it} = X_{it}\beta + W_{it}\delta_0 + \epsilon_{it}, \tag{4}$$

$$\epsilon_{it} = W'_{it}u_i + v_{it}. \tag{5}$$

Here u_i are assumed to be *i.i.d.* zero mean random variables with covariance matrix Δ. The disturbances v_{it} are taken to be *i.i.d.* random variable with a zero mean and constant variance σ^2, and uncorrelated with the regressors and u_i. In matrix form, we have:

$$y = X\beta + W\delta_0 + \epsilon, \tag{6}$$

$$\epsilon = Qu + v, \tag{7}$$

where $Q = diag(W_i)$, $i = 1, \cdots, N$ is a $NT \times NL$ matrix, and u is the associated $NL \times 1$ coefficients vector.

17.3.1.1 Implementation

Three different estimators can be derived based on differing assumptions made in regard to the correlation of the efficiency effects and the regressors, specifically, the correlation between the error term u and regressors X and W. They are the *within* (FE) estimator, which allows for correlation between all of the regressors and the effects, the *gls* estimator, which is consistent when no correlation exists between the technical efficiency term and the regressors (Pitt and Lee 1981; Kumbhakar 1990), and the *efficient instrumental variables* estimator, which can be obtained by assuming orthogonality of some of the regressors with the technical efficiency effects. The explicit formulas for deriving each estimator and methods for estimating the δ_i parameters are provided in the CSS paper. Relative efficiencies, normalized by the consistent estimate of the order statistics identifying the most efficient country, are then calculated as:

$$\widehat{\eta}(t) = \max_j [\widehat{\eta}_j(t)]$$

and

$$RE_i(t) = \widehat{\eta}(t) - \widehat{\eta}_i(t),$$

where $RE_i(t)$ is the relative efficiency of the *ith* country at time t. For this class of models the regressors X contain a time trend interpreted as the overall level of innovation. When it is combined with the efficiency term $\widehat{\eta}_j(t)$, we have a decomposition of *TFP* into innovation and catch-up. When the time trend and the efficiency term both enter the model linearly, then the decomposition is not identified using the within estimator but is for the *gls* and for selected variants of the efficient IV model, such as those used in the Cornwell et al. airline study. In the study of world productivity below we utilize the *gls* version of the CSS estimator (labelled CSSG) and the Efficiency IV estimator (labelled EIV).

17.3.2 The Kumbhakar (1990) Panel Stochastic Frontier Model

Here we consider a linear in log production function:

$$y_{it} = x_{it}\beta + \eta_i(t) + v_{it}, \tag{8}$$

where

$$\eta_i(t) = \gamma(t)\tau_i. \tag{9}$$

v_{it} is assumed *i.i.d.* with distribution $N(0, \sigma_v^2)$; $\eta_i(t)$ is the inefficiency term with time-varying factor $\gamma(t)$ and time-invariant characteristics τ_i. τ_i is assumed to be distributed as *i.i.d.* half-normal distributed $\gamma(t)$ is specified as the logistic function

$$\gamma(t) = (1 + \exp(bt + ct^2))^{-1}$$

We can see that $\gamma(t)$ is bounded between $(0,1)$ and that it accommodates increasing, decreasing, or time-invariant inefficiency behavior as the parameters b and c vary. Although the Kumbhakar model also estimates allocative efficiency from side conditions implied by cost-minimization (Schmidt and Lovell 1979), we will only examine the portion of his model that directly pertains to the technical inefficiency/innovation decomposition of productivity change.

17.3.2.1 Implementation

Parametric maximum likelihood is used for estimation the model. Using the Kumbhakar notation let $\theta_{it} = \gamma(t)\tau_i + v_{it}$. Then the joint distribution of the composed error is $f(\theta_i, \tau_i)$ and since both τ_{it} and v_{it} are i.i.d and are independent of each other, the joint pdf is $f(\theta_i, \tau_i) = f(\tau_i) \cdot (\prod_t f(v_{it})) = f(\tau_i) \prod_t f(\theta_{it} - \gamma(t)\tau_i)$.

Marginalizing over τ, one can derive the distribution of θ. The the log-likelihood function is then defined as

$$\mathcal{L} = \sum_i \ln f(\theta_i)$$

and the parameters are given by the $\arg max(\mathcal{L})$.

Consistent point estimates of the inefficiency term can be based on a method of moments estimator for the conditional mean of $\tau_i | \theta_i$. Since

$$f(\tau_i | \theta_i) = (2\pi\sigma_*^2)^{-1/2} \frac{\exp\left(-\frac{1}{2\sigma_*^2}(\tau - \mu_i^*)^2\right)}{\Phi(-\mu_i^*/\sigma_*)}, \tau_i \leq 0,$$

where Φ is the distribution function for standard normal then $E(\tau_i | \theta_i) = \mu_i^* - \sigma_* \frac{\phi(\mu_i^*/\sigma_*)}{\Phi(-\mu_i^*/\sigma_*)}$ and $\widehat{E(\tau_i | \theta_i)} = \widehat{\tau}_i$. $\sigma_* = \frac{\sigma_v \sigma_\tau}{(\sigma_v^2 + \sigma_\tau \sum_t \gamma^2(t))^{1/2}}$ and $\mu_i^* = \frac{\sigma_\tau^2 \sum_t \gamma(t)\theta_{it}}{\sigma_v^2 + \sigma_\tau^2 \sum_t \gamma^2(t)}$. The best predictor of technical efficiency is given by $E(\exp\{\gamma(t)\tau_i | \theta_i\})$ and efficiency for each firm by $\widehat{\eta}_i(t) = \gamma(t)\widehat{\tau}_i$.

17.3.3 The Battese and Coelli Model (1992, 1995)

The production function is given by the generic model

$$y_{it} = x_{it}\beta + \eta_i(t) + v_{it}, \tag{10}$$

where the effects are specified as

$$\eta_i(t) = -\{\exp[-\eta(t-T)]\}u_i,$$

where v_{it} are assumed to be a *i.i.d.* $N(0,\sigma_v^2)$ random variable and the u_{it} are assumed to follow an i.i.d. non-negative truncated $N(\mu,\sigma^2)$ distribution. η is a scalar and the temporal movement of the technical efficiency effects depends on the sign of η. Time invariant technical efficiency corresponds to $\eta = 0$. To allow for a richer temporal path for firm efficiency effects that reflect more possibility of how firm effects change over time, one can also specify $\eta(t-T)$ as

$$\eta_t(t-T) = 1 + a(t-T) + b(t-T)^2,$$

which permits the temporal pattern of technical efficiency effects to be convex or concave rather than simply increasing or decreasing at a constant rate.

17.3.3.1 Implementation

The model is:

$$y_{it} = x_{it}\beta + \eta_i(t) + v_{it} \tag{11}$$
$$\eta_i(t) = e^{-\eta(t-T)}u_i, \tag{12}$$

where the u_i's are assumed to follow the non-negative truncated $N(\mu,\sigma^2)$ distribution whose density is

$$f_{U_i}(u_i) = \frac{\exp\left[-\frac{1}{2}(u_i - \mu)^2/\sigma^2\right]}{(2\pi)^{1/2}\sigma[1 - \Phi(-\mu/\sigma)]}, \qquad u_i \geq 0$$

and where Φ is the cumulative distribution function of the standard normal random variable. The v_{it}'s are assumed i.i.d. $N(0,\sigma_v^2)$ and are independent of the u_i's. Let y_i be the $(T_i \times 1)$ vector of production level of firm i, and denote $y = (y_1', y_2', \ldots, y_N')$. Then the density function of y_i can be easily derived from the density of ϵ_i and log-likelihood function $L(\beta, \sigma_v^2, \sigma^2, \mu, \eta; y; x)$ for the model is given in Battese and Coelli (1992).

The minimum-mean-squared-error predictor of the efficiency for country (firm) i at time t is

$$E[\exp(-u_it)|\epsilon_i] = \left\{\frac{1 - \Phi[\eta_{it}\sigma_i^* - (\mu_i^*)/\sigma_i^*]}{1 - \Phi(-\mu_i^*/\sigma_i^*)}\right\}\exp\left[-\eta_{it}\mu_i^* + \frac{1}{2}\eta_{it}^2\sigma_i^{*2}\right]$$

where $\mu_i^* = \frac{\mu\sigma_v^2 - \eta_i'e_i\sigma^2}{\sigma_v^2 + \eta_i'\eta_i\sigma^2}$ and $\sigma_i^* = \frac{\sigma^2\sigma_v^2}{\sigma_v^2 + \eta_i'\eta_i\sigma^2}$. Estimates of technical change due to innovation would be based on the coefficient of a time trend in the regression. The

effect of innovation as distinct from catch-up is identified by the non-linear time effects in the linear technical efficiency term and thus the decomposition of *TFP* growth into a technological change and efficiency change component is quite natural with this estimator. Cuesta (2000) generalized Battese and Coelli (1992) by allowing each country (firm, etc.) to have its own time path of technical inefficiency. Extensions of the Battese and Coelli model that allow for technical inefficiency to be determined by a set of environmental factors that differ from those that determine the frontier itself are given in Battese and Coelli (1995). These were also addressed by Reifschneider and Stevenson (1991) and by Good, Roeller, and Sickles (1995). Environmental factors that were allowed to partially determine the level of inefficiency and productivity were introduced in Cornwell, Schmidt, and Sickles (CSS) (1990) and in Good, Nadiri, Roeller, and Sickles (1993).

17.3.4 The Park, Sickles, and Simar (1998, 2003, 2006) Models

Park, Sickles, and Simar (PSS; 1998, 2003, 2007) considered linear stochastic frontier panel models in which the distribution of country-specific technical efficiency effects is estimated nonparametrically. They used methods developed in the statistics literature to estimate robust standard errors for semi-nonparametric models based on adaptive estimation techniques for semiparametric efficient estimators. They first consider models in which various types of correlations exist between the effects and the regressors (PSS 1998). These minimax-type estimators ensure that the variances of the estimators are the smallest within the set of variances based on the class of parametric sub-models built up from the basic parametric assumptions of the model and the use of nonparametric estimators (they utilize multi-variant kernel-based estimators) for the remaining portion of the model specified in terms of nuisance parameters. The nuisance parameters are the effects, the variances of the parametric disturbance terms, and the bandwidth parameters. In PSS (2003) they extend the basic model to consider serially correlated errors and in PSS (2006) consider dynamic panel data models. In our discussion of this class of estimators we will only consider the most basic model set up in PSS (1998). Details for the semiparametric efficient panel data efficiency model with serially correlated errors or with a dynamic structure can be referred to PSS (2003, 2006). In the empirical application to estimate world productivity growth we utilize three of the estimators discussed by PSS. PSS1 is the estimator outlined above. PSS2W is the within version of the semiparametric efficient estimator with serially correlated errors to control for potential misspecified dynamics while PSS2G is the corresponding random effects version of the estimator (PSS 2003).

The basic set up of the model is again the canonical linear panel data with cross-sectionally and time varying efficiency effects given by

$$y_{it} = X'_{it}\beta + \eta_i(t) + v_{it},$$

where v_{it}'s are the statistical noise that are independently and identically distributed with $N(0, \sigma^2)$, $\eta_i(t)$ are bounded above (or below for the cost frontier model). The $(\eta_i(t), X_i)'s$ are assumed to be independently and identically distributed with some joint density $h(\cdot, \cdot)$.

PSS (1998) discuss three different cases for the dependency between the firm effects, η, and the other regressors, X. Their case 1 assumes no specific pattern of dependency between η and X, which leads to a semiparametric efficient estimator similar to the fixed effects estimator of Schmidt and Sickles (1984) and its extension to time-varying efficiency models of CSS (1990). Their case 2 assumes the firm effects are correlated with a subset of other explanatory variables, $Z \in X$. Case 3 assumes that α affects Z only through its long run changes (average movements) $\bar{Z}$. The semiparametric efficient estimators of case 2 and 3 are analogous to those proposed in Hausman and Taylor (1981), and extended to the stochastic frontier literature in CSS (1990). Derivations of the semiparametric efficiency bound and of the adaptive estimators for these many specifications are too detailed for this chapter. The interested reader is referred to the PSS papers referenced above for details. Once the parameters have been estimated the method utilized in CSS (1990) can be used to estimate the technical efficiencies and their temporal changes. As with the CSS estimator, innovation change that is shared by all countries or firms and modeled using a time trend may be identified separately from technical efficiency based on the orthogonality conditions imposed in cases 2 and 3. In case 1, which collapses to the CSS within estimator, no such distinction can be made and, although *TFP* growth can be calculated, it cannot be decomposed into innovation and catch-up.

17.3.5 The Latent Class Models of Greene, Kumbhakar, and Tsionas

In stochastic frontier models the production or cost functional relationship is usually set uniformly for all countries or firms, implying that the same technology is used as the benchmark and that relative to that benchmark countries or firms perform with different levels of efficiency. Although other authors have questioned this assumption and have provided estimators that address this issue in part, Orea and Kumbhakar (2004), Tsionas and Kumbhakar (2004), Greene (2005b), were the first to address it in such a general fashion. Their logic is clear and the arguments compelling and relate to work on production heterogeneity by Mundlak (1961, 1978) and Griliches (1979), among others. Countries that have access to the world technology, or firms within a certain industry, have different sizes, innovation abilities, targeting groups, etc., and may operate with different technologies that can take advantage of different market niches. Imposing the same functional form in the model may misidentify differences in the technology applied as technical inefficiency when it fact in is due to the appropriate

use of the available technology to a different (or constrained) set of market conditions. We have discussed this issue in earlier sections. Such constrained conditions are nonetheless suboptimal to the benchmark we establish and estimate and the technical efficiency component of *TFP* growth remains silent on the source of the technical inefficiency. That said, it is important to find a way to empirically parse the sources of variation into one may regard is or is not technical inefficiency. A straightforward way to deal with this problem is to group countries or firms into different categories by some obvious criteria and then analyze their *TFP* growth separately. We do this below in our empirical analysis of world productivity growth. In general the grouping criteria can be information about certain characteristics of countries (e.g., region, level of development, etc., or some combination of these and many other characteristics) or firms (e.g., size, location etc.), or can be based on some statistical clustering algorithm. Were these analyses to be done separately, then it is clear that information represented by correlation between different groups would not be utilized. It may also be the case that the parameters of such models can not be identified by distinct categories and thus the suitability of the grouping criteria cannot be established empirically.

In the latent class stochastic frontier model there exist J unobserved classes in the panel data giving rise to a specification of the production (or distance) function as:

$$y_{it} = x'_{it}\beta_j + \eta_i(t)|j.$$

The observed dependent variable is characterized by a conditional density function:

$$g(y_{it}|x_{it}, class_j) = f(\Theta_j, y_{it}, x_{it}).$$

The functional form $f(\cdot)$ is the same over the entire sample, while the parameter vector Θ_j is class-specified and contains all of the parameters of the class specific parameterization of the function. The inefficiency terms are latent class-specific and take the form of $\eta_i(t)|j$ and are assumed to distributed as half normal. The likelihood coming from country or firm i at time period t is

$$P(i,t|j) = f(y_{it}|x_{it};\beta_j,\sigma_j,\lambda_j) = \frac{\Phi(\lambda_j\eta_i(t)|j)}{\Phi(0)}\frac{1}{\sigma_j}\phi\left(\frac{\eta_i(t)|j}{\sigma_j}\right),$$

where $\eta_i(t)|j = y_{it} - x'_{it}\beta_j$. Assuming the inefficiency terms to be i.i.d. draws over time the conditional likelihood for country or firm i is

$$P(i|j) = \prod_{t=1}^{T} P(i,t|j)$$

and the unconditional likelihood function is

$$P(i) = \sum_{j=1}^{J}\Pi(i,j)P(i|j) = \sum_{j=1}^{J}\Pi(i,j)\prod_{t=1}^{T}P(i,t|j).$$

Here $\Pi(i,j)$ is a prior probability that establishes the distribution of firms in different classes. A relatively simple and noninformative prior is the uniform where $\Pi(i,j) = \Pi(j)$, for $i = 1,\ldots,N$. In order to allow for heterogeneity in the mixing probabilities one can adopt the multinomial logit form,

$$\Pi(i,j) = \frac{\exp(\theta_i'\pi_j)}{\sum_{m=1}^{J} \exp(\theta_i'\pi_m)}, \quad \pi_J = 0.$$

The parametric log likelihood is

$$\log L = \sum_{i=1}^{N} \log P(i),$$

Although the specification outlined by Greene (2005b) assumed that inefficiency was independent over time, the latent class model proposed by Orea and Kumbhakar (2004) allows technical efficiency change over time by following a path given by an exponential function reminiscent of earlier estimators by Battese and Coelli (1992) and Kumbhakar (1990)

$$\eta_i(t)|j = \gamma_{it}(\eta_j) \cdot \zeta_{i|j} = \exp(z_{it}'\zeta_j) \cdot \zeta_{i|j}.$$

where $z_{it} = (z_{1it},\ldots,z_{Hit})'$ is a vector of time-varying variables and $\zeta_j = (\zeta_{1j},\ldots,\zeta_{Hj})'$ the associated parameters. With such a changing path, the individual likelihood in their model is defined directly over all time periods.

17.3.5.1 Implementation

The parametric log likelihood function is maximized to solve for parameter vector Θ_j and probability π_j simultaneously. Greene (2005b) employed an Expectation-Maximization (EM) algorithm. Alternatively, the model can also be estimated using Bayesian methods (see Tsionas and Greene, 2003b). Explicit derivations can be found in Greene (2005). After classifying firms into different groups, firm-specific parameters can be estimated. After the parameters of the underlying production or distance function are estimated and the time varying effects $\eta_i(t)|j$ are identifed for class j the decomposition of *TFP* into an innovation change component and catch-up or technical efficiency component is complete.

17.3.6 The Kneip, Sickles, and Song (2012) Model

Here we assume a linear semiparametric model panel data model that allows for an arbitrary pattern of technical change $\eta_i(t)$ based on a factor model. The model takes the form

$$y_{it} = \beta_0(t) + \sum_{j=1}^{p} \beta_j x_{itj} + \eta_i(t) + v_{it}.$$

Here the $\eta_i(t)$'s are assumed to be smooth time-varying individual effects and identifiability requires that $\sum_i \eta_i(t) = 0$. $\beta_0(t)$ is some average function (or common factor) shared by all of the cross-sectional units, such as countries or firms. For purposes of developing the estimator of $\eta_i(t)$ we eliminate the common factor. However, once we have estimated the $\beta'_j s$ and the $\eta_i(t)$ terms, we can recover the common factor. For purposes of using this model as a vehicle for estimating *TFP* growth, the common factor will identify the common innovation that changes over time, while the $\eta_i(t)$ term will, after the suitable normalization developed above for the CSS counterpart, provide us with relative efficiency levels and thus their growth rates to allow for *TFP* growth to be decomposed into its two constituent parts, innovation change and technical efficiency change. The centered form of the model is

$$y_{it} - \bar{y}_t = \sum_{j=1}^{p} \beta_j(x_{itj} - \bar{x}_t j) + \eta_i(t) + v_{it} - \bar{v}_i,$$

where $\bar{y}_t = \frac{1}{n}\sum_i y_{it}$, $\bar{x}_{tj} = \frac{1}{n}\sum_i x_{itj}$ and $\bar{v}_i = \frac{1}{n}\sum_i v_{it}$. Here $\eta_i(t)$ is assumed to be a linear combination of a finite number of basis functions

$$\eta_i(t) = \sum_{r=1}^{L} \theta_{ir} g_r(t).$$

This construction is more flexible and realistic than parametric methods, which presume the change of individual effects follow some specified functional form, and the multiplicative effects models of Lee and Schmidt (1993), Ahn, Lee, and Schmidt (2007), Bai (2009), and Bai and Ng (2011). The model can be rewritten as

$$y_{it} - \bar{y}_t = \sum_{j=1}^{p} \beta_j(x_{itj} - \bar{x}_{tj}) + \sum_{r=1}^{L} \theta_{ir} g_r(t) + v_{it} - \bar{v}_i.$$

The authors introduce a suitable standardization to identify a specific basis they use in their model which results in a set of g_r's that are orthogonal and θ_{ir}'s that are empirical uncorrelated. Letting $\eta_1 = (\eta_1(1), \ldots, \eta_1(T))', \ldots, \eta_n = (\eta_n(1), \ldots, \eta_n(T))'$, then the empirical covariance matrix of $\eta_1, \ldots, \eta_n$ is $\Sigma_{n,T} = \frac{1}{n}\sum_i \eta_i \eta'_i$. Let $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_T$ be the eigenvalues of the matrix, and $\gamma_1, \gamma_2, \cdots, \gamma_T$ be the corresponding eigenvectors. Then the basis functions will be

$$g_r(t) = \sqrt{T} \cdot \gamma_{rt} \qquad \text{for all} \quad r = 1, \ldots; t = 1, \ldots, T \tag{13}$$

$$\theta_{ir} = \frac{1}{T}\sum_t v_i(t) g_r(t) \qquad \text{for all} \quad r = 1, \ldots; i = 1, \ldots, n \tag{14}$$

$$\gamma_r = \frac{T}{n}\sum_i \theta_{ir}^2 \qquad \text{for all} \quad r = 1, \ldots \tag{15}$$

And for all $l = 1, 2, \ldots$

$$\sum_{r=l+1}^{T} \gamma_r = \sum_{i,t} \left(\eta_i(t) - \sum_{r=1}^{l} \theta_{ir} g_r(t) \right)^2$$

$$= \min_{\tilde{g}_1, \ldots, \tilde{g}_l} \sum_{i} \min_{\tilde{\vartheta}_{i1}, \ldots, \tilde{\vartheta}_{il}} \sum_{t} \left(\eta_i(t) - \sum_{r=1}^{l} \vartheta_{ir} \tilde{g}_r(t) \right)^2. \tag{16}$$

$\eta_i(t) \approx \sum_{r=1}^{l} \theta_{ir} g_r(t)$ will be the best l-dimensional linear estimate, and the dimension L naturally equals to $rank(\Sigma_{n,T})$. It can be shown that for selected values of L the normalizations imply basis functions that correspond to the standard fixed effect estimator, the CSS (1990) estimator and the Battese and Coelli (1992) estimator. Kneip, Sickles, and Song (2012) provide asymptotic results for large N and large T.

17.3.6.1 Implementation

Since the η_i's are assumed to be smooth trends, we can always find m-times continuously differentiable auxiliary functional variable ν_i's with domain $[1, T]$ that can interpolate the T different values of η_i. Their method first estimates β and obtains the approximations ν_i by smoothing splines (Eubank 1988). This then determines the estimates of the basis functions $\hat{g}_r$ through the empirical covariance matrix $\hat{\Sigma}_{n,T}$, which is estimated by the $(\widehat{\eta}_1, \ldots, \widehat{\eta}_n) = (\hat{\nu}_1, \ldots, \hat{\nu}_n)$. The corresponding coefficients of the basis functions will be obtained by least squares. In the last step, they update the estimate of η_i by $\sum_{r=1}^{L} \hat{\theta}_{ir} \hat{g}_r$, which is proved to be more efficient than the approximations ν_i. Returning to the non-centered model, the general average function $\beta_0(t)$ is left unestimated. A non-parametric method similar to step 1 can be applied to get an approximation. An alternative is to assume $\beta_0(t)$ also lies in the space spanned by the set of basis functions, that is, $\beta_0(t) = \sum_{r=1}^{L} \bar{\theta}_r g_r(t)$. The coefficients can then be estimated by a similar minimization problem as step 3 with objective function $\sum_t (\bar{y}_t - \sum_{j=1}^{p} \hat{\beta}_j \bar{x}_{tj} - \sum_{r=1}^{L} \vartheta_r \hat{g}_r(t))^2$. The common factor $\beta_0(t)$ is interpreted as the shared technological innovation component and the $\eta_i(t)$ the technical efficiency component whose growth constitute *TFP* growth.

17.3.7 Ahn, Lee, and Schmidt (2013)

17.3.7.1 Model

Ahn, Lee, and Schmidt (2013) generalize Ahn, Lee, and Schmidt (2007) and consider a panel data model with multiple individual effects that also change over time:

$$y_{it} = x_{it}' \beta + \sum_{j=1}^{p} \xi_{tj} \alpha_{ij} + \epsilon_{it}. \tag{17}$$

They focus on large N and finite T asymptotics. They develop a consistent estimator for the slope coefficients β when there is correlation between individual effects and the regressors. To emphasize this feature, the model interprets ξ_{tj} as "macro shocks," and α_{ij} as "random coefficients" instead of "factors" and "factor loadings," though the model itself resembles the factor models. This model takes the form of the canonical model considered above by other researchers as it can be written as

$$y_{it} = X'_{it}\beta + \eta_i(t) + v_{it}.$$

The model for individual i in matrix form is:

$$y_i = X_i\beta + u_i, \qquad u_i = \eta_i + \epsilon_i = \Theta\alpha_i + \epsilon_i, \tag{18}$$

where $y_i = (y_{i1}, \dots, y_{iT})'$ is the dependent variable vector, $X_i = (x_{i1}, \dots, x_{iT})'$ is the $T \times K$ matrix of regressors, and β is the dimension-comformable coefficients vector. The error term u_i is composed of the random noise ϵ_i and individual effects $\eta_i = \Theta\alpha_i$. Θ is a $T \times p\,(T > p)$ matrix containing p macro shocks that vary over time. The random noise ϵ_{it} is usually assumed to be white noise to assure consistent estimates of coefficients in the case of large N and small T. This model relaxes this assumption in that it allows any kind of autocorrelation of ϵ_i and only assumes that ϵ_i is uncorrelated with regressors x_{it} while α might be correlated with x_{it}. Then for identification, it is assumed there exist instrument variables that are correlated with α_{ij} but not with ϵ_{it}.

17.3.7.2 Implementation

Due to the need for a particular rotation, it is not possible to separate the effects of Θ and α. For identification, Θ is normalized such that $\Theta = (\Theta'_1, -I_p)'$ with Θ_1 a $(T - p) \times p$ matrix. With instruments, the GMM method proposed in Ahn et al. (2001) is extended to incorporate multiple time-varying effects and two methods are proposed to estimate the true number of individual effects. They first obtain consistent estimators of β and Θ assuming the true number of effects p_0 is known, and then estimate p using their new test statistic. Detailed assumptions and discussion can be found in the paper as well as how to extract the efficiency and innovation change measures for productivity measures.

17.3.8 Additional Panel Data Estimators of in the Stochastic Frontier Literature

Space limits the possibility of dealing with the many other approaches that have been proposed to estimate the panel stochastic frontier and provide a decomposition of *TFP* growth into innovation and catch-up, or technical efficiency. Additional estimators that have been proposed for panel stochastic frontiers and that are also quite appropriate for general panel data problems are the *Bayesian Stochastic Frontier Model* (Liu,

Sickles, and Tsionas 2013), which builds on earlier work by Van den Broeck et al. (1994) and Tsionas (2006), the *Bounded Inefficiency Model* of Almanidis, Qian, and Sickles (2013) and related models of Lee (1996), Lee and Lee (2012), and Orea and Steinbuks (2012), and the *"True" Fixed Effects Model* of Greene (2005a,b). Kumbhakar, Parmeter, and Tsionas (2013) have recently considered a semiparametric smooth coefficient model to estimate the *TFP* growth of certain production technologies that addresses the *Skewness Problem* in classical SFA modeling considered by Feng, Horrace and Wu (2012), Almanidis and Sickles (2012) and Almanidis, Qian, and Sickles (2013). Recent work on spatial heterogeneity in SFA models has focused on new interpretations and measurement of spillovers in substitution possibilities, returns to scale, productivity change, and efficiency change that is spatially dimensioned instead of simply varying over time for particular firms, industries, or countries. The *Spatial Stochastic Frontier* shows great promise and has been pursued in recent work by Glass, Kenjegalieva, and Sickles (2013 a, b) based on the original contribution by Druska and Horrace (2004). Work on productivity measurement in the presence of spatial heterogeneity has also recently been pursued by Mastromarco and Shin (2013), Entur and Musolesi (2013), and Demetrescu and Homm (2013). Such spatial methods are alternatives to less structured approaches to address cross-sectional dependence in panel data models using methods such as those developed by Pesaran (2007). *Factor Models* continue to be pursued in the context of productivity modeling in panel data contexts and the space for such approaches is getting quite dense as pointed out by Kneip and Sickles (2012).

17.4 DISCUSSION ON COMBINING ESTIMATES

A solution to model uncertainty is to develop a consensus estimate by weighting or combining in some fashion estimates from various competing models. Sickles (2005) pursued this strategy in his examination of semiparametric and nonparametric panel frontier estimators. Burnham and Anderson (2002) provided a lucid and rather complete discussion of model selection criteria. However, they point out that the model selection exercise itself introduces uncertainty into the estimation process and any forecasts that result, a point also made by Hjorth (1994) and Leeb and Potscher (2005). As one can view all models as approximations and thus subject to misspecification, combining results from different models can be viewed as similar to constructing a diversified portfolio in order to reduce the risk of relying on on particular stock, of in our case, model.

Typical model selection from some encompassing supermodel can be viewed as a special case of weighting models which assigns the entire weight on one model and none on others. We do not pursue this approach in our empirical work below. Instead we utilize Insights from economics and from statistics to motivate several canonical methods to combine estimates and forecasts from a variety of potentially misspecified models. These insights are discussed in more depth in the cited works. We utilize

approaches to weighting outcomes from different models and estimators using the economic arguments of *majority voting* from the literature on social choice theory (see Moulin 1980) as well as the *contest function* of Tullock (1980); insights from statistics based on *model averaging*[4] in order to assess the proper weights to construct the weighted average; and the literature on optimal weights used in *combining forecasts*[5]. These studies provide the rationale for how we combine our many results into summary measures of weighted means and variances.

17.5 Modeling World Economic Growth with the UNIDO Data

The proper measurement of nations' productivity growth is essential to understand current and future trends in world income levels, growth in per/capita income, political stability, and international trade flows. In measuring such important economic statistics it is also essential that a method that is robust to misspecification error is used. This section of the chapter addresses the robustification of productivity growth measurement by utilizing the various economic theories explaining productivity growth as well as various estimators consistent with those particular theories. We utilize the World Productivity Database from the UNIDO to analyze productivity during the period 1970–2000 and combine and consolidate the empirical findings from a number of the statistical treatments and various economic models of economic growth and productivity that we have discussed above.

We address the heterogeneity problem in part by grouping countries according to their geographical and, for the OECD countries, their development characteristics as well as by the use of various panel data techniques. We construct consensus estimates of world productivity *TFP* growth as well as confidence intervals and find that, compared to efficiency catch-up, innovation plays a much more important factor in generating *TFP* growth at this level of country aggregation.

17.5.1 UNIDO Data Description

The World Productivity Database (WPD) provides information on measures of the level and growth of *TFP* based on 12 different empirical methods across 112 countries over the period 1960–2000. Those interested in the data and variable construction should visit the UNIDO website http://www.unido.org/statistics.html. In our analysis we utilize two factor (capital and labor) aggregate production function determining a country's level of aggregate output.

17.5.2 Empirical Findings

Comparisons of productivity changes are made among Asian, Latin American, and OECD regions. The following methods are used to estimate *TFP* change and its decomposition into technological and technical efficiency change when possible: CSSG, EIV, BC, PSS1, PSS2W, PSS2G, two fixed-effect estimators and two random-effect estimators.

There are 10 different methods to estimate *TFP* growth and 6 different methods to estimate the decomposition of *TFP* growth into innovation and technical efficiency change. Data limitations forced us to use only three of the four possible capital measures, K06, Keff, and Ks along with the two labor measures, LF and EMP as well as data only from 1970 to 2000. The results are based on 60 different sets of estimates. The panel estimators are used to estimate productivity growth and its decomposition methodologies for countries in Asia (13 countries), Latin America (12 countries), and the OECD (24 countries). The specific countries in **Asia** are: Bangladesh, China, Hong Kong (SAR of China), India, Indonesia, Israel, Malaysia, Pakistan, Philippines, Singapore, Sri Lanka, Taiwan (Province of China), and Thailand. The countries in **Latin America** are: Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, Guatemala, Jamaica, Panama, Peru, Trinidad and Tobago, and Venezuela. Finally, the countries in the **OECD** are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Japan, Republic of Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, and United States.

Our approach considers a Cobb-Douglas production function with two explanatory variables: Capital and Labor. The various measures we adopt to measure the two inputs are largely based on data limitations. K06 and K013 utilize a perpetual inventory method to measure capital services and differ based on differing but constant depreciation rates (6% and 13.3%, respectively, which correspond to about 12 and 6 year asset lives). A different way of measuring capital focuses on the profile of capital productivity and utilizes a time-varying depreciation rate. As the asset ages, its capital declines at an increasing rate. This leads to Keff. Labor input measurement involves two kinds of labor utilization rates for which labor force (LF) can be adjusted, variations in numbers employed and in hours worked. Again, for reasons of data limitations we use the second adjustment and also consider employment (EMP). Thus each region has 6 combinations of inputs. In addition to the 6 we have discussed above, we also include four simple panel data estimators (FIX1 is a fixed effect model including t as explanatory variable, FIX2 is a fixed effect model with t and t^2 as explanatory variables. RND1 is a random effect model including t as explanatory variable, RND2 is a random effect model with t and t^2 as explanatory variables). The estimation results (Table 1) are too numerous to include in this chapter and are available on the Sickles website at http://rsickles.blogs.rice.edu/files/2014/04/Figures-and-Tables.pdf as are summary results in Figures 1–8 referred to below.

We decompose *TFP* into technical efficiency change and innovation or technical change. Technical efficiency for each country is defined as the radial distance from the (possibly shifting) production frontier in a given period (Debreu 1951; Farrell 1957). The estimation methods for this component have been included in all standard stochastic frontier literature. Results are presented in Figure 1 for each of the three regions. We summarize the outcomes of technical efficiency by three different averages. The first two methods are simple average and geometric average. Since countries have different GDP sizes, instead of simply averaging in each period, it is natural to weigh the results by each country's GDP. The traditional fixed effect model and the random effect model do not estimate technical efficiency, therefore, there are 6 models for technical efficiency change in each region. From the figures, it is apparent that Asian countries' technical efficiency improvements have been on a decreasing trend since the late 1970s. Latin American countries' technical efficiency changes have been very small in magnitude. OECD countries' technical efficiency improvements increased until the mid- to late 1980s then started to decline. In the Asian countries, GDP weighted averages are somewhat larger than simple averages, which indicates that larger GDP countries (particularly China) have more technical improvements than smaller GDP countries. For OECD countries we have the opposite observation, which indicates smaller GDP countries on average have more technical efficiency improvements than larger GDP countries (such as the United States).

Technical innovation change is measured as the shift of the frontier between periods, or the time derivative of each model. In our study, we assume a constant rate of technological innovation, thus innovational progress is the coefficient of time variable. We have 60 estimates for each region as presented in Figure 2. Asian countries have the largest innovation changes among all regions on average, at around 1.56% per year. Latin American countries display very small magnitudes of innovation change. On average, the region has 0.3% increase of progress per year. OECD countries' average innovation improvement is about 0.73% per year.

TFP change is the sum of technical efficiency change and technical innovation change. As seen in Figure 3, Asian countries have the highest *TFP* improvements through the years, mainly because the innovation progress outperforms the declining trend of technical efficiency. Latin American countries have almost nonexistent improvements in productivity in most years. They even have negative TFP growth rates in a few years at the beginning and end of the sample period. OECD countries' *TFP* performances are between those of Asia and Latin America, although the trend has been decreasing throughout the periods. The overall *TFP* growth between 1972 and 2000 is 61.2% for Asian countries, 24.7% for OECD countries, and 7.46% for Latin American countries. We also used three averaging approaches to aggregate three regions to demonstrate the global trends of TFP growth, which are shown in Figure 4. These results appear to be comparable to other recent international studies based on index number approaches (Badunenko, Henderson, and Russell 2013).

Next we report the Solow Residual (hereinafter SR). The SR results based on GDP weighted growth rates across all the methods and combinations are presented in Figure 6. The average of SR is 0.78% for Asian countries, −0.07% for Latin American, countries and 0.37% for OECD countries. One of the major shortcomings of SR and growth accounting in general as pointed out by Chen (1997) is that the SR cannot differentiate disembodied technological change (similar to our definition of innovational progress) from embodied technological change (similar to our definition of efficiency change). Failure to separate different effects in addition to the input measurement problems makes *TFP* estimates using growth accounting somewhat difficult to interpret and decompose. We can decompose *TFP* into efficiency catch-up and innovation and provide a solution to this problem.

The last results we wish to discuss are the combined estimates (Figure 8). As discussed above, the motivation of employing a model averaging exercise is to obtain some consensus results based on all the competing models and data at hand. The simplest averaging is to take the arithmetic mean of all estimates, which implicitly assumes the equal importance of all models. The annual changes of technical efficiency, technical innovation, and *TFP* are −0.07%, 1.63%, and 1.56% for Asian countries, 0.01%, 0.24%, and 0.25% for Latin American countries, and −0.05%, 0.84% and 0.79% for OECD countries. The most crucial component of all "combining estimates methods" such as model averaging is how the weights are assigned. Besides simple averaging, we use four statistical criteria to assign weights. First, we simply assign weights according to R-square of each model. Since R-squares in our estimations are all close to each other, weighted results are very close to simple averaging results: technical efficiency, technical innovation, and *TFP* changes are −0.07%, 1.62%, and 1.55% for Asian countries, 0.02%, 0.22%, and 0.23% for Latin American countries, and −0.05%, 0.84%, and 0.79% for OECD countries. The second way is to set the weights as reciprocals of residual sum of squares (hereinafter RSS). RSS is a simple measure of how much the data are not explained by a particular model. Annual technical efficiency, technical innovation, and *TFP* changes are −0.04%, 1.52%, and 1.47% for Asia countries, 0.01%, 0.19%, and 0.20% for Latin American countries, and −0.04%, 0.75%, and 0.71% for OECD countries. The third method is to choose weights according to AIC. Since all the models in our study use the same variables on the same data set, we would have a simple expression of AIC, which only depends on RSS. So the results of the third method should be close to the second one. The annual technical efficiency, technical innovation, and *TFP* changes are −0.08%, 1.59%, and 1.52% for Asian countries, 0.02%, 0.18%, and 0.21% for Latin American countries, and −0.06%, 0.81%, and 0.75% for OECD countries. The last method is to use BIC as weights. BIC depends not only on RSS but also on the estimated variance of the error term. The annual technical efficiency, technical innovation, and *TFP* changes are −0.12%, 1.70% and 1.58% for Asian Countries, 0.01%, 0.20%, and 0.20% for Latin American Countries, and −0.15%, 0.88%, and 0.73% for OECD countries. As shown in the Figure 8, combined estimates of all criteria are rather similar. All of the methods we utilize tell us that

the during the 29 years span, the improvements of Asian countries and OECD countries' technical efficiencies are deteriorating. Even though Latin America countries have improved technical efficiency (very small in magnitude), because of its slower innovational progress, their *TFP* improvement has lagged behind not only Asian countries but also OECD countries. For inference purpose, the variances of combined estimates can also be calculated (Burnham et al. 2002; Huang and Lai 2012). Our results indicate significant positive *TFP* growth in Asian and the OECD while *TFP* growth in Latin America is not significantly different than zero.[6]

17.6 Conclusions and Suggestions for Future Research

In this chapter, we have focused on the role that panel data econometrics plays in formulating and estimating the most important contributors to productivity growth: innovation and catch-up. We have explained different theories on economic growth and productivity measurement and the econometric specifications they imply. Various index numbers and regression-based approaches to measuring productivity growth and its innovation and catch-up components have been discussed in detail. We have also discussed methods that can be used to combine results from the many different perspectives on how economic growth is modeled and estimated, focusing on methods used in model averaging and in the combination of forecasts. As this chapter is to provide the reader with an applied perspective, we have utilized these various panel data and model averaging methods in an analysis of world productivity growth using the World Productivity Database gathered by the United Nations Industrial Development Organization (UNIDO). We study Asian, Latin American, and OECD countries between 1970 and 2000 and find that Asian countries had the fastest *TFP* growth among the three regions, due largely to relatively rapid technical innovation. OECD countries made more moderate gains in *TFP* growth, again due largely to technical innovation as opposed to catch-up. Latin American countries overall had the slowest growth rate in TFP, although they had consistently managed positive improvements in both technical and technological efficiencies.

There are a number of research topics that we were not able to cover in this chapter. Allocative distortions as opposed to the radial technical inefficiency we have posited in our panel studies was not addressed, nor was the nascent literature on developing coverage intervals for relative efficiency levels and rankings of countries or firms. The models are of course linear and thus structural dynamic models that incorporate inefficiency as well as models that address, at a firm or industry level, the impact that deviations from neoclassical assumptions of perfectly coordinated allocations with no technical (or cost) inefficiency, may have on firm or industry level productivity has not been examined. These are areas for future research and we encourage those interested

in the intersection of more traditional productivity research, new productivity research that addresses imperfect decision making, and panel methods to pursue these topics.

Acknowledgments

Notes

1. For a survey of some of Jorgenson's voluminous work on productivity, see Dale W. Jorgenson's *Productivity*, Vol. 1 and 2 1995), Vol. 3 (2005).
2. For Griliches's work on this subject, the reader should consult the working papers of the NBER Productivity Program over the years before his untimely death in 1999, and over the years since. Mairesse (2003) contains a thoughtful overview of his many contributions to the field of productivity measurement.
3. The NBER Productivity, Innovation, and Entrepreneurship Program was led originally by Griliches who was followed by Ernst Berndt and is currently co-directed by Nicholas Bloom and Josh Lerner.
4. See, for example, Leeb and Potscher (2005), Buckland *et al.* (1997), Akaike (1973), Mallows (1973), Schwarz (1978), Hansen (2007), Carroll *et al.* (2006), Burnham and Anderson (2002), Claeskens and Hjort (2008), Raftery *et al.* (1997), Hoeting *et al.* (1999), and Koop *et al.* (2007), Timmermann (2006).
5. Se, for example, Newbold and Harvey (2002), Bates and Granger (1969), Diebold and Lopez (1996), Lahiri, et al. (2011), Clemen (1989), Timmermann (2006), Lahiri and Shaeng (2010), Zarnowitz and Lambros (1987), Lahiri and Sheng (2010), Lahiri, Peng and Sheng. (2010), Davies and Lahiri (1995), and Lahiri, Teighland, and Zaprovski (1988).
6. A more detailed discussion of the Asian experience is discussed in Sickles, Hao, and Sheng (2014).

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