Labor Composition and Economic Development in Developing Countries

Yasemin ÖZERKEK, PhD
Marmara University
Faculty of Economics, Department of Economics
Goztepe Campus, Kuyubasi, Kadikoy, Istanbul, TURKEY
E-mail: yasemin.ozerkek@marmara.edu.tr

Abstract

Because workers are heterogeneous in terms of their skill levels and competences, the composition of labor force is important for the quantity and quality of human capital. This paper concentrates on the importance of labor force quality, as measured by the change in labor composition, and its effects on economic development. The empirical analysis shows that labor composition proves to have a positive significant influence on economic development for a panel of developing countries in the period 1990-2009. Therefore, labor composition is a crucial factor in understanding economic growth and development.

Key words: Labor composition, economic development

JEL Codes: J21, J24, O10, O40

1. Introduction

Human capital plays a central role in the analyses of economic growth and development. Pissarides (2007) argues that the conclusion reached from a reading of the recent growth literature is that if we are to understand growth and development, we need to understand the creation and use of human capital. Growth rates of the countries are directly related to stock of human capital (See models of endogenous growth, e.g. Nelson and Phelps (1966), Romer (1990a), and Rebelo (1991)). Many of the previous investigations of growth focused on various measures of educational attainment as proxy for relevant human capital. The primary or secondary school enrollment rates are commonly used in the growth analysis (e.g., Romer (1990b), Barro (1991), Mankiw et al. (1992)). In the later studies, Barro and Lee (1993, 2010) provided an internationally comparable data on average years of schooling for a large sample of countries and years.
OECD (1989) argues that there are some drawbacks to using educational attainment as a proxy for labor force qualifications, particularly in international comparative analysis. Since education systems vary across countries with respect to the stages into which education is broken, these stages and duration of education are not comparable. Educational attainment represents only a part of labor force qualifications and it has limitations as a proxy for measuring the labor quality. Furthermore, the data for educational attainment do not involve the skills and competences acquired in the course of employment through informal education and training (OECD, 1989).1

Hanushek and Kim (1995) and Hanushek and Kimbo (2000) address the measurement problem of labor-force quality. Rather than relying on measures of schooling inputs, they construct measures of labor quality based on student cognitive performance by using comparative tests of mathematics and scientific skills. The results of their analyses show that labor-force quality differences have a consistent, stable, and strong relationship with economic growth. Hanushek and Woesmann (2010) also show that cognitive skills can account for growth differences within the OECD.

Hendricks (2002) estimates the human capital of workers from different countries by considering their earnings in the same labor market. Labor earnings differentials across U.S. immigrants with the same measured skills are used to understand their unmeasured human-capital endowments. Hendrick (2002) argues that this approach enables capturing measured as well as unmeasured skill differences without the need for a human capital production function.

Labor input measured in terms of total employment and total hours worked, is a labor quantity. Although labor quantity is important, labor quality is an important determinant in explaining the greater output when labor quantity is fixed. The total hours worked becomes more efficient with higher quality of labor. Zoghi (2010, p.457) points out that “a measure that only counts number of workers or hours ignores that some work hours produce more than others do. For instance, the work hour put forth by a brand new employee is not likely to produce as much output as the work hour put forth by someone who has been on the job many years. In this case, the effectiveness of the latter work hour is greater than that of the former.”

---

1 OECD (1989) stresses that, however, “measures of variations in attainment or performance, such as variations in patterns of overall schooling levels or in participation in education between subgroups of the population or the labor force, are useful for assessing developments within countries. These patterns can in turn more readily be compared across countries.” (p.48)
In this regard, labor composition can be considered to provide a good representative measure of labor input.

McNaughton (2009, p.3) states that “the rationale for adjusting labor input for changes in labor composition, is that workers are not homogenous, and as such, have different skill levels. Not only should this adjustment provide a more complete measure of labor input, but it can also provide insight into the effects that changes in labor composition have on productivity.”

This paper investigates the effects of labor quality on economic development of developing countries. Growth in the labor composition is used to measure the labor quality in the analyses. Based on baseline model of Hanushek and Kim (1995) and Hanushek and Kimbo (2000), the GDP per capita growth rates of countries are expressed as a function of the labor quality (as measured by labor composition) and other control variables. The results of the analyses show that labor composition is an important component in explaining economic development in developing countries.

The rest of the paper is organized as follows. Section 2 delineates the measurement of labor composition, Section 3 presents the data, methodology, and empirical analyses, and Section 4 concludes the paper.

2. The Measurement of Labor-Force Quality

Zoghi (2000, p.457) defines labor composition index as “an index that adjusts the total hours worked for the demographic composition of those hours, which requires identification of separate, heterogeneous groups of labor input whose work hours are likely to have varying effectiveness.”

In order to take the heterogeneity of the labor force into account, the labor composition index (also called labor quality index) is constructed based on weighted measures of different skill-level groups in the labor force, using the Törnqvist index (See Appendix).

\[
\text{DIn}LC_i = \hat{a}_i - \frac{1}{2} \hat{g}_{i,t} + \nu_{i,t} \text{DInh}_{i,t} \quad [1]
\]

in which \( \nu_{i,t} \) is the share in labor compensation by labor type \( i \) and \( \text{DInh}_{i,t} \) is the log of the change in share of hours by labor type \( i \).
Wage ratios are reconstructed using:

$$v_{j,i,t} = h_{j,i,t} \frac{w_{j,i,t}}{\bar{w}_{j,t}}$$

in which $w_{j,i,t}$ is the wage earned by labor type $i$ at time $t$ in country $j$ and $\bar{w}_{j,t}$ is the average wage at time $t$ in country $j$.

By using the above methodology, labor composition index is calculated by The Conference Board Total Economy Database, Groningen Growth, and Development Centre.\(^2\)

A positive labor composition (or labor quality) signals that the share of high-skilled workers in the labor force rises over time the hours worked shifts towards more experienced (efficient) workers.

3. Data, Methodology, and Empirical Findings

3.1 Data

The study uses annual data on the variables of growth in labor composition ($g\text{lc}$), growth of capital services provided by ICT assets ($g\text{ict}$), growth of GDP per capita in 1990 US$ ($g\text{gdp}_c$), annual population growth ($g\text{pop}$), and average years of total schooling ($s\text{ch}$). All the data except for $s\text{ch}$ is obtained from the Conference Board the Total Economy database, University of Groningen. The data source for $s\text{ch}$ is Barro and Lee (2010). The developing countries included in the analysis are Portugal, Indonesia, India, Thailand, Argentine, Chile, Turkey, Poland, Colombia, Korea, Malaysia, Mexico, Egypt, Philippines, South Africa, Brazil, and Singapore. The data is balanced panel and covers 1990-2009.

3.2 Methodology and Empirical Findings

The empirical work in this section relies on the idea of endogenous growth models where stock of human capital is a significant contributor to economic growth. Relying on the cross-country baseline models of Hanushek and Kim (1995) and Hanushek, and Kimko (2000), the following model is employed:

\(^2\) See data and further methodological information at <http://www.conference-board.org/data/economydatabase/>

\(^3\) Non-ICT capital includes three asset types: non-residential construction, transport equipment, and machinery. ICT capital also has three asset types: IT hardware, telecommunication equipment, and software.
They estimate the effects of labor quality, measured by international test scores in mathematics and science on growth. Besides the use of different measure for labor quality, the above model differs from Hanushek and Kim (1995) and Hanushek and Kimko (2000) in some other respects. They adopt a growth model that combines elements of a general endogenous growth framework and a basic augmented neoclassical approach. In their cross-country analyses, they include the initial level of income among the control variables, thereby allowing for conditional convergence, which is as a characteristic of the augmented neoclassical approach.

In the analysis, panel unit root tests of ADF-Fisher (Maddala and Wu, 1999) and Levin et al. (2002)-hereafter LLC- are performed in order to detect whether the variables have unit roots. The test of ADF-Fisher allows for individual unit root processes. The test of LLC tests the null hypothesis of a common unit root when the cross-sectional units are independent of each other. This test, which is applicable to panels with modest sample size, requires the coefficient of the lagged dependent variable to be homogenous across all units of the panel.

The test results indicate the nonexistence of unit root in the levels of variables. Therefore, the variables exhibit stationary characteristics and stationary panel data analyses can be performed.

<table>
<thead>
<tr>
<th>Table 1. Panel Unit Root Tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>ADF-Fisher</td>
</tr>
<tr>
<td>Constant&amp; trend</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>LLC</td>
</tr>
<tr>
<td>Constant&amp; trend</td>
</tr>
</tbody>
</table>

Notes: The null hypothesis for LLC is unit root. The numbers in brackets are the p-values for the tests. (*) and (**) denotes the rejection of the null of unit root at 1% and 10% significance levels, respectively.
Table 2 Estimation Results

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Period: 1990-2009</th>
<th>Fixed Effects Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>ggdpc</td>
<td>0.048(^*)</td>
<td>0.043(^*)</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>glc</td>
<td>0.166(^*)</td>
<td>0.163(^**)</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>gict</td>
<td>1.257</td>
<td></td>
</tr>
<tr>
<td>gpop</td>
<td>-0.372</td>
<td>-0.701</td>
</tr>
<tr>
<td></td>
<td>(0.467)</td>
<td>(0.431)</td>
</tr>
<tr>
<td>sch</td>
<td>-0.007(^*)</td>
<td>-0.006(^*)</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>glc*sch</td>
<td>323</td>
<td>323</td>
</tr>
<tr>
<td>Countries</td>
<td>17</td>
<td>17</td>
</tr>
</tbody>
</table>

Hausman Test

<table>
<thead>
<tr>
<th>(P&gt;chi2 =0.006)</th>
<th>(P&gt;chi2 =0.001)</th>
<th>(P&gt;chi2 =0.005)</th>
</tr>
</thead>
<tbody>
<tr>
<td>16.07</td>
<td>17.10</td>
<td>12.67</td>
</tr>
</tbody>
</table>

Robust standard errors are in parentheses. (*) (**), and (*** denote 1%, 5%, and 10% significance levels, respectively.

Table 2 reports the results of panel regressions that describe growth in real per capita GDP between 1990 and 2009. The results of Hausman (1978) specification test suggest fixed-effects models. The fixed effect models investigate the magnitude and significance of any influence of growth of labor composition (glc) on ggdpc, along with other assessed factors.\(^4\) Model 1 reports the estimation results for Equation [3]. Growth of labor composition has a positive significant effect on ggdpc, meaning that as growth in labor quality (aggregate skill level) changes, per capita GDP growth changes in the same direction also. Growth of ICT capital services (gict) has the expected positive and significant effect on ggdpc. While both gict and glc positively contribute to explaining variations in per capita growth rates, population growth (gpop) has a positive but insignificant effect. The coefficient of average years of total schooling (sch) is negative contrary to expectations but it is insignificant.\(^5\)

\(^4\) The endogeneity tests of explanatory variables is performed. The results indicate that there is no endogeneity problem.

\(^5\) Hanushek and Kim (2000) point out that the estimates of the impact of population growth on the rate of economic growth, while always negative, are quite sensitive to specification and are not significantly different from zero when labor quality is considered. They also discuss that causality from economic growth to population growth is a concern.
Besides the additive effects of school quantity and labor composition, their complementary effect is also taken into account since the level of these variables may affect each other (Hanushek and Kim, 1995). The estimated coefficient of the linear interaction term \((glc*sch)\) indicates a negative interaction. The negative sign suggests that the marginal effect of changes declines with an overall more highly schooled population and vice versa (Hanushek and Kim, 1995). However, the coefficient for the interaction term is small.

Then, Model 2 is regressed by excluding the insignificant variable, population growth \((gpop)\). The estimated coefficients in Model 2 do not differ in terms of the signs and significance levels of estimated variables from Model 1. In Model 3, this time the insignificant \(sch\) variable is dropped from the regression equation. In the new model, \(glc\), \(gict\), and the interaction term \((glc*sch)\) have expected signs with high significance levels.

The results of the analyses show that labor quality, as measured growth of labor composition, has an important ingredient in explaining economic growth. On the other hand, labor quantity variable, measured by average years of schooling \((sch)\) does not any explanatory power in this model. Yet the complementary effect of labor quantity and quality turns out to be significant.

The basic results provide strong support for the importance of labor-force quality difference as measured by labor composition in explaining per capita GDP growth.

4. Conclusion

Since workers have different skill levels and competences, the adjustment of labor input to changes in labor composition enables us to observe the possible effects on economic growth and development. This paper concentrates on the importance of labor force quality, as measured by the change in labor composition index, in explaining economic development. The results provide strong support for the importance of labor quality difference on per capita GDP growth. Change in labor composition proves to have a significant positive impact on economic development for a panel of developing countries in the period 1990-2009. The results of this analysis may prove fruitful to the policy makers in designing policies to improve labor composition for the objective of economic development.
References


**Appendix**

The labor composition model employs the following production function in which various types of labor is included in production process:

\[ Q = f(A_t, k_1, ..., k_n, h_1, ..., h_m) \]  \[ [4] \]

where \( Q \) is output produced by the technology available at time \( t \), \( A_t \), \( n \) different types of capital, \( k_1, ..., k_n \), and by \( m \) different types of labor hours, \( h_1, ..., h_m \).

Differentiating the natural logarithm of Equation [4] with respect to time, and rearranging terms, yields the following link between total factor productivity and growth rates of output and inputs:

\[ \frac{\delta Q}{Q} = \frac{\delta k}{k} + ... + \frac{\delta h}{h} \]

---

6 See Zoghi (2010) for a detailed analysis for labor composition measurement.
\[
\frac{\dot{\mathcal{A}}}{\mathcal{A}} = \frac{\dot{Q}}{Q} - \left( \frac{v_{k_1}}{k_1} + ... + \frac{v_{k_n}}{k_n} + \frac{v_{l_1}}{h_1} + ... + \frac{v_{l_m}}{h_m} \right)
\]

where the terms \(v_{k_i}\) and \(v_{l_i}\) stand for output elasticities of each type of capital and labor respectively.

Under the assumptions of constant returns to scale and perfect competition in product and input markets, \(v_{k_i}\) and \(v_{l_i}\) are equal to the share of total costs paid to those inputs.

By assuming that the labor is an input separable from capital, an aggregate labor input equation can be expressed:

\[
\frac{\dot{\mathcal{L}}}{\mathcal{L}} = \frac{\dot{h}}{h} + \frac{\dot{w}}{w}
\]

where \(\dot{h}\) is the each type worker’s share of the total compensation.

The growth rate of labor input can be measured by Törnqvist (1936) index. It employs an average of cost-share weights for the two time periods. Then the index is calculated as the difference in the natural logarithm of successive observations, with the weights equal to the mean of the factor shares in the corresponding two time periods:

\[
\Delta \ln L = \frac{1}{2} \Delta \ln h_{i,t} + v_{h_{i,t}} \Delta \ln h_{i,t}
\]

Changes in the index of labor composition, LC, are defined as follows:

\[
\Delta \ln LC = \Delta \ln L - \Delta \ln H = \Delta \ln \frac{L}{H}
\]

which is the difference between the changes in composition-adjusted labor input and the change in the sum of unweighted hours.

**Acknowledgements**

For their help and comments, I am grateful to A. Suut Dogruel, Fatma Doğruel, and Aysu İnsel.