Discussion Papers in Economics

Cross-Country Analysis of Composition of Human Capital and Total Factor Productivity Growth depending on its Distance to Frontier

Sujata Basu

July 2015

Discussion Paper 15-06

Centre for International Trade and Development

School of International Studies

Jawaharlal Nehru University

India

*

Cross-Country Analysis of Composition of Human Capital and Total Factor Productivity Growth depending on its Distance to Frontier

Sujata Basu [1]

July 3, 2015

[1]Ph.D Scholar, Center for International Trade and Development (CITD), School of International Studies (SIS), Jawaharlal Nehru University (JNU), New Delhi, INDIA

Abstract

This paper empirically examines human capital's contribution to economy-wide technological progress and also on technical efficiency gain depending on its distance to frontier in a panel of 75 countries over the period 1970 - 2010. This study illustrates that only advanced economies rely on technological change while dependence on technical efficiency gain is high for middle and poor income countries. Using stochastic frontier analysis and system generalized method of moments (GMM), it is shown that skilled human capital is important for technical efficiency gain for rich income countries whereas middle and poor income countries rely on semi-skilled human capital for technical efficiency gain. This study also analyzes the impact of skilled-unskilled human capital on total factor productivity growth for both aggregate and multiple outputs. For aggregate output, the production function has been estimated with fixed effect panel regression. It shows that elasticity of capital is higher for rich income countries than middle or poor income countries whereas ranking of coefficient associated with labor is reverse. After that, the total factor productivity would be estimated by Solow residual. In the second stage, using system GMM, it is shown that skilled human capital is important for total factor productivity growth for rich and middle income countries and unskilled human capital is growth enhancing for poor income countries. For multiple outputs, the production function has been estimated by data envelopment analysis. In the second stage by using system GMM, same findings would be revealed as in the aggregate output for total factor productivity growth.

Journal of Economic Literature Classifications: I25, O11, O31, O32, O41, O45, O47, O50.

Key Words: One-sector growth, Multi-sector Growth, Technological Change-Technical Efficiency Gain, Stochastic Frontier Analysis, Data Envelopment Analysis, System GMM.

Address correspondence to: Sujata Basu, Room No 209, Centre for International Trade and Development, School of Social Science, Jawaharlal Nehru University, New Mehrauli Road, New Delhi 110067, INDIA. Mobile: 91-9717675108. Email: sujata.eco@gmail.com

Acknowledgements

I am grateful to Prof. Alokesh Barua, Prof. Sebastian Dullien, Dr. Zhigang Huang Prof. Bishwanath Goldar, Prof. Jan Priewe, Prof. Meeta Keswani Mehra and Dr. Alejandro Mrquez Velzquez for their comments and suggestions which have helped this paper to take its present forms. I am also thankful for the comments received during the presentation of this paper at the seminars in 23^{rd} Annual Conference on the Contemporary Issues in Development Economics, 2014 Department of Economics, Jadavpur University, Kolkata, 9^{th} Annual Conference on Economic

Growth and Development, Indian Statistical Institute, New Delhi, 2013 and Centre for International Trade and Development, Jawaharlal Nehru University, New Delhi, 2013. Moreover, I would like to thanks for giving me the opportunity to present my work in the following conferences: 2014 Scottish Economic Society Annual Conference, 2014 at Perth, Scotland and 63^{rd} AFSE Congress, 2014, in Lyon (France).

1 Introduction

Ang et al. [2011] and Cerina and Manca [2012] empirically test the theoretical proposition that *skilled human capital is growth enhancing for an advanced economy and unskilled human capital is growth enhancing for a backward economy.* However, these two works come up with opposite results. While Cerina and Manca [2012] finds that skilled human capital is growth enhancing irrespective of its distance to the frontier, Ang et al. [2011] shows that skilled human capital is growth enhancing in the developed and developing economies but education does not contribute positively and significantly in the underdeveloped economy. The findings of Ang et al. [2011] are also in conflict with Krueger and Lindahl [2001]. In their survey, Krueger and Lindahl [2001] show that level of education is significantly positively correlated with the growth rate for the countries with low level of education. Moreover, since gross domestic product (GDP) per capita is low for the poor economies, they face a very tight situation with regard to allocation of resources. So, if the social rate of return of different levels of education is not the same, then to derive the maximum benefit from it, the allocation of resources should vary according to the gain from different levels of education.

Looking at the literature on institutions, composition of human capital and economic growth, it is found that at the heart of economic growth is technological progress which involves both imitation and innovation. The first generation endogenous growth theory assumes that the growth rate of human capital has positive and significant impact on total factor productivity (TFP) growth. The first generation endogenous growth theory assumes that the growth rate of human capital has positive and significant impact on total factor productivity (TFP) growth. However, Benhabib and Spiegel [1994] shows that human capital accumulation has either insignificant or significant but negative impact on per capita income growth. In comparison, the second wave of endogenous growth theory (a la Aghion and Howitt [1992] and Romer [1990]) shows that it is the level and not the rate of accumulation of human capital that matters for economic growth, which is also empirically supported by Benhabib and Spiegel [1994] in their cross-country study. This implies that considering human capital as an input in production does not raise productivity directly but it may indirectly contribute to growth by encouraging technology transfer from rest of the world or by accumulating other factors like capital. Griliches [1973], Aghion and Howitt [1992], Romer [1990] and Barro and Sala-i Martin [1995] show that Research and Development (R & D) expenditure is one of the main determinants of TFP growth.[1]

However, Krueger and Lindahl [2001], Durlauf and Johnson [1995] and Kalaitzidakis et al. [2001] show an inverted U-shaped relation between human capital and economic growth. This implies that education

[1]Also see Terleckyj [1958], Minasian [1962], Griliches [1964] and Griliches [1988] to understand the importance of R & D activity on TFP growth.

matters only for catching up to the world technology frontier but does not have any significant impact at the frontier. Vandenbussche et al. [2006] and Aghion et al. [2009] show that it is not the level of human capital but the composition of human capital that matters for economic growth, and the growth enhancing education policy varies depending on the economy's distance to the frontier. So, policy is not unique; it is context dependent. With panel estimation for Organisation for Economic Co-operation and Development (OECD) countries and inter-state data for United States of America (USA), Vandenbussche et al. [2006] and Aghion et al. [2009] respectively show that tertiary education has a significant and positive impact on economic growth. Caselli and Coleman II [2006], in a cross-country study and by using Cobb Douglas production function and income shares, shows that higher income countries use skilled human capital more efficiently whereas lower income countries use unskilled human capital more efficiently.

The basic theoretical proposition to be tested empirically is that *skilled human capital is growth enhancing for an advanced economy and unskilled human capital is growth enhancing for a backward economy.* In this paper, first empirically the contribution of the composition of human capital to economic growth for the poor, middle and rich countries is analyzed. The motivation for such analysis stems from the fact that the findings of Cerina and Manca [2012] and Ang et al. [2011] on this issue are contradictory. On the one hand, Ang et al. [2011] shows that skilled human capital is growth enhancing for the rich and middle income group countries and education does not matter for the poor income group countries. On the other hand, Cerina and Manca [2012] shows that skilled human capital is growth enhancing for all the economies irrespective of the country's distance from the world technology frontier.

Secondly, there is a scope to verify the basic structural assumptions of the Vandenbussche et al. [2006], namely (i) a technologically backward economy relies more on imitation activity and a technologically advanced economy depends more on innovation activity for economic growth; and (ii) skilled human capital is more efficient in the innovation activity and unskilled human capital is more efficient in the imitation activity. This research contributes to the growth and development literature in the following specific aspects:

1. It tries to empirically identify how the global and the country specific frontiers evolve over time. To what extent can the composition of human capital explain the cross-country productivity and income differences depending on the distance to frontier? It tries to test empirically whether whether *growth is stimulated by skilled human capital in the rich and middle income group countries and by semi-skilled human capital in the poor income group countries.*

2. Unlike related research on the same issue like Vandenbussche et al. [2006], Aghion et al. [2009], Ang et al. [2011] and Cerina and Manca [2012], the focus of this study is not confined only to the

TFP. In this study, TFP growth is decomposed into two components – technological change (that is, innovation) and technical efficiency gain (that is, imitation). Technological change measures how the frontier evolves over time. In contrast, technical efficiency gain involves the catching up process. This research provides an empirical support to the proposition that *a backward economy would tend to depend more on technical efficiency gain whereas an advanced economy would tend to rely more on technological change*.

3. The focus of study is specifically for the technologically backward economy (as mentioned above, those countries have a higher resource constraint). Thus, one aim of the analysis is to ascertain which factor is playing a more important role in explaining the cross-country productivity differences and catch up to the frontier. Both skilled and unskilled human capital are required for the technical efficiency gain and the technological change. So, an empirical test has been done to verify whether *for technical efficiency gain, semi-skilled human capital is more important than skilled human capital irrespective of the income level of an economy*.

This study makes some additional contributions on methodological aspects in comparison to the earlier research:

1. Vandenbussche et al. [2006], Aghion et al. [2009], Ang et al. [2011] and Cerina and Manca [2012] have considered a single output economy and hence, an aggregate production function of the final good. Therefore, first all the above hypotheses have been tested under the assumption that an aggregate production function exists. The novelty of this analysis presented in this study is that the analysis has been extended to a multiple outputs (for sectoral differentiation) framework. There are two reasons for using a multiple outputs framework. First, countries differ in efficiency but the gap for certain products may be much higher than that for the other products. If one takes only one homogeneous output, the technological or productivity gap may not be accurately measured. Second, the structure of production differs across countries. The relative prices of goods also differ. Thus, aggregate value added as a measure of output does not directly capture the inter-country differences in the level of output and industrial structure. The use of a multi-products framework is therefore more satisfactory.

2. Furthermore, all of the earlier mentioned works have assumed that there exist a contant returns to scale (CRS) production function and that the elasticities of labor (exogenously assumed to be 0.7) and capital (also exogenously assumed as 0.3) are constant irrespective of the economy's distance to the world technology frontier. In the analysis presented here, the cross-country production function has been estimated for all the economies put together (irrespective of their income level) as well

as separately for rich, middle and poor income group countries (which allows the labor and capital elasticities to differ). Moreover, the assumption of CRS has been relaxed.

The rest of the paper is organised as follows. In Section 2, the empirical framework of this research is explained. In Section 4, the key findings of this research are presented. Section 5 concludes this study.

2 Empirical Framework

In this section, the overall empirical framework of this analysis is discussed. To capture the importance of the different education levels on TFP growth as well as on technical efficiency gain, the two stage regression analysis has been carried out for 75 countries over the period 1970-2010. In the first stage the Cobb-Douglas production function has been estimated. This provides TFP growth, technical efficiency gain and distance to frontier of a country in period t. In the second stage the importance of the human capital on TFP growth and technical efficiency gain have been studied with the help of regression analysis. The two stage regression analysis has been carried out since Benhabib and Spiegel [1994] shows that per capita human capital does not have any significant impact on per capita growth rate. However, human capital plays a significant role by assisting technical change and technical efficiency gain and thus contributes to productivity growth indirectly.

First, the discussion starts with methodology adopted for analyzing the impact of education on TFP growth. The analysis has been done by using two scenarios: (i) there is single output and aggregate production function exists and (ii) there are multiple outputs (for sectoral differentiation) and the production function is specified accordingly. For the single output case, TFP growth has been taken care of by econometric analysis. Multiple outputs scenario is dealt with by using data envelopment analysis (DEA). Finally, the focus concentrates on studying the contribution of different human capital to technical efficiency gain, which is addressed by stochastic frontier analysis (SFA).

2.1 Single Output Case Using Panel Regression

For the single-output case a broad form of the production function has been postulated for the rich (22 countries have been considered), middle (40 countries are taken) and poor (13 countries are taken into account) income countries as well as by combining all the economies together (75 countries are considered) irrespective of their income level. The function is:

$$Y_{\mathrm{jt}} = F(K_{\mathrm{jt}}, LQ_{\mathrm{jt}}), \tag{1}$$

where j stands for country index and t stands for time period. In the single output case Y_{jt} stands for the aggregate output. K_{jt} and LQ_{jt} are capital stock and quality adjusted labor force participation aged above

15 respectively in an economy. In the single output case, in the first stage, aggregate production function (eq. (1)) has been estimated by using two inputs – capital and quality adjusted labor with country fixed effects. Estimation of production function involves large T (that is, 41 time periods) in a combination of large N (that is, in total 75 countries).[2] Therefore, as mentioned in Roodman [2009], dynamic panel bias becomes insignificant and fixed effect panel regression provides consistent estimate. Moreover, Hausman test as mentioned in Greene [2008, Chapter 8] shows that the specification of the fixed effect model is more suitable than the random effect model. Additionally, Hausman [1978] specification test shows the presence of heteroscedasticity and autocorrelation in the error terms. To counter that, Huber [1967], White [1980] and White [1982] sandwich estimator has been used to get a robust variance estimate.

The Cobb-Douglas production function can also be estimated by generalized method of moments (GMM) estimator by using Blundell and Bond [2000]. But that methodology has not been adopted because of the following reasons. First, the panel regression has large time periods. As mentioned by Arellano and Bond [1991] and Roodman [2009], a large number of observations per individual (that is, a high value of T) in a panel data set provides inconsistent estimate in a dynamic panel regression by generating large number of instrumental variables (since it can yield a downward bias standard error). Second, given that the education data is available at 5 years gap, the second stage regression has been done at 5 years time span. Therefore, one can perform the first stage production function estimation also at 5 years gap. However, intuitively that implies today's production depends on today's capital and quality adjusted labor force as well as the 5 year back inputs level. To avoid this, a fixed effect panel regression has been done in the first stage estimation.

After estimating the parameters (α, β) of the Cobb-Douglas production function, the level of TFP of country j in period t has been obtained by using the Solow residual approach, that is, $A_{\text{jt}} = \frac{Y_{\text{jt}}}{K_{\text{jt}}^{\alpha} L_{\text{jt}}^{\beta}}$, where α and β are respectively the elasticities of capital and quality adjusted labor force.

In the second stage the importance of different components of human capital on economic growth has been estimated depending on its distance to frontier. The equation to be estimated can be written as:

$$g_{\text{jt}} = \vartheta_0 + \vartheta_1 \ln a_{\text{j,t-1}} + \vartheta_2' H_{\text{j,t-1}} + \vartheta_3' H_{\text{j,t-1}} \ln a_{\text{j,t-1}} + \vartheta_4' Z_{\text{j,t-1}} + c_{\text{i}} + t_{\text{t}} + \epsilon_{\text{jt}}. \tag{2}$$

To explain the notation, $g_{\text{jt}} = \ln A_{\text{jt}} - \ln A_{\text{j,t-1}}$ measures the TFP growth of the j^{th} country in period t, A_{jt} measures the technology level of country j in period t, $\ln a_{\text{j,t-1}} = \ln A_{\text{j,t-1}} - \ln \overline{A}_{\text{USA,t-1}}$ measures the relative distance of the j^{th} country from the world technology leader in period $t-1$, $\overline{A}_{\text{USA,t-1}}$ measures the technology level of the USA. Similar to Vandenbussche et al. [2006], Ang et al. [2011] and Cerina and Manca [2012] it is assumed that the USA has the highest technology level. This implies that the USA

[2] N is the Number of countries and T denotes the number of observations per countries in a panel data set.

is the world technology leader. Additionally, $H_{j,t}$ measures the different levels of human capital, Z_{jt} are the other control variables (inflation in terms of consumer price index, net foreign direct investment (FDI) inflow, trade openness, domestic credit provided by the banking sector as a percentage of GDP), c_i and t_t respectively measure the unobserved country specific time invariant and time variant fixed effects and ϵ_{jt} measures the stochastic error component of country j in period t.

The second stage regression analysis has been carried out at 5 years time span since education data is available at 5 years gap. The estimation of eq. (2) involves some econometric challenges. First, as pointed out by Nickel [1981], dynamic panel biases may occur as the lagged dependent variable becomes correlated with the fixed component of the error term. This bias may arise in estimating eq. (2), since $A_{j,t-1}$ is coming in both the left (via g_{jt}) hand and right (through $a_{j,t-1}$) hand sides of this equation. This problem has been first mentioned by Hausman and Taylor [1981] for the static error component model with both time varying and time invariant models. Bhargava and Sargan [1983] considers a dynamic panel model with dynamic error components and allows for correlation between the regressors and the unobservable fixed effects. As mentioned by Roodman [2009], one can use least square dummy variable (LSDV) to capture the fixed effect in the error term. However, according to Nickel [1981] and Bond [2002], within group estimator with small T is not able to solve the problem of dynamic panel bias and the estimate becomes inconsistent as well as inefficient. Moreover, as Roodman [2009] mentions one cannot use lagged values of the endogenous variable as an instrument to that particular independent variable in the within group estimation with small T. This is so because lagged values of the endogenous variables become correlated with the error term. For the balanced panel, Kiviet [1995] corrected the bias from the LSDV estimate with a great precision and provides approximately a consistent and asymptotically efficient estimate. However, this correction does not work for the unbalanced panel and also does not address the potential endogeneity for other regressors.

Second challenge in the estimation of eq. (2) is the following: as mentioned by Bils and Klenow [2000] the education data face endogeneity problem. Therefore, a true identification strategy is very important. Moreover, Bils and Klenow [2000] mentions that the reverse causality from growth to education decision is playing a vital role behind the positive significance between these two variables. To offset this endogeneity problem, Vandenbussche et al. [2006] used 10 years lagged public expenditure on education as an instrument for the education attainment data. However, Aghion and Howitt [2009] mentions that the lagged variables are not able to overcome the country specific omitted variable (for instance institutions) biases. As mentioned by Cerina and Manca [2012], these biases exaggerate since education data is persistent.

To solve these above mentioned issues Arellano and Bond [1991] and Arellano and Bover [1995] or

Blundell and Bond [1998] generates internal instrument for the endogenous/ predetermined variables. Arellano and Bond [1991] provides estimation by transforming all regressors by first-differences (that is, subtracting the previous observations from the contemporaneous one). After the transformation GMM has been used to estimate the parameters. This estimation methodology has been adapted from Holtz-Eakin et al. [1988]. After the difference the fixed component of the error term vanished. Arellano and Bond [1991] used lagged level variables as the instrument for first difference endogenous variables which are orthogonal to the error term. Moreover, their study gives some specification test to check whether identified internal instruments are not over-identified as well as the presence of no serial correlation in the error term. However, this process of estimation (due to the first-difference transformation) amplify the gap in unbalanced panels. Moreover, Blundell and Bond [1998] shows that if dependent variable has high persistence effect, that is, it is close to a random walk model then the consistency of the estimation of Arellano and Bond [1991] is limited. In that scenario, past levels have very limited explanatory power for future changes. By resolving these issues Arellano and Bover [1995] and Blundell and Bond [1998] generate forward orthogonal deviations (that is, subtracting the average of all future available observations from the contemporaneous one) transformation. This transformation would not enlarge the gap in unbalanced panels. Along with that the assumption that first differences of instrument variables are uncorrelated with the fixed effects helps to make a system of two equations. Arellano and Bover [1995] and Blundell and Bond [1998] instrument forward orthogonal deviations with levels and levels with differences whereas Arellano and Bond [1991] instruments only differences with levels. This helps to generate more instruments as well as to solve the problem faced by the estimation of Arellano and Bond [1991]. This methodology is known as system GMM which provides a consistent and asymptotically efficient estimator.

The system GMM estimators can be applied in the following situations: (i) dynamic linear panel regression with large N and small T, (ii) dependent variable depends on its own past realizations, (iii) independent variables can be either exogenous or endogenous or predetermined, (iv) error term is composed of by the individual specific fixed effect and by the idiosyncratic disturbances, (v) idiosyncratic disturbances have individual specific heteroskedasticity and serial correlation, whereas disturbances are uncorrelated across individuals. All of these characteristics are relevant for the estimation of eq. (2). Therefore, system GMM has been used to estimate this equation.

The parameters of main interest in the estimation of eq. (2) are different components of human capital (ϑ_2') and the interaction of human capital with the proximity to frontier (ϑ_3'). The theoretical prediction that skilled human capital is growth enhancing in the innovation-only and imitation-innovation regimes and unskilled human capital is growth spurring in the imitation-only regime (as is shown in **Proposition 1** in Basu and Mehra [2014]) implies that $\frac{\partial g_{\mathrm{jt}}}{\partial H_{\mathrm{j,t\text{-}1}}} = \vartheta_2' + \vartheta_3' \ln a_{\mathrm{j,t\text{-}1}}$ is positive for tertiary education (which constitutes skilled human capital) for the rich and the middle income group countries and is negative for the poor income group countries. However, $\frac{\partial g_{\text{jt}}}{\partial H_{\text{j,t-1}}}$ is negative for primary and secondary education (which constitutes unskilled and semi-skilled human capital) for the rich and the middle income group countries and is positive for the poor income group countries.

For the rich countries $A_{\text{t-1}}$ is sufficiently close to $\overline{A}_{\text{t-1}}$. This in turn implies that the distance to the world technology frontier, that is, $\ln a_{\text{j,t-1}}$ converges to zero and $\frac{\partial g_{\text{jt}}}{\partial H_{\text{j,t-1}}} \mid_{A_{\text{t-1}} \to \overline{A}_{\text{t-1}}}$ approximates to $\vartheta_2' > 0$. According to Vandenbussche et al. [2006] (with exogenously given composition of human capital) and Basu and Mehra [2014] (with endogenous allocation of human capital with perfect capital market), the coefficient associated with the interaction term between human capital and distance to frontier (that is, ϑ_3') is positive for tertiary education and is negative for primary and secondary education for the middle income group countries. However with the assumption of the imperfect capital market, the sign of ϑ_3' depends on the persistent inequality level of an economy. By allowing different returns to scale (CRS, increasing returns to scale or decreasing returns to scale) in the imitation and innovation activities, Cerina and Manca [2012] shows that the sign of ϑ_3' depends on the returns to scale of these two activities as well as on the intensity of skilled human capital in the innovation activity. The absolute convergence hypothesis of Basu and Mehra [2014] in **Proposition 2** ensures that there exists a negative relation between distance to frontier and growth rate (that is, $\vartheta_1 < 0$).

2.2 Multiple Output Case Using Data Envelopment Analysis

In this subsection, the methodology for the multiple outputs scenario is discussed which has been used to identify the importance of the different components of human capital on TFP growth. The analysis has been done for 69 countries for the time period 1970-2010. In the first stage, the Malmquist index of TFP has been estimated. This methodology is based on distance functions implemented by DEA by combining all the economies irrespective of their distance to technology frontier for the entire time span. The estimation has been done by using the software provided by Coelli et al. [2005] which is based on Fare et al. [1994b]. From the Malmquist index, not only the TFP growth is obtained but also the decomposition into three factors – technical efficiency gain and technological change and scale efficiency change – can been done. Moreover, the analysis allows variable returns to scale along with the CRS as is discussed in Fare et al. [1994a]. For our analysis, CRS output oriented Malmquist data envelopment analysis has been considered.[3] The specific production function for the multiple outputs case will be set up as:

$$\Theta(\vec{Y}_{\text{jt}}, K_{\text{jt}}, LQ_{\text{jt}}, E_{\text{jt}}, LA_{\text{jt}}) = 0, \tag{3}$$

[3]However, for the CRS production structure output and input oriented measures provide the same inefficiency in terms of TFP growth, technical inefficiency and allocative inefficiency.

To elucidate the notations, E_{jt} and LA_{jt} respectively measure energy consumption and land. In the multiple outputs case $\vec{Y}_{jt}$ is a vector. A 4x4 input-output structure has been used. Capital, quality adjusted labor, energy consumption and land have been used to produce the output of following four sectors – agriculture (agriculture, hunting, forestry and fishing), industry (mining, manufacturing and utilities), service (construction, wholesale, retail trade, restaurants and hotels, transport and storage & communication) and other activities.

In the second stage, similar to the single output case, eq. (2) has been estimated by system GMM for 5 years time span. The analysis has been done by combining all the economies irrespective of their distance to frontier as well as by segregating the economies in terms of their income level (that is, separately for rich, middle and poor income countries). It helps to analyze the importance of human capital on TFP growth depending on the economy's distance to frontier for the multiple outputs case.

2.3 Single Output Case Using Stochastic Frontier Analysis

Till now, the analysis has been done for assessing the impact of the composition of human capital on TFP growth. Next, the importance of the composition of human capital for imitation activity (that is, on technical efficiency gain) has been analyzed. This analysis has been done for the single output scenario – one output and two inputs framework (as specified in eq. (1)). In the first stage, the frontier production function has been estimated for each year by using SFA for 75 countries, (that is, for all the economies together irrespective of their income level) from 1970-2010 at 5 years interval, except for the year 2000.[4] Similar to Meeusen and Van den Broeck [1977] and Aigner et al. [1977], the specific yearly production for country j is estimated to be the following:

$$Y_j = F(K_j, LQ_j)exp(v_j - u_j). \tag{4}$$

To illuminate the notations, v_j measures the symmetric disturbance term which is independently identically distributed as $N(0, \sigma_v^2)$. The error component u_j is assumed to be independent of v_j, and also $u_j \geqslant 0$. u_j captures the technical inefficiency. Therefore, it assumed that the producer is either on the frontier (in case of $u_j = 0$) or beneath of it (when $u_j > 0$). Meeusen and Van den Broeck [1977] assumed u_j follows an exponential distribution whereas Battese et al. [1977] assumed a half-normal distribution. Aigner et al. [1977] considered both half-normal and exponential distributions. In our analysis, in the first stage for Barro and Lee [2013] data set inefficiency is considered to follow an exponential distribution; however for Cohen and Soto [2007] data set it is taken as half-normal distribution. The composed error $(v_j - u_j)$

[4]In this subsection, the year 2000 has been dropped from this analysis, since that particular year is showing no technical inefficiency within the countries.

follows a negatively skewed distribution. The production function has been estimated by using maximum likelihood. The estimation of u_{j} helps to obtain the technical efficiency (that is, te) gain for each country for every time period.

In the second stage, the importance of the different components of human capital on technical efficiency gain are estimated. The empirical framework for the second stage analysis is as follows:

$$TEG_{\mathrm{jt}} = \vartheta_{\mathrm{e0}} + \vartheta_{\mathrm{e1}} \ln \frac{te_{\mathrm{j,t\text{-}1}}}{te_{\mathrm{USA,t}}} + \vartheta'_{\mathrm{e2}} H_{\mathrm{j,t\text{-}1}} + \vartheta'_{\mathrm{e3}} H_{\mathrm{j,t\text{-}1}} \ln \frac{te_{\mathrm{j,t\text{-}1}}}{te_{\mathrm{US,t}}} + \vartheta'_{\mathrm{e4}} Z_{\mathrm{j,t\text{-}1}} + c_{\mathrm{i}} + t_{\mathrm{t}} + \epsilon_{\mathrm{jt}}, \tag{5}$$

where TEG_{jt} measures technological efficiency gain of the j^{th} country in period t, te_{jt} measures technical efficiency of country j in period t and $te_{\mathrm{USA,t}}$ measures technical efficiency of the USA in period t. According to the prediction of Basu and Mehra [2014], $\frac{\partial TE_{\mathrm{jt}}}{\partial H_{\mathrm{j,t\text{-}1}}} = \vartheta'_{\mathrm{e2}} + \vartheta'_{\mathrm{e3}} \ln a_{\mathrm{j,t\text{-}1}}$ is positive for both semi-skilled or unskilled human capital for developing and underdeveloped economies. This is now empirically tested. The empirical specification of eq. (5) is in a similar pattern as in eq. (2). Therefore, the estimation of eq. (5) faces the same problem as mentioned in Subsection 2.1 on page 5 onward. Therefore, system GMM has been applied to estimate the eq. (5) by 5 years gap. The second stage analysis has been done for all the economies together irrespective of their distance from the world technology frontier as well as for the rich, middle and poor income group countries.

3 Data Series Construction

The sample is divided into 22 high, 40 middle and 13 low income countries for the period 1970-2010. As mentioned earlier, to estimate the production function for a single aggregate output, two inputs have been considered – capital and quality adjusted labor. First, the discussion focuses on the construction of the aggregate output data set. The purchasing power parity (PPP) adjusted GDP per capita (Chain Series) at 2005 constant prices and population data have been taken from the PTW [July 2012]. Multiplying these two data series, the aggregate output data have been obtained.

Now, the construction of the data on capital stock is done as follows. The investment share of GDP data has been taken from the PTW [July 2012]. Multiplying this with total GDP (just constructed above), the investment level of country j for each year t in the period under the study is obtained. After this, the capital stock data has been generated by using the perpetual inventory method (PIM) with constant depreciation rate of $\delta = 0.06$. PIM takes the following specification:[5]

$$K_{\mathrm{j,1970}} = \sum_{t=1950}^{1970} I_{jt}(1-\delta)^{1970-t} \quad \text{and} \quad K_{\mathrm{jt}} = (1-\delta)K_{\mathrm{j,t\text{-}1}} + I_{\mathrm{jt}}, \quad \text{for } t \geq 1971,$$

[5]Like Vandenbussche et al. [2006], Aghion et al. [2009].

Variables	obs	Mean	Std. Dev.	Min	Max
Y	3075	4.13e+08	1.21e+09	1543242	1.32e+10
K	3075	1.03e+11	2.99e+11	7.93e+07	3.22e+12
LQ	3075	1.84e+10	7.37e+10	4.24e+07	1.01e+12
YearsP	3075	591.4039	240.4044	31.2	1005
YearsSe	3075	271.0346	188.0849	4.5	826.2
YearsT	3075	36.84427	37.79356	0	208.4
YearsU	3075	224.972	112.1724	6.3	624.9
YearsSS	3075	473.7097	295.7779	6.9	1302.6
YearsS	3075	199.4453	203.296	0	1144.4

Table 1: Descriptive Statistics: Full Sample

where I_{jt} represents the level of investment of country j in period t. The capital stock for the period 1970 has been constructed by adding up the past 20 years' total investment. From 1971 onward, the capital stock data have been constructed by summing up the investment of the current period with the earlier period's non-depreciated capital stock.

The data on labor force participation (in percentage) for the population aged above 15 have been collected from two data sources - Gapminder [2010] (available from 1980 to 2007) and World Bank (WB [2012]) (available from 1990 to 2010). The data for the time period 1970 to 1979 have been estimated by using 1980 data from Gapminder [2010] assuming the labor force paricipation rate to be constant over the time period. From 1980 to 2007, Gapminder [2010] data have been used. From 2008 to 2010, the data from WB [2012] has been used after multiplying it by the ratio of Gapminder [2010] data of 2007 to that of WB [2012] data for 2007. The rate thus obtained is multiplied with total above 15 population of the country, taken from WB [2012], to get the total labor force participation.

To measure the importance of the composition of human capital Barro and Lee [2013] data set has been used.[6] The quality adjusted labor force participation data are measured as following:

$$LQ_{\text{jt}} = L_{\text{jt}} e^{0.06s},$$

where L_{jt} measures total labor force participation aged above 15. In Barro and Lee [2013] data s measures

[6] All the above analyses also have been performed for Cohen and Soto [2007] dataset. These analyses also give similar kind of results as shown below. If anyone is interested to get the results, please contact the authors.

Variables	obs	Mean	Std. Dev.	Min	Max
Y	902	1.01e+09	1.89e+09	3.01e+07	1.32e+10
K2	902	2.43e+11	4.40e+11	4.83e+09	3.22e+12
LQ	902	4.13e+09	7.51e+09	2.64e+08	4.34e+10
YearsP	902	834.6708	96.78634	446.7	1005
YearsSe	902	448.2682	173.204	50.4	826.2
YearsT	902	70.99493	42.44621	5.2	208.4
YearsU	902	247.1789	138.0125	6.3	624.9
YearsSS	902	721.6035	257.4485	99	1302.6
YearsS	902	382.8835	230.1234	29.2	1144.4

Table 2: Descriptive Statistics: Rich Income Group Countries

the average years of total schooling. Given that Barro and Lee [2013] data are available for 5 years span, geometric interpolation has been done to construct the average years of schooling for every year from 1970-2010.

Like Vandenbussche et al. [2006], Ang et al. [2011] and Cerina and Manca [2012], for the second stage analysis, to capture the importance of the education attainment data, two different types of education data have been constructed. The first specification of education attainment is as follows:[7]

$$\text{YearsP} = \sum_{j=1}^{3}\left(\sum_{i=j}^{7} p_{\rm i}\right) n_{\rm j};$$

$$\text{YearsSe} = \sum_{j=4}^{5}\left(\sum_{i=j}^{7} p_{\rm i}\right) n_{\rm j};$$

$$\text{YearsT} = (p_6 + p_7)n_6 + p_7 n_7.$$

The notations $n_{\rm j}$ and $p_{\rm i}$ respectively denote the number of extra years of education which an individual in category i has accumulated over an individual in category $(i-1)$ and fraction of population in category i of schooling attainment. The seven categories taken for analysis are: no schooling, enrolled in primary education, completed primary education, enrolled in secondary education, completed secondary education, enrolled in tertiary education and completed tertiary education. YearsP (resp. YearsSe and YearsT) denotes the number of years of primary (resp. secondary and tertiary) education. The specific parameter

[7]Similar to Ang et al. [2011]

Variables	obs	Mean	Std. Dev.	Min	Max
Y	1640	2.12e+08	7.09e+08	1601001	9.84e+09
K	1640	5.81e+10	2.12e+11	2.85e+08	3.07e+12
LQ	1640	1.01e+10	2.54e+10	4.24e+07	1.62e+11
YearsP	1640	553.5659	178.023	91.2	894
YearsSe	1640	237.9428	131.3191	15.6	599.4
YearsT	1640	28.48503	25.22602	.8	149.6
YearsU	1640	224.9938	89.02223	30	448.5
YearsSS	1640	439.2667	229.9789	33	1137.3
YearsS	1640	154.8471	134.0143	4.4	772.4

Table 3: Descriptive Statistics: Middle Income Group Countries

values assumed are: $(n_1, n_2, n_3, n_4, n_5, n_6, n_7) = (0,\ 3,\ 3,\ 3,\ 3,\ 2,\ 2)$. This specification implies that a tertiary educated individual contributes 6 years to YearsP and another 6 years to YearsSe and 4 years to YearsT. This also implies that an additional year of tertiary education is sufficient to transform 12 years of secondary education to tertiary education.

The second specification of education attainment data is the following:[8]

$$\text{YearsU} = \sum_{i=1}^{3}(\sum_{j=1}^{i} n_{\text{j}})p_{\text{i}};$$

$$\text{YearsSS} = \sum_{i=4}^{5}(\sum_{j=1}^{i} n_{\text{j}})p_{\text{i}};$$

$$\text{YearsS} = p_6 \sum_{j=0}^{6} n_{\text{j}} + p_7 \sum_{j=0}^{7} n_{\text{j}},$$

where YearsU (resp. YearsSS and YearsS) denotes the number of years of unskilled (resp. semi-skilled and skilled) education. With these assumptions, a tertiary educated individual contributes 16 years to YearsS and 0 years to YearsU and YearsSS.

The multiple outputs data have been collected from UNSD [2014]. Along with the earlier two inputs (capital and quality adjusted labor), now two additional inputs have been added here, which are total energy consumption and agricultural land. Total energy consumption data are constructed by multiplying

[8] Similar to Ang et al. [2011]

Variables	obs	Mean	Std. Dev.	Min	Max
Y	533	1.78e+07	2.98e+07	1543242	2.15e+08
K	533	2.81e+09	4.81e+09	7.93e+07	4.19e+10
Lq	533	6.79e+10	1.62e+11	3.10e+08	1.01e+12
YearsP	533	296.146	168.3796	31.2	690.3
YearsSe	533	72.9214	67.20679	4.5	298.5
YearsT	533	4.771596	4.251645	0	15.8
YearsU	533	187.3242	117.3645	15.9	547.8
YearsSS	533	160.1755	154.8214	6.9	645.9
YearsS	533	26.23681	23.40554	0	86.6

Table 4: Descriptive Statistics: Poor Income Group Countries

per capita energy consumption with total population of a country; both of these data have been taken from WB [2012]. To construct total agricultural land, the percentage of agricultural land has been multiplied with the total land of a country; both of these data have also been collected from WB [2012].

Like Ang et al. [2011], the following control variables have been used – rate of consumer price index inflation, trade openness (export plus imports over GDP), ratio of net foreign direct inflows to GDP, financial development (the ratio of private credit to GDP), geographical location (landlockness), all of which have been collected from WB [2012]. Along with the default instrumental variables, some additional instruments have been used, such as lagged public expenditure on primary, secondary and tertiary education, life expectancy and effectiveness of legislature, for which data have been collected from WB [2012]. Hansen and Difference in Hansen tests have been performed to check orthogonality between instrumental variables and the error terms and also to check for the over identifying restrictions of the instrumental variables.

Tables 1, 2, 3 and 4 on pages 11 - 14 present the descriptive statistics for output, capital, quality adjusted labor force participation, education decomposed into primary(P), secondary (Se), tertiary(T), skilled (S), semi-skilled (SS) and unskilled (U) human capital for all, rich, middle and poor income group countries. It is observed that average aggregate output and capital stock is higher for the rich than the poor income countries. The values for middle income group countries fall in between these two. The

Table 5: Econometric Approach – Production Function BL [a]

	Full Sample		Rich		Middle		Poor	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\ln K$	.56***	.49***	.62***	.47***	.68***	.58***	.34***	.36***
	(.049)	(.048)	(.04)	(.078)	(.059)	(.056)	(.049)	(.05)
$\ln LQ$	.42***	.21***	.48***	.42***	.25***	-.105	.6005***	1.08***
	(.07)	(.067)	(.102)	(.09)	(.08)	(.14)	(.047)	(.31)
year		.009***		.006**		.015***		-.017
		(.002)		(.003)		(.005)		(.01)
constant	-4.08***	-15.66***	-6.18***	-12.33***	-3.22***	-23.85***	-5.05***	16.25
	(.88)	(2.34)	(1.53)	(2.73)	(.97)	(6.58)	(1.23)	(14.96)

[a] *Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors.

mean values for primary(P), secondary (Se), tertiary(T), skilled (S), semi-skilled (SS) and unskilled (U) human capital also follow the same pattern as mentioned for the above mentioned variables. However, quality adjusted labor force has highest mean value for the poor income countries followed by the middle and the rich income countries.

4 Key Results

Key findings of this paper are elaborated in this section. First the discussion starts with the case of the single output where panel regression has been used for the analysis. After that, the key results have been highlighted for the multiple outputs case where the Malmquist index has been used for this research. Finally, the talk moves to the case of single output where analysis has been done by utilizing the SFA is taken up.

4.1 Single Output Case using Panel Regression

Table 5 on page 15 presents the production function estimates of eq. (1). It has been assumed that technology is represented by a Cobb-Douglas production function exists. The coefficients of capital and quality adjusted labor differ significantly among rich, middle and poor countries. The elasticity of capital is found to be higher in case of rich and middle countries (approximately around 0.65; at 1% significance levels) than the poor income countries (around 0.35; at 1% significance level). The elasticity of quality adjusted labor force is higher (close to 0.6; at 1% significance level) in poor income group than the rich and middle income group (approximately around 0.4; at 1% significance levels). Moreover, time variable has a significant positive impact only for the rich countries (at 5% level). This implies that the technology underlying the production function for the rich income group countries is different from that for the poor income group countries. Technological change (which has been captured by the year coefficient) has a positive and significant impact only for the rich income countries.

Furthermore, to measure the TFP growth of the j^{th} country in period t for the rich income group countries, those parameters have been considered where time factor has been included to estimate the production function (that is, column 4, in Table 5, on page 15). For the full sample, middle and poor income countries, to measure TFP of country j in period t, those estimated parameters have been considered where the production function is estimated without the variable year (that is, column numbers 1, 5 and 7 respectively in Table 5 on page 15).

In Tables 6 and 7 on pages 17 and 18, the importance of the different compositions of human capital on TFP growth has been demonstrated. The analysis done by combining all the countries together shows that primary, secondary and tertiary education have either negative or insignificant impact on growth. For the full sample, tertiary education or skilled labor force have either insignificant or negative significance at 1% level on growth. This implies that education does not matter for growth.

	Full Sample	Rich	Middle	Poor
$g_{t\text{-}1}$	-.0322719	-.0398036	-.0280498	-.215069**
	(.0629976)	(.0601387)	(.066265)	(.1031194)
$\ln a_{t\text{-}1}$	-.2796108***	-.1358904	-.2280932*	-.176942***
	(.0902133)	(.1724166)	(.1359074)	(.0640798)
$P_{t\text{-}1}$	.0000826	-.0001885	.0000887	.0000973
	(.0003456)	(.0001612)	(.0003102)	(.0004267)
$Se_{t\text{-}1}$	-.0002694	.000062	.0001347*	.0026468*
	(.0003745)	(.0001477)	(.0004459)	(.0014708)
$T_{t\text{-}1}$	.0006289	.0008642***	-.0018908*	.0080573
	(.0008715)	(.0003297)	(.0011188)	(.0081648)
$\ln a_{t\text{-}1}{*}P_{t\text{-}1}$	.000577**	.0001612	.0004787	.0002219
	(.0002389)	(.0003227)	(.0003211)	(.0001714)
$\ln a_{t\text{-}1}{*}Se_{t\text{-}1}$	-.0006663*	-.0000347	-.0004485	.0002946
	(.0003612)	(.000291)	(.0004246)	(.0004697)
$\ln a_{t\text{-}1}{*}T_{t\text{-}1}$	.0017595*	.0008229	-.0017449	.0043191
	(.0009349)	(.0006479)	(.0012246)	(.0031714)
constant	.2804888***	.0790659	.0244107	.0429973
	(.0737028)	(.0752921)	(.0805736)	(.2192192)
sum $\ln a_{t\text{-}1}$	-1.0976	-.4196645	-0.62207	-2.45294
Impact of P	-0.00055*	-0.00026**	-0.00021	-0.00045
Impact of Se	0.000462	7.66E-05	0.000414	0.001924***
Impact of T	-0.0013	0.000519***	-0.00081	-0.00254

[a]*Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors. Other control variables have been used but that have not been reported for brevity.

Table 6: Impact of human capital on TFP growth with First specification of Education Attainment Data [a]

	F	R	M	P
g_{t-1}	-.0680294	-.0415831	-.191199***	-.2174671**
	(.0543464)	(.0605366)	(.0566013)	(.1039379)
$\ln a_{t-1}$	-.0396747	-.0841195	.1256292	-.1622628***
	(.0568613)	(.1474633)	(.1060024)	(.0622892)
U_{t-1}	-.0001373	-.0001833	-.0001628	.000114
	(.0001853)	(.0001417)	(.0002438)	(.000424)
SS_{t-1}	-.0000806	-.0000756	-.0001838*	.0010022**
	(.0000878)	(.0000619)	(.0001102)	(.0004296)
S_{t-1}	-.0000587*	.0001146**	-.0004831***	.0026948*
	(.0000326)	(.0000539)	(.0001674)	(.0015095)
$\ln a_{t-1}*U_{t-1}$	-.0000433	.000044	-.0000856	.0001598
	(.0001444)	(.0002873)	(.0002613)	(.0001682)
$\ln a_{t-1}*SS_{t-1}$	.0000525	.0000636	-.0000676	.0002124*
	(.0000588)	(.0001003)	(.0000963)	(.0001162)
$\ln a_{t-1}*S_{t-1}$	-.0000748**	.0001855*	-.0004214**	.0009784*
	(.0000388)	(.0000986)	(.000176)	(.0005651)
constant	.0434884	-.000383	.0626334	.1033446
	(.0530385)	(.0003674)	(.0607702)	(.2238923)
sum $\ln a_{t-1}$	-1.0976	-.4196645	-0.62207	-2.45294
Impact of U	-9E-05	-0.0002**	-0.00011	-0.00028
Impact of SS	-0.00014*	-0.0001**	-0.00014	0.000481**
Impact of S	2.34E-05	3.68E-05	-0.00022*	0.000295

[a]*Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors. Other control variables have been used but that have not been reported for brevity.

Table 7: Impact of human capital on TFP growth with Second specification of Education Attainment Data [a]

For the rich country group, both tertiary education and skilled labor force have positive and significant impact on economic growth. The coefficients are respectively significant at 1% and 5% levels. However, primary and secondary education or unskilled and semi-skilled human capital have either positive or negative insignificant impact on economic growth. For the poor income countries, secondary education and semi-skilled human capital have positive and significant impact on growth. The coefficients are respectively significant at 1% and 5% levels. However, tertiary education and skilled human capital have either negative or positive insignificant impact on growth for the poor income countries. That is, it is found that skilled human capital or tertiary educated people are more important for higher growth rate for the rich income countries, whereas, secondary educated or semi-skilled human capital are more growth enhancing for the poor income countries.

Convergence hypothesis (as mentioned by Basu and Mehra [2014]) is also verified for the poor and middle income group countries. The coefficients associated with $\ln a_{t-1}$ show as an economy progresses technologically growth rate falls (at 1% and 5% significance levels respectively) which is in line with the findings of Barro et al. [1991], Barro et al. [1992], Sala-i Martin [1994] and Sala-i Martin [1996].

4.2 Multiple Outputs Case Using Data Envelopment Analysis

This subsection discusses the key finding of the analysis undertaken by using the multiple outputs framework. After estimating the production function by using the Malmquist index based on DEA, the second stage regression analysis has been done by using system GMM. In the analysis of multiple outputs case with DEA, one technical issue arises:

1. DEA compares a country's technology level from the highest technology level. The methodology is such that if a country has a very high capital-labor ratio or a very low capital-labor ratio, the country tends to be on the frontier. The implication is that the estimates show both the extremely poor and rich countries to be very efficient. As a consequence, it assumes that the extremely poor countries to be at the frontier. This is the limitation of the DEA methodology. To overcome this problem, a dummy variable has been used (that is a_d in Tables 8 and 9 on pages 20 and 21). The dummy takes a value of 1 if the country is 100 percent efficient otherwise it is 0. One can also observe that, as a consequence of this, the average distance to frontier of different income group countries are not an increasing function of the level of development of the economies. This also disturbs the decomposition of TFP into two components. As a result, the analysis of the impact of human capital on technical efficiency gain and technological change becomes counter intuitive.[9]

[9] The results are not provided here for brevity. These can be obtained from the researcher upon request.

	Full Sample	Rich	Middle	Poor
$g_{\text{t-1}}$	-.11**	-.094	-.01	-.36**
	(.047)	(.08)	(.06)	(.16)
$\ln a_{\text{t-1}}$	.47	-4.86	-1.65**	-3.19***
	(.59)	(2.99)	(.79)	(.95)
$P_{\text{t-1}}$	.005	-.004	.002*	.02**
	(.004)	(.006)	(.001)	(.007)
$Se_{\text{t-1}}$	-.01**	-.001	-.003*	-.007
	(.004)	(.004)	(.002)	(.01)
$T_{\text{t-1}}$	.03**	.03**	.02**	.002
	(.01)	(.01)	(.01)	(.09)
$\ln a_{\text{t-1}} {}^{*} P_{\text{t-1}}$	-.004***	.004	.001	-.00001
	(.001)	(.005)	(.002)	(.002)
$\ln a_{\text{t-1}} {}^{*} Se_{\text{t-1}}$	.004*	.0005	-.002	-.04**
	(.002)	(.003)	(.002)	(.02)
$\ln a_{\text{t-1}} {}^{*} T_{\text{t-1}}$	-.01	-.002	-.05	1.1***
	(.01)	(.01)	(.01)	(.4)
a_{d}		.87***	.79***	.76**
		(.17)	(.12)	(.34)
constant	-.48	.4	-1.33**	-3.38
	(.58)	(2.52)	(.67)	(3.11)
sum $lna_{\text{t-1}}$	-0.38	-.46	-.33	-.21
Impact of P	0.007*	-0.005	0.002*	0.02**
Impact of Se	-0.01**	-0.001	-0.003*	0.002
Impact of T	0.03***	0.03***	0.02**	-0.22*

[a] *Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors. Other control variables have been used but that have not been reported for brevity.

Table 8: DEA – Impact of Human Capital on TFP growth with First specification of Education Attainment Data [a]

	Full Sample	Rich	Middle	Poor
$g_{\text{t-1}}$	-.1**	-.16**	.001	-.03
	(.05)	(.08)	(.07)	(.16)
$\ln a_{\text{t-1}}$	.84	-2.8	-2.29***	-.85
	(.61)	(2.84)	(.86)	(1.46)
$U_{\text{t-1}}$	.0001	-3.71e-06	-.0002	.02*
	(.001)	(.01)	(.003)	(.01)
$SS_{\text{t-1}}$	-.002	-.002	.002	.001
	(.001)	(.003)	(.002)	(.004)
$S_{\text{t-1}}$	.003*	.006***	.005**	.006
	(.002)	(.002)	(.002)	(.01)
$\ln a_{\text{t-1}}$*$U_{\text{t-1}}$	-.003**	-.0004	.002	-.02**
	(.002)	(.004)	(.002)	(.01)
$\ln a_{\text{t-1}}$*$SS_{\text{t-1}}$	-.001**	.001	.0004	-.0004
	(.001)	(.002)	(.001)	(.01)
$\ln a_{\text{t-1}}$*$S_{\text{t-1}}$	-.001	.0002	-.00002	.06
	(.001)	(.002)	(.001)	(.09)
a_{d}		-.32	.73***	.55
		(2.18)	(.13)	(.34)
constant	-.05	-.32	-.72	-2.2
	(.64)	(2.18)	(.73)	(3.33)
sum $\ln a_{\text{t-1}}$	-.36	-.46	-.33	-0.21
Impact of U	0.001	0.0002	-0.002	0.02**
Impact of SS	-0.001	-0.003	0.002	0.01
Impact of S	0.004*	0.01***	0.005**	-0.01

[a] *Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors. Other control variables have been used but that have not been reported for brevity.

Table 9: DEA – Impact of Human Capital on TFP growth with Second specification of Education Attainment Data [a]

The second stage regression analysis has been presented in Tables 8 and 9 on pages 20 and 21. It is shown that the tertiary education and skilled human capital (significant at 1% level) are growth enhancing and semi-skilled/ unskilled human capital does not matter for growth in the rich income countries. Also, for the middle income countries it is confirmed that tertiary education and skilled human are growth enhancing at 5% significance level. However, for the poor income countries primary education or unskilled human capital have positive impact on growth at 5% significance level. These findings are in line with the result of the aggregate output case, which has been discussed above in Subsection 4.1 from page 16 onward.

4.3 Single Output Case Utilizing Stochastic Frontier Analysis

Next, the key findings of the analysis based on SFA are discussed. In Tables 10 and 11 on pages 23 and 24, the estimates of the stochastic frontier production function are presented. The functional form of the production function is taken as Cobb-Douglas. The production function has been estimated for eight years between 1970 and 2010 using data for all the economies together irrespective of their income levels. The capital coefficient is estimated to be significantly higher as compared to that for quality adjusted labor. This part of the analysis does not directly use the estimated elasticity of different inputs, so the fact that has been ignored is that the coefficients associated with the elasticity of inputs are not consistent with the findings of the Subsection 4.1. The focus of this analysis is on estimating the technical efficiency gain which has been obtained from the one sided error component which follows exponential distribution for the Barro and Lee [2013] data set and half normal distribution for the Cohen and Soto [2007] data set.

The second stage regression analysis which captures the importance of the different components of human capital on technical efficiency gain has been elaborated in Tables 12 and 13 on pages 25 and 26. It is observed that the ranking of the economies in terms of technical efficiency is highly positively correlated with its income level. That is, sum of $\ln te_{t-1}$ rises as an economy moves from the poor to middle to rich income group. This implies that technologically backward economies rely more on technical efficiency gain than technologically advanced economies.

Tertiary education is important for technical efficiency gain for the developed economies, that is, for the rich income group countries. The coefficient is significant at 5% level. But secondary education or semi-skilled human capital have positive significant impact on technical efficiency gain for the developing economies, that is, for the economies which are in the middle and poor income group. The coefficients are respectively significant at 5% and 1% levels.

Further, the analysis has been carried out for the full sample (combining all the economies irrespective of their income level) and it is found that education does not matter at all for technical efficiency gain.

	1970	1975	1980	1985
$\ln K$	.83***	.85***	.89***	.91***
	(.02)	(.02)	(.03)	(.02)
$\ln LQ$	.17***	.13***	.11***	.09***
	(.03)	(.03)	(.03)	(.02)
constant	-4.49***	-4.3***	-4.77***	-5.19***
	(.52)	(.59)	(.57)	(.62)
$\ln \sigma_v^2$	-4.04***	-3.83	-3.97***	-3.8***
	(.53)	(.44)	(.77)	(.59)
$\ln \sigma_u^2$	-1.79***	-1.99***	-2.29***	-2.5***
	(.35)	(.38)	(.52)	(.54)

[a] u_{j} captures the inefficiency of country j. v_{j} measures the random error of country j. σ denotes the variance. *Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors.

Table 10: SFA – Production Function (1970 – 1985) [a]

For the full sample, secondary education or unskilled and semi-skilled human capital have significantly (at 5% level) negative impact on technical efficiency gain. To capture the influence of the composition of human capital on technical efficiency gain, one needs to introduce the concept of distance to frontier. It also illustrates that poor income group countries are converging in terms of the technical efficiency. It is captured through the effect of the concerned economy's relative gap of the technical efficiency from the world leader's technical efficiency (that is, $\ln \frac{te_{t-1}}{te_{US}}$) on the technical efficiency gain (that is, te_{t-1}). This implies that the scope of imitation (which is measured by technical efficiency) is high for the poor income group countries.

5 Conclusion

Technological progress can occur through two channels – imitating from the world technology frontier or by innovating new knowledge. By using SFA for 75 countries over the period 1970-2010 at time intervals of 5 years, it is shown that rich countries mainly rely on technological change whereas middle income countries rely on both imitation and innovation activities for further improvement. Poor countries rely

	1990	1995	2005	2010
$\ln K$	.89***	.9***	.9***	.88***
	(.03)	(.03)	(.03)	(.04)
$\ln LQ$	.1**	.09***	.07***	.08**
	(.05)	(.03)	(.03)	(.04)
constant	-4.86***	-4.76***	-4.42***	-4.2***
	(.47)	(.57)	(.61)	(.69)
$\ln \sigma_v^2$	-4.59**	-3.01***	-3.04***	-3.21***
	(1.84)	(.49)	(.51)	(.8)
$\ln \sigma_u^2$	-2.11***	-2.8***	-3.5	-3.44
	(.56)	(.62)	(1.93)	(6.44)

[a] u_{j} captures the inefficiency of country j. v_{j} measures the random error of country j. σ denotes the variance. *Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors.

Table 11: SFA – Production Function (1990 – 1995) and (2005 – 2010) [a]

on imitation activities only. Moreover, by using the system GMM, it is also shown that skilled human capital is important for technical efficiency gain for rich income countries whereas middle and poor income countries rely on semi-skilled human capital for technical efficiency gain. To capture the importance of skilled, semi-skilled and unskilled human capital on TFP growth, both aggregate output framework and multiple outputs framework have been considered. For the aggregate output framework, the production function has been estimated by using fixed effect panel regression whereas for the multiple outputs case, DEA based Malmquist index has been used. For the aggregate output framework, it is assumed that the technology is characterized by Cobb-Douglas production function. The DEA based analysis does not make any assumption about the form of production function. For the second stage analysis, this research is utilizing the system GMM approach. For both aggregate and multiple outputs, it is found that skilled human capital contributes to growth more for the rich and middle income countries whereas semi-skilled human capital is growth enhancing in the poor income countries, where growth is proxied by gain in TFP.

	Full Sample	Rich	Middle	Poor
$te_{\text{t-1}}$	.04	-.82	-3.19***	-.72***
	(.17)	(1.07)	(1.24)	(.22)
$\ln \frac{te_{\text{t-1}}}{te_{\text{USA}}}$	.49	.4	-.97	-.37***
	(.53)	(1.32)	(.93)	(.13)
$P_{\text{t-1}}$	.001	-.001	.0004	.003**
	(.001)	(.001)	(.001)	(.002)
$Se_{\text{t-1}}$	-.004**	.0002	.005	3.69e-06
	(.002)	(.001)	(.004)	(.002)
$T_{\text{t-1}}$	-.01	.0005	-.01	-.037**
	(.01)	(.001)	(.01)	(.02)
$\ln \frac{te_{\text{t-1}}}{te_{\text{USA}}} * P_{\text{t-1}}$	-.002	.0002	.01**	.001*
	(.003)	(.002)	(.004)	(.001)
$\ln \frac{te_{\text{t-1}}}{te_{\text{USA}}} * Se_{\text{t-1}}$	-.001	-.0002	-.01**	-.01
	(.005)	(.001)	(.01)	(.004)
$\ln \frac{te_{\text{t-1}}}{te_{\text{USA}}} * T_{\text{t-1}}$	.01	-.003	.03*	-.01
	(.01)	(.003)	(.02)	(.04)
constant	.1	.7	-.79	.8
	(.46)	(.44)	(.78)	(1.11)
sum $\ln te_{\text{t-1}}$	-.31	-0.24	-.34	-0.48
Impact of P	0.001	-0.002*	-0.003***	0.002*
Impact of Se	-0.004**	0.0002	0.01**	0.002
Impact of T	-0.01	0.001**	-0.02**	-0.03**

[a]*Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors. Other control variables have been used but that have not been reported for brevity.

Table 12: SFA – Impact of human capital on technical efficiency gain with First specification of Education Attainment Data [a]

	Full Sample	Rich	Middle	Poor
$te_{\text{t-1}}$	.03	-.19	-2.27	
	(.19)	(.15)	(1.18)	
$\ln \frac{te_{\text{t-1}}}{te_{\text{USA}}}$	-.63	-1.09	.0014	-1.3***
	(.78)	(.93)	(.94)	(.35)
$U_{\text{t-1}}$	-.01**	-.0003	.0004	.003*
	(.003)	(.001)	(.001)	(.002)
$SS_{\text{t-1}}$	-.003**	-.0002	.0005	.004**
	(.001)	(.0002)	(.001)	(.002)
$S_{\text{t-1}}$	-.001	-.0001	.001	-.005**
	(.002)	(.0001)	(.001)	(.003)
$\ln \frac{te_{\text{t-1}}}{te_{\text{USA}}} * U_{\text{t-1}}$	.003	.002	.01	.003*
	(.004)	(.002)	(.004)	(.002)
$\ln \frac{te_{\text{t-1}}}{te_{\text{USA}}} * SS_{\text{t-1}}$	-.0002	.0004	-.001	.0003
	(.001)	(.001)	(.001)	(.002)
$\ln \frac{te_{\text{t-1}}}{te_{\text{USA}}} * S_{t-1}$	-.001	.0001	.01*	-.01
	(.002)	(.001)	(.002)	(.01)
constant	.17	.36	-.47	.83
	(.58)	(.28)	(.76)	(1.28)
sum $\ln te_{\text{t-1}}$	-.31	-.24	-.34	-.48
Impact of U	-0.01***	-0.001**	-0.002	0.002
Impact of SS	-0.003**	-0.0003***	0.001	0.004***
Impact of S	-0.001	-0.0001	-0.001	0.001

[a]*Indicates 10% level of significance. ** Indicates 5% level of significance. *** Indicates 1% level of significance. The numbers in parentheses are robust standard errors. Other control variables have been used but that have not been reported for brevity.

Table 13: SFA – Impact of human capital on technical efficiency gain with Second specification of Education Attainment Data [a]

Table 14: Country Name

Rich	Middle	Poor
Australia	Cyprus	Kenya
Australia	Singapore	Mali
Belgium	Trinidad &Tobago	Mozambique
Canada	Algeria	Tanzania
Denmark	Argentina	Uganda
Finland	Chile	Bangladesh
France	China	Benin
Germany	Colombia	Central African Republic
Greece	Costa Rica	Haiti
Hungary	Ecuador	Malawi
Ireland	Gabon	Nepal
Italy	Jamaica	Niger
Japan	Jordan	Zimbabwe
Netherlands	Malaysia	
New Zealand	Mauritius	
Norway	Mexico	
Portugal	Panama	
Spain	Peru	
Sweden	Romania	
Switzerland	South Africa	
United Kingdom	Thailand	
United States	Tunisia	
	Uruguay	
	Bolivia	
	Egypt	
	El Salvador	
	Ghana	
	Guatemala	
	Honduras	
	India	
	Indonesia	
	Morocco	
	Nicaragua	
	Paraguay	
	Philippines	
	Senegal	
	Zambia	
	Syria	
	Cameroon	
	Dominican Republic	

Bibliography

P. Aghion and P. Howitt. A model of growth through creative destruction. *Econometrica*, 60(2):323–351, 1992. 1

P. Aghion and P. Howitt. The economics of growth. 2009. 6

P. Aghion, L. Boustan, C. Hoxby, and J. Vandenbussche. Exploiting states mistakes to identify the causal impact of higher education on growth. *NBER Working Paper. Forthcoming*, 2009. 2, 3, 10

D. Aigner, C. K. Lovell, and P. Schmidt. Formulation and estimation of stochastic frontier production function models. *journal of Econometrics*, 6(1):21–37, 1977. 9

J. B. Ang, J. B. Madsen, and M. R. Islam. The effects of human capital composition on technological convergence. *Journal of Macroeconomics*, 33(3):465–476, 2011. 1, 2, 3, 5, 12, 13, 14

M. Arellano and S. Bond. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The review of economic studies*, 58(2):277–297, 1991. 5, 6, 7

M. Arellano and O. Bover. Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, 68(1):29–51, 1995. 6, 7

R. J. Barro and J. W. Lee. A new data set of educational attainment in the world, 1950–2010. *Journal of development economics*, 104:184–198, 2013. 9, 11, 12, 22

R. J. Barro and X. Sala-i Martin. *Economic growth*. MIT Press, 1995. 1

R. J. Barro, X. Sala-i Martin, O. J. Blanchard, and R. E. Hall. Convergence across states and regions. *Brookings papers on economic activity*, pages 107–182, 1991. 19

R. J. Barro, X. Sala-i Martin, O. J. Blanchard, and R. E. Hall. Convergence. *Journal of Political Economy*, 100(2):223–251, 1992. 19

S. Basu and M. K. Mehra. Endogenous human capital formation, distance to frontier and growth. *Research in Economics*, 68(2):117–132, 2014. 7, 8, 10, 19

G. E. Battese, G. S. Corra, et al. Estimation of a production frontier model: with application to the pastoral zone of eastern australia. *Australian journal of agricultural economics*, 21(3):169–179, 1977. 9

J. Benhabib and M. M. Spiegel. The role of human capital in economic development evidence from aggregate cross-country data. *Journal of Monetary economics*, 34(2):143–173, 1994. 1, 4

A. Bhargava and J. D. Sargan. Estimating dynamic random effects models from panel data covering short time periods. *Econometrica: Journal of the Econometric Society*, pages 1635–1659, 1983. 6

M. Bils and P. J. Klenow. Does schooling cause growth? *American economic review*, pages 1160–1183, 2000. 6

R. Blundell and S. Bond. Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, 87(1):115–143, 1998. 7

R. Blundell and S. Bond. Gmm estimation with persistent panel data: an application to production functions. *Econometric reviews*, 19(3):321–340, 2000. 5

S. R. Bond. Dynamic panel data models: a guide to micro data methods and practice. *Portuguese economic journal*, 1(2):141–162, 2002. 6

F. Caselli and W. J. Coleman II. The world technology frontier. *The American Economic Review*, 96(3): 499–522, 2006. 2

F. Cerina and F. Manca. Catch me if you learn: development-specific education and economic growth. Technical report, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia, 2012. 1, 2, 3, 5, 6, 8, 12

T. J. Coelli, D. Prasada Rao, C. J. ODonnell, and G. E. Battese. Data envelopment analysis. *An Introduction to Efficiency and Productivity Analysis*, pages 161–181, 2005. 8

D. Cohen and M. Soto. Growth and human capital: good data, good results. *Journal of economic growth*, 12(1):51–76, 2007. 9, 11, 22

S. N. Durlauf and P. A. Johnson. Multiple regimes and cross-country growth behaviour. *Journal of Applied Econometrics*, 10(4):365–384, 1995. 1

R. Fare, S. Grosskopf, and C. K. Lovell. *Production frontiers*. Cambridge University Press, 1994a. 8

R. Fare, S. Grosskopf, M. Norris, and Z. Zhang. Productivity growth, technical progress, and efficiency change in industrialized countries. *The American economic review*, pages 66–83, 1994b. 8

Gapminder. International labour organization through www.gapminder.org, 2010. 11

W. Greene. *Econometric analysis*. Granite Hill Publishers, 2008. 5

Z. Griliches. Research expenditures, education, and the aggregate agricultural production function. *The American Economic Review*, pages 961–974, 1964. 1

Z. Griliches. Research expenditure and growth accounting. Technical report, B. R. Williams, ed., Science and Technology in Economic Growth. New York: Macmillan, 1973. 1

Z. Griliches. Productivity puzzles and r & d: another nonexplanation. *The Journal of Economic Perspectives*, pages 9–21, 1988. 1

J. Hausman. Specification tests in econometrics. *Econometric*, 6(46):1251–1271, 1978. 5

J. A. Hausman and W. E. Taylor. Panel data and unobservable individual effects. *Econometrica: Journal of the Econometric Society*, pages 1377–1398, 1981. 6

D. Holtz-Eakin, W. Newey, and H. S. Rosen. Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, pages 1371–1395, 1988. 7

P. J. Huber. The behavior of maximum likelihood estimates under nonstandard conditions. *In Vol. 1 of Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, 1:221–233, 1967. 5

P. Kalaitzidakis, T. P. Mamuneas, A. Savvides, and T. Stengos. Measures of human capital and nonlinearities in economic growth. *Journal of Economic Growth*, 6(3):229–254, 2001. 1

J. F. Kiviet. On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of econometrics*, 68(1):53–78, 1995. 6

A. B. Krueger and M. Lindahl. Education for growth: Why and for whom? *Journal of Economic Literature*, 39(4):1101–1136, 2001. 1

W. Meeusen and J. Van den Broeck. Efficiency estimation from cobb-douglas production functions with composed error. *International economic review*, pages 435–444, 1977. 9

J. R. Minasian. The economics of research and development. In *The Rate and Direction of Inventive Activity: Economic and Social Factors*, pages 93–142. Princeton University Press, 1962. 1

S. Nickel. Biases in the dynamic models with fixed effects. *Econometrica*, 49(6):1417–1426, 1981. 6

PTW. Alan heston, robert summers and bettina aten, penn world table version 7.1, center for international comparisons of production, income and prices at the university of pennsylvania, July 2012. 10

P. M. Romer. Endogenous technological change. *The Journal of Political Economy*, 98(5):S71–S102, 1990. 1

D. Roodman. How to do xtabond2: An introduction to difference and system gmm in stata. *Stata Journal*, (9):86–136, 2009. 5, 6

X. Sala-i Martin. Cross-sectional regressions and the empirics of economic growth. *European Economic Review*, 38(3):739–747, 1994. 19

X. X. Sala-i Martin. Regional cohesion: evidence and theories of regional growth and convergence. *European Economic Review*, 40(6):1325–1352, 1996. 19

N. E. Terleckyj. Factors underlying productivity-some empirical observations. In *Journal of the American Statistical Association*, volume 53, pages 593–593. Amer Statistical Assoc 1429 Duke ST, Alexandria, VA 22314, 1958. 1

UNSD. United nations statistics divisions. http://unstats.un.org/unsd/snaama/dnllist.asp, 2014. 13

J. Vandenbussche, P. Aghion, and C. Meghir. Growth, distance to frontier and composition of human capital. *Journal of economic growth*, 11(2):97–127, 2006. 2, 3, 5, 6, 8, 10, 12

WB. World development indicators, world bank, 2012. 11, 14

H. White. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, (48):817–838, 1980. 5

H. White. Maximum likelihood estimation of misspecified models. *Econometrica 48: 817838.*, (50):1–25, 1982. 5