THE IMPACT OF LIFE EXPECTANCY ON ECONOMIC GROWTH: PANEL COINTEGRATION AND CAUSALITY ANALYSES FOR OECD COUNTRIES

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Abstract

This paper examines the impact of life expectancy at birth on economic growth for 21 OECD countries using panel data for the period of 1970-2010 in the context of panel cointegration and causality tests. Three different model specifications are considered for this purpose. We use the variable of life expectancy as an indicator of health and also employ real per capita gross domestic product (constant 2000 $) as a criterion of economic growth. The other independent variables are real exports, real fixed capital and energy use per capita. Based on the findings of the empirical analyses, some important findings can be suggested. Firstly, the results of the LLC, IPS and Breitung panel unit root tests indicate that all of the series are I(1). Secondly, by using Kao and Maddala-Wu cointegration tests, it is showed that there is a long-run relationship between the variables. Thirdly, based on panel OLS, Pedroni DOLS and FMOLS techniques, the estimated coefficient for life expectancy is found positive and statistically significant. Fourthly, the results of panel Granger causality tests based on panel VAR models indicate that there is a unidirectional causality running from life expectancy to real per capita GDP. Thus, this paper provides some important evidence that life expectancy is a fundamental determinant of economic growth in the OECD countries for the period considered for all of three models. Additionally, some important policy implications are drawn from the findings of this study.

Key Words: Health, Life Expectancy, Economic Growth, Panel Cointegration, Panel Causality.

1.0 INTRODUCTION

Examining the link between health outcomes and economic growth at the macroeconomic level has been getting interested in theorists and policy makers. Why healthier people might be richer than others? Do improvements in health help to boost economic growth? Can health explain cross-country differences in levels and growth rates of income? The answer is that health may lead to income growth through its effect on human capital accumulation provided that people have sufficient food and satisfactory educational opportunities.

Economic growth theories or models should be considered to evaluate the link between health and economic growth realistically. The modern explanation of economic growth began with the classical economists, notably Smith (1776) and Ricardo (1817), argued that industrial growth fueled by the expansion of domestic and international markets was the driving force behind economic growth (Barro, 1996). Harrod (1939) and Domar (1946), who are the pioneers of Keynesian economics, argued that economic growth depends on policies to increase investment, by increasing saving, and using that investment more efficiently through technological advances. The Harrod-Domar model was extended by the neo-classical economists (Solow, 1956; Swan, 1956) by including productivity growth. But neo-classical growth models could not explain the source of technological progress. Moreover, in these models health and determinants of health were not taken into consideration.

Nowadays, it is known that investment in human capital, innovation and knowledge are significant contributors to economic growth. Two key components of human capital are education and health. Human capital theory, which is primarily developed by Schultz (1961), Becker (1962), Denison (1962) and Mincer (1974), is about the role of human capital in the production process and about the incentives to invest in skills, including in the forms of schooling and training.

The first generation endogenous growth models, such as Romer (1986, 1990), Grossman and Helpman (1991) and Aghion and Howitt (1992), focused on education, R&D and innovation rather than health. Mushkin (1962), who first emphasized the importance of health, pointed out that health constitutes an important form of investment unlike other forms of human capital formation like education. Nelson and Phelps (1966) argued that a higher stock of health could stimulate growth by facilitating technological innovation. Accordingly, productivity growth should be positively correlated with the level of health, in particular with the
average level of life expectancy in a country. Thereafter, Grossman (1972) constructed a model of the demand for the commodity “good health”. According to Grossman, health can be viewed as a durable capital stock that produces an output of healthy time. This triggered the developing of new theoretical models (Mankiw et al., 1992, Barro, 1996, and Barro and Sala-i-Martin, 2004) incorporating health as a determinant of economic growth.

Weil (2005) examines the relationship between health investment and economic growth by considering both macroeconomic and microeconomic foundations. According to Weil, studies examining the link between health and economic performance have generally investigated health inputs or health outcomes. Health inputs are the physical factors that influence the individual’s health such as nutrition, exposure to pathogens, and the availability of medical care. Health outcomes include life expectancy, the ability to work hard, and cognitive functioning. For the purpose, in explaining income differences among countries, life expectancy can be one of the key health outcomes.

With respect to the empirical literature, Knowles and Owen (1995, 1997); Hamoudi and Sachs (1999); Bloom et al. (2001); Devlin and Hansen (2001); McDonald and Roberts (2002) and Li and Liang (2010) emphasized the importance of health in a country’s economic growth. Knowles and Owen (1995, 1997) indicated that there is a significant statistical relationship between health and growth. Hamoudi and Sachs (1999) demonstrated an endogenous relationship between the variables. Bloom et al. (2001) extending the Solow model with human capital found that there is a significant relationship between health capital and economic growth. Li and Liang (2010) showed that the impact of the stock of health and education on economic growth is statistically significant and that the statistical impact of health on growth is stronger than that of education.

Recently, an important literature group dealing with the impact of life expectancy as an indicator of health on economic growth has been developing. For example; Barro (1997) has found that 10% increase in life expectancy lead to a four-tenth percent increase in economic growth. For every 10% increase in life expectancy you can expect almost half a percent in economic growth.

Bloom, Canning, and Sevilla (2004) indicated that the panel results, which come from regressing residual productivity provided that a one-year increase in life expectancy raises output by 4 percent. Barro and Sala-i-

Martin (2004) using a panel dataset of some countries indicated that the life expectancy has a positive and statistically significant effect on the rate of economic growth with a coefficient of 0.042, which implies an annual rate of increase of per capita real GDP about 4.2%.

Acemoglu and Johnson (2007) following a Lucas approach regressed income growth on the increase in life expectancy between the period of 1940 and 1980. They showed that life expectancy has no significant effect on income growth over the period. Lorentzen, McMillan and Wacziarg (2008) adopting a Nelson-Phelps model argued that the effect of life expectancy on income per capita is non-monotonic. They found that life expectancy after the onset of the demographic transition has a positive effect on wealth.

Barro and Lee (2010) which examine low-income and high-income countries and use cross-country OLS found that life expectancy has a weak or negative effect on economic growth. Aghion et al. (2010) reconsidered the relationship between health and growth in the context of endogenous growth theory. They used a unified framework which includes Lucas and Nelson-Phelps approaches. The results of cross-country regressions over the period 1960-2000 showed that a higher initial level and a higher rate of improvement in life expectancy were significantly positive impact on per capita GDP growth. Finally, Hansen (2012) investigating the non-linearity dimension and using 10-yearly observations from 1940 to 1980 presented a non-monotonic relationship between life expectancy and per capita GDP.

These findings have very important implications for the academic researches as well as for the policy debate because they challenge the view that improving health is beneficial for economic development. Nowadays, panel data analyses on the relationship between life expectancy and economic growth estimate long-run parameters using different panel estimation methods as in Table 1. It reports a selection of the empirical studies that include health as a determinant of economic growth and the findings of them. It also provides eight panel data and three cross-country studies investigating relationship between life expectancy and economic growth. It can be said that the results are more complex and the question whether the improvements in life expectancy cause increases in per capita income is the subject of a lively debate. But these studies do not take the issues of panel unit root, cointegration and causality into consideration. From this aspect, our paper becomes somewhat different from this empirical literature.
Table 1: Overview of Selected Empirical Studies (Dependent variable: Life expectancy)

<table>
<thead>
<tr>
<th>Study</th>
<th>Country</th>
<th>Period</th>
<th>Other Independent Variables</th>
<th>Econometric Technique(s)</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barro (1996)</td>
<td>Sub-Saharan Africa, Latin America, East Asia</td>
<td>1965-75, 1975-85, 1985-90</td>
<td>Male secondary and higher schooling, log(GDP) X male schooling, log fertility rate, government consumption ratio, rule of law index, terms of trade change, democracy index, democracy index squared, inflation rate, continental dummies</td>
<td>Panel data Three-stage OLS</td>
<td>Life expectancy has a positive effect on economic growth.</td>
</tr>
<tr>
<td>Caselli, Esquivel and Lefort (1996)</td>
<td>Developed and Developing Countries</td>
<td>1965-85, 1965-87</td>
<td>Male education, female education, revolutions, assassinations, terms of trade, investment ratio, government consumption ratio, log (1+black market premium),</td>
<td>Panel data OLS, GMM</td>
<td>Life expectancy has a positive effect on growth. Life expectancy has a negative and insignificant effect on economic growth.</td>
</tr>
<tr>
<td>Bloom and Williamson (1998)</td>
<td>78 Asian and non-Asian Countries</td>
<td>1965-90</td>
<td>Log years of secondary schooling, natural resource abundance, openness, quality of institutions, access to ports dummy, average government savings rate, tropics dummy, ratio of coastline to land area</td>
<td>Panel data OLS, Instrumental Variables</td>
<td>Life expectancy has a positive effect on economic growth.</td>
</tr>
<tr>
<td>Bloom, Canning and Malaney (1999)</td>
<td>East Asia</td>
<td>1965-90</td>
<td>Log GDP per capita, log GDP per worker, located in the tropics, access to ports (landlocked), quality of institutions, openness, log years of secondary schooling, growth in total population, growth in working age population, log of coastal population density, log of inland population density.</td>
<td>Panel data OLS, Instrumental Variables</td>
<td>Increases in life expectancy have a large effect on economic growth in East Asia.</td>
</tr>
<tr>
<td>Bloom, Canning and Sevilla (2004)</td>
<td>104 countries</td>
<td>1960-90, Ten year intervals</td>
<td>Capital, labor, schooling, experience, technological catch-up, percentage of land area in the tropics, governance</td>
<td>Panel data Non-linear two-stage OLS</td>
<td>Life expectancy has a weak effect on economic growth.</td>
</tr>
<tr>
<td>Acemoğlu and Johnson (2007)</td>
<td>120 countries</td>
<td>1940-80, 1960-00</td>
<td>Log population, log total births, log GDP per working age population, log years of schooling</td>
<td>Panel data Two-stage OLS, Instrumental Variables, GMM</td>
<td>Life expectancy has a negative effect on economic growth.</td>
</tr>
<tr>
<td>Aghion, Howitt and Martin (2010)</td>
<td>Sub-Saharan Africa, Developed and</td>
<td>1960-00</td>
<td>Initial log GDP per capita, average infant mortality, Initial adult</td>
<td>Panel data</td>
<td>Life expectancy has a positive impact on economic growth.</td>
</tr>
</tbody>
</table>
Barro and Lee (2010)  
Low-income countries  
High-income countries  
1965-75  
1975-85  
1985-95  
Male upper-level schooling, log total fertility rate, government consumption ratio, rule of law, democracy, openness ratio, change in terms of trade, investment ratio, inflation rate  
Cross-country OLS  
Life expectancy has a weak or negative effect on economic growth  

Hassan and Cooray (2012)  
84 countries  
1960-09  
Capital, labor, male primary enrolment, female primary enrolment, male secondary enrolment, female secondary enrolment  
Panel data OLS, SGMM, LSDVC  
Male life expectancy has a positive effect on economic growth

Sources: Author

The main objective of this study is to test the effect of health on economic growth. It is preferred the variable of life expectancy as a health indicator like the other empirical studies. In this paper, a further panel data analysis in the context of cointegration and causality relationship is provided for 21 OECD countries spanning over 1970-2010. The panel unit root tests proposed by Levin et al. (2002), Im et al. (2003) and Breitung (2000) are implemented. More precisely, panel cointegration tests developed by Kao (1999) and Maddala and Wu (1999) are used. Nowadays, Pedroni (2000) DOLS and FMOLS techniques are among the most popular and common estimators in panel data analyses. I employ the panel OLS, Pedroni DOLS and FMOLS estimators to investigate long-run parameters in three different model specifications. Finally, panel Granger causality test is used to analyze the causal relationship between life expectancy and real per capita GDP.

This paper provides some important findings. The results show that (i) life expectancy has a positive and statistically significant effect on real per capita GDP in the long run, (ii) there is a Granger causality running from life expectancy to real per capita GDP. Thus, these findings provide an empirical evidence supporting the hypothesis of life expectancy oriented economic growth in OECD countries in three cases.

The rest of the paper is organized as follows. Section 2 presents the data and model specifications. Section 3 provides the econometric methodology and findings. Section 4 submits the conclusion and policy implications.

2. The Data and Model Specifications

The data of our study setting are derived from World Bank’s World Development Indicators, 2012 in an attempt to test the cointegration and causality relationship between life expectancy and economic growth in a panel data. I use the variable of life expectancy as an indicator of health and also employ real per capita GDP as a criterion of economic growth. The other dependent variables are real exports, real fixed capital and energy use per capita. The study uses annual data and covers the period of 1970 to 2010 for 21 OECD countries. The logarithms of the variables are used in the empirical analyses.

All the variables and their descriptive statistics are reported in Table 2. The cross-sectional dimension is 21 units and the time dimension is 41 years. In total, there are 861 observations for each variable. For all variables, it seems that there are no strong outliers. On the other hand, Figure 1 shows the series in natural logarithm over the period.

The following linear panel data specifications are used in the empirical analyses to evaluate how life expectancy has affected real per capita GDP. Panel cointegration and causality tests are conducted for three cases because the variables are cointegrated only under these cases:

Model 1. lnpercapita GDP=f(lnlife, lnexports)  (1)

1 The countries considered in this study are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Japan, Luxemburg, Netherland, Norway, Portugal, Spain, Sweden, United Kingdom and United States.
Model2. \( \text{Inpercapita GDP} = f(\text{lnlife}, \text{lnexports}, \text{lncapital}) \) 

Model3. \( \text{Inpercapita GDP} = f(\text{lnlife}, \text{lnenergy}, \text{lncapital}) \)

Table 2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Descriptions</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnlife</td>
<td>Life expectancy at birth</td>
<td>4.329</td>
<td>4.333</td>
<td>0.041</td>
<td>4.201</td>
<td>4.418</td>
</tr>
<tr>
<td>lnpercapitaGDP</td>
<td>Per capita GDP (constant 2000 $)</td>
<td>9.774</td>
<td>9.853</td>
<td>0.530</td>
<td>7.786</td>
<td>10.940</td>
</tr>
<tr>
<td>lnenergy</td>
<td>Energy use (kg of oil equivalent per capita)</td>
<td>10.941</td>
<td>10.832</td>
<td>1.587</td>
<td>6.762</td>
<td>14.664</td>
</tr>
</tbody>
</table>

Figure 1: The Plots of the Series (1970-2010)
3.0 Econometric Methods and Findings

The main aim of the study is to analyze the impact of life expectancy on economic growth in the context of cointegration and causality relationship. The cointegration and causality tests will be performed in four steps. Firstly, I test for the order of integration in the variables and implement the panel unit root tests proposed by Levin et al. (2002), Im et al. (2003) and Breitung (2000). Secondly, conditional on finding that these variables are integrated of order one I test for panel cointegration using the approaches suggested by Kao (1999) and Maddala and Wu (1999). Thirdly, I estimate the long-run parameters using panel OLS, Pedroni DOLS and FMOLS estimators. Finally, I test for Granger causality between life expectancy and real per capita GDP.

3.1. Panel Unit Root Tests

In panel cointegration, an essential step is to examine whether the variables contain a panel unit root. Non-stationary panels have become extremely popular and have attracted much attention in both theoretical and empirical research over the last decade. A number of panel unit root tests have been proposed in the literature which include Levin et al. (2002), Im et al. (2003), Breitung (2000), Maddala and Wu (1999), Choi (2001) and Hadri (2000). Technically, all first generation tests share the null hypothesis of stationarity but diverge on the alternative one, which can be homogeneous or heterogeneous.

In this study I adopt three different methods, namely those of Levin et al. (2002) (LLC), Im et al. (2003) (IPS) and Breitung (2000). These tests don’t consider cross-sectional dependency. Levin et al. (2002) generalized the individual unit root test to panels with heterogeneous serially correlated errors, fixed effects and individual deterministic trends. One of the drawbacks of the Levin et al. (2002) is that, it requires a homogeneous autoregressive root under the alternative hypothesis. However, Im et al. (2003) proposed a panel unit root test that allows for a heterogeneous autoregressive coefficient under the alternative hypothesis.

Im et al. (2003) exhibit a power comparison of the LLC and IPS tests and argue that the IPS test is more powerful than the LLC test. Although the null hypothesis is the same in the two tests, the alternative hypothesis is different. Both the Levin et al. (2002) and Im et al. (2003) tests suffer from a dramatic loss of power when individual specific trends are included, which is due to the bias correction. However, the Breitung (2000) panel unit root test does not rely on bias correction factors. Monte Carlo experiments showed that the Breitung (2000) test yields substantially higher power and smallest size distortions compared to Levin et al. (2002) and Im et al. (2003).

Panel unit root test results obtaining from the model with constant and trend terms are illustrated in Table 3. It is seen that the panel variables are not stationary at level. When the tests are applied to the first-differenced variables, however, all of the variables are found to be stationary. From these panel unit root tests I conclude that all variables are integrated at order of I(1).

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The former two are widely used panel unit root analysis in the literature on panel cointegration. The null hypothesis of the tests is a unit root in the panel. However, while IPS (2003) assumes that the cross-sectional units have individual unit root process, LLC (2002) and Breitung (2000) assume that the cross-sectional units share a common unit root process.
Table 3: Panel Unit Root Test Results

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Series in levels</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In per capita GDP</td>
<td>0.612</td>
<td>0.729</td>
<td>2.071</td>
</tr>
<tr>
<td>In life</td>
<td>-0.786</td>
<td>0.215</td>
<td>-0.377</td>
</tr>
<tr>
<td>In exports</td>
<td>0.807</td>
<td>0.790</td>
<td>1.184</td>
</tr>
<tr>
<td>In capital</td>
<td>-2.518*</td>
<td>0.005</td>
<td>-0.857</td>
</tr>
<tr>
<td>In energy</td>
<td>-1.524</td>
<td>0.063</td>
<td>-1.575</td>
</tr>
<tr>
<td><strong>Series in first differences</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>△ln per capita GDP</td>
<td>-14.571*</td>
<td>0.000</td>
<td>-17.224*</td>
</tr>
<tr>
<td>△ln life</td>
<td>-31.224*</td>
<td>0.000</td>
<td>-30.190*</td>
</tr>
<tr>
<td>△ln exports</td>
<td>-18.894*</td>
<td>0.000</td>
<td>-21.705*</td>
</tr>
<tr>
<td>△ ln capital</td>
<td>-</td>
<td>-</td>
<td>-16.873*</td>
</tr>
<tr>
<td>△ln energy</td>
<td>-20.937*</td>
<td>0.000</td>
<td>-19.977*</td>
</tr>
</tbody>
</table>

Note: * denote significance at the 1% level. △ is the first difference operator. Newey-West bandwidth selection with Bartlett kernel was used for the LLC test. Schwarz Bayesian Criterion was used to determine the optimal lag length.

3.2. Panel Cointegration Tests

The cointegration methodology as applied to time series data was first introduced in the 1980s as in Engle and Granger (1987), Johansen (1988, 1991), Johansen and Juselius (1990), and others. The econometric methodology behind testing and estimation in cointegrated panels has only recently been developed. Important contributions in this field have been made by for instance Pedroni (1999), McKoskey and Kao (1998), Kao (1999), Maddala and Wu (1999), Breitung (2005), Westerlund (2007) and Larsson and Lyhagen (2007).

In analyzing of cointegration and causality, secondly, I test for panel cointegration using the approaches suggested by Kao (1999) and Maddala and Wu (1999). Consider the following system of cointegrated regressions:

\[ y_{it} = \alpha_i + \beta_i x_{it} + u_{it} \]  

Where \( i = 1, \ldots, N, t = 1, \ldots, T, \) \( \alpha_i \) are individual constant terms, \( \beta_i \) is the slope parameter, it \( u_{it} \) are stationary disturbance terms, and finally, by construction, it \( y_{it} \) and it \( x_{it} \) are integrated processes of order one for all \( i \). Kao (1999) derives two types of panel cointegration tests. The first is a Dickey-Fuller (DF) type test and the second is an Augmented Dickey-Fuller (ADF) type test. DF-type test can be computed from the estimated residuals as:

\[ \hat{u}_{it} = \rho \hat{u}_{i,t-1} + v_{it} \]  

For the ADF test, I run the following ADF regression:

\[ \hat{u}_{it} = \rho \hat{u}_{i,t-1} + \sum_{j=1}^{p} \phi_j \Delta \hat{u}_{i,t-j} + v_{it} \]  

Where the residuals \( \hat{u}_{it} \) are obtained from equation (4). The following specification of null and alternative hypotheses is used.

\[ H_0: \rho = 1, \] for all \( i \) and \( H_A: \rho < 1, \) for all \( i \)

Kao (1999) proposes four DF-type statistics. The first two DF statistics are based on assuming strict exogeneity of the regressors with respect to the errors in the equation, while the remaining two allow for endogeneity of the
regressors. In addition, Kao (1999) proposes an ADF test statistic. Finally the DF statistics, which allow for endogeneity, and the ADF statistic involve deriving some nuisance parameters from the long run conditional variances \( \Omega \). The asymptotic distributions of all tests converge to a standard normal distribution \( N(0, 1) \) as \( T \to \infty \) and \( N \to \infty \). The ADF test statistic is as follows:

\[
 t_{ADF} = \frac{(\hat{\rho} - 1) \left[ \sum_{i=1}^{N} (e_i^t Q_i e_i) \right]^{\frac{1}{2}}}{S_n}
\]  

(7)

Kao cointegration tests results are seen from the Table 4. For three models, the findings indicate existence of long run relationship between variables.

The second panel cointegration test applied is the Johansen-Fisher type panel cointegration test developed by Maddala and Wu (1999). They use Fisher’s result to propose an alternative approach to test for cointegration in panel data by combining tests from individual cross-sections to obtain a test statistic for the full panel. The Johansen-Fisher panel cointegration test is panel version of the individual Johansen cointegration test. The Johansen-Fisher panel cointegration test is based on the aggregates of the \( p \)-values of the individual Johansen maximum eigenvalues and trace statistic. If \( p_i \) is the \( p \)-value from an individual cointegration test for cross-section \( i \), under the null hypothesis for the panel

\[
 -2 \sum_{i=1}^{n} \log(p_i) \sim \chi^2_{2n}
\]  

(8)

Where \( \chi^2_{2n} \) is a chi-square distribution with \( 2N \) degrees of freedom. The \( \chi^2 \) value is based on MacKinnon-Haug-Michelis (1999) \( p \)-values for Johansen’s cointegration trace test and maximum eigenvalue test. In the Johansen type panel cointegration tests results heavily depends on the number of lags of the VAR system. The results for Johansen-Fisher based panel cointegration test are presented in Table 5. The findings strongly support an evidence of cointegration relationships between variables in all models.

### Table 4: Kao Panel Cointegration Test Results

<table>
<thead>
<tr>
<th>Models</th>
<th>ADF</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>-5.032*</td>
<td>0.000</td>
</tr>
<tr>
<td>Model 2</td>
<td>-5.234*</td>
<td>0.000</td>
</tr>
<tr>
<td>Model 3</td>
<td>-6.758*</td>
<td>0.000</td>
</tr>
</tbody>
</table>

* denote significance at the 1% level. Schwarz Bayesian Criterion was used to determine the optimal lag length.

### Table 5: Johansen-Fisher based Panel Cointegration Test Results

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>None</td>
<td>115.70*</td>
<td>0.000</td>
<td>107.70*</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>At most 1</td>
<td>44.47</td>
<td>0.368</td>
<td>40.21</td>
<td>0.549</td>
</tr>
<tr>
<td></td>
<td>At most 2</td>
<td>28.23</td>
<td>0.948</td>
<td>28.23</td>
<td>0.948</td>
</tr>
<tr>
<td>Model 2</td>
<td>None</td>
<td>165.80*</td>
<td>0.000</td>
<td>99.20*</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>At most 1</td>
<td>91.70*</td>
<td>0.000</td>
<td>68.06*</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>At most 2</td>
<td>50.09</td>
<td>0.183</td>
<td>46.36</td>
<td>0.297</td>
</tr>
<tr>
<td></td>
<td>At most 3</td>
<td>28.92</td>
<td>0.937</td>
<td>28.92</td>
<td>0.937</td>
</tr>
<tr>
<td>Model 3</td>
<td>None</td>
<td>204.9*</td>
<td>0.000</td>
<td>143.20*</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>At most 1</td>
<td>95.97*</td>
<td>0.000</td>
<td>71.77*</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>At most 2</td>
<td>50.60</td>
<td>0.170</td>
<td>41.60</td>
<td>0.488</td>
</tr>
<tr>
<td></td>
<td>At most 3</td>
<td>36.01</td>
<td>0.730</td>
<td>36.01</td>
<td>0.730</td>
</tr>
</tbody>
</table>
3.3. Panel Cointegration Estimation

Once the cointegration relationship is established, the next step is to estimate the long-run parameters. In order to estimate panel cointegration parameters, various methods have been proposed, namely panel pooled OLS, panel dynamic OLS (DOLS), and panel fully modified OLS (FMOLS). The study employs all of three estimation methods.

A standard panel OLS estimator for the coefficient $\beta_i$ in equation (4) is given by:

$$\hat{\beta}_{i,OLS} = \left( \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)^2 \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i)$$  (9)

Where $\bar{x}_i$ and $\bar{y}_i$ refer to the individual means for each $i$ member of the cross section. According to Pedroni (2000) this estimator is asymptotically biased and its distribution is dependent on nuisance parameters associated with the dynamics underlying the processes determining $x$ and $y$. Only if $x$ is strictly exogenous and the dynamics are homogeneous across $i$ members of the panel $\hat{\beta}_{i,OLS}$ is unbiased.

The FMOLS and DOLS methodologies are proposed by Kao and Chiang (2000) to estimate the long-run cointegration vector, for non-stationary panels. These estimators correct the standard pooled OLS for serial correlation and endogeneity of regressors that are normally present in long-run relationships. Pedroni (2000) has suggested the group-mean FMOLS and DOLS estimators. According to Pedroni (2000) group mean tests are preferred over the pooled tests since they allow greater flexibility under alternative hypotheses.

The test statistics derived from the group-mean estimators are constructed to test the null hypothesis,

$$H_0 : \beta_i = \beta_0 \quad \text{for all} \quad i$$

against the alternative

$$H_1 : \beta_i \neq \beta_0$$

so that the values for $\beta_i$ are not constrained to be the same under the alternative hypothesis. Consider the following co-integrated system for a panel of $i = 1, 2, \ldots, N$ members,

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it}$$  (10)

$$x_{it} = x_{it-1} + e_{it}$$

Where $z_{it} = (y_{it}, x_{it}) \sim \text{I}(1)$, and $\xi_{it} = (u_{it} \oplus e_{it}) \sim \text{I}(0)$ with long run covariance matrix $\Omega_i = L \cdot \Omega_i$, ($L_i$ is a lower triangular decomposition of $\Omega_i$). In this case, the variables are said to be cointegrated for each member of the panel, with cointegrating vector $\beta$. The terms $\alpha_i$ allow the cointegrating relationship to include member specific fixed effect. The covariance matrix can also be decomposed as

$$\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i'$$

Where $\Omega_i^0$ is the contemporaneous covariance and is a weighted sum of autocovariances. The Panel FMOLS estimator which is parametric approach for the coefficient $\beta$ is defined as follows:

$$\hat{\beta}_{i,FMOLS} = N^{-1} \sum_{i=1}^{N} \left( \sum_{t=1}^{T} (x_{it} - \bar{x}_i)^2 \right)^{-1} \left( \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i) \right)$$  (11)

Where

$$y_{it}^* = (y_{it} - \bar{y}_i) - \hat{\Gamma}_{\Delta x_{it}}$$

$$\hat{x}_{it} = \hat{\Gamma} + \hat{\Omega}_{22} - \hat{\Omega}_{22} \hat{\Omega}_{22} - \hat{\Omega}_{22}$$

and $L_i$ is a lower triangular decomposition of $\Omega_i$ defined as follows:

$$\Omega_i = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix}$$

Pedroni (2001) also considers a group-mean DOLS estimator which is non-parametric approach. This is done modifying equation (10) to include lead and lag dynamics:

$$y_{it} = \alpha_i + \beta_i x_{it} + \sum_{j=-k_i}^{k_i} \gamma_{ij} \Delta x_{it-j} + e_{it}$$  (12)

and the estimated coefficient $\beta$ is given by:
I provide pooled OLS, group-mean DOLS and FMOLS results of the cointegration slopes for three different models. Based on these findings, the estimated coefficient for life expectancy is positive and statistically significant in three cases. This means that life expectancy has a positive effect on real per capita GDP. The results indicate that life expectancy is a fundamental determinant of economic growth in OECD countries (Table 6).

Table 6: Panel OLS, DOLS and FMOLS Estimates

<table>
<thead>
<tr>
<th>Models</th>
<th>Variables</th>
<th>OLS</th>
<th>$t$-statistics</th>
<th>DOLS</th>
<th>$t$-statistics</th>
<th>FMOLS</th>
<th>$t$-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>Inlife</td>
<td>2.277</td>
<td>11.251</td>
<td>2.314</td>
<td>9.971</td>
<td>1.69</td>
<td>5.02</td>
</tr>
<tr>
<td></td>
<td>Inexports</td>
<td>0.260</td>
<td>22.710</td>
<td>0.193</td>
<td>14.819</td>
<td>0.23</td>
<td>12.92</td>
</tr>
<tr>
<td>Model 2</td>
<td>Inlife</td>
<td>1.805</td>
<td>10.207</td>
<td>2.155</td>
<td>9.014</td>
<td>1.37</td>
<td>4.95</td>
</tr>
<tr>
<td></td>
<td>Inexports</td>
<td>0.189</td>
<td>14.615</td>
<td>0.106</td>
<td>15.379</td>
<td>0.16</td>
<td>12.49</td>
</tr>
<tr>
<td></td>
<td>Incapital</td>
<td>0.194</td>
<td>13.464</td>
<td>0.196</td>
<td>16.363</td>
<td>0.21</td>
<td>13.66</td>
</tr>
<tr>
<td></td>
<td>Inenergy</td>
<td>0.030</td>
<td>36.006</td>
<td>0.275</td>
<td>8.537</td>
<td>0.27</td>
<td>7.99</td>
</tr>
<tr>
<td></td>
<td>Incapital</td>
<td>0.274</td>
<td>21.704</td>
<td>0.193</td>
<td>17.797</td>
<td>0.22</td>
<td>15.64</td>
</tr>
</tbody>
</table>

Note: * and ** denote significance at 1% and 5% respectively.

3.4. Panel Causality Test

Kao and Maddala-Wu tests don’t indicate the direction of causality when the variables are co-integrated. Panel Granger causality which is based on panel VAR model can be used to assess the long-run causal relationship and the direction of causality between life expectancy and real per capita GDP. For the panel Granger causality test, the following model is estimated:

$$\Delta y_{it} = \theta_0 + \sum_{k=1}^{p} \theta_{1k}\Delta y_{i,t-k} + \sum_{k=1}^{p} \theta_{2k}\Delta x_{i,t-k} + u_{it} \quad (14)$$

$$H_0 : \theta_{12k} = 0 \quad H_1 : \theta_{12k} \neq 0 \quad (15)$$

Wald $F$ and $\chi^2$ tests are applied to the hypothesis above. The appropriate lag lengths are selected using AIC for variables. After defining the appropriate lag lengths, the long-run causality is investigated for three models. The results of panel Granger causality tests are presented in Table 7. According to the results, there is Granger causality running from life expectancy to real per capita GDP, which is significant in 1%. Thus, these findings suggest that life expectancy affects economic growth in three cases.

Table 7: Panel Granger Causality Test Results

<table>
<thead>
<tr>
<th>Models</th>
<th>Hypotheses</th>
<th>Wald $F$-test</th>
<th>Prob.</th>
<th>Wald $\chi^2$-test</th>
<th>Prob.</th>
<th>Causality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>$\Delta$lnlife doesn’t Granger cause $\Delta$lnpercapitaGDP</td>
<td>4.228*</td>
<td>0.002</td>
<td>16.915*</td>
<td>0.002</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>$\Delta$lnexports doesn’t Granger cause $\Delta$lnpercapitaGDP</td>
<td>2.170**</td>
<td>0.070</td>
<td>8.683**</td>
<td>0.060</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Model 2  | Δlnlife doesn’t Granger cause ΔlnpercapitaGDP | 4.038* | 0.003 | 16.154* | 0.002 | Yes  
Δlnexports doesn’t Granger cause ΔlnpercapitaGDP | 0.990 | 0.411 | 3.962 | 0.411 | No  
Δlncapital doesn’t Granger cause ΔlnpercapitaGDP | 3.403* | 0.009 | 13.615* | 0.008 | Yes  
Model 3  | Δlnlife doesn’t Granger cause ΔlnpercapitaGDP | 4.120* | 0.002 | 16.481* | 0.002 | Yes  
Δlncapital doesn’t Granger cause ΔlnpercapitaGDP | 4.464* | 0.001 | 17.858* | 0.001 | Yes  
Δlnenergy doesn’t Granger cause ΔlnpercapitaGDP | 1.613 | 0.169 | 6.452 | 0.167 | No  

Note: * and ** denote significance at 1% and 10% respectively. Akaike Information Criterion was used to determine the optimal lag length.

4.0 CONCLUSION

Growth and development economists have commonly accepted that the role of human capital is one of the main determinants of sustained economic growth. New endogenous growth theorists such as Grossman (1972), Mankiw et al. (1992), Barro (1996) and Barro and Sala-i-Martin (2004) have modeled health as human capital. These economists agree that health raises the level of human capital and has a positive effect on productivity and economic growth. But determining the cointegration and causal relationship between health and economic growth is not simple owing to the features of the variables used.

This paper has examined the role of life expectancy in economic growth in 21 OECD countries over the period 1970-2010 by using cointegration and causality methods. I adopt three different panel unit root tests, namely those of Levin et al. (2002) (LLC), Im et al. (2003) (IPS) and Breitung (2000). The results of panel unit root tests indicate that all variables are integrated at order of I(1). Secondly, I test for panel cointegration using the approaches suggested by Kao (1999) and Maddala and Wu (1999). Panel cointegration tests strongly support the existence of cointegration relationships between the variables in three specifications.

In order to estimate panel cointegration parameters, I employ different estimators, namely panel OLS, Pedroni DOLS, and Pedroni FMOLS. The results indicate that the coefficient of life expectancy is positive and statistically significant in three cases. In other words, life expectancy has a positive effect on real per capita GDP. These findings are consistent with the results of Bloom et al. (1999), Bhargava et al. (2001), Canning and Sevilla (2002) and Aghion et al. (2010). I also employ panel Granger causality test based on panel VAR model. According to the findings, in all models there is a Granger causality running from life expectancy to real per capita GDP, which is significant at 1%. Thus, these estimations and causality findings suggest that life expectancy is a fundamental determinant of economic growth for OECD countries over the period in three cases.

Nearly all of the OECD countries have experienced large gains in life expectancy over the past five decades. Across OECD countries, on average, life expectancy for the whole population reached 79.5 years in 2009. Gains in life expectancy in OECD countries in recent decades can be attributed to a number of factors, including rising in living standards, improving in lifestyle and better education opportunities, as well as greater access to quality health services. For this reason, the policies improving life expectancy of population for sustainable economic growth should take into consideration these factors. However, another empirical study to investigate the main determinants of life expectancy in OECD countries can be performed.
REFERENCES


