The effects of human capital on economic growth in the Arab countries compared to some Asian and OECD countries

EL Mostafa Bentour

Arab Monetary Fund

June 2020

©Arab Monetary Fund 2020

All Rights Reserved

The material in these publications are copyrighted. No part of this study may be Copied and/or translated or re-reproduced in any form without a written consent by AMF except in the case of brief quotations where reference must be quoted.

The views expressed in these studies are those of the author (s) and do not necessarily reflect the views of the AMF.

These economic studies are the product of the staff of the Economic Department at the Arab Monetary Fund (AMF). The Fund publishes these studies which survey issues pertinent to monetary, fiscal, banking, trade and capital market policies and their impact on Arab economies.

All correspondences should be addressed to:

Economic Department
Arab Monetary Fund
P.O. Box 2818
United Arab Emirates
Telephone No.: +9712-6171552
Fax No: +9712-6326454
Email: economic@amfad.org.ae
Website: www.amf.org.ae

Table of Contents

Executive summary

This paper estimates the impact of human capital on economic growth in a sample of twelve Arab countries, namely, Algeria, Bahrain, Egypt, Jordan, Kuwait, Mauritania, Morocco, Qatar, Saudi Arabia, Sudan, Tunisia, and the United Arab Emirates, and compares the results to two samples of Asian and advanced countries. Our calculations show that the overall cross-country and average elasticity for the twelve Arab countries is approximately 0.5. Thus, a 1 percent increase in human capital increases the GDP growth by about half percentage point. The average elasticity of human capital per unit of labor variable in the Asian sample is about 0.6, which is slightly higher than the elasticity estimated for the Arab countries. For the advanced countries, the value of the elasticity stands higher at nearly 0.9.

Considering these results, the paper confirmed the important positive contribution of human capital to the economic growth in the Arab countries. Compared to the benchmark of Asian countries, the sample of Arab countries is not roughly lagging in terms of the contribution of human capital to GDP growth. However, compared to advanced countries, a lot of efforts are needed to catch up with the developed world as the contribution of the human capital in the Arab countries is almost half the level observed in advanced countries.

Furthermore, results also revealed that the production function, in the three studied groups of countries, exhibits increasing returns to scale to the three production factors: human capital, physical capital, and labor. This leads to say that the production process in the presence of human capital is efficient, as the increasing returns to scale means that doubling output requires less than doubling inputs. This is an important contribution once considering human capital as an explicit additional factor of production than the only physical capital and rough labor traditionally considered. Nevertheless, this efficiency is higher in the advanced countries as the increasing returns to scale is more happening in the sample of advanced countries than in the Arab and Asian countries.

This paper also examines the two-way direction of causality between GDP and human capital, which means that while human capital is causing the GDP, the latter also has feedback effects on the former. This involves obviously important policy implications. The bidirectional causality creates a loop of effects between human capital and GDP. Henceforth, increasing the contribution of human capital to sustain long-term growth requires investments in key sectors that directly enhance human capital. These sectors involve particularly the people's conventional education and vocational training, their health, and the investment in research and development for innovative ideas and inventions, which have higher implications on their long-run productivity. Therefore,

governments should give such sectors priority in their expenditures policies which is likely to sharpen workers' skills and enhance productivity leading to positive feedbacks on GDP.

Our findings also, suggest that governments, which are interested in enhancing human capital, should adopt policies that boost not only the stock of human capital, but also its quality. This would, in turn, give private investors (local and foreign as well) incentives to invest in the production of skill-intensive and high technology goods with higher value-added compared to labor-intensive goods. Another reason for governments to consider human capital among its top priorities is that all the economies are shifting towards a knowledge-based economy (or the economy of knowledge as interchangeably used in the literature). This requires empowering human skills and their capabilities to catch up with the advanced countries and reduce the gap and inequalities in the area of human capital, hence, help to achieve sustainable goals. Finally, Arab countries, while investing in human capital, are also encouraged to develop human capital statistics by adopting international methodologies used to measure the quality of human capital particularly.

Introduction

The trend of economic literature has tendency to emphasize the vital role of the human capital on the countries' economic development. Believing in such role, countries and international organizations have recently renewed the interest in encouraging investment in human capital to increase the standards of living through boosting productivity, lowering the unemployment rate, and alleviating poverty. Consequently, the World Bank launched a human capital project in 2017[1] gathering countries around the world to promote investment in human capital and reduce gaps in this area. Further, other institutions such as the World Economic Forum[2] and the United Nations agencies considered the importance of human capital and involve in building methodologies for its measurement.

The importance of human capital lies in the overall impacts at the individual and macroeconomic levels. At the individual level, education and training, one of the main tools for gaining knowledge and practical experience, are among the important factors in improving a person's income. For example, the "Mincer" model (Mincer, 1974) was used in many studies to assess the return on education in many countries, using statistical surveys. The results of these studies concluded the

[1] https://www.worldbank.org/en/publication/human-capital

[2] The World Economic Forum (2017).

positive relationship between income and education levels. At the macroeconomic level, the results of studies that have adopted macroeconomic models indicated the importance of human capital in promoting long-term growth. In this regard, the theory of accumulation of human capital was considered as an important engine for the growth of gross national product (Solow, 1988; Romer, 1990).

The relationship between human capital and economic development is rather a long-run relationship. In this way, all the theories and models highlight the positive effects of human capital on the growth of long-run income per capita is guaranteed particularly through enhancing economic productivity (Barro and Sala-i-Martin, 2003; Durlauf and al., 2005). Krugman (1994) stated that *"Productivity is not everything, but, in the long run, it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker."* The productivity is therefore believed to be the important factor by which economies grow in the long run. Besides, an important issue creating controversies between economists is the direction of causality between many macroeconomic variables. Knowing the direction of causality between two economic variables helps policymakers in taking accurate and efficient policies on such economic aggregates. Likewise, this paper is also interested in determining the causality direction between human capital and economic growth.

The paper aims at scrutinizing the effects of human capital on the long-run economic growth in a sample of twelve Arab countries by studying first the causality between the two variables and estimating the impact of the human capital on economic growth. Furthermore, the results of the Arab sample are compared to a sample of Asian developing countries as well as a sample of advanced OECD countries. The rest of the paper is organized as follows: The first section summarizes the literature review on the role of human capital in theories and models. The second section displays the adopted econometric model. The third section presents data and causality analysis between human capital and GDP. The fourth section shows estimations and discusses the results. The last section concludes.

1. Literature review on human capital and long run economic growth

The definitions of human capital are numerous and evolve over time. An important definition adopted by most researchers, international organizations, and institutions is the one of the

Organization for Economic Cooperation and Development (OECD). According to the OECD (2001), human capital is defined as "*the knowledge, skills, competencies, and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being*." Similarly, the World Bank (2018), adopts a nearly similar definition of human capital that "*consists of the knowledge, skills and health capabilities that people accumulate throughout their lives, enabling them to realize their potential as productive members of society*". [3] The difference between the OECD and the World Bank definitions is that the latter considered the health dimension and links the human capital properties to potential productivity.

In terms of literature, there is thorough research on technology diffusion where human capital is a crucial factor. The theories of human capital are well established by many pioneering researches such as in Nelson and Phelps (1966), Grossman and Helpman (1991), and Barro and Sala-i-Martin (2003). The empirical literature on human capital and its effects on the economic development is diverse and very large to cite but has some distinguished works that are widely cited, particularly the works of Borensztein et al. (1998) and Benhabib and Spiegel (1994). In modelling, the human capital effects are mainly considered, theoretically, and empirically as well in the class of endogenous growth models. The pioneering contributions in this modelling area flourished with this class of models, especially by Romer (1986) and Lucas (1988). These models were brought as an alternative to the neoclassical growth model of Solow (1956) and Swan (1956) (Solow-Swan model). The principal characteristics of such models are their focus on the accumulation of knowledge and its endogenization, whether this knowledge is embodied in the form of technological progress, ideas, or in the form of human capital.

Historically, models of endogenous growth theory were developed to endogenize the role of externalities and their contribution to explaining the persistence of the long-run per capita growth rate, as an alternative to the rival neoclassical Solow-Swan model (Solow, 1956; Swan, 1956).[4] The latter considers the role of such externalities or what is assumed to be the technical progress as exogenous. Indeed, the steady-state growth rate in the Solow-Swan model is determined entirely

[3] The measurement of the human capital is difficult as the knowledge, capabilities and skills embodied in people used in production to create personal and social well-being as stated in the previous definitions, cannot be separated from people compared to the financial and physical assets that can be separated.

[4] Solow and Swan published in 1956 two distinct papers on the same issue, and their model is referred to as the Solow-Swan model or often as only the Solow model in reference to the more famous of the two economists.

by exogenous elements and, the macroeconomic aggregates (capital, output, and consumption) grow at a constant exogenous rate of the population growth, which makes the per capita corresponding quantities constant and hence do not grow. Hence, according to Barro and Sala-i-Martin (2003), the main substantive conclusions about the long run are that steady-state growth rates are independent of the saving rate or the level of technology. Especially, a model without technological change (like the Solow-Swan model) predicts economies to converge to a steady-state with zero per capita growth because of the diminishing returns to scale.

Solow (1956) model also appeared to be outdated since the Total Factor Productivity (TFP) measure estimated the share of growth explained by technical progress to more than 50% as reported by Jones and Romer (2010) or ranging between 50 to 70% as raised by Hsieh and Klenov (2010). This constitutes an “empirical” argument for the strength of endogenous growth models compared to the neoclassical Solow-Swan model. The latter, with its standard framework, was unable to explain the persistent per capita non-zero growth rates in many developed economies and hence was pointed for missing the determinants of the long-run growth. Thus, the crucial goal of the pioneers of the endogenous growth theory is to encompass other determinants of the long-run growth. This includes broadening the concept of capital, in which the assumption of diminishing return to scale is avoided, to include other determinants as production inputs such as human capital (Lucas, 1988; Romer, 1990), innovation, ideas and knowledge (Grossman and El Hanan, 1991; Jones, 1995; 2003).

Consequently, according to Barro and Sala-i-Martin (2003), the presence of human capital as an explicit factor of production may relax the assumption of diminishing returns to a broad concept of capital (in the classical models) and leads to long-term per capita growth in the absence of exogenous technology, hence, playing the role of such technology. [5] Since then, many sources of growth directly or indirectly related to human capabilities were particularly integrated to the production function as inputs such as innovation, ideas, human capital and research and development (R&D) expenditures (Jones, 2005; Jones and Romer, 2010).

[5] The only difference is that technology, in the form of ideas or knowledge could be shared once discovered between people, which makes them nonrival goods, while, thinking of human capital as skills and capabilities embedded on people, the use of such skills in one activity prevents their use in another activity leading to qualifying human capital as a rival good.

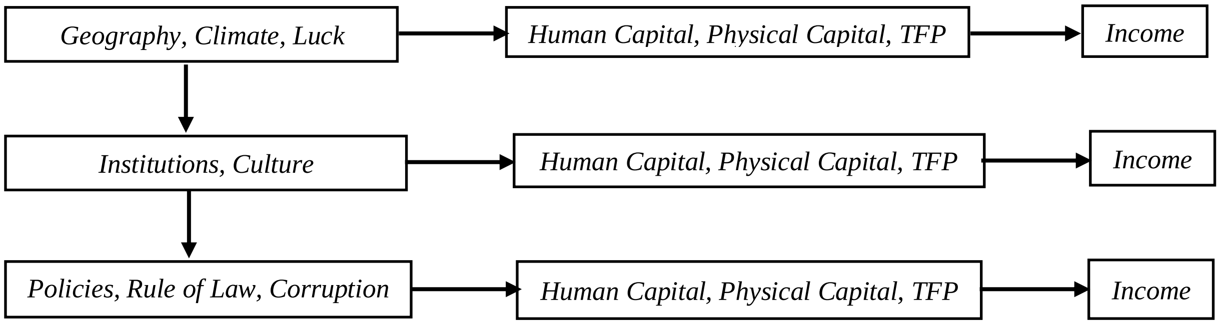
The important role of human capital highly emphasized in various categories of endogenous growth theory has many public policies implications. Indeed, public spending policies encompasses a variety of expenditures and transfers that directly impact the human capital and these policies are determinant in building human capital and its quality. These policies cover diverse sectors of health, education, research activities (Research and Development, R&D). Some of these spending items may also have externalities on other sectors producing knowledge, ideas and powering human capital by affecting their productivity. Many economists considered the role of human capital interacting with other types of public expenditures (flows and stocks as well) adopting endogenous growth models (Barro, 1990; Futagami et al., 1993; Corsetti and Roubini, 1996).

Another important issue creating controversies between economists is the direction of causality between many macroeconomic variables. Knowing the direction of causality between two economic variables helps policymakers in adopting accurate and efficient policies on such economic aggregates. Likewise, this paper is also interested in determining the causality direction between human capital and economic growth. In fact, across different views and literature involving human capital, the main research built a consensus about the effect of human capital on the countries' GDP which leads to say that human capital causes -economic growth. However, GDP also plays an important role in building the level and quality of human capital. Higher GDP is likely to allocate dedicated resources to sectors affecting directly human capital, particularly, education[6] and health, determined by the government expenditures on these sectors. Other expenditures and investments related to capacity building and training, as well as investment in research and development[7], are likely to endorse the level and quality of human capital. As a summary, GDP is likely to have direct feedback effects on human capital, leading to reverse causality. The reverse causality is a phenomenon disrupting and challenging econometric

[6] For example, the causality in both ways between education and growth is pointed in an OECD book by the statement: "*Does education spur growth, or does growth spur individuals to consume more education? In practice, it is likely that causality operates in both directions.*" (Keely, 2007).

[7] A current example of the crucial role of human capital, related to health, education and R&D sectors directly impacting the human capital, is greatly highlighted during the present health crisis of the cofid-19 virus, where health professionals and researchers in laboratories have found themselves in the front line to rescue the human species.

estimations.[8] Furthermore, human capital causes GDP to act as a passthrough of other economic and institutional policies effects on GDP. Indeed, human capital receives feedbacks from many exogenous factors (geography, institutions, culture) and economic and institutional policies., which are well summarized by Hsieh and Klenow (2010) in the following form:



2. Econometric Methodology

Empirically, assessing the contribution of human capital to economic growth requires estimation of the elasticity of GDP with respect to human capital stock (i.e., the percentage change in GDP over the percentage change in human capital stock). For this purpose, we adopt a theory-based framework. Specifically, we use the production function to describe the relationship between inputs and output variables, choosing a Cobb-Douglas production function, as mainly considered in the endogenous growth models. This production function is, despite some criticisms, very well-supported in economic theory, with a good empirical fit (Miller, 2008). We augment the production function with an additional variable of human capital as an explicit factor of production along with the classical factors that are labor and physical capital. Human capital can either be an additional factor of production as considered, for example, in Mankiw and al. (1992) or a factor influencing technical progress in the production function. In either way, it is considered as an additional regressor.[9] Therefore, the Cobb-Douglas production function is:

$$Y_{it} = A_i {H_{it}}^{\alpha} {K_{it}}^{\beta} L_{it}^{\gamma} \quad (1)$$

[8] Section 3 and 4 explains respectively the causality tests and the appropriate method to deal with issues of reverse causality.

[9] Following almost the same approach, Razzak and Bentour (2013) augmented the production function by FDI capital stock and domestic capital stock to assess the rate of return on the FDI on five Arabic countries (Algeria, Egypt, Jordan, Morocco and Tunisia).

Where for each country i(10) and time t, Y_{it} is the total GDP and; H_{it} the human capital stock, K_{it} the capital stock, and L_{it} the total employment (labor), are the three explicit factors used to produce such GDP, at respectively the shares parametrized by α, β and γ. A_i is a constant exogenous technical progress. Rescaling by employment L we get:

$$\frac{Y_{it}}{L_{it}} = \left(\frac{Y}{L}\right)_{it} = A_i \frac{{H_{it}}^{\alpha}}{L_{it}^{\alpha}} \frac{{K_{it}}^{\beta}}{L_{it}^{\beta}} L_{it}^{\gamma+\alpha+\beta-1} = A_i \left(\frac{H}{L}\right)_{it}^{\alpha} \left(\frac{K}{L}\right)_{it}^{\beta} L_{it}^{\gamma+\alpha+\beta-1} \quad (2)$$

Putting $\delta = \gamma + \alpha + \beta - 1$ and, denoting $y_{it} = \left(\frac{Y}{L}\right)_{it}$ the GDP per unit of labor, $h_{it} = \left(\frac{H}{L}\right)_{it}$ the human capital per unit of labor and $k_{it} = \left(\frac{K}{L}\right)_{it}$ the physical capital per unit of labor, yields:

$$y_{it} = A_i h_{it}^{\alpha} k_{it}^{\beta} L_{it}^{\delta} \quad (3)$$

Note that the sign of δ determines the way the returns to scale are happening. In this case, there is constant returns to scale to the three inputs (human capital, physical capital and labor) if $\delta = 0$, while $\delta > 0$ ($\delta < 0$) guarantees increasing (decreasing) returns to scale.[11] For the special case of constant returns to scale, equation (3) becomes:

$$y_{it} = A_i h_{it}^{\alpha} k_{it}^{\beta} \quad (4)$$

The previous condition vanishes the explicit labor factor from the equation, ensuring constant returns to scale to all three factors. There is a variety of models imposing the condition of constant returns to scale (Barro and al., 1995; Barro and Sala-i-Martin, 2003) yielding to the form described in equation (4). Others, however, prefer to let the estimations determine the sign of the parameter δ, which determine the way the returns to scale are evolving. In the latter case, the labor factor

[10] We keep the subscript "*i*" as we will apply this model to a panel of data consists of a group of cross-sectional units that are observed over time. The number of cross-sectional units in our application is 12 which smaller than the time range which is 48 years (1970-2017).

[11] "*Returns to scale refers to the rate by which output changes if all inputs are changed by the same factor. Constant returns to scale: a k-fold change in all inputs leads to a k-fold change in output. Under increasing returns to scale, the change in output is more than k-fold, under decreasing returns to scale; it is less than k- fold.*" Source: OECD (2001).

appears explicitly as described in equation (3).[12] Linearizing equation (3) by introducing the logarithm leads to the log-linearized form, augmented by an econometric error term ε_{it} as usual:

$$l\,n(y_{it}) = a_i + \alpha l\,n(h_{it}) + \beta ln(k_{it}) + \delta ln\,(L_{it}) + \varepsilon_{it} \tag{5}$$

3. Data description, causality tests and panel estimation methods

3.1 Data: Source, coverage, and description of the variables

To estimate equation (5), data set covers annual measures on four variables of the model for 12 Arab countries for which data of human capital are available in addition to other involved aggregates in the model. For regional and international comparisons, we run estimations also for two groups of countries taken as benchmarks: the Asian group of six countries and the advanced OECD group covering 12 countries (Table 1).

Table 1. Samples of countries

Arab countries Sample		Asian countries Sample	Advanced Economies Sample	
Algeria	Morocco	China	Australia	Netherlands
Bahrain	Qatar	Indonesia	Canada	New Zealand
Egypt	Saudi Arabia	Malaysia	Denmark	Norway
Jordan	Sudan	Philippines	France	Switzerland
Kuwait	Tunisia	Singapore	Germany	United Kingdom
Mauritania	United Arab Emirates	Thailand	Japan	United States

The data used in this paper are all extracted from the Penn World Table (WPT. 9.1) database. It consists of data on national accounts that was developed and updated by the University of California and the Groningen Growth Development Centre of the University of Groningen. The data cover a relatively long historical period, for 167 countries, going back to 1950 for many advanced countries and to 1970 for many developing countries. It includes data on capital, productivity, employment, and shares to GDP. The monetary data are displayed in current and constant $US (base year = 2011). These are also displayed in Purchasing Power Parity (PPP). The real aggregates allow to use the data in modelling and regressions while the PPP's in $US data conversion allows international comparisons across countries and time and ensures data

[12] For example, Park and Ryu (2006) find increasing returns to scale in East Asian countries, rejecting the constant returns to scale assumption, stating that "*the role of technical progress is overestimated when constant returns to scale is assumed*".

homogeneity when estimating panel models. The description of the methodologies producing these data set is published in Feenstra and al. (2015).

For the purpose of this study, the economic variables extracted from this database, over the period 1970–2017, are real GDP, real physical capital stock (both in millions of $US, constant), employment (in millions) and human capital index. The human capital is a newly added variable to the database and constructed based on the average years of schooling produced by Barro and Lee (2013).[13] The Barro-Lee data are produced every five years which was extrapolated and adjusted for the quality of human capital by the rate of return to education, following the methodology of Caselli (2005). Table 2 summarizes the description of the variables.

Table 2. Description of the variables used in this study

Variable name	**Variable definition**
Employment (Labor)	Number of persons engaged (in millions)
Human capital	Human capital index, based on years of schooling and returns to education.
Real GDP	Real GDP at constant 2011 national prices (in mil. 2011US$)
Real capital stock	Capital stock at constant 2011 national prices (in mil. 2011US$)

Source: The data are extracted from Penn World Table, version 9.1. Description is at the reference: Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" *American Economic Review*, 105(10), 3150-3182, available for download at www.ggdc.net/pwt.

Besides, table 3 (in the appendix) displays descriptive statistics for those variables. Skewness, Kurtosis and Jarque-Bera statistics gives indicative characteristics about the distribution and normality of the variables for each country. The main conclusion is the observation of some differences across countries about the normality distribution of the data.

3.2. Assessing causality between human capital and GDP

Researches highlighted the role of human capital in determining the level of the long-run growth rate. However, one of the issues when dealing with the Ordinary Least Squares (OLS) time series regressions is the endogeneity problem. Running a regression with an OLS method is supposing (among the well-known six hypotheses of the OLS method) that the explanatory variables are purely exogenous (orthogonal) to the error term in the equation. Otherwise, when this is not the

[13] A survey covering important international methodologies used to calculate human capital indicators is recently published in the Arab Monetary Fund economic studies and presented in the 6th Arabstat conference in November 2019 (Bentour, 2020; available in Arabic language).

case, the endogeneity problem induces the estimators to be biased (not consistent). The endogeneity issue is particularly present whenever there are omitted explanatory variables, or with the measurement error on the variables, or also when there is a causality running from the endogenous variable to the explanatory variables. In other words, there is a reverse causality.

In many econometric relations, the problem of reverse causality challenges the methods of estimations by impacting the quality of estimators creating an endogenous bias. Correcting the endogeneity issue, by constructing appropriate instrumental variables, is the role of alternative methods such as the Two Stages Least Squares (TSLS) method or the Generalized Method of Moments (GMM) method, which both employ the instrumental variables.

Granger (1969) defined causality between two random stationary variables X_t and Y_t, by stating that "*X is causing Y if we are better able to predict Y using all available information than if the information apart from X had been used*" (Granger, 1969). Many recent empirical studies on a variety of economic phenomena warned about the effect of reverse causality. This is also distinguished by Granger (1969) as feedback effects. Accordingly, the feedback or reverse causality is occurring when causality between X and Y is running both ways.

Table 2.A presents the correlations in levels and first differences between human capital and GDP. But according to the common econometric statement that correlation does not mean causation, the Granger causality between human capital and real GDP growth is important to test for the above-mentioned endogeneity issue. This can be tested using the following bivariate finite-order vector autoregressive (VAR) model:

$$\begin{cases} Y_{i,t} = \alpha_{1it} + \sum_{j=1}^{l} \beta_{1j} Y_{i,t-j} + \sum_{j=1}^{l} \gamma_{1j} X_{i,t-j} + \varepsilon_{1it} \\ X_{i,t} = \alpha_{2it} + \sum_{j=1}^{l} \beta_{2j} Y_{i,t-j} + \sum_{j=1}^{l} \gamma_{2j} X_{i,t-j} + \varepsilon_{2it} \end{cases} \quad (6)$$

Where index t refers to the time period, i to countries ($t = 1, \dots, T;\ i = 1, \dots, N$) and l to the optimal lags generally selected by information criteria such as Schwartz Information Criterion (SC) and Akaike Information Criterion (AIC). ε_{1it} and ε_{2it} are supposed to be white-noise errors.

With respect to this system, in each country, there is one-way Granger causality running from X to Y if in the first equation (of the system equation (7)) not all $\gamma_{1j}{}'s$ are zero but in the second all

$\beta_{2j}{}'s$ are zero. Similarly, there is one-way Granger causality from Y to X if in the first equation all $\gamma_{1j}{}'s$ are zero, but in the second not all $\beta_{2j}{}'s$ are zero. Further, there is two-way Granger causality between Y and X if neither all $\gamma_{1j}{}'s$ nor all $\beta_{2j}{}'s$ are zero, while there is no Granger causality between the two variables if all $\gamma_{1j}{}'s$ and $\beta_{2j}{}'s$ are zero.

Besides, another test for the causality is provided also by Dumitrescu and Hurlin (2012) as an extension designed to detect causality in panel data. The underlying regression (6) becomes:

$$\begin{cases} Y_{i,t} = \alpha_{1it} + \sum_{j=1}^{l} \beta_{1ij} Y_{i,t-j} + \sum_{j=1}^{l} \gamma_{1ij} X_{i,t-j} + \varepsilon_{1it} \\ X_{i,t} = \alpha_{2it} + \sum_{j=1}^{l} \beta_{2ij} Y_{i,t-j} + \sum_{j=1}^{l} \gamma_{2ij} X_{i,t-j} + \varepsilon_{2it} \end{cases} \quad (7)$$

Note in this equation that coefficients can differ across individuals (the i subscript attached to coefficients is added). The lag order l is assumed to be identical for all individuals and the panel must be balanced (all the three samples we study are balanced, i.e., all countries have the same number of observations). The procedure of this test is the same as described in the Granger causality when testing the null hypothesis for the associated coefficients $\gamma_{1ij}{}'s$ and $\beta_{2ij}{}'s$. For example, the null hypothesis testing the causality from X to Y is:

$$H_0: \gamma_{11i} = \gamma_{12i} = \cdots = \gamma_{1il} = 0;\ \forall\, i = 1, \ldots, N \quad (8)$$

This corresponds to causality absence for all individuals in the panel. The test assumes causality for at some individuals but not necessarily for all (Lopez and Weber, 2017).

3.3 Results and discussion

Before estimating the model described by the equation (5), we discuss and resolve a set of econometric issues related to stationarity, causality as well as the methods of estimations.

Panel unit root tests

Testing the unit root test in time series is an issue, whether in individual data or panel sample. Therefore, there is no unique test but a multiplicity of tests, and each one has its pros and cons. There is a variety of tests for the panel unit root implemented in econometrical software such as EViews and Stata. These are Levin, Lin and Chu (2002), Breitung (2000), Im, Pesaran and Shin

(2003), Fisher-type tests using ADF and PP tests, Maddala and Wu (1999), Choi (2001), and Hadri (2000). For the purpose of this study, we run tests under EViews, which computes and displays a summary of the results of the following the four first previous tests. The results are shown in table (3.A) confirming that all the scaled variables (by labor) in the three samples are stationary at least for the first test except for the GDP per labor in Asian sample, that seems to be integrated. However, at the individual levels, the data are clearly integrated. Although the interest in the issue of the unit root is of less importance since we are interested in the long-run relationship between human capital and GDP as the link between the two variables are studied in the long run, and also because of our theory-based framework. Therefore, the first condition of cointegration is enough to estimate the equation (5) without urging to adopt any error correction modelling form.[14] The only condition is to ensure the stability and normality of the residuals, which was validated in our estimations.[15]

Causality tests results

For the three studied panels, we run the causality tests of Pairwise Granger Causality Tests and Pairwise Dumitrescu and Hurlin (2012) Panel Causality Tests (equations (6) and (7)). The results displayed in table (4.A) (Appendix of table) show that both tests reveal a causality running in both ways between human capital and real GDP. The associated probabilities of the null hypothesis are below the threshold probability of reject (5%) especially for the Dumitrescu-Hurlin test. The presence of causality and reverse causality goes in line with what we raised previously in the literature review about the mutual effects between human capital and GDP. To run the causality tests, the number of lags for the bi-variate equations (6) and (7) are determined by Information Criteria which are presented in table (5.A). These tests confirmed an optimal lag of 1 for the sample

[14] We do not run cointegration tests as we are interested with the long run impact of human capital as the latter is accumulated over a long run period and its effects are assessed in an endogenous growth framework with relation to the long run per capita GDP. Furthermore, writing an error correction model, in case of cointegrated variables, with a Cobb-Douglas function leads categorically to change the form the Cobb-Douglas function and drift it away from its founded framework, hence disrupting the economic interpretations (elasticities and returns to scale assumptions).

[15] For the stability, panel unit root tests are conducted later after the estimations confirming the stationarity of the residuals and displayed in table 9.A (Appendix of tables), while normality is also checked and validated through statistical properties of Skewness, Kurtosis and Jarque-Berra (Figures 5, 6, and 7 in the Appendix of figures).

of Arab countries (indicated by Schwartz criterion) and an optimal lag of 2 for the other two samples of Asian and advanced countries.

Furthermore, we also provide individual causality tests for each country of the sample of the Arab countries. Table (6.A) shows that causality runs from human capital to GDP for the countries of Bahrain, Kuwait, Mauritania, Sudan, and UAE, while it runs the opposite way only for Egypt and Qatar. The causality and its reverse exist for Algeria, Morocco, KSA and Tunisia.

Methods of estimation

We start out estimations with the EGLS (Estimated Generalized Least Squares) estimator. EGLS method is used in case of heteroskedasticity or autocorrelation problems. This method delivers better results and high significance most of time. However, EGLS estimator, may be biased in the presence of endogeneity, nonlinearity and other specification and estimation issues. To correct the endogeneity bias that could arise from reverse causality running from GDP to human capital, as revealed by the previous tests of causality, we use the Generalized Method of Moments (GMM) to estimate the same specification (equation 5).

This method deals well with endogeneity issues, conditioned by a selection of suitable instrumental variables.[16] With these two methods of regression, we use the "SUR" option for panel estimations. The acronym SUR stands for Seemingly Unrelated Regression equations described by Zellner (1962). It constitutes a tool to estimate panel data models that are long (large T, T is time) but not large (small N, N is the number of countries in the sample), which is the case for the three samples considered in this paper (T=48 and N={12;6;12}).[17] The selection of the instrumental variables is also an issue. Many econometricians use the lagged explanatory variables in the absence of clear instrumental variables. Selection of instrumental variables is validated through the Sargan-Hansen test (the J-statistics). In our estimations, we use the lagged variables for the three explanatory

[16] Instrumental variables are selected to be correlated with exogenous variables but not with the endogenous variable.

[17] The SUR method assumes homoscedastic errors and linearly independent within each equation. It also assumes a contemporaneous correlation where each equation is correlated with the others in the same period. Furthermore, selecting the SUR option requires arranging data as stacked time series.

variables and the constant. Three calculated J-statistics are displayed, showing that the instrumental variables we considered in all our estimations are powerful.

Fixed versus random effects model

We run some tests to determine the panel properties model to estimate. Important tests in panel data are to test the model with fixed effects versus one with random effects. To decide between these two types of effects, Hausman test is usually used, where the null hypothesis is that the preferred model is random effects versus the fixed effects alternative (Green, 2008). It tests whether the errors are correlated with the regressors, assuming they are not for the null hypothesis. Therefore, Hausman test is also a test of the endogeneity issue, which may be caused by many sources such as misspecification, reverse causality or by omitted variables. Table (7.A) show the results rejecting the null hypothesis of random effects.

We also run a variety of tests for no cross-section dependence for the estimated panels. Table (8.A) summarizes results that highly reject the null hypothesis of no cross-section dependence, at respectively, 1% for the Arabic sample (p-value test = 0.0013<1%), 5% for the Asian sample (p-value = 0.012<5%) and 10% for the OECD sample (p-value=0.08<10%). Therefore, for the three samples, considering the three levels of significance (we can always reach the rejection level at 10%), the fixed effect model is the appropriate model to run for the three samples of countries.

Results analysis

Using the Estimated Generalized Least Squares (EGLS) method, table (3) shows the results for the estimated specification of the equation (6) with cross-section SUR option. For the three samples, the overall properties of the three estimations are highly significant with all the coefficients of the model highly accepted. Focusing on the human capital coefficient, we can deduce that the elasticity of human capital to GDP (α) is high around 1.1 for the Arab sample, 0.9 for the Asian sample and 1.3 for the Advanced countries sample. However, comparing the three group, on these elasticities leads to conclude that what is gained for one group in human capital elasticity is reduced or lost in term of physical capital per unit of worker. Indeed, the physical capital elasticity (β) is around 0.3 for the Arab sample, 0.6 for Asian countries and 0.4 for advanced countries. Nevertheless, considering the results of the bidirectional causality proven in the tests, we can conclude that the results of the EGLS method might be biased by the endogeneity issue raised by such bidirectional causality (as formerly explained). Therefore, the GMM method was used to remedy and test the robustness of these estimations.

Moreover, another issue that could create a biased estimator is the autocorrelations of the residuals which is clearly indicated present in these regressions by the weak value of the Durbin-Watson statistics as shown in table (3). In the same issue, Sun (2004) created a new class of estimators for the long-run average relationship in nonstationary panel time series. Specifically, for the least squares' estimator with the fixed effects estimator. He proved that the new estimators are consistent and asymptotically normal under both the sequential limit, wherein $T \rightarrow \infty$ followed by $n \rightarrow \infty$, and the joint limit where $T, N \rightarrow \infty$ simultaneously. The rate condition for the joint limit to hold is relaxed to $\sqrt{N}/T \rightarrow 0$. The new estimators can deliver more efficient estimates of the long-run average coefficient.[18]

Table 3. Panel Estimated Generalized Least Squares results

		Specification: $ln(y_{it}) = a_i + \alpha ln(h_{it}) + \beta ln(k_{it}) + \delta ln(L_{it}) + \varepsilon_{it}$					
		Arabic Countries Panel Sample (N=12; T=48)					
Variables (in logarithm)		Coefficient	Std. Error	t-Statistic	Prob.	*Panel Statistics*	
Constant term	a	6.7357	0.1192	56.5149	0.0000	Adj. R^2 =	0.973
Human Capital per unit of labor	α	1.1240	0.0757	14.8469	0.0000	F-Stat. =	2771.1
Physical Capital per unit of labor	β	0.3208	0.0109	29.4498	0.0000	F-Stat. Prob. =	0.000
Labor	δ	0.6408	0.0551	11.6391	0.0000	D.W.	0.166
		Asian Countries Panel Sample (N=6; T=48)					
Variables (in logarithm)		Coefficient	Std. Error	t-Statistic	Prob.	*Panel Statistics*	
Constant term	a	2.7497	0.1122	24.5160	0.0000	Adj. R^2 =	0.988
Human Capital per unit of labor	α	0.8798	0.0718	12.2483	0.0000	F-Stat. =	5379.7
Physical Capital per unit of labor	β	0.6322	0.0089	71.2533	0.0000	F-Stat. Prob. =	0.000
Labor	δ	0.6682	0.0500	13.3768	0.0000	D.W.	0.162
		Advanced Countries Panel Sample (N=12; T=48)					
Variables (in logarithm)		Coefficient	Std. Error	t-Statistic	Prob.	*Panel Statistics*	
Constant term	a	3.8142	0.1796	21.2346	0.0000	Adj. R^2 =	0.972
Human Capital per unit of labor	α	1.2919	0.0540	23.9199	0.0000	F-Stat. =	1801.4
Physical Capital per unit of labor	β	0.4407	0.0164	26.8710	0.0000	F-Stat. Prob. =	0.000
Labor	δ	1.4211	0.0492	28.8713	0.0000	D.W.	0.100

[18] In our case, $T = 48$ (1970-2017) and $N \in \{12; 6; 12\}$, leading the rate condition to $\frac{\sqrt{N}}{T} \in \{0.07; 0.05; 0.05\}$.

Table (4) presents the results of the GMM method. The overall estimations are all robust for the three samples as; all the coefficients are accepted, with high global adjustment (higher adjusted R squares) and the instrumental chosen variables are validated by the J-Sargan-Hansen test statistics for over-identification (the J-Statistics probabilities are under 5%). Focusing on the human capital elasticity (α), the latter is highly significant for the three samples and has values of 0.50 for Arab countries, 0.60 for Asian countries, and about 0.93 for the sample of the advanced countries. Considering these values means that a 1% increase in the human capital per unit of labor, which is an index combining average years of schooling (quantity) for adult population and the return to education (quality) is likely to increase the GDP growth by 0.5%, 0.6% and 0.93% in the respective samples of Arab, Asian, and advanced countries respectively.

By comparison, the positive effects of human capital in the Arab countries is about 46% ($\frac{0.5-0.93}{0.93} \cong -0.46$) lower compared to the effects of human capital on GDP in the advanced countries. Compared to Asian countries, the differences in elasticity is about 0.1 yielding to percentage gap of about 16.7% ($\frac{0.5-0.6}{0.6} \cong -0.167$) between the two groups.

The results show also that the physical capital per unit of labor has almost similar contribution to the economic growth for the Arab countries and Asian countries, with the associated elasticity β around 0.68 and 0.66 for the two sets of countries, respectively. Besides, the elasticity of the physical capital for the advanced countries is slightly lower, estimated to 0.55. However, we notice that the coefficient δ associated with the labor in the estimated specification is significantly positive for all the three samples in the GMM estimations, with a higher value for the advanced countries and lower value for the Arab countries. This coefficient measures the distance from a constant return to scale to the three inputs factors (human capital, physical capital, and labor) as explained in the model formulation in section 3. A significant positive coefficient δ as reported for the three groups, means that doubling output requires less than doubling inputs in the three groups of countries. But, the increasing returns to scale is more likely to happen in the sample of advanced countries than in the sample of Arab and Asian countries.[19]

[19] Note that the original formulation ($Y_{it} = A_i {H_{it}}^{\alpha} {K_{it}}^{\beta} L_{it}^{\gamma}$) associate γ as the coefficient to the labor variable. After rescaling by the labor variable ($y_{it} = A_i h_{it}^{\alpha} k_{it}^{\beta} L_{it}^{\delta}$), the new coefficient $\delta = \gamma + \alpha + \beta - 1$ becomes associated with labor but measure the distance to returns to scale as we explained. The coefficient γ can be indirectly calculated as

Table 4: Panel Generalized Method of Moments (GMM) estimation results[20]

		Specification: $ln(y_{it}) = a_i + \alpha ln(h_{it}) + \beta ln(k_{it}) + \delta ln\,(L_{it}) + \varepsilon_{it}$					
		Arabic Countries Panel Sample (N=12; T=48)					
Variables (in logarithm)		Coefficient	Std. Error	t-Statistic	Prob.	*Panel Statistics*	
Constant term	a	2.7139	0.3947	6.8755	0.0000	Adj. R^2 =	0.96
Human Capital per unit of labor	α	0.5043	0.1245	4.0517	0.0001	J-Stat. =	36.01
Physical Capital per unit of labor	β	0.6811	0.0369	18.4477	0.0000	Rank =	19
Labor	δ	0.2154	0.0819	2.6308	0.0088	J-Stat. Prob. =	0.00
		Asian Countries Panel Sample (N=6; T=48)					
Variables (in logarithm)		Coefficient	Std. Error	t-Statistic	Prob.	*Panel Statistics*	
Constant term	a	2.1784	0.3301	6.5997	0.0000	Adj. R^2 =	0.99
Human Capital per unit of labor	α	0.6020	0.1930	3.1195	0.0020	J-Stat. =	32.47
Physical Capital per unit of labor	β	0.6662	0.0134	49.5418	0.0000	Rank =	13
Labor	δ	0.5116	0.0908	5.6365	0.0000	J-Stat. Prob. =	0.00
		Advanced Countries Panel Sample (N=12; T=48)					
Variables (in logarithm)		Coefficient	Std. Error	t-Statistic	Prob.	*Panel Statistics*	
Constant term	a	2.7869	0.2076	13.4272	0.0000	Adj. R^2 =	0.97
Human Capital per unit of labor	α	0.9277	0.0600	15.4694	0.0000	J-Stat. =	38.77
Physical Capital per unit of labor	β	0.5515	0.0187	29.4343	0.0000	Rank =	19
Labor	δ	1.0839	0.0566	19.1521	0.0000	J-Stat. Prob. =	0.00

Table (5) reports the coefficients confidence intervals shown at the three level respectively 1%, 5% and 10%. From this table, for example at 5% level, the elasticity α of human capital per unit of labor could range between 0.3 and 0.7 for the Arab countries sample, 0.2 up to 1 for the sample of Asian countries and between 0.8 and 1 for the Advanced countries sample. For the physical capital elasticity β, it ranges nearly between 0.6 up to 0.75 for the Arabic sample, 0.6 to 0.7 for the Asian countries and between 0.5 and 0.6 for the OECD sample. For the coefficient δ measuring the distance to returns to scale, it varies approximately between 0.1 and 0.3 for the Arabic countries sample, 0.3 and 0.7 for the Asian countries sample and, between 1 and 1.2 for the OECD countries sample.

$\gamma = \delta - \alpha - \beta + 1$ which leads to $\gamma = 0.03$ for the Arabic sample, $\gamma = 0.24$ for the Asian sample and $\gamma = 0.60$ for the advanced countries.

[20] We used for the panel GMM regression fixed effect the options of; cross-section weights for GLS weight, white cross section for GMM weighting matrix, and white cross section for coefficients standard errors and covariance matrix (with corrected degree of freedom).

Table 5. Coefficient Confidence Intervals

Arab sample			90% CI		95% CI		99% CI	
variable	*Coefficient*		*Low*	*High*	*Low*	*High*	*Low*	*High*
Constant term	a =	2.714	2.139	3.288	2.029	3.399	1.813	3.615
Human Capital	α =	0.504	0.346	0.663	0.315	0.694	0.255	0.753
Physical Capital	β =	0.681	0.628	0.734	0.618	0.744	0.598	0.764
Labor	δ =	0.215	0.108	0.323	0.087	0.343	0.047	0.384
Asian sample			90% CI		95% CI		99% CI	
variable	*Coefficient*		*Low*	*High*	*Low*	*High*	*Low*	*High*
Constant term	a =	2.178	1.604	2.753	1.493	2.863	1.276	3.081
Human Capital	α =	0.602	0.258	0.945	0.192	1.012	0.062	1.142
Physical Capital	β =	0.666	0.639	0.693	0.634	0.698	0.624	0.708
Labor	δ =	0.512	0.336	0.687	0.302	0.721	0.236	0.787
Advanced sample			90% CI		95% CI		99% CI	
variable	*Coefficient*		*Low*	*High*	*Low*	*High*	*Low*	*High*
Constant term	a =	2.787	2.445	3.129	2.379	3.195	2.250	3.323
Human Capital	α =	0.928	0.829	1.027	0.810	1.046	0.773	1.083
Physical Capital	β =	0.552	0.521	0.582	0.515	0.588	0.503	0.600
Labor	δ =	1.084	0.991	1.177	0.973	1.195	0.938	1.230

4. Results discussion and data limitations

There is no doubt that human capital is necessary for the development and its positive effect on economic growth, which is confirmed by this study, has been proven in the empirical literature using different methods and different variables approaching the measure of human capital (Wilson R. A. and Briscoe G., 2004; Erosa and al., 2010; Acemoglu and Autor, 2012; Diebolt and Hippe 2019;). But because of the differences and methods as well, the comparison of such effect in terms of scale, in the empirical literature, is difficult. Indeed, researchers using the same variable, could not use the same method or model of estimation, while those using the same methods could have used different measures human capital across. Therefore, in many different studies involving such subject, there is always comparisons of samples and countries in the same study rather than with other studies, which we adopted in this work, by invoking two benchmark samples of Asian and OECD countries. Nevertheless, some rare studies could be examined to compare our results to which seems to go in lines with their findings.

For example, An and al. (2019) studying the substitution between public and private capital for a large sample of countries (Least developed, Emerging and Advanced countries), used the same data we used on human capital (the World Penn Table 9.1), and slightly different approach by considering the labor commonly with the human capital index (that is the raw labor adjusted by human capital). The considered framework is a nested constant elasticity of substitution (CES) Cobb-Douglas production function. The coefficient of the labor adjusted by human capital is found to around 0.6 for all countries, particularly higher in the emerging countries (about 0.8), and slightly lower in the advanced countries (around 0.5). The difference in the two elasticities between the two groups could be attributed to the labor scale than human capital scale. Considering the same approach as we adopted in this paper, but with the average years of schooling as a measure for human capital (not adjusted for quality as we considered here), Razzak and Bentour (2013) studying the FDI effects and its interaction with human capital, found an elasticity of human capital around 0.25 for five Arab countries (Algeria, Egypt, Jordan, Morocco and Tunisia) and 0.2 for a comparing benchmark of Asian countries (China, Korea, Malaysia and Thailand).

Furthermore, in terms of returns to scale, our results are generally in line with what is assumed and proved in the theory of endogenous growth models showing that considering human capital leads to increasing returns to scale (see the literature section; Lucas, 1986, Barro, 1990, Romer, 1990 and many others). The returns to scale are also found to be determined by the level of income of the country as higher income countries have tendency to enjoy increasing returns to scale in the presence of qualified and skilled human capital.

Finally, we should point to some challenges related to data constructions and which could alter the quality of all the estimations in the literature and ours as well. First challenge is related to construction of the human capital variable. Thus, measuring human capital involves principally measuring embedded soft skills and health capabilities as reported by the human capital definitions. There are many methodologies that tried to measure human capital. We used the one we consider involving the human capital quantity adjusted for quality with enough observations. The World Bank recent work to construct the human capital index (World Bank project, 2017) presents an innovative methodology that links the human capital to other factors than the rate of return on education; these are the health of pupils considered as the base of the future human capital, and the expected labor productivity. However, the short number of observations (the project started only in 2017) of this measure discouraged us from using it for our approach of estimations. Consequently, while investing in human capital, Arab countries are also encouraged to involve in enhancing the human capital statistics by participating to international programs that measure particularly the quality of human capital.

The physical capital stock also is not a directly observable but rather a calculated variable, generally approached by the recurrent perpetual inventory equation, as one of the most used methods. The equation relates the current stock to the previous one minus the depreciated previous stock and augmented by the flow of current investments. Such recurrent equation requires some assumptions particularly on the first point of the time series and the depreciation rate. The accuracy of these assumptions determines the quality of the deduced capital stock. However, this is a general issue and challenges facing all the empirical literature which could alter the true elasticities values and call for more caution in interpreting empirical works and also more efforts in enhancing the quality of the data.

5. Conclusion

Considered in the endogenous growth theory, human capital is often perceived as a source of raising economic growth in the long run. It is often designated as one of the most important sources of the long-run growth that explains cross-country differences in development. This paper highlighted the important positive contribution of human capital to economic growth for a sample of twelve Arab countries. Compared to a benchmark of six Asian countries (China, Indonesia, Malaysia, Philippines, Singapore, and Thailand), the sample of the Arab countries is not broadly lagging in terms of contribution of human capital to GDP growth. However, compared to advanced countries (Australia, Canada, Denmark, France, Germany, Japan, Netherlands, New Zealand, Norway, Switzerland, United Kingdom, and the United States), a lot of efforts are needed to catch up the developed world as the contribution of the human capital in the Arab countries is almost half the one observed in the advanced countries sample.

This paper also tested the direction of causality between GDP and human capital, which means that while human capital is causing the GDP, the latter also has feedback effects on the former. This involves obviously important policy implications. The bidirectional causality creates a loop of effects between human capital and GDP. Henceforth, increasing the contribution of human capital to sustain long-term growth requires investments in key sectors that directly support human capital. These sectors involve particularly the education sector, vocational training, health sector, and research and development for innovative ideas and inventions, which have higher implications on workers long-run productivity. Therefore, governments should give such sectors priority in their expenditures policies, which is likely to sharpen workers' skills and enhance productivity leading to positive feedbacks on GDP. Furthermore, technological advances are rapidly transforming and changing our world, impacting our way of living in a globalized competitive world. Thus, to be eager to compete and prosper in such a changing environment, countries should invest in their people enhancing their skills and potential knowledge, which in turn will lead, in the long run, to important benefits for their economy and societies.

References

Acemoglu D. and Autor D. (2012). What does human capital do? A review of golden and Katz's the race between education and technology. NBER Working Paper 17820, Massachusetts Avenue Cambridge, MA.

Barro, R. J. and Lee J. W. (2013). A new data set of educational attainment in the world, 1950-2010. *Journal of Development Economics*, 104, pp.184–198.

Barro, Robert J. (1990). Government spending in a simple model of endogenous growth. *Journal of Political Economy*, 98(S5), 103-125.

Barro, Robert J. and Sala-I-Martin, Xavier I. (2003). *Economic growth*. MIT Press.

Benhabib R. and Spiegel M. (1994), The role of human capital in economic development: evidence from aggregate cross-country data. *Journal of Monetary Economics*, 34; 143-173.

Bentour, E. M. (2020). Methodologies for building and calculating human capital indices with reference to the status of Arab countries. AMF Economic Studies, March (in Arabic language).

Borensztein, E., De Gregorio J. and Lee J.W. (1998). How Does Foreign Direct Investment Affect Economic Growth? *Journal of International Economics*, 45, 115-135.

Breitung, J. (2000). The Local Power of Some Unit Root Tests for Panel Data. *Advances in Econometrics*, vol.15, 161-177.

Caselli F. 2005. *Accounting for Cross-Country Income Differences*. In Handbook of Economic Growth, Vol.1A, ed. Philippe Aghion and Durlauf, S. N. 679–741. New York: North-Holland.

Choi, I. (2001), Unit Root Tests for Panel Data, *Journal of International Money and Finance*, 20, 249-272.

Corsetti G. and Roubini N. (1996). Optimal Government Spending and Taxation in Endogenous Growth Models, NBER working paper 5851, National Bureau of Economic Research.

Diebolt C. and Hippe R. (2019). The long-run impact of human capital on innovation and economic development in the regions of Europe. *Applied Economics*, 51(5), 542-563.

Dumitrescu E. I. and Hurlin C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, 29(4), 1450-1460

Durlauf, S. N., Johnson P. A. and Temple J. R. W. (2005). *Growth Econometrics*, in S.N. Durlauf and P. Aghion (Eds.), Handbook of Economic Growth, Elsevier.

Erosa A, Koreshkova T. A. and Restuccia D. (2010). How Important is Human Capital? A Quantitative Theory Assessment of World Income Inequality. *Review of Economic Studies*, 01, 1-32.

Feenstra, R. C., Inklaar R. and Timmer M. P. (2015), The Next Generation of the Penn World Table. *American Economic Review*. 105(10), 3150-3182.

Futagami K., Morita Y. and Shibata A. (1993). Dynamic analysis of an endogenous growth model with public capital, *Scandinavian Journal of Economics*, 95, 607-625.

Granger, C. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, 37(3), 424-438.

Greene W. H. (2008). *Econometric Analysis*, Upper Saddle River, New Jersey 07458, 6th edition, Prentice Hall.

Grossman G. and Helpman E. (1991). *Innovation and Growth in the Global Economy*, Cambridge, MIT Press, 119.

Hadri, K. (2000), Testing for Unit Roots in Heterogeneous Panel Data. *Econometrics Journal*, 3, 148-161.

Hsieh, Chang-Tai, and Peter J. Klenow. 2010. Development Accounting. *American Economic Journal: Macroeconomics*, 2(1), 207-223.

Jones C. I. (1995). R&D-Based Models of Economic Growth. *Journal of Political Economy*, 103(4), 759-784.

Jones C. I. (2003). Population and Ideas: A Theory of Endogenous Growth. In P. Aghion, R. Frydman, J. Stiglitz, and M. Woodford, eds., *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, Princeton University Press.

Jones C. I. and Romer P. M. (2010). The New Kaldor Facts: Ideas, Institutions, Population, and Human Capital. *American Economic Journal: Macroeconomics*, 2(1), 224-245.

Jones C. I. (2005). Growth and Ideas. In P. Aghion and Durlauf S., eds, *Handbook of Economic Growth*, edition 1, 1, chapter 16, 1063-1111.

Keely, B. (2007). *Human Capital: How what you know shapes your life*. OECD, Paris.

Krugman P. (1994). *The Age of Diminished Expectations: U.S. Economic Policy in the 1990s*. MIT Press.

Levin, Lin and Chu (2002), Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, vol 108(1), 1-24.

Lopez L. and Weber S. (2017). Testing for Granger causality in panel data, Institute of Economic Research IRENE Working paper number17-03.

Lucas, Robert E., (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, 22, 3–42.

Maddala, G.S. and Wu, S. (1999), A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test. *Oxford Bulletin of Economics and Statistics*, special issue, pp.631- 652

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, 107, 407–437.

Miller E. (2008). An assessment of CES and Cobb-Douglas Production Functions. Congressional Budget Office, WP/05.

Mincer J. (1974), Schooling, Experience, and Earnings. National Bureau of Economic Research.

Nelson R. and Phelps E. (1966). Investments in Humans, Technology Diffusion, and Economic Growth. *American Economic Review*, 56(2), 69-75.

OECD (2001). *The Well-being of Nations: The Role of Human and Social Capital.* OECD, Paris.

OECD Productivity Manual. (2001). *A Guide to the Measurement of Industry-Level and Aggregate Productivity Growth*. OECD, Paris, March 2001, Annex 1 – Glossary.

Park, J., Ryu, H.K. (2006). Accumulation, Technical Progress, and Increasing Returns in the Economic Growth of East Asia, *Journal of Productivity Analysis*, 25, 243–255.

Razzak W. A. and Bentour E. M. 2013. Do developing countries benefit from foreign direct investments? An analysis of some Arab and Asian countries. *Review of Middle East Economics and Finance*, 9 (3), 357-388.

Romer Paul M. (1986). Increasing Returns and Long-Run Growth, *The Journal of Political Economy*, 94(4), 1002-1037.

Romer, Paul M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5), 21-32.

Solow, R. (1988). Growth Theory and After. *American Economic Review*, 78, 307-317.

Solow, Robert (1956). A Contribution to the Theory of Economic Growth. *Quarterly Journal of Economics*, 70, 65-94.

Sun, Y. (2004). Estimation of the long-run average relationship in nonstationary panel time series. *Econometric Theory*. 20(6), 1227-1260.

WEF (2017). *The Global Human Capital Report 2017*. WEF, Geneva, Switzerland.

Wilson R. A. and Briscoe G. (2004). The impact of human capital on economic growth: a review. In: Descy, P.; Tessaring, M. (eds) *Impact of education and training*. Third report on vocational training research in Europe: background report. Luxembourg: Office for Official Publications of the European Communities, (Cedefop Reference series, 54)

World Bank. (2018). *The Human Capital Project. World Bank Report*, Washington, DC.

Zellner A. (1962) An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias, *Journal of the American Statistical Association*, 57(298), 348-368.

Appendix of Tables

Table 1.A. Descriptive statistics

Employment in millions	Algeria	Bahrain	Egypt	Jordan	Kuwait	Mauritania	Morocco	Qatar	KSA	Sudan	Tunisia	UAE
Mean	4.7438	0.3574	17.4516	1.1244	1.0229	0.6585	7.8586	0.6205	6.5110	5.0687	2.4224	1.8391
Median	3.9428	0.2357	16.8345	1.1548	0.8313	0.6420	6.9748	0.2991	6.0237	5.0617	2.3784	1.4667
Maximum	9.3776	0.8286	29.0585	2.2714	2.0444	1.1830	13.0082	2.2927	12.4164	8.5596	3.4007	3.8919
Minimum	2.5072	0.1036	9.7728	0.3584	0.3693	0.2529	4.1742	0.0922	2.4611	2.4171	1.3037	0.3830
Std. Dev.	2.0982	0.2381	6.2417	0.6018	0.4909	0.2748	2.7353	0.6528	2.7226	1.7891	0.7201	1.2115
Skewness	0.9131	0.8144	0.5109	0.3611	0.8369	0.2249	0.6187	1.3691	0.6009	0.2220	-0.0733	0.5501
Kurtosis	2.4854	2.0890	1.8985	1.9486	2.4329	1.9176	2.0423	3.5200	2.5553	1.8793	1.4933	1.8400
Jarque-Bera	6.1500	5.9497	3.8562	2.7792	5.3351	2.3469	4.1827	13.2706	2.8053	2.4824	3.9147	4.3671
Probability	0.0462	0.0511	0.1454	0.2492	0.0694	0.3093	0.1235	0.0013	0.2459	0.2890	0.1412	0.1126
Human capital index	Algeria	Bahrain	Egypt	Jordan	Kuwait	Mauritania	Morocco	Qatar	KSA	Sudan	Tunisia	UAE
Mean	1.6709	2.0163	1.7947	2.1296	1.9443	1.4385	1.4333	2.1284	2.0711	1.3042	1.7281	2.1710
Median	1.6810	2.1991	1.7826	2.1502	2.0154	1.3969	1.3978	2.0432	2.0709	1.2781	1.6915	2.2338
Maximum	2.2628	2.3419	2.6177	2.8746	2.2432	1.7869	1.8929	3.0921	2.6680	1.5911	2.6110	2.7401
Minimum	1.0915	1.2862	1.1736	1.3516	1.4753	1.2267	1.0788	1.5476	1.5327	1.0822	1.1441	1.3767
Std. Dev.	0.4052	0.3359	0.4594	0.5395	0.2348	0.1728	0.2589	0.4190	0.3611	0.1741	0.4327	0.5047
Skewness	0.0163	-0.9537	0.2094	-0.0426	-0.8928	0.5352	0.2466	0.6618	0.0367	0.2312	0.3757	-0.2123
Kurtosis	1.5041	2.4626	1.7787	1.4413	2.5248	1.9755	1.6856	2.5029	1.7369	1.5353	2.0289	1.4224
Jarque-Bera	4.4775	7.8546	3.3341	4.8739	6.8279	4.3908	3.9417	3.9980	3.2016	4.7181	3.0151	5.3383
Probability	0.1066	0.0197	0.1888	0.0874	0.0329	0.1113	0.1393	0.1355	0.2017	0.0945	0.2215	0.0693
Real Capital stock in millions of US. $ (ppp)	Algeria	Bahrain	Egypt	Jordan	Kuwait	Mauritania	Morocco	Qatar	KSA	Sudan	Tunisia	UAE
Mean	356971	110534	582129	124630	218961	17212	657641	251234	2296661	181006	331026	1245763
Median	347393	94214	446055	112550	181047	12509	565621	84081	1987918	39229	305488	1174524
Maximum	949218	294802	1563258	293967	627162	53260	1566488	1228383	6142069	791889	641371	2684114
Minimum	50847	19036	73813	17956	47001	4920	163592	21270	329956	9815	95058	234226
Std. Dev.	203566	75308	443228	79597	146466	12256	390953	324344	1552914	235583	156703	682140
Skewness	0.9252	0.8988	0.6881	0.5123	1.2203	1.6252	0.7584	1.7051	0.9210	1.3061	0.3448	0.4042
Kurtosis	4.2990	2.8591	2.2746	2.2713	3.7923	4.6311	2.5854	4.6381	3.1018	3.2936	2.1111	2.3515
Jarque-Bera	10.2221	6.5022	4.8397	3.1621	13.1694	26.4513	4.9451	28.6259	6.8073	13.8205	2.5311	2.1479
Probability	0.0060	0.0387	0.0889	0.2058	0.0014	0.0000	0.0844	0.0000	0.0333	0.0010	0.2821	0.3417
Real GDP in millions of US. $ (ppp)	Algeria	Bahrain	Egypt	Jordan	Kuwait	Mauritania	Morocco	Qatar	KSA	Sudan	Tunisia	UAE
Mean	216376	26777	462034	40866	154449	6968	130174	104486	935533	74279	63908	322399
Median	168465	21987	397199	32593	135119	5830	109287	44249	877671	51357	54363	241210
Maximum	597894	60402	1095920	90272	280643	14452	299993	360722	1712755	171779	127214	727098
Minimum	57081	8515	89582	11341	48121	3463	42393	20167	320631	23412	16243	56194
Std. Dev.	142446	15001	306127	24619	66813	3289	71812	109050	357920	47981	35282	198990
Skewness	1.3354	0.8378	0.5232	0.6727	0.6348	0.9594	0.8260	1.3624	0.6890	0.7588	0.4454	0.5987
Kurtosis	3.9856	2.4325	2.0537	2.1846	2.0679	2.6187	2.6177	3.3029	2.7168	2.0700	1.8172	2.0977
Jarque-Bera	16.2086	6.2590	3.9810	4.9499	4.9619	7.6547	5.7504	15.0328	3.9587	6.3363	4.3853	4.4956
Probability	0.0003	0.0437	0.1366	0.0842	0.0837	0.0218	0.0564	0.0005	0.1382	0.0421	0.1116	0.1056

Table 2.A: Pearson correlations between human capital and GDP

	Algeria	Bahrain	Egypt	Jordan	Kuwait	Mauritania	Morocco	Qatar	Saudi Arabia	Sudan	Tunisia	United Arab Emirates
In levels	95.8%	68.6%	99.2%	93.1%	58.0%	97.9%	96.9%	94.0%	89.5%	96.5%	99.1%	90.1%
In differences	-7.0%	-46.7%	53.1%	-21.8%	-19.4%	46.6%	27.8%	68.6%	-3.3%	35.8%	10.5%	-18.1%

Table 3.A: Panel unit root tests summary of results

Arabic Sample	*lny*		*lnh*		*lnk*		*L*	
	Statistic	Prob.*	Statistic	Prob.*	Statistic	Prob.*	Statistic	Prob.*
Levin, Lin & Chu	-2.84852	0.0022	-1.80751	0.0353	-1.85905	0.0315	-2.66565	0.0038
Im, Pesaran and Shin W-stat	-0.10077	0.4599	1.82556	0.966	-0.61687	0.2687	1.91771	0.9724
ADF - Fisher Chi-square	21.8759	0.5867	15.1395	0.9166	25.9758	0.3544	15.0551	0.9191
PP - Fisher Chi-square	24.6107	0.4272	32.4609	0.116	23.1355	0.5118	33.4829	0.0943
Asian Sample	*lny*		*lnh*		*lnk*		*L*	
Levin, Lin & Chu	-0.89601	0.1851	-2.2292	0.0129	-1.28457	0.0995	-4.8805	0.0000
Im, Pesaran and Shin W-stat	2.27353	0.9885	-0.23776	0.406	1.02935	0.8483	-1.96482	0.0247
ADF - Fisher Chi-square	9.03771	0.6997	14.2858	0.2828	7.86653	0.7955	24.9192	0.0152
PP - Fisher Chi-square	7.94734	0.7892	21.9311	0.0383	21.2503	0.0468	59.1484	0.000
Advanced Sample	*lny*		*lnh*		*lnk*		*L*	
Levin, Lin & Chu	-13.4431	0.00	-5.72862	0.0000	-10.2586	0.0000	-1.42204	0.0775
Im, Pesaran and Shin W-stat	-8.4668	0.000	-0.5122	0.3043	-6.13764	0.0000	2.59894	0.9953
ADF - Fisher Chi-square	127.608	0.000	24.0101	0.4610	85.1011	0.0000	15.8379	0.8938
PP - Fisher Chi-square	220.866	0.000	88.8128	0.0000	156.508	0.0000	32.7293	0.1099

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.
The first test assumes as null hypothesis common unit root process, while the rest of the tests assumes individual unit root process

Table 4.A. Results of Pairwise Granger Causality Tests and Pairwise Dumitrescu Hurlin Panel Causality Tests for the three panels of countries

Arabic sample (Lags: 1)						
Pairwise Granger Causality Tests			***Pairwise Dumitrescu Hurlin Panel Causality Tests***			
Null Hypothesis:	F-Statistic	Prob.	Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
Log human capital per unit of labor does not	3.58	0.06	Log human capital per unit of labor does not	2.70	3.72	0.00
Log real GDP per unit of labor does not	32.46	0.00	Log real GDP per unit of labor does not homogeneously	3.23	4.92	0.00
Asian Sample (Lags: 2)						
Log human capital per unit of labor does not	2.65	0.07	Log human capital per unit of labor does not	5.91	4.21	0.00
Log real GDP per unit of labor does not	8.05	0.00	Log real GDP per unit of labor does not homogeneously	4.48	2.63	0.01
Advanced Sample (Lags: 2)						
Log human capital per unit of labor does not	21.91	0.00	Log human capital per unit of labor does not	10.36	13.43	0.00
Log real GDP per unit of labor does not	23.91	0.00	Log real GDP per unit of labor does not homogeneously	10.84	14.21	0.00

Table 5.A. VAR Lag Order Selection Criteria for the causality tests.

Lag	LogL	LR	FPE	AIC	SC	HQ
Arabic Sample						
0	-1456.956	NA	1.680999	6.195143	6.212785	6.202083
1	1459.018	5794.802	7.17E-06	-6.169927	**-6.116999***	-6.149105
2	1469.77	21.27596	6.97E-06	-6.198598	-6.110385	-6.163896
3	1482.14	**24.37348***	**6.72e-06***	**-6.234142***	-6.110643	**-6.185559***
4	1484.005	3.657431	6.78E-06	-6.225073	-6.066289	-6.162609
5	1484.644	1.248941	6.88E-06	-6.210803	-6.016734	-6.134458
Asian Sample						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-668.8462	NA	0.918174	5.590385	5.619391	5.602072
1	1043.377	3381.642	6.03E-07	-8.644811	-8.557795	-8.60975
2	1073.437	58.86738	**4.86e-07***	**-8.861977***	**-8.716951***	**-8.803542***
3	1075.218	3.456994	4.95E-07	-8.843481	-8.640443	-8.761671
4	1081.333	**11.77264***	4.86E-07	-8.861111	-8.600063	-8.755928
5	1083.632	4.386196	4.93E-07	-8.846932	-8.527873	-8.718374
Advanced Sample						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1588.423	NA	0.284247	4.417841	4.430561	4.422751
1	3899.104	10929.32	6.89E-08	-10.81418	-10.77602	-10.79945
2	4078.928	357.1503	4.23E-08	-11.30258	**-11.23898***	-11.27802
3	4084.674	11.38072	4.21E-08	-11.30743	-11.21839	-11.27305
4	4102.419	35.04624	4.05E-08	-11.34561	-11.23113	**-11.30141***
5	4104.616	4.327616	4.07E-08	-11.3406	-11.20068	-11.28658

* indicates optimal lag, LR: sequential modified LR test (each test at 5% level), FPE: Final prediction error, AIC:

Table 6.A. Granger causality tests for Human capital and real GDP

Null Hypothesis: Variable X does not cause Variable Y		F-Statistic	Probability	Conclusion
Algeria	Real GDP does not Granger Cause Human Capital	4.91	0.01***	Causality runs both ways
	Human Capital does not Granger Cause Real GDP	9.59	0.00***	
Bahrain	Real GDP does not Granger Cause Human Capital	0.55	0.58	Human Capital causes GDP
	Human Capital does not Granger Cause Real GDP	3.07	0.06*	
Egypt	Real GDP does not Granger Cause Human Capital	8.68	0.00***	GDP causes Human Capital
	Human Capital does not Granger Cause Real GDP	1.19	0.32	
Jordan	Real GDP does not Granger Cause Human Capital	1.61	0.21	Human Capital causes GDP
	Human Capital does not Granger Cause Real GDP	2.65	0.08*	
Kuwait	Real GDP does not Granger Cause Human Capital	1.01	0.41	Human Capital causes GDP
	Human Capital does not Granger Cause Real GDP	2.24	0.08*	
Mauritania	Real GDP does not Granger Cause Human Capital	0.75	0.48	Human Capital causes GDP
	Human Capital does not Granger Cause Real GDP	6.92	0.00**	
Morocco	Real GDP does not Granger Cause Human Capital	3.08	0.06*	Causality runs both ways
	Human Capital does not Granger Cause Real GDP	5.00	0.01***	
Qatar	Real GDP does not Granger Cause Human Capital	3.48	0.04**	GDP causes Human Capital
	Human Capital does not Granger Cause Real GDP	0.34	0.72	
Saudi Arabia	Real GDP does not Granger Cause Human Capital	6.19	0.00***	Causality runs both ways
	Human Capital does not Granger Cause Real GDP	2.84	0.07*	
Sudan	Real GDP does not Granger Cause Human Capital	0.43	0.65	Human Capital causes GDP
	Human Capital does not Granger Cause Real GDP	8.69	0.00***	
Tunisia	Real GDP does not Granger Cause Human Capital	2.68	0.08*	Causality runs both ways
	Human Capital does not Granger Cause Real GDP	3.36	0.04**	
United Arab Emirates	Real GDP does not Granger Cause Human Capital	1.16	0.32	Human Capital causes GDP
	Human Capital does not Granger Cause Real GDP	3.39	0.04**	

Notes: *, ** and ***: significant at 10%, 5% and 1% respectively. The minimum number of lags is 2 for all countries except for Kuwait where the number of lags is 4. For this country, the number of lags equal 2 leads to no causality in both ways.

Table 7.A. Hausman tests for random versus fixed effects model.

Arab sample countries				
Test Summary		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random		15.688298	3	0.0013
Cross-section random effects test comparisons:				
Variable	Fixed	Random	Var(Diff.)	Prob.
Log Human Capital per unit of labor	0.953677	0.906039	0.000418	0.0199
Log Physical Capital per unit of labor	0.351354	0.359339	0.00001	0.0123
Log Labor	0.486433	0.454346	0.000188	0.0192
Asian sample countries				
Test Summary		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random		10.946242	3	0.012
Cross-section random effects test comparisons:				
Variable	Fixed	Random	Var(Diff.)	Prob.
Log Human Capital per unit of labor	1.215607	1.242488	0.000175	0.042
Log Physical Capital per unit of labor	0.48777	0.497402	0.000015	0.0122
Log Labor	1.300297	1.292542	0.000084	0.3978
Advanced sample countries				
Test Summary		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random		6.718995	3	0.0814
Cross-section random effects test comparisons:				
Variable	Fixed	Random	Var(Diff.)	Prob.
Log Human Capital per unit of labor	0.955385	0.730757	0.008688	0.016
Log Physical Capital per unit of labor	0.626476	0.633757	0.000014	0.0479
Log Labor	0.699348	0.590273	0.002108	0.0175

Table 8.A Cross-section dependence tests for the panel samples.

Residual Cross-Section Dependence Test: 1970-2017						
Null hypothesis: No cross-section dependence (correlation) in weighted residuals						
	Arabic Sample Cross-sections: 12 Total observations: 576		Asian Sample Cross-sections included: 6 Total observations: 288		Advanced Sample Cross-sections: 12 Total observations: 576	
Test	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Breusch-Pagan LM	610.04	0.00	129.55	0.00	715.18	0.00
Pesaran scaled LM	47.35	0.00	20.91	0.00	56.50	0.00
Bias-corrected scaled LM	47.22	0.00	20.85	0.00	56.38	0.00
Pesaran CD	7.17	0.00	8.35	0.00	10.25	0.00
Test employs centered correlations computed from pairwise samples						

Table 9.A. Panel unit root tests for residuals of estimated models

Exogenous variables: Individual effects	Arabic sample		Asian sample		OECD sample	
Sample: 1970 2017	Statistic	Prob.***	Statistic	Prob.***	Statistic	Prob.***
Levin, Lin & Chu test *	-1.747	0.040	-1.463	0.072	-2.309	0.011
Im, Pesaran and Shin W-stat test **	-1.335	0.091	-1.711	0.044	-2.005	0.023
ADF - Fisher Chi-square test **	30.771	0.161	21.159	0.048	44.826	0.006
PP - Fisher Chi-square test **	24.987	0.407	11.507	0.486	28.347	0.246
Exogenous variables: None	Arabic sample		Asian sample		OECD sample	
Sample: 1970 2017	Statistic	Prob.***	Statistic	Prob.***	Statistic	Prob.***
Levin, Lin & Chu test *	-4.173	0.000	-4.581	0.000	-5.483	0.000
ADF - Fisher Chi-square test **	61.200	0.000	44.328	0.000	69.822	0.000
PP - Fisher Chi-square test **	63.552	0.000	30.518	0.002	65.558	0.000

* Null: assumes common unit root process; ** Null: assumes individual unit root process; *** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Appendix of figures

Figure 1: Employment in millions of people

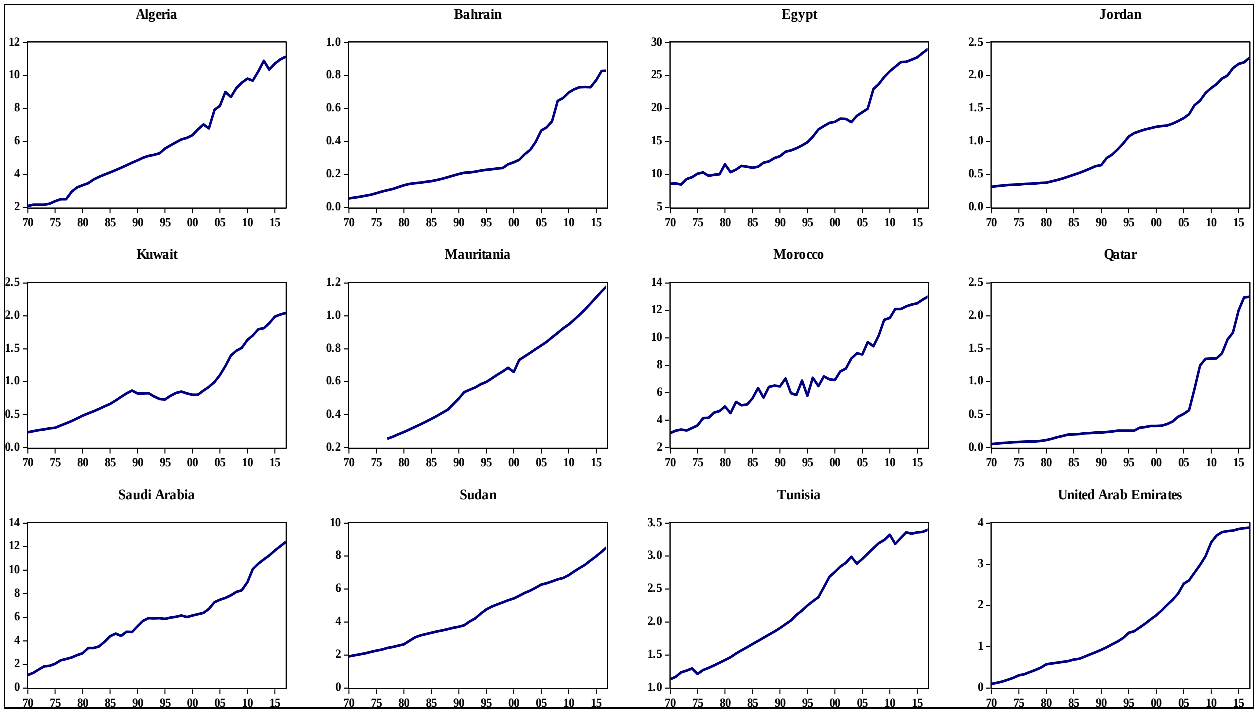


Figure 2: Human capital Charts

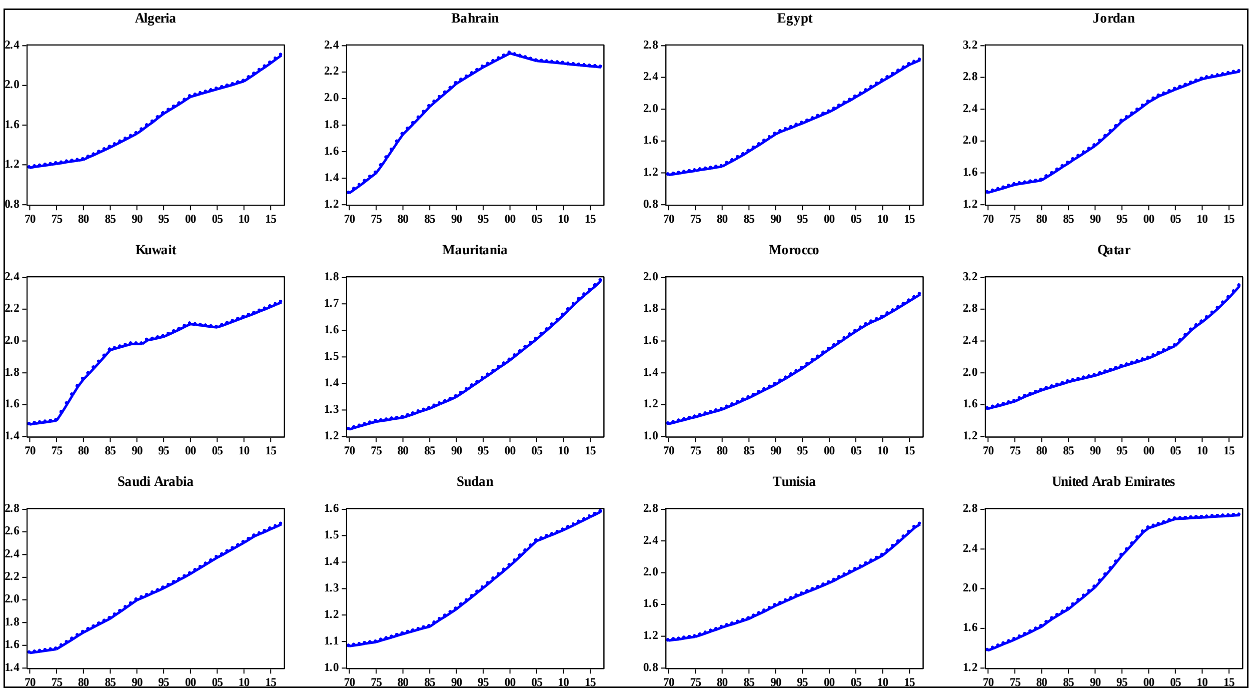


Figure 3: Real physical capital stock Charts

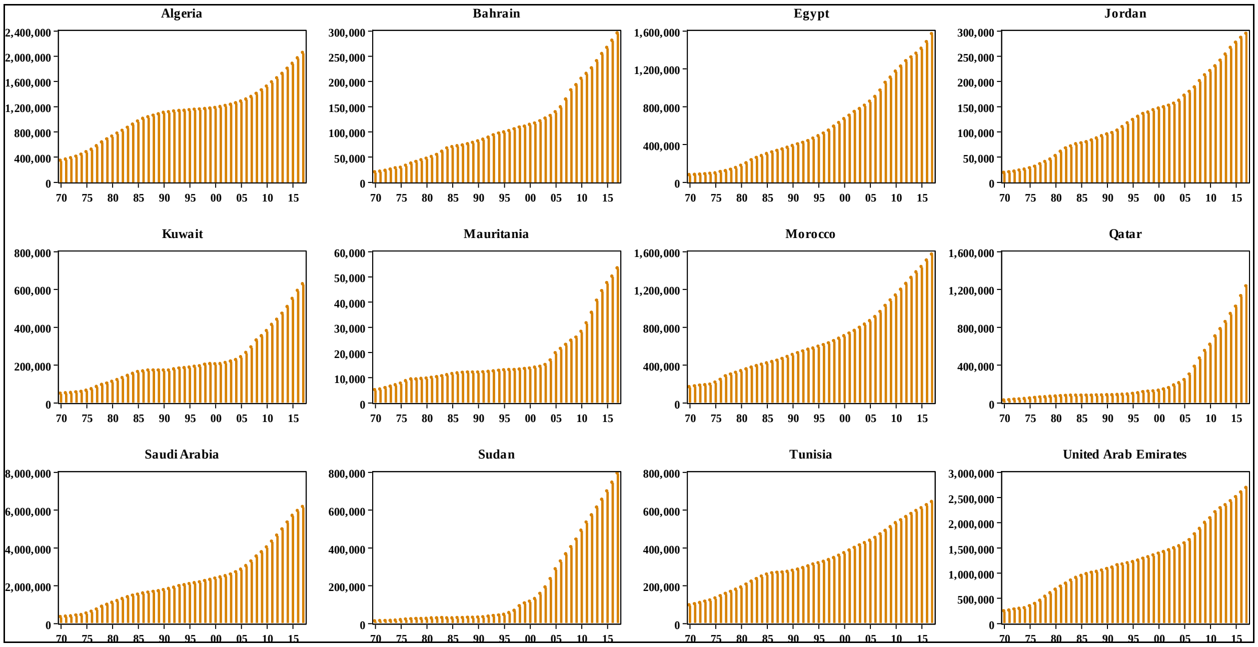


Figure 4: Real GDP Charts

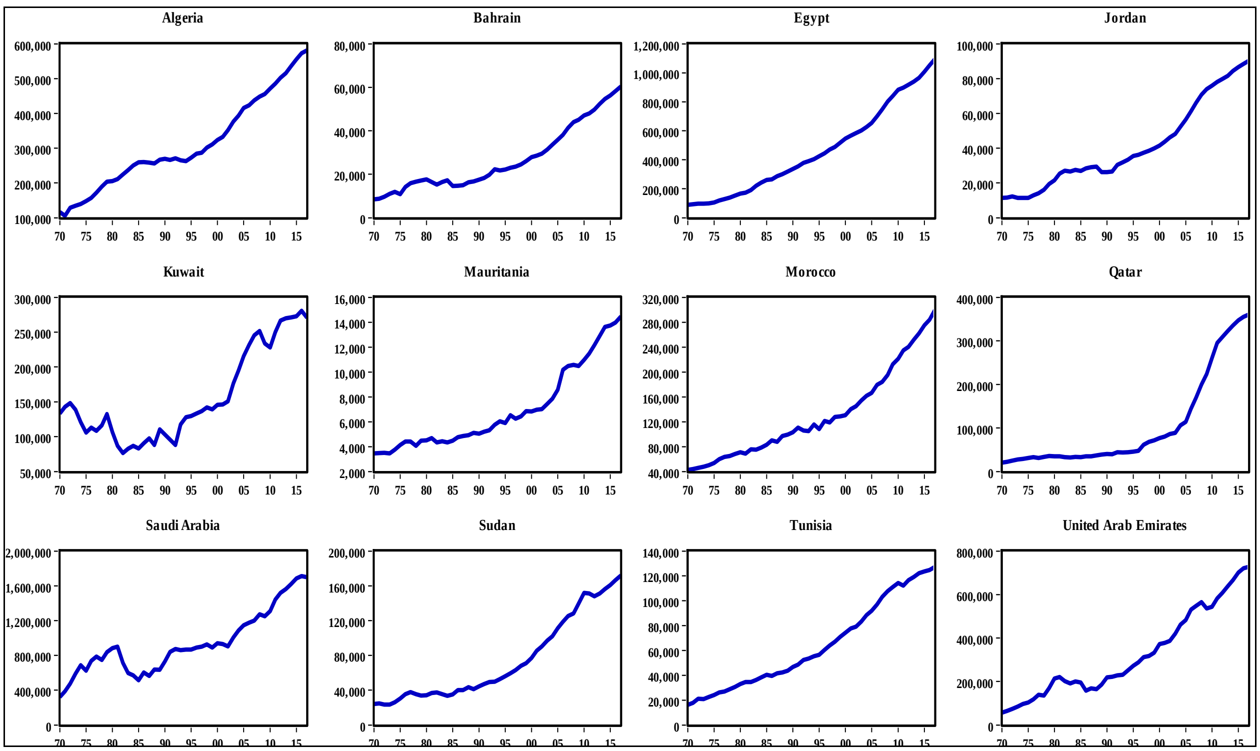


Figure 5. Test for residuals normality for the Arabic sample of countries

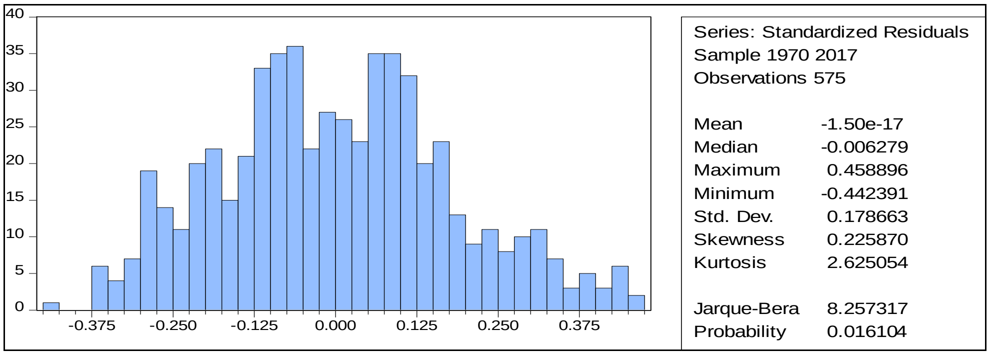


Figure 6. Test for residuals normality for the Asian sample of countries

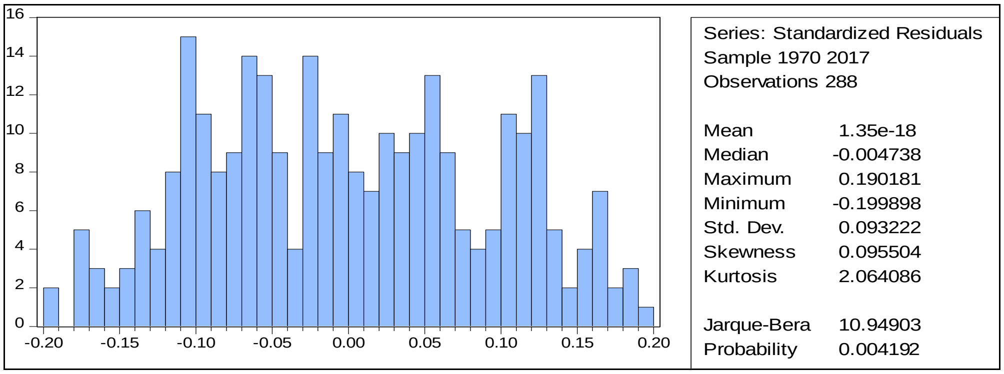


Figure 7. Test for residuals normality for the Advanced sample of countries