

Heshmati, Almas; Rashidghalam, Masoomah

Working Paper

Estimation of Technical Change and TFP Growth based on Observable Technology Shifters

GLO Discussion Paper, No. 8

Provided in Cooperation with:

Global Labor Organization (GLO)

Suggested Citation: Heshmati, Almas; Rashidghalam, Masoomah (2017) : Estimation of Technical Change and TFP Growth based on Observable Technology Shifters, GLO Discussion Paper, No. 8, Global Labor Organization (GLO), Maastricht

This Version is available at:

<https://hdl.handle.net/10419/152325>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Estimation of Technical Change and TFP Growth based on Observable Technology Shifters

Almas Heshmati¹ and Masoomeh Rashidghalam²

¹ Department of Economics, Sogang University,
Seoul, Korea, and
IZA Institute of Labor Economics
E-mail: heshmati@sogang.ac.kr

² Department of Agricultural Economics,
University of Tabriz, Tabriz, Iran
E-mail: maso.azar@gmail.com

November 30, 2016

Abstract

This paper models and estimates total factor productivity (TFP) growth parametrically. The model is a generalization of the traditional production model where technology is represented by a time trend. TFP growth is decomposed into unobservable technical change, scale economies and observable technology shifter index components. The empirical results are based on an unbalanced panel data at the global level for 190 countries observed over the period 1996-2013. A number of exogenous growth factors are used in modeling four technology shifter indices to explore development infrastructure, finances, technology and human development determinants of TFP growth. Our results show that unobservable technical changes remain the most important component of TFP growth. The observable technology indices-based component is lower than the simple unobserved time trend model based one. By comparing the performance of the time trend and technology index models in terms of TFP growth rates, we arrive at the conclusion that the technology index model predicts a more realistic picture of the TFP growth pattern as compared to the traditional time trend model. Our results also indicate that technical change and TFP growth are negative across country groups and years in the technology index model influenced by the global economic crisis.

Keywords: Technical change, total factor productivity growth, technology indicators, technology shifters.

JEL Classification Codes: C33; C43; D24; O33; O47; O50.

1. Introduction

Growth of total factor productivity (TFP) provides society with an opportunity to increase the economic welfare of the people. It is, therefore, worthwhile to ask: What determinants should policymaking focus on to enhance the performance of TFP growth. Literature on technical change (TC) and TFP growth can be classified into four groups (Diewert, 1981): parametric estimation, non-parametric indices, exact index numbers and linear programming approaches for measuring technical change and TFP growth.

Following Solow (1957) the studies in the first group use parametric estimations of production and cost functions which are based on an estimation of the Cobb-Douglas production functions. Solow proposed the existence of an exogenous residual capturing TFP and argued that cross-country differences in this exogenous residual (that is, in TFP) might generate important cross-country differences in income per capita (Isaksson, 2007). The main issue with this approach, known as the residual approach, is that it assumes that all the production units are efficient and no distinction is made between technical progress and changes in technical efficiency. In other words, no separate adjustments for technical improvements (changes in efficiency) embodied in labor or capital stock are considered (Danquah et al., 2014). The other issue is that although lots of studies have focused on specific variables which affect productivity (for example, Benhabib and Spiegel, 1994, 2005; Barro, 1991; Kneller and Stevens, 2006; Miller and Upadhyay, 2000; Vandenbussche et al., 2006), no attempt has been made to search for the main determinants of TFP growth and its components in these studies. Collins and Bosworth (1996) and Nehru and Dhareshwar (1993) are two other examples of growth accounting exercises involving broad cross-country samples (Kruger, 2003).

In the second group, non-parametric indices are used to measure TFP growth. Irrespective of the method used to calculate the distance, growth in TFP is subsequently quantified by the Malmquist index (Malmquist, 1953) in a consumption context and by Caves et al. (1982) as a productivity index. This TFP index has two essential advantages as compared to growth accounting. First, no factor price information and no equilibrium assumption necessary for equating price and marginal product are required. However, the Malmquist index cannot be calculated for a country in isolation but instead needs a balanced panel of quantity data for the inputs and output. The second advantage of the Malmquist index is that a change in TFP can be decomposed as a change of productive efficiency and technological change. This is a substantial gain in informational content as compared to growth accounting. Färe et al. (1994), Koop et al. (1999), Maudos et al. (2000) and Henderson and Russell (2001) are some examples of studies which use non-parametric indices.

The third group of studies use exact index numbers for measuring TFP. Ahn and Abt (2003) calculate price index numbers with the chain-type Fisher formula and use these as the values of the deflators without employing published price index numbers. The price index is most likely constructed with the fixed year-based Laspeyres formula. The Fisher index is consistent with a flexible aggregator function and has the property of self-duality. Self-duality warrants that the direct Fisher quantity index based on actual observed quantities is the same as the indirect quantity index number derived by deflating the values with the Fisher price index. The property of self-duality is particularly desirable in application given that most available data is likely to be in values.

Finally non-parametric methods using linear programming comprise the fourth group of studies. This was first introduced by Aigner and Chu's (1968) study, in which the authors used linear programming methods and applied them to social sector panel data from Yugoslavia to construct

parametric production frontiers and subsequently measure TFP growth as the sum of an efficiency change component and a technical change component.

Our study uses an econometric approach and uses the translog production function to estimate rates of technical change and TFP growth. It also identifies several determinants that have an impact on TFP growth and its decomposition. Understanding and modeling the sources of TFP growth are important at least in a policy context. Of these determinants, development infrastructure, finances, technology and human development appear to be the most important.

Development infrastructure: Infrastructure such as technology transfers, internet and the role of communication is expanding the capacity of production resources. Investments in physical infrastructure account for a large proportion of country budgets. It is hardly surprising that improvements in physical infrastructure (for example, roads, water and sewage systems and electricity supply) are correlated with productivity. Causality running from infrastructure to productivity can easily be envisaged. Yet, comparatively little attention has been paid to quantifying the effects of infrastructure on productivity. Trade in the service of technology transfers was seen to have an indirect effect on TFP; hence here both an indirect and a direct view may be more appropriately taken. For example, insofar as there are learning effects of export activities they should readily affect TFP, while imports of foreign capital add to investments and have indirect effects by increasing capital formation. However, technology embodied in relatively advanced capital imports directly affects TFP (Isaksson, 2007).

Finances: Traditionally, foreign direct investment (FDI) is viewed as being a key channel for the transfer of advanced technology and superior organizational forms from industrialized to developing countries. Further, FDI is believed to generate positive externalities in the form of knowledge spillovers to the receiving economy through, for instance, linkages with local suppliers and clients (so called backward and forward linkages), learning from nearby foreign firms and employee training programs. Other determinants include saving rate and stock market capitalization.

Technology: Change in the stock of knowledge is a result of various domestic investments, for example, in R&D (public and private) and education, although the size of the population (or rather, the number of persons involved in knowledge production) also matters. Here we focus on R&D expenditure, high technology export and patent applications. Knowledge could also be imported through several channels. For example, a better-educated and healthier population is in a better position to learn and absorb knowledge. Human capital and R&D are important means of increasing a country's absorptive capacity. Other tools may include information and communication technology (ICT) and the overall institutional setting (Isaksson, 2007).

Human development: Health influences TFP growth directly through household income and wealth and indirectly through labor productivity, savings, investments and demography by reducing various forms of capital and technology adoption. Healthy workers are more productive, *ceteris paribus*. With lower mortality rates, the incentive to save increases thus leading to higher TFP growth. A country in which workers are exposed to a relatively high disease burden does not attract foreign investors. In addition, school attendance rates are higher if children are healthier and have better cognitive abilities. Further, a longer life span is likely to increase the attractiveness of human capital investments (Isaksson, 2007). In sum all these will result in positive TFP growth. Here we focus on health and education expenditures and tertiary education. Human capital, for example, in the form of level of education has an important effect on TFP because of its role as a

determinant of an economy's capacity to carry out technological innovations (Romer, 1990) and, for developing countries in particular, to adopt foreign technology. Basic and higher education affect TFP in different ways. The former is important for learning-capacity and using information, while the latter is necessary for technological innovations (Isaksson, 2007).

Our study models and estimates TFP growth parametrically. The model is a generalization of the traditional production model where technology is represented by a simple time trend. TFP growth is decomposed into components attributed to the unobservable time trend rate of technical change, scale economies and the observable technology shifter index. The empirical results are based on an unbalanced panel data at the global level for 190 countries observed over the period 1996-2013. A number of identified exogenous growth factors are used in modeling four technology shifter indices to explore the effects of development infrastructure, finances, technology and human development determinants of TFP growth. Our results show that the unobservable time trend-based rate of technical change remains the most important component of TFP growth. The observable technology indices based component predict a more realistic picture of the pattern of TFP growth. Our results also indicate that technical change and TFP growth rates through the technology index channels were negatively influenced by the global economic crisis.

The rest of the paper is organized as follows. Section 2 reviews literature for establishing the research methodology. The models are outlined in Section 3 while Section 4 describes the data. Section 5 reports and interprets the empirical results and the final section gives a conclusion by summarizing its main findings.

2. Literature review

Literature on measuring and analyzing productivity growth and technological change is comprehensive and diverse. It covers a range of dimensions such as the concept, modeling, estimation, identification of determinants, channels, effects and policy implications at different levels of aggregation. This review provides a general picture of the literature and its strengths and limitations where our study attempts to make a contribution.

Griffith et al., (2000), covering 13 manufacturing industries in 12 OECD countries between 1970 and 1992, asked whether R&D had a direct effect on a country's rate of TFP growth through innovation, and whether R&D's effect on TFP growth depended on a country's level of TFP relative to the technology frontier. According to their results, R&D had a positive and statistically significant effect on both innovation and technology transfer rates. They also found that educational attainment was an important and conditional element for TFP growth through both innovation and technology transfer. However, trade with a country on the world technology frontier showed a slight positive effect on TFP growth.

Using data from 83 countries between 1960 and 1989, Miller and Upadhyay (2002) found that trade, measured as exports in GDP, was positively associated with TFP growth. They also showed that human capital was a threshold variable. A positive and statistically significant effect of trade on TFP growth was detected, although its effects were negative for low per capita income countries. They also found that at low levels of income the interaction term between human capital and trade was positive. This means that for low-income countries a certain level of human capital was necessary to enjoy the benefits of trade.

Isaksson (2002) studied the links between human capital and economic growth. According to his study, the relationship between growth and human capital weakened and the parameter sign switched over time. He also concludes that to the extent that human capital is significant, marginal returns to human capital are high for countries where it is scarce, although the issue of causality remains unresolved. Another plausible explanation as to why education fails to show its importance is provided by Jones (1996) who contends that it is not the percentage change in educational attainment that counts, that is, the way education normally enters the regression, but rather the change in levels. This is in line with the original work of Mincer (1974).

Heshmati and Kumbhakar (2011) modeled TC via a time trend (external non-economic) and other exogenous factors (technology shifters). They used balanced panel data on output and inputs and production and technology characteristics for Chinese provinces for the period 1993 to 2003. In their study technology indices were defined based on external economic factors and time trend. The time driven part of TC varied significantly across the provinces and regions and its impacts on TFP steadily declined over time. The technology index-based rate was composed of two technology indices. They represented infrastructure and carriers of technological change. The margin contribution from ICT and FDI was negative, but that of human capital and reforms was positive to the rate of technological change. Their negative interactive coefficient suggests a substitution relationship.

Mastromarco and Zago (2012) investigated the determinants of TFP growth of Italian manufacturing firms in 1998-2003. Using stochastic frontier techniques, they considered three approaches for taking into account the influence of external factors, that is, the determinants or drivers of growth. First, external factors may influence the technological progress that is a shift of the frontier. To model this possible unexplored effect, they extended the standard time trend model to make it a function of external factors. Then, following more standard approaches, they modeled external factors as either influencing the distance from the frontier, that is, inefficiency, or the shape of the technology. Their study found that technological investments and spillovers, human capital and regional banking inefficiencies all had a significant effect on TFP growth.

Tugcu and Tiwari (2016) examined the causal relationship between different types of energy consumption and TFP growth in BRICS (Brazil, Russia, India, China and South Africa) countries from 1992 to 2012. They employed Kónya's (2006) panel bootstrap Granger causality test to investigate the direction of a possible connection between energy consumption and TFP growth. Their results indicate no remarkable causal link between renewable energy consumption and TFP growth in BRICS. However, in the case of non-renewables, energy consumption created a positive externality that contributed to economic development in Brazil and South Africa by a growth in TFP and energy use itself.

In another study, Ulku (2004) suggests that innovation is important for GDP per capita as well as for TFP. According to his study, there are some qualifications in that only large OECD countries are able to increase their levels of innovation through R&D investments; smaller OECD countries learn from that group to promote their own innovations. Another important result is that innovations only lead to short-term increases in the output growth rate.

3. The models

The model used in our paper is drawn from Heshmati and Kumbhakar (2014). In this section we discuss the definition and measurement issues associated with different approaches to empirically measure productivity growth. First, we focus on TFP as an appropriate measure of productivity. A very simple method to measure TFP growth is the Divisia index, which has been used in literature very often. It can be computed from the observed data without any estimation. Production process can be a single or multi-output operation. In a single output case TFP growth (\dot{TFP}) is defined as ($\dot{TFP} = \dot{Y} - \sum_j S_j \dot{X}_j$), where Y is aggregate output, X_j is a vector of inputs ($j=1,2,\dots,J$), S_j is the share of input X_j in the total cost, $S_j = w_j X_j / \sum_j w_j X_j$, w_j is the price of input X_j (dots over the variables indicate annual rate of change). If there are multiple outputs, the TFP growth is expressed ($\dot{TFP} = \sum_m R_m \dot{Y}_m - \sum_j S_j \dot{X}_j$), where R_m is the output value share, $R_m = P_m Y_m / \sum_m P_m Y_m$, and P_m is the price of output Y_m ($m=1,\dots,M$). Using these definitions, the \dot{TFP} measure can be computed from the observed data without any estimation.

The Divisia index is non-parametric and as such it does not provide information on the factors affecting productivity growth. The main advantage of the parametric or econometric approach is that we can estimate and decompose TFP growth and control for production and environmental, management and technology factors. The econometric approach can be based on primal (production), dual (cost) or profit functions. In our study we employ a production function approach. The main advantages of a production function are that it does not require information on prices and it allows for non-constant returns to scale. It has several desirable properties such as positive marginal product of inputs, non-emptiness of output, symmetry, monotonicity and convexity. In addition, the production function is assumed to be continuous at any point and twice-continuously differentiable. The translog production function with a time trend representing exogenous TC can be written as:

$$(1) \quad \ln Y_{it} = \beta_0 + \sum_{j=1}^J \beta_j \ln X_{jit} + \beta_t T_t + \frac{1}{2} \left(\sum_{j=1}^J \sum_{k=1}^K \beta_{jk} \ln X_{jit} \ln X_{kit} + \beta_{tt} T_t^2 \right) + \sum_{j=1}^J \beta_{jt} \ln X_{jit} T_t + \varepsilon_{it}$$

where $\ln Y_{it}$ is the logarithm of output measure of total GDP of country i ($i=1,2,\dots,N$) in period t ($t=1,2,\dots,T$) and $\ln X_{jit}$ is a vector of logarithm of J ($j=1,\dots,J$) inputs. T is a time trend and β s are unknown parameters to be estimated. The error term is decomposed into time-invariant country-specific effects (μ_i) and a random error term (v_{it}), that is, $\varepsilon_{it} = \mu_i + v_{it}$. μ_i is assumed to be a fixed parameter and is captured by $N-1$ country dummies. The random error term is assumed distributed with mean zero and constant variance, σ_v^2 .

The specification of TC in equation 1 is represented by a simple time trend. Now we consider our extension that includes several ‘technology shifters’ that are functions of exogenous factors:

$$(2) \quad \ln Y_{it} = \beta_0 + \sum_{j=1}^J \beta_j \ln X_{jit} + \beta_t T_t + \sum_{m=1}^M \eta_m T_m(Z_{it}^m) + \frac{1}{2} \left(\sum_{j=1}^J \sum_{k=1}^K \beta_{jk} \ln X_{jit} \ln X_{kit} + \beta_{tt} T_t^2 + \sum_{m=1}^M \sum_{l=1}^L \eta_{ml} T_m(Z_{it}^m) T_l(Z_{it}^l) \right) \\ + \sum_{j=1}^J \beta_{jt} \ln X_{jit} T_t + \sum_{j=1}^J \sum_{m=1}^M \gamma_{jm} \ln X_{jit} T_m(Z_{it}^m) + \sum_{m=1}^M \theta_m T_m(Z_{it}^m) + \varepsilon_{it}$$

where $T_m(Z_{it}^m)$ are technology indices and Z^m are external economic factors (labeled as technology shifters). That is, given the traditional inputs, output can change depending on the level of the variables that can shift the production function. These shifter variables can be grouped into various components (technology indices), $T_m(Z_{it}^m)$, where each component depends on a sub-set of mutually exclusive shift variables. Thus, we can specify $T_m(Z_{it}^m)$ as:

$$(3) \quad T_m(Z_{it}^m) = \ln\left(\sum_{p=1}^{P_m} \gamma_p^m Z_{pit}^m\right), \quad \sum_{p=1}^{P_m} \gamma_p^m = 1 \quad \forall m.$$

In Eq. 3 the sum of the weights is restricted to be unity for identification reasons and to interpret the weights as the importance of each shifter on the technology component. In equation 3 P_m is the number of technology shifters in technology index $T_m(\cdot)$. In our paper we use four technology indices, each based on three technology shifters. The first technology index, $T_1(\cdot)$, is the infrastructure index which is constructed from trade openness, internet users and mobile phone subscribers. The second index, called the finance index, $T_2(\cdot)$, comprises of the savings percentage of GDP, FDI percentage of GDP and stock market capitalization percentage. The third index, $T_3(\cdot)$, is constructed around the technology index and is based on R&D expenditure, hi-tech exports and patent applications by non-residents. Finally, the fourth index, $T_4(\cdot)$, comprises of health spending as a percentage of GDP, education spending as a percentage of GDP and tertiary school enrollments.

The translog production models in Models 1 and 2 are estimated using the fixed effect panel data approach. The first model is labeled as single time trend (TT) and the second is called the technology index (TI) model. The two models are nested. The TT model is a restricted version of the TI model. Based on equations 2 and 3, input elasticities (E) and the rate of technical change (TC) can be calculated for each of the two models as:

$$(4a) \quad E_{jit}^{TT} = \partial \ln Y_{it} / \partial \ln X_{jit} = \beta_j + \sum_{k=1} \beta_{jk} \ln X_{kit} + \beta_{jt} T_t;$$

$$(4b) \quad E_{jit}^{TI} = \partial \ln Y_{it} / \partial \ln X_{jit} = \beta_j + \sum_k \beta_{jk} \ln X_{kit} + \beta_{jt} T_t + \sum_{m=1} \gamma_{jm} T_m(Z_{it}^m);$$

$$(5a) \quad TC_{it}^{TT} = \partial \ln Y_{it} / \partial \ln T_t = \beta_t + \beta_{it} T_t + \sum_j \beta_{jt} \ln X_{jit};$$

$$(5b) \quad TC_{it}^{TI} = \partial \ln Y_{it} / \partial \ln T_t = \beta_t + \beta_{it} T_t + \sum_{j=1} \beta_{jt} \ln X_{jit} + \sum_{m=1} \theta_{tm} T_m(Z_{it}^m).$$

In a similar way the elasticity for each technology index, $T_m(Z_{it}^m)$, is calculated as:

$$(6) \quad E_{mit}^Z = \partial \ln Y_{it} / \partial \ln T_m(Z_{it}^m) = \eta_m + \sum_{l=1} \eta_{ml} T_l(Z_{it}^l) + \sum_{j=1} \gamma_{jm} \ln X_{jit} + \theta_{tm} T_t$$

Note that the pure exogenous technical change (TC^{TT}) in equation 5b can further be decomposed into the pure ($\beta_t + \beta_{it} T_t$), non-neutral ($\sum_j \beta_{jt} \ln X_{jit}$) and technology index ($\sum_m \theta_{tm} T_m(Z_{it}^m)$) components. Pure TC refers to a neutral shift of the production function due to time alone, non-

neutral TC means input biased TC and technology index components are a result of the effect of known exogenous technology shifters on production. TC is biased if the marginal rate of substitution between any two inputs measured along a ray through the origin is affected by TC. This implies that TC will tend to influence the relative contribution of each input to the production process. Summing up all the input elasticities in each model allows returns to scale (RTS) to be obtained as:

$$(7) \quad RTS_{it}^{TT} = \sum_{j=1}^J E_{jit}^{TT} \quad \text{and} \quad RTS_{it}^{TI} = \sum_{j=1}^J E_{jit}^{TI}$$

where E_{jit} is the elasticity of output for country i with respect to input j at period t . It measures the percentage change in output resulting from a proportional 1 per cent increase in all inputs simultaneously. If technology exhibits increasing (decreasing) returns to scale, the economy will become more (less) productive by an expansion of the scale. All input elasticities, returns to scale and rate of TC are computed at every point of the data. By using equations 4 through 8, the parametric TFP growth based on the translog production function for both TT and TI models can be obtained as:

$$(8a) \quad \dot{TFP}_{it}^{TT} = TC_{it}^{TT} + (RTS_{it}^{TT} - 1) \sum_{j=1}^J E_{jit}^{TT} \dot{X}_{jit} = TC_{it}^{TT} + SCALE_{it}^{TT}$$

$$(8b) \quad \dot{TFP}_{it}^{TI} = TC_{it}^{TT} + (RTS_{it}^{TI} - 1) \sum_{j=1}^J E_{jit}^{TI} \dot{X}_{jit} + \sum_{m=1}^M E_{mit}^Z \dot{T}_m(Z_{it}^m) = TC_{it}^{TT} + SCALE_{it}^{TI} + TZ_{it}$$

where TZ and TC^{TT} together measure the overall rate of TC. The TC^{TT} part is due to time representing unknown effects alone, whereas the TZ part is due to other observable external economic technology factors. In our application, TZ is a weighted average of the four technology index components, where the weights are the marginal effects of the index components. The overall TZ index is the sum of the product of technology elasticity and the growth rate of the technology index:

$$(9) \quad TZ_{it} = \sum_{m=1}^M (\partial \ln Y_{it} / \partial \ln T_m(Z_{it}^m)) (\dot{T}_m(Z_{it}^m)) .$$

Under strong assumptions of constant returns to scale (CRS) and competitive output markets, TFP growth and TC are identical (Solow, 1957). In such a case it is not necessary to estimate anything econometrically. The Divisia index which can be directly computed from the data will measure both TFP change and TC. However, if the objective of the producers is to minimize costs (given output and input prices) or to maximize output (for given inputs), and the constant returns to scale and perfectly competitive output (input) market assumptions are relaxed, then it is possible to establish a relationship between the Divisia index and TFP growth components (Denny et al., 1981). TFP growth in equations 8a and 8b can be obtained from a parametric cost function or production function. The first component of TFP growth is TC and the second component is the scale component, which is zero if RTS is unity. The last component is zero if either the marginal effect of every technology shifter is zero, or these shift variables are time-invariant. Note that in defining TFP change we are not taking into account the cost of these technology shifter variables.

It should be noted that even with a CRS technology, other factors that can explain productivity growth may exist. If these factors are observed, we can separate the contribution of factors that are under a producer's control and those that are exogenous to a firm by estimating the underlying production technology econometrically. The external factors which define the environment where the producers operate could affect profitability, survival and productivity growth of firms. These factors are usually taken into account in endogenous growth literature. Morrison (1986) and Morrison and Siegel (1999) include these factors in their productivity growth analyses. They point out that such external factors affect the cost-output relationship of a firm and can be explicitly included in the model as non-neutral shift variables. Additional explanations are found in Winston (1993) and Vickers (1995). We use the mentioned technology related factors as technology shifters and in the context of technological change.

4. Data

Our study uses cross-country unbalanced panel data on the global level for 190 countries during the period 1996-2013. The total number of observations is 3,362. The data is obtained from Global Economy.com. The data provides information on contributing factors to the level and development of TC and TFP growth. Output is measured as aggregate gross domestic product (GDP). The input variables include labor (LABOR) measured by the number of persons employed at year-end, capital investment (CAPINV) in dollars and aggregate energy use (ENEUSE). Different countries are divided into five groups according to their income levels as very low, low, medium, high and very high income groups, each accounting for about 20 per cent of the sample. In order to avoid loss of information due to missing unit observations the missing values of some of the explanatory variables are imputed using country's own averages.

To specify technology shifters we used four indices. The first index, infrastructure index, includes trade openness (OPEN), internet users (INTUSE) and mobile phone (MOBSUB) subscribers per 100 people. The second index, finance index, comprises of the savings percentage of GDP (SAVP), foreign direct investment percentage of GDP (FDIP) and stock market capitalization percentage of GDP (STOCK). The third index, technology index, includes research and development expenditure (RDEXP), hi-tech exports (HTEXP) and patent applications (PATNR) by non-residents. Finally the forth index, human capital index, comprises of healthcare (HEALEXP) spending as percentage of GDP, education spending (EDUEXP) as percentage of GDP and tertiary school enrollments (TERSCH) as percentage of eligible children. In addition to these observable determinants/shifters of technology, we used time trend to capture the unobserved rate of technological change.

We begin with a summary statistics of the data for the input and output variables and identified technology shifters (Table 1). As seen in Table 1, GDP per capita averaged US\$ 244,607 with dispersion 4.28 times the mean. The average employment at the country level was 21 million persons. Capital investments, energy use per capita and time trend were the other three variables which affected total TFP with means of 65, 66, 388 and 10 respectively. Energy use per capita also showed large variations among the sample countries.

Therefore, in addition to the basic factors of production considered to estimate TFP growth and its components, we considered data on 12 candidate determinants of TFP growth borrowed from literature on empirical TFP growth. We considered them in four indices which are introduced in previous parts. The values of hi-tech exports indicate considerable variations in the dataset. Mean

patent applications by non-residents was 4,280 with a large standard deviation of 15,972. On average 6.2 and 4.5 per cent of GDP was spent on health and education respectively. Around 29 per cent of all eligible children were enrolled in tertiary schools.

Table 1. Summary statistics of the data, 1996-2013 (NT=3,362)

Variable	Variable definition	Mean	Std Dev
Output and input variables:			
GDP	Aggregate GDP (constant 2005 dollars)	244,606.800	1,048,744.000
LABOR	Employment (in million) adjusted for unemployment	20.689	83.408
CAPINV	Capital investment in dollars	65.290	268.179
ENEUSE	Aggregate energy use	66,388.000	218,490.200
Trend	Time trend	9.516	5.160
Group	Countries grouped by income level		
Group1	Very low income	0.198	0.398
Group2	Low income	0.198	0.399
Group3	Medium income	0.207	0.405
Group4	High income	0.193	0.395
Group5	Very high income	0.203	0.403
Technology shifters:			
OPEN	Trade openness (export+import)/GDP	90.011	52.037
INTUSE	Internet users per 100 persons	20.413	24.742
MOBSUB	Mobile phone subscribers per 100 persons	48.975	48.335
SAVP	Savings percent of GDP	20.002	17.197
FDIP	Foreign Direct Investment per cent of GDP	5.046	10.929
STOCK	Stock market capitalization per cent of GDP	55.100	68.648
RDEXP	R&D expenditure share of GDP	0.739	0.711
HTEXP	Hi-tech exports (in millions)	8,037.474	29,987.210
PATNR	Patent applications by non-residents	4,280.481	15,971.220
HELEXP	Health spending as per cent of GDP	6.248	2.416
EDUEXP	Education spending as per cent of GDP	4.468	1.874
TERSCH	Tertiary school enrollment (per cent of eligible children)	28.740	23.513

In order to check for collinearity among the variables, a correlation matrix of all 17 output, inputs, trend and technology shifter variables is presented in Table 2. We investigated the issues of multi-collinearity and possible confounded effects. The explanatory variables labor, capital and energy use are all positively and significantly correlated with the dependent variable GDP. Between these three variables capital and energy use were highly correlated with GDP. There was also a positive association between GDP and time trend (0.03). Only trade openness (-0.16) and foreign direct investment (-0.05) showed a negative correlation with GDP. Labor (0.01) and energy use (0.02) were not correlated with time trend, but capital was (0.08). Capital and labor were weakly (0.50) correlated and energy use was correlated with labor (0.86) and capital stock (0.90) with possible confounded input elasticity effects. However, the effect on estimated rates of TC and TFP very likely will be small. Most pairs of variables are low correlated with each other and do not show

any sign of serious multi-collinearity. Hi-tech exports, patent applications by non-residents and R&D expenditure positively contributed to GDP.

Table 1. Correlation matrix of the variables (N=3,362)

	GDP	Labor	Capinv	Eneuse	Trend	open	Intuse	Mobsub	Savp	FDIp	Stock	R&Dexp	HTexp	Patnr	Helexp	Eduexp	Tersch
GDP	1.00																
Labor	0.32 (0.00)	1.00															
Capinv	0.91 (0.00)	0.50 (0.00)	1.00														
Eneuse	0.86 (0.00)	0.67 (0.00)	0.90 (0.00)	1.00													
Trend	0.03 (0.06)	0.01 (0.46)	0.08 (0.00)	0.02 (0.26)	1.00												
Open	-0.16 (0.00)	-0.17 (0.00)	-0.16 (0.00)	-0.19 (0.00)	0.08 (0.00)	1.00											
Intuse	0.25 (0.00)	-0.03 (0.06)	0.25 (0.00)	0.14 (0.00)	0.49 (0.00)	0.21 (0.00)	1.00										
Mobsub	0.11 (0.00)	-0.04 (0.02)	0.12 (0.00)	0.04 (0.02)	0.70 (0.00)	0.25 (0.00)	0.78 (0.00)	1.00									
Savp	0.05 (0.00)	0.13 (0.00)	0.09 (0.00)	0.10 (0.00)	0.03 (0.07)	-0.05 (0.00)	0.16 (0.00)	0.14 (0.00)	1.00								
FDIp	-0.05 (0.00)	-0.05 (0.00)	-0.05 (0.00)	-0.06 (0.00)	0.05 (0.00)	0.38 (0.00)	0.08 (0.00)	0.12 (0.00)	-0.13 (0.00)	1.00							
Stock	0.11 (0.00)	0.00 (0.80)	0.09 (0.00)	0.07 (0.00)	0.04 (0.01)	0.40 (0.00)	0.21 (0.00)	0.20 (0.00)	0.08 (0.00)	0.15 (0.00)	1.00						
R&Dexp	0.40 (0.00)	0.08 (0.00)	0.37 (0.00)	0.29 (0.00)	0.04 (0.01)	0.04 (0.02)	0.53 (0.00)	0.28 (0.00)	0.06 (0.00)	0.02 (0.38)	0.18 (0.00)	1.00					
HTexp	0.69 (0.00)	0.50 (0.00)	0.84 (0.00)	0.74 (0.00)	0.07 (0.00)	0.01 (0.50)	0.29 (0.00)	0.14 (0.00)	0.13 (0.00)	-0.01 (0.41)	0.12 (0.00)	0.44 (0.00)	1.00				
Patnr	0.91 (0.00)	0.41 (0.00)	0.89 (0.00)	0.87 (0.00)	0.04 (0.02)	-0.12 (0.00)	0.18 (0.00)	0.05 (0.00)	0.04 (0.03)	-0.04 (0.03)	0.12 (0.00)	0.32 (0.00)	0.67 (0.00)	1.00			
Helexp	0.35 (0.00)	-0.06 (0.00)	0.29 (0.00)	0.22 (0.00)	0.16 (0.00)	-0.05 (0.00)	0.38 (0.00)	0.22 (0.00)	-0.04 (0.01)	0.01 (0.45)	0.07 (0.00)	0.42 (0.00)	0.20 (0.00)	0.25 (0.00)	1.00		
Eduexp	0.02 (0.36)	-0.13 (0.00)	-0.01 (0.43)	-0.06 (0.00)	0.04 (0.01)	0.09 (0.00)	0.10 (0.00)	0.04 (0.01)	0.05 (0.00)	-0.02 (0.17)	0.03 (0.08)	0.20 (0.00)	-0.04 (0.01)	-0.02 (0.37)	0.31 (0.00)	1.00	
Tersch	0.29 (0.00)	-0.03 (0.07)	0.25 (0.00)	0.19 (0.00)	0.16 (0.00)	0.04 (0.04)	0.64 (0.00)	0.50 (0.00)	0.16 (0.00)	-0.01 (0.05)	0.10 (0.00)	0.51 (0.00)	0.23 (0.00)	0.20 (0.00)	0.43 (0.00)	0.18 (0.00)	1.00

Note: Probabilities in parenthesis.

5. The results

5.1 Estimation results

The estimation results for Cobb–Douglas time trend (Model 1), translog time trend (Model 2) and non-linear translog technology index (Model 3) are presented in Table 3. In the case of the Cobb–Douglas model (Model 1), three parameters of labor, capital investment and energy use are highly significant and positively contributed to GDP.

Although the translog form (Model 2) coefficients cannot be directly interpreted economically, it is interesting to note that they are all statistically significant at less than the 1 per cent level, except for energy use interacted with time trend. Therefore, this indicates that the fit of the model is very good. In the case of the technology index model (Model 3), six out of eight technology-related parameters were highly statistically significant. Between these variables only internet use negatively affected GDP. Other parameters of technology shifters such as health spending and education spending were insignificant. In the technology index model, all the time trend coefficients and their interactions with the exception of interaction of trend and technology index1 and index2 were statistically significant. The coefficients of technology index shifters and their squares were also statistically significant. In addition, all their interactions with one exception were

significantly different from zero. On the whole, only six of the 53 parameters that were associated with inputs, time trend and technology indices were statistically insignificant at less than the 10 per cent level in this model which is a sign of a good specification of the function.

Table 2. Cobb-Douglas, translog time trend and non-linear translog technology index production function parameter estimates (N=3,362)

Variable	Model 1:		Model 2:		Model 3:	
	Cobb-Douglas		Translog time trend		Translog technology index	
	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error
Open	-	-	-	-	0.229 ^a	0.025
Intuse	-	-	-	-	-0.156 ^a	0.064
Savep	-	-	-	-	0.214 ^a	0.014
FDI _p	-	-	-	-	0.106 ^a	0.033
RD _{exp}	-	-	-	-	0.056 ^a	0.025
HT _{exp}	-	-	-	-	0.944 ^a	0.025
HE _{exp}	-	-	-	-	-0.011	0.036
Edu _{exp}	-	-	-	-	-0.008	0.027
Constant	5.900 ^a	0.117	-1.696 ^a	0.278	-0.848 ^a	0.800
Labor	0.447 ^a	0.022	-1.396 ^a	0.136	1.155 ^a	0.194
Cap _{inv}	0.579 ^a	0.015	0.554 ^a	0.048	-1.040 ^a	0.129
Eneuse	0.222 ^a	0.014	2.483 ^a	0.070	0.987 ^a	0.094
T	-0.004	0.005	0.047 ^a	0.019	-0.019	0.029
Ind1	-	-	-	-	1.198 ^a	0.285
Ind2	-	-	-	-	0.636 ^a	0.174
Ind3	-	-	-	-	0.508 ^a	0.045
Ind4	-	-	-	-	0.490 ^a	0.127
(Labor)(Labor)	-	-	-0.369 ^a	0.010	-0.404 ^a	0.011
(Cap _{inv})(Cap _{inv})	-	-	-0.112 ^a	0.007	-0.189 ^a	0.007
(Eneuse)(Eneuse)	-	-	-0.155 ^a	0.005	-0.108 ^a	0.004
(T)(T)	-	-	-0.002 ^a	0.001	-0.002 ^a	0.001
(Ind1)(Ind1)	-	-	-	-	-0.222 ^a	0.033
(Ind2)(Ind2)	-	-	-	-	-0.054 ^a	0.014
(Ind3)(Ind3)	-	-	-	-	-0.004 ^a	0.001
(Ind4)(Ind4)	-	-	-	-	-0.034 ^a	0.013
(Labor)(Cap _{inv})	-	-	0.310 ^a	0.012	0.470 ^a	0.013
(Labor)(Eneuse)	-	-	0.274 ^a	0.015	0.307 ^a	0.012
(labor)(T)	-	-	-0.027 ^a	0.003	0.029 ^a	0.004
(Labor)(Ind1)	-	-	-	-	-0.584 ^a	0.036
(Labor)(Ind2)	-	-	-	-	-0.131 ^a	0.023
(Labor)(Ind3)	-	-	-	-	-0.042 ^a	0.004
(Labor)(Ind4)	-	-	-	-	-0.255 ^a	0.020
(Cap _{inv})(eneuse)	-	-	0.011 ^a	0.005	-0.099 ^a	0.005
(Cap _{inv})(t)	-	-	0.006 ^a	0.002	-0.021 ^a	0.003
(Cap _{inv})(Ind1)	-	-	-	-	0.406 ^a	0.027
(Cap _{inv})(Ind2)	-	-	-	-	0.135 ^a	0.020
(Cap _{inv})(Ind3)	-	-	-	-	0.054 ^a	0.003
(Cap _{inv})(Ind4)	-	-	-	-	0.194 ^a	0.015
(Eneuse)(T)	-	-	0.0001	0.002	-0.018 ^a	0.002

(Eneuse)(Ind1)	-	-	-	-	0.166 ^a	0.015
(Eneuse)(Ind2)	-	-	-	-	0.017	0.017
(Eneuse)(Ind3)	-	-	-	-	-0.011 ^a	0.003
(Eneuse)(Ind4)	-	-	-	-	0.099 ^a	0.009
(T)(Ind1)	-	-	-	-	0.032 ^a	0.007
(T)(Ind2)	-	-	-	-	0.007	0.005
(T)(Ind3)	-	-	-	-	0.005 ^a	0.001
(T)(Ind4)	-	-	-	-	0.009	0.003
(Ind1)(Ind2)	-	-	-	-	-0.036	0.038
(Ind1)(Ind3)	-	-	-	-	-0.070 ^a	0.008
(Ind1)(Ind4)	-	-	-	-	-0.228 ^a	0.025
(Ind2)(Ind3)	-	-	-	-	-0.031 ^a	0.007
(Ind2)(Ind4)	-	-	-	-	-0.043 ^a	0.018
(Ind3)(Ind4)	-	-	-	-	-0.009 ^a	0.004
R ² adjusted	0.693	-	0.865	-	0.946	-
RMSE	1.319	-	0.875	-	0.553	-
Iterations	-	-	-	-	40	-

Notes: Significant at less than 1% level of significance.

5.2 Results based on the time trend translog model

Table 4 presents mean elasticities, TFP growth and its components by country group and year in a simple time trend translog model. Elasticities are estimated from the derivatives of the production functions with respect to inputs. Labor and capital elasticities across all country groups were positive. The middle income country group had the lowest labor elasticity but the largest energy elasticity. Energy elasticities were negative only for high income and very high income countries (-0.045 and -0.212) respectively. The very low income group had the largest energy elasticity. All input elasticities were positive over time. Mean elasticity of inputs was also positive at 0.350, 0.752 and 0.082. Labor elasticities decreased over time. There were large variations in capital elasticity, it increased from 1996 to 2002 and then it switched from an increasing trend to a decreasing trend in 2002 and decreased to 0.694 in 2008. Energy elasticity was almost constant in the study period except for a slight increase in 2012 and 2013.

RTS is greater than one for all years and country income groups, suggesting increasing returns to scale in production by sample countries; it also decreased slowly during the study period. Mean returns to scale was about 1.184. The very low income group 5 had the largest RTS (1.323).

According to Model 2 in Table 3, all the first- and second-order coefficients of time were statistically significant suggesting decreasing growth at a decreasing rate. Technology change was negative in all country income groups except for the very low income group. It also decreased from being positive from 1996 to 2000 and then negative during 2001-13. The average TC rate was -0.018 which ranged in the interval 0 per cent in 2000 and 1.7 per cent in 1996.

Table 3. Mean elasticities and TFP components by country income groups and year (translog time trend model)

	Labor elasticity	Capital elasticity	Energy elasticity	TC	RTS	Scale	TFP
--	---------------------	-----------------------	----------------------	----	-----	-------	-----

By income group:							
Very low	0.186	0.604	0.533	0.008	1.323	0.000	0.008
Low	0.215	0.910	0.003	-0.014	1.128	0.000	-0.014
Medium	0.084	0.906	0.135	-0.020	1.125	0.004	-0.016
High	0.471	0.738	-0.045	-0.024	1.164	0.006	-0.019
Very high	0.796	0.596	-0.212	-0.037	1.180	0.002	-0.035
By year:							
1996	0.506	0.753	0.074	0.017	1.333	0.000	0.017
1997	0.483	0.757	0.074	0.013	1.314	0.009	0.021
1998	0.448	0.767	0.076	0.008	1.292	0.007	0.015
1999	0.406	0.785	0.075	0.004	1.266	-0.002	0.002
2000	0.392	0.781	0.078	0.000	1.251	0.002	0.001
2001	0.363	0.788	0.080	-0.004	1.231	0.002	-0.001
2002	0.338	0.795	0.076	-0.008	1.210	0.004	-0.004
2003	0.344	0.781	0.073	-0.012	1.198	0.009	-0.003
2004	0.346	0.767	0.073	-0.016	1.186	0.006	-0.010
2005	0.352	0.752	0.071	-0.019	1.175	0.009	-0.010
2006	0.358	0.737	0.068	-0.023	1.163	0.007	-0.017
2007	0.373	0.714	0.068	-0.026	1.155	0.009	-0.017
2008	0.381	0.694	0.071	-0.030	1.146	0.003	-0.027
2009	0.281	0.743	0.083	-0.035	1.108	-0.010	-0.046
2010	0.268	0.736	0.089	-0.040	1.093	-0.005	-0.045
2011	0.269	0.722	0.090	-0.043	1.081	0.001	-0.042
2012	0.213	0.724	0.128	-0.047	1.065	-0.001	-0.048
2013	0.178	0.732	0.134	-0.052	1.044	-0.002	-0.054
Overall Mean:							
Mean	0.350	0.752	0.082	-0.018	1.184	0.003	-0.015
Std Dev	0.884	0.427	0.546	0.039	0.233	0.029	0.055

The TC rate was positive only in the case of the very low income group of countries and in the other income groups of countries technical change was negative. Average TC rate was also negative indicating technical failure at the rate of -0.018 per cent per annum. It was the main contributor to the negative TFP growth. It was positively related with TFP, but negatively with the scale effect component. The negative rate of technical change accomplished by a small positive (0.003) scale effect produced negative total factor productivity growth (-0.015).

5.3 Results based on the technology index translog model

Input elasticities in the translog technology index model are reported in Table 5. The input elasticities were positive, 0.360, 0.590 and 0.038 and were consistent with those based on the simple translog time trend model results. The highest labor elasticity is attributed to the very high income group, the highest capital investment elasticity to the middle income group and the highest energy use elasticity to the very low income group. The estimated average RTS was 0.998, which is lower than the corresponding one from the time trend model and indicates constant RTS. Labor and capital elasticities across country income groups and over time were positive. In examining the differences across income groups, we observe that the mean energy elasticity was negative for low, high and very high income groups. They were positive over the years. RTS was larger than one during 1996-2004 and less than one during 2004-13, suggesting decreasing and increasing

economies of scale respectively. Labor elasticity and capital elasticity show a negative and positive trend respectively and energy elasticity showed more fluctuations during the study period.

According to Table 5 the rates of technical change and TFP growth were negative across all country income groups and years in the translog technology index model. Technical change declined over time. The mean rate of TC was -0.034 per cent per annum. It varied from -0.047 per cent to -0.023 per cent.

Table 5. Mean elasticities and TFP components by country income groups and year (translog technology index model)

	Labor elasticity	Capital elasticity	Energy elasticity	TC	RTS	Scale	Index	TFP growth
By income groups:								
Very low	0.412	0.338	0.303	-0.028	1.052	0.000	0.007	-0.022
Low	0.398	0.612	-0.011	-0.035	0.998	-0.002	-0.001	-0.039
Medium	0.105	0.760	0.135	-0.023	1.000	-0.004	0.000	-0.026
High	0.323	0.692	-0.029	-0.034	0.987	-0.004	-0.002	-0.041
Very high	0.569	0.589	-0.204	-0.051	0.954	-0.005	0.005	-0.051
By year:								
1996	0.586	0.452	0.052	-0.023	1.090	0.000	0.000	-0.023
1997	0.565	0.465	0.052	-0.025	1.082	0.002	0.010	-0.014
1998	0.541	0.483	0.048	-0.027	1.072	0.002	-0.004	-0.030
1999	0.498	0.521	0.040	-0.027	1.059	-0.001	0.004	-0.025
2000	0.464	0.537	0.048	-0.028	1.049	-0.001	0.004	-0.028
2001	0.433	0.553	0.052	-0.030	1.039	0.000	0.001	-0.028
2002	0.411	0.571	0.045	-0.031	1.028	-0.001	0.007	-0.025
2003	0.409	0.571	0.035	-0.033	1.015	0.000	-0.008	-0.041
2004	0.373	0.598	0.035	-0.034	1.006	-0.002	0.007	-0.029
2005	0.342	0.621	0.032	-0.034	0.995	-0.002	0.010	-0.027
2006	0.309	0.646	0.029	-0.035	0.984	-0.004	0.000	-0.039
2007	0.291	0.656	0.026	-0.036	0.972	-0.006	0.004	-0.038
2008	0.320	0.618	0.018	-0.040	0.956	-0.008	-0.018	-0.067
2009	0.191	0.712	0.045	-0.037	0.948	0.001	0.007	-0.030
2010	0.184	0.710	0.042	-0.040	0.936	-0.012	0.003	-0.050
2011	0.211	0.686	0.025	-0.043	0.923	-0.016	-0.001	-0.054
2012	0.181	0.691	0.040	-0.044	0.912	-0.006	0.005	-0.045
2013	0.181	0.690	0.029	-0.047	0.901	-0.003	0.000	-0.050
Overall:								
Mean	0.360	0.599	0.038	-0.034	0.998	-0.003	0.002	-0.036
Std Dev	0.839	0.529	0.431	0.042	0.095	0.033	0.072	0.082

The elasticities of production with respect to technology indices and their marginal effects are reported in Table 6. The mean elasticities of production with respect to the technology shifter index 1 through index 4 were 3.826, 3.450, 3.912 and 2.867 respectively. The elasticity of technology index 3 (3.912) was higher than the other indices. Technology index 3 showed negative values for marginal effects, while the average marginal effect of indices 1, 2 and 4 were all positive.

Table 6. Mean elasticities and marginal effects of the technology indices

		Mean	Std Dev	Minimum	Maximum
Elasticity of Technology index	Index 1	3.826	0.850	1.409	5.746
	Index 2	3.450	0.793	-2.244	6.762
	Index 3	3.912	4.332	-6.784	13.178
	Index 4	2.867	1.201	-2.216	4.787
Marginal Effect (ME) of technology indices	ME Index 1	0.181	0.613	-1.071	2.257
	ME Index 2	0.167	0.185	-0.248	0.807
	ME Index 3	-0.043	0.090	-0.203	0.281
	ME Index 4	0.234	0.315	-0.374	1.256
	Mean index	0.002	0.072	-0.295	0.283

According to the results in Table 5, TFP growth was negative across all countries. The very low income group had the lowest TFP growth among country groups. It was also negative during the study period. Average TFP growth was -0.036 and average TC rate (-0.034) was the main component of TFP growth. The scale component also had a negative (-0.003) contribution to TFP growth. TFP growth (-0.003) obtained from the technology index model was lower than the one obtained from the time trend production model (-0.015).

6. Summary and conclusions

Our paper applied the parametric method to estimate total factor productivity growth and decomposed the growth rate into rate of technical change, scale economies and technology shifter index components. Our empirical study used cross-country unbalanced panel data on the global level for 190 countries over the period 1996–2013. In this regard, 12 exogenous economic technology related factors were used to define four technology indices. These technology indices were used in a translog production function in a flexible manner to represent observable technology determinants. Time trend was also used to capture the unobservable technology determinants. The marginal effects of individual technology indicators on productivity growth were also estimated along with various input elasticities and the measure of economies of scale.

Our results show that labor and capital elasticities across all country income groups were positive as expected. Returns to scale was found to be more than one for all years and country income groups in the time trend model, suggesting increasing returns to scale. However, our results imply that technical change and TFP growth were negative across all country income groups and years in the translog technology index model. Technical change also declined over time. A decomposition of TFP growth rate into technical change and economies of scale shows that the contribution of technical change was high for most of the years in both time trend and technology index models. TFP growth obtained from the technology index model was lower than the time trend model. A comparison of the performance of the time trend and technology shifter models in terms of TFP growth rates shows that the technology shifter model predicted a less smooth pattern of TFP growth than the time trend model.

References

- Ahn, S.E. and B. Abt (2003). Total Factor Productivity Measurement with Improved Index Numbers, in S.O. Moffat (ed.), *Bugs, Budgets, Mergers, and Fire: Disturbance Economics*. Proceedings of the 2003 Southern Forest Economics Workers Annual Meeting, 17 and 18 March, New Orleans, Louisiana, pp. 287-297.
- Aigner, D.J. and S.F. Chu (1968). On estimating the industry production function. *American Economic Review*, 58, 826-839.
- Barro, R. (1991). Economic growth in a cross section of countries. *The Quarterly Journal of Economics*, 106, 407-443.
- Benhabib, J. and M. Spiegel (2005). Human capital and technology diffusion, in P. Aghion and S. Durlauf (eds), *Handbook of Economic Growth*, 4. Amsterdam: North Holland.
- Caves, D.W., L.R. Christensen and W.E. Diewert (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica*, 50(6), 1393-1414.
- Collins, S.M. and B.P. Bosworth (1996). Economic growth in East Asia: accumulation versus assimilation. *Brookings Papers on Economic Activity*, 2, 135-203.
- Danquah, M., M. Moral-Benito, and B. Ouattara (2014). TFP Growth and its determinants: a model averaging approach. *Empirical Economics*, 47(1), 227-251.
- Denny, M., M. Fuss, and L. Waverman (1981). The measurement and interpretation of total factor productivity in regulated industries, with an application to Canadian telecommunications, in Thomas G. Cowing and Rodney E. Stevenson (eds), *Productivity Measurement in Regulated Industries*. New York: Academic Press, pp. 179-212.
- Diewert, W.E. (1981). The theory of total factor productivity measurement in regulated industries, in T.G. Cowing and R.E. Stevenson (eds), *Productivity Measurement in Regulated Industries*. New York: Academic Press.
- Färe, R., S. Grosskopf, M. Norris, and Z. Zhang (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 84, 66-83.
- Griffith, R., S. Redding, and J. Van Reenen (2000). Mapping the two faces of R&D: productivity growth in a panel of OECD industries. CEPR Discussion Paper No. 2457. London: CEPR.
- Henderson, D.J. and R.R. Russell (2001). Human capital convergence: A production frontier approach. Working Paper, University of California, Riverside.
- Heshmati, A. and S.C. Kumbhakar (2011). Technical change and total factor productivity growth: The case of Chinese provinces. *Technological Forecasting and Social Change*, 78, 575-590.
- Heshmati, A. and S.C. Kumbhakar (2014). A general model of technical change with an application to the OECD countries. *Economics of Innovation and New Technology*, 23(1), 25-48.
- Isaksson, A. (2002). Human capital and economic growth: a survey of the empirical literature from 1990 to the present. Mimeo. Vienna: UNIDO.
- Isaksson, A. (2007). Determinants of total factor productivity: a literature review. Research and Statistics Branch Staff Working Paper. 02/2007. Vienna: UNIDO.
- Jones, C.I. (1996). Human capital, ideas, and economic growth. Mimeo. Stanford: Stanford University.

- Kneller, R. and P. Stevens (2006). Frontier technology and absorptive capacity: evidence from OECD manufacturing industries. *Oxford Bulletin of Economics and Statistics*, 68, 1-21.
- Kónya, L. (2006). Exports and growth: Granger causality analysis on OECD countries with a panel data approach. *Econometric Modelling*, 23, 978-992.
- Koop, G., J. Osiewalski, and M.F.J. Steel (1999). The components of output growth: a stochastic frontier analysis. *Oxford Bulletin of Economics and Statistics*, 61, 455-487.
- Kruger, J. (2003). The global trends of total factor productivity: evidence from the nonparametric Malmquist index approach. *Oxford Economic Papers*, 55, 265-286.
- Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de Elastistica*, 4, 209-242.
- Mastromarco, C. and A. Zago (2012). On modeling the determinants of TFP growth. *Structural Change and Economic Dynamics*, 23(4), 373-382.
- Maudos, J., J.M. Pastor, and L. Serrano (2000). Convergence in OECD countries: technical change, efficiency and productivity. *Applied Economics*, 32, 757-765.
- Miller, S.M. and M.P. Upadhyay (2000). The effects of openness, trade orientation, and human capital on total factor productivity. *Journal of Development Economics*, 63, 399-423.
- Miller, S.M. and M.P. Upadhyay (2002). Total factor productivity, human capital, and outward orientation: differences by stage of development and geographic regions. Mimeo. Las Vegas: University of Nevada.
- Mincer, J. (1974). *Schooling, experience, and earnings*. New York: Columbia University Press.
- Morrison, C. (1986). Productivity measurement with non-static expectations and varying capacity utilization: an integrated approach. *Journal of Econometrics*, 33(1-2), 51-74.
- Morrison, C., and D.S. Siegel. (1999). Scale economies and industry agglomeration externalities: a dynamic cost function approach. *American Economic Review*, 89(1), 272-290.
- Nehru, V. and A. Dhareshwar (1993). A new database on physical capital stock: sources, methodology and results. *Revista de Analisis Economico*, 8, 37-59.
- Romer, P. (1990). Endogenous technological change. *Journal of Political Economy*, 96, S71-S102.
- Solow, R. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics*, 39, 313-320.
- Tugcu, C.T. and A.K. Tiwari (2016). Does renewable and/or non-renewable energy consumption matter for total factor productivity (TFP) growth? Evidence from the BRICS. *Renewable and Sustainable Energy Reviews*, 65, 610-616.
- Ulku, H. (2004). R&D, innovation, and economic growth: an empirical analysis. IMF Working Paper. WP/04/185. Washington, DC: the International Monetary Fund.
- Vickers, J. (1995). Concepts of competition. *Oxford Economic Papers*, 47(1), 1-23.
- Vandenbussche, J., P. Aghion, and C. Meghir (2006). Growth, distance to frontier and composition of human capital. *Journal of Economic Growth*, 11, 97-12.

Winston, C. (1993). Economic deregulation: days of reckoning for microeconomists. *Journal of Economic Literature*, 31(3), 1263-1289.