The Importance of Higher Education on Economic Growth

**Abstract**:

It is very important for countries to stimulate their economic prosperity and reduce poverty. While it is commonly accepted that education of all forms enhances economic performance of a country, yet the question of which level of education, secondary or tertiary, is more important to fuel the economy is not conclusively answered.

The finding in Abraham Cohen’s PhD thesis is that education, as measured by published research, is strongly associated with Artificial Intelligence index of countries. Also, he found that AI is strongly associated with GDP. His findings encourage the idea that higher education, which is needed for Artificial Intelligence (AI), will be a dominant factor for economic growth in general; hereby, policy makers should investment in higher education to ensure economic affluence.

Enrollment rates for higher education in Sub-Saharan Africa are by far the lowest in the world and the academic research output in the region is among the world’s lowest. Because of a belief that primary and secondary schooling are more important than tertiary education for poverty reduction, the international development community has encouraged African governments’ relative neglect of higher education.

Using methodology of fuzzy logic-based soft regression, this study challenges these beliefs and demonstrates that economic growth is almost exclusively determined by higher education. Also, the importance of higher education relative to secondary education is more so in recent years relative to a decade or two ago.

Motivated by this finding, I propose to find the right branch of higher education for every country based on its economic competitive advantage that will impact its economic growth best.

**Keywords:** Education, Economic Growth, Artificial Intelligence, fuzzy logic, soft regression

**Introduction**

It is a long and important question that policy makers have to decide when allocating resources for education. Simply stated: to which level of education more resources should be allocated, to secondary education or tertiary level, to stimulate economic growth and prosperity while reducing poverty in a country?

Enrollment rates for higher education in Sub-Saharan Africa are by far the lowest in the world at 6%. Yet because of conventional beliefs that tertiary education is less important for poverty reduction, the international development community has encouraged African governments’ relative neglect of higher education (Bloom et al., 2014). (Friedman & Friedman, 1980) claimed that there was no evidence to suggest that “higher education yields ‘social benefits’ over and above the benefits that accrue to the students themselves.”. Moreover, they hypothesized that higher education may promote “social unrest and political instability”.

At the same time, (Marquez-Ramos & Mourelle, 2019) in their research conclude: “The results show that both secondary and tertiary education matter for economic growth”. Similarly (Zhang et al., 2021) found ambivalent results on the importance of higher education stating: “The study found a fluctuating economic growth indicator during the research period … the result of the sub-sample showed a heterogeneous effect on high GDP per capita countries”.

The above findings which cover the last few decades, are troubling for not finding clear-cut result showing the importance of higher education. Tertiary education organizations are at the center of the large revolutions required throughout cost-cutting and civilizations. Tertiary education is essential for the development of human capital and innovation. As the world seeks to advance toward a new age of green and fair economic growth, operational and strategic investments in tertiary education can serve the poorest to the richest countries by increasing its skills, capacity and leadership, creating, and spreading knowledge to local and global encounters, and partaking in the global knowledge economy. Operative tertiary education segments guarantee that countries have well-trained professional engineers, technicians, teachers, doctors, nurses and managers who are the core actors of effective education delivery for private and public sectors development. Years of inadequate and fruitless investment in post-secondary education and the advanced skills advanced through higher learning opportunities have only intensified global equity gaps (Mogas et al., 2022).

Therefore, to reach a conclusive and robust result on this issue, the main hypothesis of this study is:

**Hypothesis**: “Secondaryeducation is more important than tertiaryeducation to stimulate the economy.”

In this paper, I focused on large scale, cross country study of over 150 countries. To substantiate the result and find a trend in the importance of higher education for economic growth, the study includes three periods 2000, 2007 and 2014. Furthermore, to overcome many limitations of other studies which use variation of Multi Variant Regressions (MVR), this study provides an extensive sample analysed with well-established methodology of fuzzy logic-based soft regression as outlined by (Shnaider, E. and Yosef, A., 2018) and implemented in (Cohen A 2023). Determining the relative importance (weight) of secondary and higher education to be adopted by countries (the explanatory variables in this study) is an important and challenging task. The ability to determine relative importance of these education levels and the reliability of such outcome are of ultimate importance to the policy makers, who apply such models as components of decision support or decision making. Soft regression is definitely more reliable and consistent tool to determine relative importance of explanatory variables then traditional method of multiple linear regression (Shnaider, E. and Yosef, A., 2018).

Needless to say, that a primary and secondary education is a must in modern society (Boland, 1993). My findings show that secondary and higher education are important for economic growth. Yet, higher education is substantially more important than secondary education to ensure economic prosperity. Moreover, this study shows that the importance of higher education relative to secondary education is growing over time. In fact, it is safe to say that in recent years only higher education is relevant for economic growth.

**Literature review:**

The theoretical foundations of the economic effects of better education were laid out in the seminal contributions of (Schultz, 1961), (Becker, 1964), and (Mincer, 1974). (Bradley and Green, 2020) provide an excellent up-to-date overview of research in the economics of education. The work of Baker and Mincer developed the theory of human capital based on individuals investing in their own education in a way that is analogous to physical capital, and at the same way, generates a stream of future returns. Their work generated an enormous amount of research in the field of human capital.

The search for evidence that tertiary education is essential for economic prosperity, also, goes back several decades. (Friedman & Friedman, 1980) concluded that there was no evidence to suggest that “higher education yields ‘social benefits’ over and above the benefits that accrue to the students themselves.” Likewise, Wolff (2001) revealed that the number of higher education graduates does not significantly affect economic productivity. Similarly, Vedder (2004) conducted research on US States, found that states with greater public expenditures on higher education did not obtain more economic growth in the US. In the same group of researchers, (Guo & Jia, 2009) constructed a two-step human capital accumulation model and observed that compared to primary education, the effect of higher education on economic productivity is ambiguous.

Other studies try to come up with explanation of these results and show their inconsistency. (Birdsall, 1996) argue that higher education could increase employment and improve the safety of society, and any results that do not consider these points are biased. According to Hanushek (2016), extending the years of education without improving human capital does not influence economic productivity. Lastly, Di and Sun (2014) and (Sun, & Ning, 2016) revealed that different types of higher education have distinct impacts on economic efficiency and growth. Overall, the overwhelming majority of the literature has discussed education in general, but few studies have distinguished among various higher education levels.

More recent research studies have had the same difficulty to reach conclusive conclusion as to the importance of higher education relative to secondary education. (Marquez-Ramos & Mourelle, 2019) concluded that both secondary and tertiary education matter for economic growth. They have not attempted to measure the importance of each of these education levels on economic prosperity of a country. The same could be said on the study of (Zhang et al., 2021). His findings were ambivalent on the importance of higher education.

(Rahman et al., 2019) analyze empirically the contribution of tertiary level education by fields on economic growth for developed and developing countries. They found that in the developed countries graduates from science faculties make the most contribution to economic growth, but in developing countries graduates from education, humanities and social sciences faculties contributed the most to economic growth. Also, they found that, having human capital from different fields in both developed and developing countries positively affects economic growth.

Enrollment rates for higher education in Sub- Saharan Africa are by far the lowest in the world. Currently, the gross enrollment ratio in the region stands at only 6 percent. Many African countries struggle to maintain even low enrollment levels, and the academic research output in the region is among the world’s lowest. Because of a belief that primary and secondary schooling are more important than tertiary education for poverty reduction, the international development community has encouraged African governments’ relative neglect of higher education. For example, from 1985 to 1989, 17 percent of the World Bank’s worldwide education-sector spending was on higher education. But from 1995 to 1999, the proportion allotted to higher education declined to just 7 percent (Gyimah-Brempong et al., 2006).

In this study I demonstrate that higher education is substantially more important than secondary education to ensure economic prosperity and this relative importance is growing over time. Therefore, I recommend that African countries should increase their investment in higher education to reduce poverty and increase economic growth.

1. **Method**

**Modeling Tool**

I utilize Soft Regression (a soft computing method) as a modeling tool due to its major advantages in comparison to the traditional MVR (Multi-Variable Regression) methods. First, we briefly describe some important deficiencies of the MVR methods:

Ever since the introduction of computerized methods, the modeling in economics, management, finance, marketing, etc. has been mostly based on econometric tools (various statistical techniques, some extremely complex and considered highly sophisticated). However, in parallel to substantial achievements attained with the help of econometric tools, the practitioners of modeling in those fields are well aware of enormous difficulties and profound failures in numerous modeling projects. Even in “successful” and “workable” models developed with the help of econometric tools, very often-human intervention (use of “Add Factors”) has been essential to avoid outright failures.

MVR requires precise and complete model specification in order to generate reliable results. When a model is incomplete, or when its functional form is incorrect, this leads to a misspecification bias: distorted and unreliable results. However, from the practical standpoint one should ask, whether under severe conditions of uncertainty, do we always know all the relevant variables? Moreover, even if we know, do we always have data for all of them? Do we know the exact functional form of how the variables interact? In numerous decision-making or decision supporting systems and in countless events where decision makers must make fateful decisions, they would answer negatively to these questions.

Soft Regression (SR) is a modeling tool based on Fuzzy Logic. It is a modeling tool which does not require restrictive conditions. It is not designed to generate precise mathematical function characterized by a small random deviation. However, it is capable of correctly identifing the relevant factors for the model, whether a relation is direct or inverse, and in addition, its greatest advantage is its capability to reliably compute the relative importance of various explanatory variables included in the model even when the model is partial and incomplete (in such cases MVR models generate distorted and unreliable results by definition since it requires precise and complete model specification). The ratio of relative importance values among explanatory variables included in various specifications remains the same (when using SR), no matter if we add or remove explanatory variables. This is in contrast to MLR, where changing specification also changes (in some cases even drastically) the ratio between relative importance values of explanatory variables.

We will briefly list several of the important features of the Soft Regression that constitute a major advantage in comparison to the MVR, in particular when constructing a model characterized by highly interrelated explanatory variables.

1. SR does not require precise model specification. This regression tool is based on Fuzzy Logic, which is designed in the first place to handle information under severe conditions of uncertainty and imprecision. The idea here is to give up on the possibility of building a precise model and satisfying ourselves with the opportunity to work with whatever data are available. We generate a partial/less-precise model and expect it to be very reliable in a general direction of its conclusions because it avoids the problem of misspecification bias. It allows the use of partial and unreliable data to make reliable but broad (not precise) conclusions in comparison to mis-specified MVR model based on these data. Of course, in the case of partial data (some potentially important variables excluded due to lack of data), the MVR model is mis-specified by definition and subject to misspecification bias.
2. Soft regression calculates reliable weights (relative importance) of the explanatory variables, in contrast to the traditional regression tools, where calculated relative weights are unreliable [7], [13].
3. The significance of the explanatory variables and the relative importance of those variables among themselves are not affected by adding additional variables to the model or removing some variables from it (in contrast to MVR). When a partial model is constructed, the significance of the explanatory variables and the ratio between relative importance values of those variables among themselves are not affected by adding additional variables to the model, or removing some variables from it. This is in contrast to the behavior of MLR, where addition or removal of an explanatory variable can change drastically the significance of other explanatory variables of the model. This characteristic of the SR adds an important feature of stability and confidence to the decision making.
4. Explanatory variables are not required to be independent of each other. In the fields such as Economics, Finance, Political Science etc. the variables are usually intangible concepts, that are often highly correlated among themselves mathematically even while logically they could each represent separate and independent (at least to some extent) concepts. When using MVR, high correlation among explanatory variables causes some of the important explanatory variables to appear as insignificant, and therefore being removed from the model - thus leading to model misspecification. In Soft Regression, the modeling process and the results are not affected by multicollinearity. Hence, this feature of SR (not requiring independence of explanatory variables) constitutes a major advantage in comparison to MVR, in particular if explanatory variables are highly correlated.
5. The method utilizes heuristically determined Low-cut and High-cut (for minimum and maximum values of membership function – further explanations appear below). Membership function is designed to determine, to what extent each value of the processed data is a member in a predefined fuzzy set [10], [11]. This brings the membership function utilized in SR more in line with “human thinking” and thus allowing the modeler to monitor the logic of the information processing throughout the analysis. This feature of the SR helps to handle the distortions due to outlying values in a user-based logical approach (in contrast to strictly mathematical method utilized in Robust Regression approach).
6. There are no technical issues that could cause model distortions. Wrong results are only possible if the model specification contradicts human reasoning and common sense, or if the membership functions used during the data normalization are illogical. As long as logical integrity during the model construction is maintained, the model will be reliable. This means: no unrealistic assumptions (which contradict real world conditions) are allowed. The normalizing process must be transparent, and in line with common sense.

**Data preparation**

The data preparation involves several stages of addressing outliers as carefully as possible, without deleting records containing the outlier from the data matrix (this will be explained below). The process also allows for the identification of records where data appear to be severely unreliable and inconsistent. In such cases, these records are deleted from the analysis of that specific time period. In the vast majority of the cases, there have been very few records deleted from the analysis for any given time period due to extreme inconsistency of data, and thus had very little influence on the results of the model.

One of the most important rules in Data Science is: every piece of information is important and should be included in the analysis (unless there is a convincing reason to believe that the data are severely distorted and misleading). For numerous factors, there is more than one way to measure them. Also, for some data series there have been differences in measurement methodology over the years. Despite the fact that all these measurements are (from our perspective) measuring essentially the same thing, there could be very substantial differences among various data series in terms of values, and even in their scale. In the cases where the variables are represented by any number of numerical vectors each, the amount of the regression runs testing all the possible combinations of such variables would be enormous. The problem is not only the amount of work, but also the question of how to summarize so many results and to reach meaningful conclusion? It would require hundreds or even thousands of regression runs, which in turn had to be summarized and interpreted, and could open the possibility of inconsistencies, when there are so many results.

In most cases, modelers do not use all the possible data series, but rather select one or several such series. The question is: which of the various data series to select? Most modelers either select the most popular and easiest to obtain variables. In some other cases the decision is based upon the availability of data, number of missing observations, etc. The less legitimate approach is to try several different variables, and then select the ones generating results that best serve modelers’ goals (without mentioning other results). Of course, there is always a possibility of criticism: why a given selection among the data series was made, and not another. The method utilized in this study precludes such criticism, since all the data series are utilized.

**Advantages of utilizing intervals**

In this study I am utilizing quantitative modeling method capable of using ranges (intervals) of values that are derived from all the available data series. There are several important advantages of transforming available data into intervals of values:

1. The very basic principle in the field of Information Systems is: all available data are valuable (unless suspected of being severely distorted) and should be utilized in the modeling process.
2. Confidence in the modeling results: when the approach is inclusive and involves all the available data series, then obviously the confidence in results is greater vs. modeling process involving selected data series while ignoring others.
3. Efficient handling of missing observations: This issue arises when in many data series there is a large number of missing measurements. In addition, the set of missing records is not expected to be the same in different data series. However, we can construct intervals for every record, for which there is at least one measurement. Of course, in some intervals there will be more data points and in others less, but we can include all these records in the modeling process, and thus increase our confidence in the results.
4. It is much easier to reach meaningful and unambiguous conclusions due to the drastic reduction of the amount of regression runs. When using the method presented here, the amount of regression runs drops to 4:
5. Regression using only Minimum values.
6. Regression using only Maximum values.
7. Regression of Minimum for dependent variable vs. Maximum of explanatory variables.
8. Regression of Maximum for dependent variable vs. Minimum of explanatory variables.

Note: it does not matter how many explanatory variables are expressed in terms of intervals, the method will still require only four regression runs.

The four regression runs generate four results, which again can be reduced to an interval between the minimum and the maximum value of the results, and this interval can be used to draw conclusions as well as for further computations.

In the case where the dependent variable is a regular single numerical vector, and only some of the explanatory variables appear as intervals, then the amount of regression runs drops to two:

1. Regression of dependent variable vs. Minimum of explanatory variables
2. Regression of dependent variable vs. Maximum of explanatory variables

Similarly, in the case when only the dependent variable is expressed as interval, and explanatory variables are ordinary numerical vectors, there will be only two regression runs:

1. Regression of Minimum for dependent variable vs. explanatory variables
2. Regression of Maximum for dependent variable vs. explanatory variables

**The process of Range Reduction**:

When many data series represent a given variable, we can identify (in approximate terms) the center of gravity of that variable (for each record), and thus ignore extreme outlying measurements (as explained below).

For that purpose, I apply the Range Reduction Algorithm (RRA); see detailed explanation in [12], [8]. The main objective is to extract as much information as possible from available data, while eliminating potential outliers, which from our perspective are measurements that represent distorted, mistaken, misleading, etc. data points.

In some cases, the entire data series are distorted (or are inappropriate as being proxy variables in a specific model). A problem of this type appears when there is a problematic measurement methodology applied throughout the numerical vector, causing it to be way out of line in comparison to other measurement methodologies of additional numerical vectors representing the same factor. When there are many data series representing the same factor (either dependent or explanatory), then by combining all the data of those data series into intervals of values, the distorted data series will appear on the edges of such intervals and could be handled effectively by the RRA.

In addition to the problem of the whole data series being inappropriate, we also address the reliability of specific records of the data series (countries), where some records could be reliable and some not. This problem can also be mitigated by applying RRA [12], [8]. By reducing an interval, we are bringing it closer to its core area that reflects the center of gravity of the interval. Such core (center of gravity) areas effectively represent most of the information regarding that factor (measured in different ways by different proxy variables). The outliers on the edges of intervals are deleted without much danger of losing important information.

When the decision is made to utilize several data series to represent the same factor, each data record will be represented by a range of values: the minimum and the maximum. However, before converting each record into the range between its minimum and maximum value, all the data series representing that specific variable, must be recalculated in order to bring all of them into the same scale, otherwise the combining of data series, each measured indifferent ways and scales, is meaningless. In general, bringing all the different numerical vectors into the same scale is possible by recalculating all of them based on the same reference point. Selected reference point should be reasonable and reliable. When utilizing a method based on Fuzzy Set Theory (such as Soft Regression), then defining all the numerical vectors in terms of membership in the same fuzzy set is an additional (and very effective) way to address the scale problem, and allow application of RRA. The normalization process based on the Fuzzy Set Theory is presented below:

**Normalizing procedure and applying RRA:**

SR is a modeling tool based on Fuzzy Logic and Fuzzy Set Theory. We start the data preparation process by defining a fuzzy set for a given category (for example, High-Income economies, profitable companies, winning sports clubs, etc.). We consider such sets as being fuzzy sets, because it is a group of specific data points, where the boundary of the set is unknown. The Fuzzy Set Theory divides the data domain into three parts: (1) data elements that definitely and fully belong to the set, (2) Data elements that partially (to some degree) belong to the set, and (3) data elements that definitely do **not** belong to the set. The definite members of the fuzzy set will be assigned value of 1, those who definitely do not belong to the fuzzy set will be assigned the value of 0, and partial members of the fuzzy set will be assigned values between 0 and 1, proportionally. Based on these definitions, we proceed to normalize data as follows:

We normalize data by introducing the heuristically determined maximum and minimum thresholds. Data normalizing requires projection of the values from every numerical vector into equivalent normalized numerical vector having values between zero and one, based on predefined function which is expected logically to reflect common sense in projecting such values, while maintaining the integrity of the data. For example, if we define a fuzzy set “High Income Economies”, we include the most successfully performing economies in the set. The normalizing process is expected to determine which countries are definitely members of this fuzzy set (and are assigned value of 1), which countries belong to the fuzzy set only to some degree (values above 0 and below 1) and countries that are definitely not members of this fuzzy set (assigned value of 0).

The first step in the normalizing process is to define as the value in a selected vector of the dependent variable such that all elements equal to or greater than are definitely members of the fuzzy set and thus are assigned the value of one. Accordingly, the equivalent elements in all other vectors are necessarily also members of that same fuzzy set.

The next step is to identify records that are definitely not members of the fuzzy set. We define as the value of the same selected vector of the dependent variable, such that all elements equal to or smaller than are not considered members of the fuzzy set and are assigned the value of zero. Similarly, to the explanation above, the equivalent elements in all other vectors are also not members of that fuzzy set.

We emphasize again: and must be determined based on logic and common sense for each domain (for every variable), so as not to distort the data.

For all other elements (between and) we project all the other vector elements into the interval [0,1] proportionally. Thus and are Maximum and Minimum thresholds. As stated above, the same group must be consistent for all other vectors in the model: both dependent and explanatory.

Note: in the cases of several numerical vectors which essentially represent the same variable, data normalizing procedure explained above brings all these vectors into the same scale, thus helping to express all of them in terms of undistorted intervals (ranges) of values.

In mathematical form, the function used for normalization is:

Let’s assume that we have numerical vectors, each consisting of elements. We use these numerical vectors to construct a matrix: where is a number of rows and is a number of columns. We normalize all the numerical vectors by applying relevant membership function, such that the resulting elements of the numerical vectors will consist of values [0,1], which represent degree of membership in the same fuzzy set, i.e., a fuzzy matrix of is a matrix:

(1)

where for all and is a membership function for all .

and

(2)

where is a matrix of original raw data (before normalization), and are the Minimum and Maximum thresholds as explained above.

Another important issue to consider when constructing intervals is the potential presence of outliers and their implications. The outliers that are expected to appear in various data series can substantially widen the intervals to a degree that is detrimental for successful modeling. The cut-off points applied in membership functions by their nature tend to alleviate, at least to some extent, the problem of outliers. In other words, when different measurements are full members of the fuzzy set, they are all assigned the value of 1, no matter how much their original values differ. The same holds for measurements that are definitely not members of the fuzzy set – all of them are assigned the value of 0, no matter how much their original values differ.

Once all the values of the matrix are converted into the grades of membership, then we can sort values in each row from the smallest to the largest since now they are all members of the same fuzzy set. This way, for every row (for every record), we construct intervals consisting of grades of membership.

Note: Following this stage, the new matrix loses its original structure by its initial vectors. Now we have a matrix, such that in each row, the first element on the left side is the minimum value for that row, the next one is the second smallest value and so on until we reach the last value on the right side, which is the maximum for that row.

We utilize the Range Reduction Algorithm (RRA), which is explained in detail in [12] and [8]. RRA is applied to reduce the range of intervals by deleting outliers. RRA also identifies cases where interval reduction is not working, and the length of the interval is such, as to seriously question the reliability of the data in that record. In such cases the data for that specific record are deleted.

**Soft Regression**

**Basic Terms**

**Similarity**: Denoted and ranges between 0 and 1.

In the Soft Regression method, we utilize the measure of similarity which indicates the degree to which explanatory variable () behaves in a similar pattern, whether direct or inverse, in comparison to dependent variable (). Therefore, the measure of similarity is an equivalent to the statistical measures of significance (t-tests or sig.). Significant relation is found with similarity levels of. However, in addition to fully significant relation, there is an option of partial significance, so that as is approaching closer to 0.7, it is closer to insignificance (Yosef et.al, 2021). When the similarity measure is below 0.7, the explanatory variable is insignificant. The gradual transition from being fully significant to being fully insignificant provides additional stability to the modeling process while utilizing SR.

**Combined Similarity** **of all explanatory variables to the dependent variable**:

Denoted and ranges between 0 and 1. Once similarity measures are computed for all the explanatory variables (), the next step is to calculate collective contribution of all the explanatory variables combined in explaining the behavior of dependent variable (). This measure is denoted . It reflects, to what degree all the explanatory variables combined, explain the behavior of the dependent variable, which is equivalent to adjusted, used in the conventional regression methods. One important difference between the two measurement methods is that by using we allow for overlap of explanatory variables in their relations with the dependent variable (which is of course more reasonable and more in line with the “real world” behavior), and therefore explanatory variables are not required to be independent of each other.

**Relative Importance of explanatory variables**: Denoted RELIMP

The way to compute relative importance of the explanatory variables () is to find out how much each of them contributes to the . To compute Adjusted RELIMP we divide the RELIMP of each explanatory variable by . For models characterized by high value of , both RELIMP and the Adjusted RELIMP generate very similar results. However, when the value of is low, Adjusted RELIMP is preferable, as its value is more reasonable for variables, which are close to being insignificant.

Relative importance of a given explanatory variable (in contrast to traditional regression methods) is not affected by correlation with other explanatory variables and is determined solely by the contribution of a given explanatory variable to explaining the behavior of the dependent variable. In models characterized by a substantial correlation among at least some explanatory variables, SR is a more reliable tool to compute RELIMP in comparison to MVR [7], [13].

As was described in the section “Data Preparation”, when using data expressed as intervals of values, it is necessary to run soft regression four times for every year (Max values for all variables, Min values for all variables, Max for dependent variables vs. Min values of explanatory variables, and Min for dependent variable vs. Max values of explanatory variables). The four regression runs generate four results, which again appear as a range between the lowest result and the highest results. Hence, the value of a potential is expressed as an interval.

**Data and Research methodology:**

The data utilized in this research were downloaded mostly from the World Bank database. Some of the data series appear more than once because each time such data were downloaded, the values were different for the same year. There are following reasons for the difference in values:

1. The base years for measurements in constant US dollars were different.
2. Changes of definitions for measuring any given data series took place several times. The timing of such changes has been unpredictable, and when new definition was applied, all the data for previous periods were deleted from the database, thus causing loss of information.
3. Since not all countries responded immediately to new definitions, for some countries no new data appeared, while old data were deleted, which means that in different downloads, the set of countries is not the same.

It should be kept in mind, that Soft Regression is a soft computing tool that is designed in the first place to handle imprecise (in terms of definition and measurement) data, and therefore is appropriate tool for utilization of different data series that supposedly measure the same thing. Utilizing as many data series (representing the same factor) as possible increases the amount of countries analyzed and increases confidence in model’s conclusions.

Table 1 describes the variables used in this study and the number of estimators used to estimate the range of each one of the three variables. In Appendix A, a complete description of every estimator is given.

Table 1 Description of variables and composite of its estimators

|  |  |  |
| --- | --- | --- |
| Variables | Description | Source |
| GDP | For 2014 there are 10 estimators  For 2007 there are 16 estimators  For 2000 there are 20 estimators | World Bank  BarroLeeDataset |
| Secondary Education | For 2014 there are 3 estimators  For 2007 there are 3 estimators  For 2000 there are 4 estimators | World Bank  BarroLeeDataset |
| Tertiary Education | For 2014 there are 3 estimators  For 2007 there are 3 estimators  For 2000 there are 4 estimators | World Bank  BarroLeeDataset |

One of the common methods to show relationship of explanatory variables to a dependent variable is Multi Variable Regression (MVR). As we see below, this method could not be used here due to the existence of high correlation among the two explanatory variables, secondary and tertiary education. Hence, to answer the research questions in this study, the fuzzy logic-based soft regression (SR) is being used to show the relationship between the secondary and tertiary education and the Gross Domestic Product (GDP). The SR methodology implemented in this paper is similar to the methodology described in chapter 9 in (Cohen 2023). Cohen implemented the SR methodology to show the relationship between the investment of a country in Artificial Intelligence (AI) and its powers such as its military, education, resources and others.

Fuzzy logic-based soft regression is a modeling tool based on soft computing concepts. The important features of the preferred SR compared to the traditional multivariate regression (MVR) when building a model characterized by interrelated variables are:

1. Soft regression does not require precise model specification for reliable results.

The interrelation of the variables and their relative importance among themselves are not affected by adding or removing additional variables to/from the model.

Variables are not required to be independent of each other.

There are no technical problems that could cause distortions in the model. If logical integrity is maintained during the construction of the model - the model will be reliable.

Based on the Fuzzy methodology, all variables are normalized and outliers are removed (Schneider, M. 1987). In the first normalization stage, values equal to or greater than the max cut were converted to 1, values equal to or lower than low cut were converted to 0 and values between the min and max cuts were converted to numbers between 0 to one. This normalization stage removes outliers; this normalization process is formally given in (Cohen 2023) section 9, Equation 1. This process of normalization makes all the vectors in a group of estimators of a variable to be comparable and it removes outliers in an estimator. To utilize equation 1, I used the average of Low-Income Countries for the Min Cut and the average for High-Income Countries for the Max Cut.

After preparing the variables, a range reduction process was used to moderate to a large extent the measurement of each of the three variables for a specific country. First, for each country estimators that are too close are compared and one of them is removed using the process described in (Cohen, 2023) for equation 3. Second, if there are more than 4 estimators for a country additional reduction is done using equation 4 and 5 in (Cohen, 2023), These two processes ensure that there will not be close estimators for a specific country. Finally, countries which still have a large range of estimating a variable were removed to avoid measurement error.

As the last stage in data preparation to estimate a range for each of my variable, I take the minimum value and the maximum value for every country for every variable. Putting these in one table of six columns (vectors) presented in Appendix A.

The next stage is to find the similarity or closeness of every education type (secondary and tertiary) to the GDP is calculated using (Cohen 2023) equation 13. I estimated four different possibilities; using the minimum estimation of GDP with the minimum and maximum estimation of secondary and tertiary education and using the maximum estimation of GDP with the minimum and maximum estimation of secondary and tertiary education. Then, the collective contribution of the two explanatory variables in combination with the explanation of the behavior of the dependent variable (GDP) is calculated using (Cohen 2023) equation 15. Finally, to answer the research question, the adjusted contribution is calculated, (Cohen 2023) equation 17 (multiplied by the SComb estimation), and the Relative Importance (RI) of every education type, (Cohen 2023) equation 16, in explaining the GDP are calculated.

To confirm that a traditional MVR will fall to estimate the importance of the various variables, I computed the correlation matrix of the two explanatory variables for the three periods. All the correlations are very high, higher than 0.8, and the results are presented in table 2. The high correlation of secondary and tertiary education in all three periods indicate the existent of multi-co-linearity problem and will cause that the coefficient estimation in a MVR to be non-significant.

Table 2. Correlation between the secondary education and tertiary education variables in three periods.

|  |  |  |  |
| --- | --- | --- | --- |
|  | 2014 | 2007 | 2000 |
| Correlation | 0.815 | 0.825 | 0.858 |

**Results and Discussion:**

After the preprocessing stage, I calculated the similarity of the two education variables and the net GDP variable using equation 13 in (Cohen 2023) section 9. These calculations are presented in table 3. In addition, I calculated the combined similarity (SComb) index, using equations 14 and 15 in (Cohen 2023) section 9 which is presented in the last row for every period of table 3.

Several important findings presented in the similarity table. First, the secondary education is barely significant (around 0.7) in 2000 but not significant for the years 2007 and 2014. On the other hand, tertiary education is always strongly significant (around 0.8 or above) for all the periods.

Table 3. Similarity and combined similarity.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | **mm** | **mx** | **xm** | **xx** |
| 2014 | **Tertiary** | 0.78 | 0.77 | 0.84 | 0.83 |
| **Secondary** | 0.62 | 0.60 | 0.71 | 0.69 |
| **SComb** | 0.79 | 0.77 | 0.85 | 0.84 |
| 2007 | **Tertiary** | 0.78 | 0.78 | 0.83 | 0.82 |
| **Secondary** | 0.67 | 0.64 | 0.73 | 0.70 |
| **SComb** | 0.81 | 0.79 | 0.85 | 0.84 |
| 2000 | **Tertiary** | 0.81 | 0.79 | 0.84 | 0.82 |
| **Secondary** | 0.74 | 0.66 | 0.79 | 0.72 |
| **SComb** | 0.84 | 0.81 | 0.88 | 0.84 |

The same conclusion could be seen in calculating relative importance of the two education variables which are presented in Table 4. The combined similarity (SComb) index was utilized to measure the relative importance of every education type relative to the other. This index is a combination of the two educations. It was constructed as follows: for every country, the value of the education type which is the closest to the GDP variable was used. This construction of an index ensures that it will be closer to the GDP variable than any of the education variables. The "Similarity Combo" is composed of most or might be all both variables. By finding the contribution of each education variable to this combined similarity index, the importance of each education variable relative to the other in explaining the GDP variable was found.

The findings in table 4 are straight forward. The relative importance of tertiary education is substantially higher than the contribution of secondary education in all the periods. Moreover, this significant relative importance is increasing from 2000 to 2014.

The results of this section are unambiguous and reject the hypothesis I stated in the introduction: “Secondary education is more important than tertiary education to stimulate the economy.” In fact, it is safe to say that tertiary education exclusively determines economic status of a country.

Table 4. Relative Importance.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | **mm** | **mx** | **xm** | **xx** |
| 2014 | **Tertiary** | 1 | 1 | 0.800273 | 0.899869 |
| **Secondary** | 0 | 0 | 0.199727 | 0.100131 |
| 2007 | **Tertiary** | 0.956776 | 1 | 0.702461 | 0.81483 |
| **Secondary** | 0.043224 | 0 | 0.297539 | 0.18517 |
| 2000 | **Tertiary** | 0.680599 | 1 | 0.592354 | 0.764373 |
| **Secondary** | 0.319401 | 0 | 0.407646 | 0.235627 |

**Conclusions**:

It is commonly accepted in the academic community that human capital is an essential resource to stimulate economic growth and some argue that it is even more important than physical capital. While some previous research raised the question of the importance of secondary education relative to tertiary education there was not a conclusive answer and some policy makers have advocated to increase primary and secondary education in Africa with the belief that they will increase economic growth.

This study contributes to the topic of human capital and economic growth by introducing a well-established methodology fuzzy logic-based soft regression to rank the importance of education levels in which countries should invest to ensure economic prosperity and poverty reduction. This robust methodology provides unambiguous results which opens the door for many other future research studies.

The results of this study are clear-cut that tertiary education is the engine for economic growth. The results are strongly significant showing the importance of tertiary education relative to secondary in increasing economic growth for all the periods of the study 2000, 2007 and 2014. Furthermore, its relative importance is increasing over time. This can be explained by the fact that primary and secondary education become necessary education levels in modern society. Yet, it is not enough to create competitive advantage and develop innovative skills.

Inspired by this finding, I recommend future research focusing on matching specific higher education fields that a country should promote to achieve economic competitive advantage based on its resources and geographic location.

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**Appendix**:

**A**. Range estimation for the three periods: 200, 2007, 2014

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 2000 | | | | | | 2007 | | | | | | | 2014 | | | | | |
|  | Seco. |  | Ter. |  | GDP |  | Seco. |  | Ter. |  | GDP |  | Seco. | |  | Ter. |  | GDP |  |
| Country | Min | Mx | Min | Mx | Min | Mx | Min | Mx | Tertiary | Mx | Min | Mx | Min | | Mx | Min | Mx | Min | Mx |
| Afghanistan | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | Tertiary | 0.00 | 0.00 | 0.00 | 0.22 | | 0.24 | 0.00 | 0.01 | 0.00 | 0.00 |
| Albania | 0.54 | 0.61 | 0.17 | 0.20 | 0.04 | 0.11 | 0.73 | 0.75 | Tertiary | 0.42 | 0.10 | 0.16 | 0.94 | | 0.96 | 0.87 | 0.94 | 0.09 | 0.23 |
| Algeria | 0.28 | 0.63 | 0.17 | 0.22 | 0.07 | 0.17 | 0.53 | 0.55 | Tertiary | 0.28 | 0.10 | 0.20 |  | |  |  |  |  |  |
| Angola | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.00 | 0.00 | Tertiary | 0.00 | 0.07 | 0.11 | 0.16 | | 0.19 | 0.00 | 0.01 | 0.07 | 0.13 |
| Argentina | 0.80 | 0.94 | 0.89 | 0.94 | 0.29 | 0.40 | 0.79 | 0.91 | Tertiary | 0.98 |  |  | 1.00 | | 1.00 | 1.00 | 1.00 | 0.24 | 0.48 |
| Armenia | 0.75 | 0.90 | 0.35 | 0.59 | 0.02 | 0.04 | 0.95 | 0.96 | Tertiary | 0.64 | 0.07 | 0.16 | 0.76 | | 0.77 | 0.57 | 0.59 | 0.07 | 0.16 |
| Australia | 1.00 | 1.00 | 1.00 | 1.00 | 0.95 | 1.00 | 1.00 | 1.00 | Tertiary | 1.00 | 1.00 | 1.00 | 1.00 | | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Austria | 0.98 | 1.00 | 0.98 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | Tertiary | 0.92 | 1.00 | 1.00 | 0.99 | | 0.99 | 1.00 | 1.00 | 1.00 | 1.00 |
| Azerbaijan | 0.63 | 0.64 | 0.32 | 0.32 | 0.00 | 0.05 | 0.99 | 0.99 | Tertiary | 0.21 | 0.10 | 0.23 | 0.84 | | 0.84 | 0.21 | 0.23 | 0.12 | 0.38 |
| Bahrain |  |  |  |  |  |  | 0.91 | 0.91 | Tertiary | 0.27 | 1.00 | 1.00 |  | |  |  |  |  |  |
| Bangladesh | 0.04 | 0.28 | 0.01 | 0.02 | 0.00 | 0.01 | 0.15 | 0.21 | Tertiary | 0.02 | 0.01 | 0.01 | 0.38 | | 0.39 | 0.07 | 0.09 | 0.01 | 0.03 |
| Belarus | 0.73 | 0.81 | 0.94 | 1.00 | 0.03 | 0.16 | 1.00 | 1.00 | Tertiary | 1.00 | 0.12 | 0.29 | 1.00 | | 1.00 | 1.00 | 1.00 | 0.15 | 0.41 |
| Belgium | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | Tertiary | 0.90 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.96 | 0.98 | 0.98 | 1.00 |
| Benin | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | Tertiary | 0.03 | 0.01 | 0.01 | 0.26 | | 0.28 | 0.10 | 0.13 | 0.00 | 0.00 |
| Bhutan | 0.00 | 0.13 | 0.00 | 0.00 | 0.02 | 0.06 | 0.25 | 0.26 | Tertiary | 0.00 | 0.04 | 0.10 | 0.69 | | 0.72 | 0.02 | 0.05 | 0.04 | 0.14 |
| Bolivia | 0.64 | 0.71 | 0.59 | 0.60 | 0.02 | 0.08 | 0.70 | 0.79 | Tertiary | 0.51 | 0.03 | 0.08 |  | |  |  |  |  |  |
| Botswana | 0.52 | 0.66 | 0.00 | 0.03 | 0.16 | 0.31 | 0.71 | 0.77 | Tertiary | 0.13 | 0.18 | 0.28 |  | |  |  |  |  |  |
| Brazil | 0.86 | 1.00 | 0.19 | 0.23 | 0.15 | 0.25 | 0.93 | 0.93 | Tertiary | 0.40 | 0.24 | 0.29 | 1.00 | | 1.00 | 0.62 | 0.63 | 0.25 | 0.34 |
| Bulgaria | 0.87 | 0.94 | 0.65 | 0.78 | 0.04 | 0.20 | 0.85 | 0.91 | Tertiary | 0.72 | 0.15 | 0.31 | 1.00 | | 1.00 | 0.88 | 0.90 | 0.16 | 0.38 |
| Burkina Faso | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | Tertiary | 0.00 | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Burundi | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | Tertiary | 0.00 | 0.00 | 0.00 | 0.00 | | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cabo Verde |  |  |  |  |  |  | 0.72 | 0.78 | Tertiary | 0.06 | 0.07 | 0.10 | 0.77 | | 0.92 | 0.22 | 0.24 | 0.06 | 0.11 |
| Cambodia | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.08 | 0.13 | Tertiary | 0.02 | 0.01 | 0.01 |  | |  |  |  |  |  |
| Cameroon | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 | 0.02 | 0.00 | 0.00 | Tertiary | 0.02 | 0.02 | 0.02 | 0.30 | | 0.32 | 0.11 | 0.14 | 0.01 | 0.03 |
| Canada | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | Tertiary | 0.93 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.86 | 0.86 | 1.00 | 1.00 |
| Central African Republic | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | Tertiary | 0.00 | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Chad | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | Tertiary | 0.00 | 0.00 | 0.01 | 0.00 | | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| Chile | 0.74 | 0.78 | 0.60 | 0.64 | 0.22 | 0.36 | 0.88 | 0.93 | Tertiary | 0.77 | 0.29 | 0.41 | 0.99 | | 1.00 | 1.00 | 1.00 | 0.32 | 0.52 |
| China | 0.41 | 0.47 | 0.05 | 0.13 | 0.03 | 0.08 | 0.57 | 0.65 | Tertiary | 0.23 | 0.05 | 0.11 | 0.92 | | 0.92 | 0.49 | 0.51 | 0.14 | 0.28 |
| Colombia | 0.46 | 0.62 | 0.33 | 0.39 | 0.06 | 0.17 | 0.84 | 0.87 | Tertiary | 0.44 | 0.13 | 0.22 | 0.92 | | 0.98 | 0.65 | 0.68 | 0.16 | 0.28 |
| Comoros | 0.00 | 0.04 | 0.00 | 0.00 | 0.00 | 0.01 |  |  |  |  |  |  | 0.34 | | 0.36 | 0.00 | 0.02 | 0.00 | 0.00 |
| Congo, Dem. Rep. |  |  |  |  |  |  |  |  |  |  |  |  | 0.08 | | 0.11 | 0.00 | 0.00 | 0.00 | 0.00 |
| Congo, Rep. | 0.00 | 0.13 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.19 | | 0.22 | 0.00 | 0.03 | 0.04 | 0.11 |
| Costa Rica | 0.30 | 0.45 | 0.20 | 0.23 | 0.16 | 0.29 |  |  |  |  |  |  | 1.00 | | 1.00 | 0.66 | 0.68 | 0.20 | 0.32 |
| Cote d'Ivoire | 0.00 | 0.00 | 0.01 | 0.06 | 0.01 | 0.02 |  |  |  |  |  |  | 0.00 | | 0.00 | 0.00 | 0.01 | 0.01 | 0.03 |
| Croatia | 0.78 | 0.82 | 0.51 | 0.53 | 0.22 | 0.31 | 0.95 | 0.99 | 0.66 | 0.68 | 0.37 | 0.52 | 0.98 | | 0.98 | 0.88 | 0.90 | 0.29 | 0.48 |
| Cuba | 0.69 | 0.80 | 0.34 | 0.35 | 0.08 | 0.34 |  |  |  |  |  |  | 0.95 | | 0.98 | 0.47 | 0.49 | 0.14 | 0.15 |
| Cyprus | 0.88 | 0.95 | 0.29 | 0.31 | 0.60 | 0.76 | 0.97 | 1.00 | 0.48 | 0.49 | 0.82 | 0.86 | 0.99 | | 0.99 | 0.66 | 0.68 | 0.59 | 0.71 |
| Czech Republic | 0.82 | 0.90 | 0.46 | 0.48 | 0.39 | 0.65 | 0.92 | 0.94 | 0.77 | 0.78 | 0.49 | 0.69 | 1.00 | | 1.00 | 0.85 | 0.87 | 0.43 | 0.73 |
| Denmark | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Djibouti | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.03 |  | |  |  |  |  |  |
| Dominican Republic | 0.28 | 0.45 | 0.48 | 0.48 | 0.11 | 0.17 |  |  |  |  |  |  | 0.63 | | 0.67 | 0.58 | 0.61 | 0.13 | 0.29 |
| Ecuador | 0.24 | 0.44 | 0.46 | 0.46 | 0.05 | 0.15 | 0.48 | 0.50 | 0.52 | 0.53 | 0.09 | 0.18 | 1.00 | | 1.00 | 0.51 | 0.57 | 0.12 | 0.23 |
| Egypt, Arab Rep. | 0.74 | 0.82 | 0.52 | 0.62 | 0.04 | 0.11 | 0.49 | 0.61 | 0.37 | 0.42 | 0.04 | 0.18 | 0.69 | | 0.72 | 0.33 | 0.35 | 0.05 | 0.21 |
| El Salvador | 0.18 | 0.39 | 0.21 | 0.33 | 0.08 | 0.13 | 0.41 | 0.50 | 0.26 | 0.29 | 0.09 | 0.12 | 0.61 | | 0.62 | 0.29 | 0.31 | 0.07 | 0.15 |
| Equatorial Guinea | 0.00 | 0.02 | 0.00 | 0.00 | 0.10 | 0.31 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Eritrea | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.11 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.33 | 0.00 | 0.00 | 0.00 | 0.00 |
| Estonia | 0.88 | 1.00 | 0.99 | 1.00 | 0.18 | 0.36 | 1.00 | 1.00 | 0.99 | 1.00 | 0.43 | 0.58 | 1.00 | | 1.00 | 0.97 | 0.98 | 0.41 | 0.64 |
| Ethiopia | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 |
| Fiji | 0.64 | 0.72 | 0.21 | 0.21 | 0.09 | 0.11 | 0.83 | 0.86 | 0.15 | 0.16 | 0.08 | 0.20 |  | |  |  |  |  |  |
| Finland | 1.00 | 1.00 | 1.00 | 1.00 | 0.93 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | | 1.00 | 1.00 | 1.00 | 0.92 | 1.00 |
| France | 1.00 | 1.00 | 0.91 | 1.00 | 0.96 | 1.00 | 1.00 | 1.00 | 0.75 | 0.76 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.79 | 0.85 | 0.91 | 1.00 |
| Gabon | 0.11 | 0.34 | 0.01 | 0.08 | 0.14 | 0.43 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Gambia, The | 0.00 | 0.10 | 0.00 | 0.00 | 0.00 | 0.01 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Georgia | 0.52 | 0.72 | 0.54 | 0.65 | 0.01 | 0.05 | 0.82 | 1.00 | 0.49 | 0.57 | 0.05 | 0.12 | 0.96 | | 0.98 | 0.48 | 0.51 | 0.08 | 0.17 |
| Germany | 0.97 | 0.98 | 0.77 | 0.86 | 0.96 | 1.00 |  |  |  |  |  |  | 1.00 | | 1.00 | 0.83 | 0.86 | 1.00 | 1.00 |
| Ghana | 0.00 | 0.20 | 0.00 | 0.00 | 0.00 | 0.01 | 0.17 | 0.27 | 0.00 | 0.00 | 0.01 | 0.03 | 0.27 | | 0.41 | 0.09 | 0.13 | 0.01 | 0.05 |
| Greece | 0.84 | 0.92 | 0.90 | 1.00 | 0.59 | 0.77 | 0.93 | 1.00 | 1.00 | 1.00 | 0.78 | 0.81 | 0.99 | | 1.00 | 1.00 | 1.00 | 0.48 | 0.60 |
| Guatemala | 0.00 | 0.16 | 0.09 | 0.10 | 0.04 | 0.10 | 0.16 | 0.30 | 0.17 | 0.19 | 0.06 | 0.12 | 0.22 | | 0.38 | 0.13 | 0.15 | 0.06 | 0.13 |
| Guinea | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.03 | 0.00 | 0.00 | 0.00 | | 0.01 | 0.03 | 0.05 | 0.00 | 0.00 |
| Guinea-Bissau | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |  | |  |  |  |  |  |
| Guyana | 0.71 | 0.99 | 0.13 | 0.13 | 0.03 | 0.08 | 0.72 | 0.92 | 0.08 | 0.09 | 0.02 | 0.18 | 0.96 | | 0.98 | 0.04 | 0.06 | 0.07 | 0.13 |
| Haiti | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.01 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Honduras | 0.28 | 0.28 | 0.17 | 0.21 | 0.02 | 0.06 | 0.39 | 0.44 | 0.18 | 0.20 | 0.04 | 0.06 | 0.19 | | 0.41 | 0.16 | 0.18 | 0.03 | 0.07 |
| Hong Kong, China | 0.67 | 0.72 | 0.44 | 0.44 | 0.98 | 1.00 | 0.75 | 0.77 | 0.57 | 0.58 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.90 | 0.92 | 0.90 | 1.00 |
| Hungary | 0.95 | 0.99 | 0.61 | 0.65 | 0.31 | 0.54 | 0.94 | 0.98 | 0.99 | 1.00 | 0.37 | 0.50 | 1.00 | | 1.00 | 0.65 | 0.66 | 0.30 | 0.57 |
| India | 0.08 | 0.26 | 0.09 | 0.12 | 0.01 | 0.03 | 0.35 | 0.36 | 0.10 | 0.12 | 0.01 | 0.04 | 0.56 | | 0.58 | 0.25 | 0.27 | 0.02 | 0.09 |
| Indonesia | 0.23 | 0.44 | 0.16 | 0.21 | 0.01 | 0.05 | 0.54 | 0.58 | 0.18 | 0.20 | 0.03 | 0.15 | 0.72 | | 0.73 | 0.31 | 0.33 | 0.06 | 0.21 |
| Iran, Islamic Rep. | 0.64 | 0.72 | 0.27 | 0.29 | 0.06 | 0.22 | 0.65 | 0.68 | 0.38 | 0.40 | 0.14 | 0.26 | 0.76 | | 0.80 | 0.85 | 0.89 | 0.10 | 0.38 |
| Iraq |  |  |  |  |  |  | 0.26 | 0.30 | 0.15 | 0.16 | 0.08 | 0.13 |  | |  |  |  |  |  |
| Ireland | 1.00 | 1.00 | 0.79 | 0.88 | 1.00 | 1.00 | 1.00 | 1.00 | 0.84 | 0.88 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.98 | 0.88 | 0.99 | 1.00 |
| Israel | 0.88 | 1.00 | 0.87 | 0.90 | 0.69 | 0.80 | 1.00 | 1.00 | 0.88 | 0.89 | 0.72 | 0.73 | 1.00 | | 1.00 | 0.86 | 0.84 | 0.74 | 0.90 |
| Italy | 0.89 | 0.93 | 0.84 | 0.86 | 0.92 | 1.00 | 0.99 | 1.00 | 0.97 | 0.98 | 0.98 | 1.00 | 1.00 | | 1.00 | 0.80 | 0.29 | 0.79 | 0.85 |
| Jamaica | 0.70 | 0.87 | 0.19 | 0.22 | 0.10 | 0.16 | 0.88 | 0.96 | 0.23 | 0.31 | 0.13 | 0.18 | 0.69 | | 0.70 | 0.27 | 0.83 | 0.09 | 0.16 |
| Japan | 1.00 | 1.00 | 0.80 | 0.86 | 1.00 | 1.00 | 0.98 | 1.00 | 0.82 | 0.84 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.81 | 0.45 | 0.82 | 1.00 |
| Jordan | 0.76 | 0.86 | 0.46 | 0.48 | 0.04 | 0.09 | 0.78 | 0.93 | 0.51 | 0.57 | 0.08 | 0.22 | 0.49 | | 0.50 | 0.42 | 0.61 | 0.07 | 0.24 |
| Kazakhstan | 0.80 | 0.97 | 0.45 | 0.55 | 0.03 | 0.15 | 0.98 | 1.00 | 0.83 | 0.87 | 0.19 | 0.40 |  | |  |  |  |  |  |
| Kenya | 0.00 | 0.13 | 0.00 | 0.00 | 0.00 | 0.01 | 0.25 | 0.26 | 0.00 | 0.00 | 0.01 | 0.02 |  | |  |  |  |  |  |
| Korea, Rep. |  |  |  |  |  |  | 0.93 | 0.98 | 1.00 | 1.00 | 0.68 | 0.74 | 1.00 | | 1.00 | 1.00 | 0.58 | 0.60 | 0.80 |
| Kyrgyz Republic | 0.74 | 0.80 | 0.58 | 0.67 | 0.00 | 0.01 | 0.79 | 0.83 | 0.59 | 0.59 | 0.01 | 0.03 | 0.85 | | 0.87 | 0.56 | 0.16 | 0.01 | 0.03 |
| Lao PDR | 0.00 | 0.06 | 0.00 | 0.00 | 0.00 | 0.01 | 0.08 | 0.14 | 0.07 | 0.09 | 0.01 | 0.04 | 0.31 | | 0.33 | 0.14 | 0.94 | 0.02 | 0.09 |
| Latvia | 0.85 | 0.90 | 1.00 | 1.00 | 0.16 | 0.31 | 1.00 | 1.00 | 1.00 | 1.00 | 0.41 | 0.56 | 1.00 | | 1.00 | 0.88 | 0.53 | 0.33 | 0.52 |
| Lebanon | 0.56 | 0.93 | 0.56 | 0.70 | 0.13 | 0.25 | 0.64 | 0.65 | 0.66 | 0.66 | 0.18 | 0.31 | 0.35 | | 0.37 | 0.51 | 0.04 | 0.17 | 0.38 |
| Lesotho | 0.00 | 0.05 | 0.00 | 0.00 | 0.01 | 0.02 | 0.08 | 0.13 | 0.00 | 0.00 | 0.02 | 0.02 | 0.19 | | 0.35 | 0.02 | 0.06 | 0.01 | 0.03 |
| Liberia | 0.00 | 0.13 | 0.04 | 0.29 | 0.00 | 0.00 |  |  |  |  |  |  | 0.00 | | 0.00 | 0.04 | 0.94 | 0.00 | 0.00 |
| Libya | 0.87 | 1.00 | 0.80 | 0.89 | 0.08 | 0.37 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Lithuania | 0.97 | 1.00 | 0.88 | 1.00 | 0.27 | 0.28 | 1.00 | 1.00 | 1.00 | 1.00 | 0.31 | 0.51 | 1.00 | | 1.00 | 0.91 | 0.18 | 0.36 | 0.63 |
| Luxembourg |  |  |  |  |  |  | 0.95 | 0.99 | 0.06 | 0.07 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.16 | 0.46 | 1.00 | 1.00 |
| Macedonia, FYR | 0.72 | 0.78 | 0.34 | 0.36 | 0.07 | 0.20 | 0.71 | 0.72 | 0.45 | 0.46 | 0.08 | 0.21 | 0.67 | | 0.68 | 0.44 | 0.00 | 0.11 | 0.27 |
| Madagascar | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Malawi | 0.00 | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.02 | 0.00 | 0.46 | 0.00 | 0.00 |
| Malaysia | 0.45 | 0.58 | 0.39 | 0.42 | 0.11 | 0.32 | 0.48 | 0.66 | 0.38 | 0.39 | 0.16 | 0.40 |  | |  |  |  |  |  |
| Mali | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.05 | | 0.08 | 0.00 | 0.00 | 0.00 | 0.00 |
| Mauritania | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.06 | 0.00 | | 0.00 | 0.00 | 0.47 | 0.01 | 0.06 |
| Mauritius | 0.58 | 0.69 | 0.05 | 0.14 | 0.16 | 0.31 | 0.82 | 0.90 | 0.29 | 0.30 | 0.18 | 0.31 | 1.00 | | 1.00 | 0.45 | 0.34 | 0.21 | 0.42 |
| Mexico | 0.53 | 0.62 | 0.28 | 0.29 | 0.25 | 0.34 | 0.74 | 0.77 | 0.29 | 0.30 | 0.26 | 0.37 | 0.86 | | 0.96 | 0.32 | 0.66 | 0.22 | 0.38 |
| Moldova | 0.49 | 0.76 | 0.42 | 0.55 | 0.00 | 0.01 | 0.83 | 0.85 | 0.56 | 0.57 | 0.04 | 0.07 | 0.79 | | 1.00 | 0.49 | 0.85 | 0.03 | 0.09 |
| Mongolia | 0.44 | 0.52 | 0.47 | 0.52 | 0.00 | 0.03 | 0.85 | 0.88 | 0.66 | 0.66 | 0.02 | 0.14 | 0.86 | | 0.86 | 0.80 | 0.76 | 0.07 | 0.24 |
| Montenegro |  |  |  |  |  |  | 0.94 | 0.96 | 0.43 | 0.46 | 0.17 | 0.34 | 0.88 | | 0.88 | 0.72 | 0.26 | 0.15 | 0.33 |
| Morocco | 0.00 | 0.12 | 0.08 | 0.10 | 0.03 | 0.06 | 0.30 | 0.33 | 0.08 | 0.09 | 0.05 | 0.08 | 0.49 | | 0.50 | 0.24 | 0.00 | 0.05 | 0.14 |
| Mozambique | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.09 | 0.00 | 0.00 |
| Namibia | 0.30 | 0.44 | 0.02 | 0.06 | 0.09 | 0.17 | 0.46 | 0.48 | 0.01 | 0.05 | 0.12 | 0.17 |  | |  |  |  |  |  |
| Myanmar |  |  |  |  |  |  | 0.15 | 0.20 | 0.06 | 0.07 | 0.00 | 0.02 | 0.20 | | 0.21 | 0.07 | 0.16 | 0.01 | 0.07 |
| Nepal | 0.00 | 0.11 | 0.00 | 0.00 | 0.00 | 0.00 | 0.16 | 0.17 | 0.05 | 0.07 | 0.00 | 0.00 | 0.44 | | 0.46 | 0.10 | 1.00 | 0.00 | 0.01 |
| Netherlands | 1.00 | 1.00 | 0.92 | 0.94 | 1.00 | 1.00 | 1.00 | 1.00 | 0.87 | 0.88 | 1.00 | 1.00 | 1.00 | | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| New Zealand | 0.96 | 1.00 | 1.00 | 1.00 | 0.62 | 0.83 | 1.00 | 1.00 | 1.00 | 1.00 | 0.83 | 0.85 | 1.00 | | 1.00 | 1.00 | 0.15 | 0.79 | 1.00 |
| Nicaragua | 0.18 | 0.35 | 0.24 | 0.27 | 0.02 | 0.04 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Niger | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 |
| Nigeria | 0.00 | 0.00 | 0.03 | 0.04 | 0.00 | 0.01 | 0.00 | 0.00 | 0.06 | 0.07 | 0.03 | 0.06 |  | |  |  |  |  |  |
| Norway | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | | 1.00 | 1.00 | 0.42 | 1.00 | 1.00 |
| Oman | 0.58 | 0.73 | 0.03 | 0.18 | 0.33 | 0.54 | 0.82 | 0.86 | 0.22 | 0.24 | 0.45 | 0.72 |  | |  |  |  |  |  |
| Pakistan | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 0.01 | 0.00 | 0.00 | 0.01 | 0.04 | 0.00 | | 0.03 | 0.01 | 0.55 | 0.01 | 0.08 |
| Panama | 0.41 | 0.52 | 0.53 | 0.76 | 0.14 | 0.25 | 0.50 | 0.51 | 0.59 | 0.60 | 0.18 | 0.33 | 0.58 | | 0.59 | 0.53 | 0.00 | 0.23 | 0.46 |
| Papua New Guinea | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.03 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Paraguay | 0.29 | 0.50 | 0.19 | 0.23 | 0.05 | 0.11 | 0.47 | 0.49 | 0.36 | 0.37 | 0.07 | 0.14 | 0.60 | | 0.61 | 0.00 | 0.91 | 0.07 | 0.17 |
| Peru | 0.67 | 0.81 | 0.52 | 0.58 | 0.08 | 0.16 | 0.81 | 0.87 | 0.45 | 0.46 | 0.09 | 0.16 | 0.93 | | 0.95 | 0.67 | 0.42 | 0.12 | 0.25 |
| Philippines | 0.59 | 0.68 | 0.47 | 0.51 | 0.02 | 0.08 | 0.71 | 0.74 | 0.35 | 0.36 | 0.04 | 0.09 | 0.79 | | 0.81 | 0.40 | 0.91 | 0.05 | 0.16 |
| Poland | 1.00 | 1.00 | 0.87 | 0.95 | 0.21 | 0.37 | 0.97 | 1.00 | 0.98 | 0.99 | 0.30 | 0.41 | 1.00 | | 1.00 | 0.89 | 0.86 | 0.31 | 0.57 |
| Portugal | 1.00 | 1.00 | 0.84 | 0.85 | 0.55 | 0.70 | 1.00 | 1.00 | 0.83 | 0.83 | 0.64 | 0.68 | 1.00 | | 1.00 | 0.84 | 0.60 | 0.49 | 0.64 |
| Romania | 0.68 | 0.77 | 0.37 | 0.41 | 0.07 | 0.20 | 0.80 | 0.82 | 0.78 | 0.84 | 0.21 | 0.35 | 0.88 | | 0.91 | 0.58 | 1.00 | 0.21 | 0.45 |
| Russian Federation | 0.70 | 0.95 | 0.98 | 1.00 | 0.09 | 0.26 | 0.74 | 0.76 | 1.00 | 1.00 | 0.25 | 0.45 |  | |  |  |  |  |  |
| Rwanda | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.02 | 0.00 | 0.75 | 0.00 | 0.00 |
| Saudi Arabia | 0.44 | 0.44 | 0.31 | 0.36 | 0.37 | 0.64 |  |  |  |  | 0.01 | 0.03 |  | |  |  |  |  |  |
| Senegal | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.02 | 0.15 | | 0.18 | 0.02 | 0.76 | 0.01 | 0.01 |
| Serbia | 0.66 | 0.90 | 0.58 | 0.65 | 0.09 | 0.22 | 0.84 | 0.87 | 0.67 | 0.68 | 0.14 | 0.26 | 0.90 | | 0.91 | 0.74 | 1.00 | 0.12 | 0.29 |
| Sierra Leone | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Singapore |  |  |  |  |  |  |  |  |  |  |  |  | 1.00 | | 1.00 | 1.00 | 0.68 | 1.00 | 1.00 |
| Slovak Republic | 0.77 | 0.83 | 0.46 | 0.47 | 0.33 | 0.46 | 0.88 | 0.92 | 0.71 | 0.71 | 0.45 | 0.52 | 0.84 | | 0.85 | 0.66 | 1.00 | 0.41 | 0.65 |
| Slovenia | 1.00 | 1.00 | 0.98 | 1.00 | 0.57 | 0.72 | 0.98 | 1.00 | 1.00 | 1.00 | 0.66 | 0.75 | 1.00 | | 1.00 | 1.00 | 0.18 | 0.54 | 0.69 |
| South Africa | 0.64 | 0.80 | 0.16 | 0.20 | 0.16 | 0.30 |  |  |  |  |  |  | 1.00 | | 1.00 | 0.16 | 0.00 | 0.13 | 0.27 |
| Spain | 0.91 | 1.00 | 0.98 | 1.00 | 0.71 | 0.90 | 1.00 | 1.00 | 1.00 | 1.00 | 0.85 | 0.91 | 1.00 | | 1.00 | 1.00 | 0.17 | 0.68 | 0.76 |
| Sri Lanka | 0.66 | 0.79 | 0.10 | 0.10 | 0.02 | 0.06 |  |  |  |  |  |  | 0.99 | | 0.99 | 0.15 | 0.14 | 0.06 | 0.22 |
| Sudan | 0.00 | 0.05 | 0.01 | 0.05 | 0.00 | 0.01 | 0.00 | 0.03 | 0.11 | 0.12 | 0.01 | 0.02 | 0.07 | | 0.10 | 0.12 | 0.00 | 0.03 | 0.06 |
| South Sudan |  |  |  |  |  |  |  |  |  |  |  |  | 0.00 | | 0.00 | 0.00 | 1.00 | 0.00 | 0.01 |
| Suriname | 0.58 | 0.76 | 0.12 | 0.15 | 0.08 | 0.14 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Swaziland | 0.02 | 0.17 | 0.00 | 0.01 | 0.06 | 0.13 | 0.28 | 0.41 | 0.00 | 0.00 | 0.08 | 0.12 | 0.40 | | 0.57 | 0.00 | 0.82 | 0.06 | 0.18 |
| Sweden | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.80 | 0.74 | 1.00 | 1.00 |
| Switzerland | 0.91 | 0.99 | 0.62 | 0.69 | 1.00 | 1.00 | 0.93 | 0.97 | 0.66 | 0.66 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.72 | 0.54 | 1.00 | 1.00 |
| Syrian Arab Republic | 0.00 | 0.20 | 0.00 | 0.16 | 0.01 | 0.06 | 0.57 | 0.58 | 0.25 | 0.27 | 0.04 | 0.05 |  | |  |  |  |  |  |
| Tajikistan | 0.61 | 0.64 | 0.15 | 0.27 | 0.00 | 0.00 | 0.73 | 0.75 | 0.26 | 0.27 | 0.00 | 0.00 | 0.79 | | 0.81 | 0.23 | 0.00 | 0.00 | 0.03 |
| Tanzania | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |  |  |  |  |  |  | 0.00 | | 0.00 | 0.00 | 0.64 | 0.00 | 0.02 |
| Thailand | 0.45 | 0.69 | 0.57 | 0.60 | 0.06 | 0.18 | 0.67 | 0.69 | 0.68 | 0.69 | 0.08 | 0.27 | 1.00 | | 1.00 | 0.62 | 0.04 | 0.12 | 0.33 |
| Timor-Leste |  |  |  |  |  |  | 0.18 | 0.26 | 0.16 | 0.18 | 0.00 | 0.04 |  | |  |  |  |  |  |
| Togo | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.11 | 0.17 | 0.00 | 0.00 | 0.00 | 0.00 | 0.23 | | 0.23 | 0.02 | 0.41 | 0.00 | 0.00 |
| Trinidad and Tobago | 0.62 | 0.68 | 0.00 | 0.04 | 0.23 | 0.39 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Tunisia | 0.50 | 0.66 | 0.27 | 0.29 | 0.09 | 0.17 | 0.86 | 0.88 | 0.42 | 0.43 | 0.10 | 0.17 | 0.79 | | 0.80 | 0.39 | 1.00 | 0.08 | 0.23 |
| Turkey | 0.52 | 0.67 | 0.34 | 0.41 | 0.17 | 0.30 | 0.85 | 0.88 | 0.52 | 0.53 | 0.25 | 0.38 |  | |  |  |  |  |  |
| Turkmenistan |  |  |  |  |  |  |  |  |  |  |  |  | 0.76 | | 0.76 | 0.00 | 0.00 | 0.15 | 0.32 |
| Uganda | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 |
| Ukraine | 0.93 | 1.00 | 0.86 | 0.91 | 0.02 | 0.10 | 0.95 | 0.96 | 1.00 | 1.00 | 0.07 | 0.19 | 0.93 | | 0.95 | 1.00 | 0.74 | 0.05 | 0.16 |
| United Kingdom | 0.99 | 1.00 | 1.00 | 1.00 | 0.94 | 1.00 | 0.96 | 1.00 | 0.84 | 0.85 | 1.00 | 1.00 | 1.00 | | 1.00 | 0.73 | 1.00 | 0.90 | 1.00 |
| United States | 0.89 | 0.92 | 1.00 | 1.00 | 1.00 | 1.00 | 0.93 | 0.96 | 1.00 | 1.00 | 1.00 | 1.00 | 0.93 | | 0.95 | 1.00 | 0.79 | 1.00 | 1.00 |
| Uruguay | 0.86 | 1.00 | 0.58 | 0.62 | 0.18 | 0.31 | 0.88 | 0.91 | 0.72 | 0.93 | 0.23 | 0.33 | 1.00 | | 1.00 | 0.78 | 0.01 | 0.32 | 0.46 |
| Uzbekistan | 0.82 | 0.98 | 0.06 | 0.16 | 0.01 | 0.02 | 0.84 | 1.00 | 0.05 | 0.06 | 0.01 | 0.04 | 0.86 | | 0.87 | 0.00 | 0.34 | 0.03 | 0.10 |
| Venezuela, RB | 0.39 | 0.44 | 0.32 | 0.46 | 0.10 | 0.29 | 0.67 | 0.70 | 1.00 | 1.00 | 0.35 | 0.46 |  | |  |  |  |  |  |
| Vietnam | 0.40 | 0.47 | 0.07 | 0.10 | 0.00 | 0.02 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Yemen, Rep. | 0.04 | 0.23 | 0.09 | 0.14 | 0.00 | 0.03 | 0.10 | 0.13 | 0.06 | 0.07 | 0.01 | 0.09 |  | |  |  |  |  |  |
| Zambia | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |  |  |  |  |  |  |  | |  |  |  |  |  |
| Zimbabwe | 0.00 | 0.20 | 0.00 | 0.00 | 0.01 | 0.03 |  |  |  |  |  |  | 0.10 | | 0.22 | 0.00 | 0.01 | 0.00 | 0.01 |

**B**. Description of Estimators of GDP, Secondary and tertiary education

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Estimators for GDP for the year 2000 |  |  | Estimators for GDP for the year 2014 |
| GDP1 | Per Capita GDP (1990 International Geary-Khamis dollars) |  | GDP1 | GDP per capita (current US$) 2018 file |
| GDP2 | GDP per Capita (current US$) |  | GDP2 | GDP per capita (constant 2010 US$) 2018 file |
| GDP3 | GDP per capita (constant 1995 US$) |  | GDP3 | GDP per capita, PPP (current international $) 2018 file |
| GDP4 | GNI per capita, Atlas method (current US$), 2004 file |  | GDP4 | GDP per capita, PPP (constant 2011 international $) 2018 file |
| GDP5 | GDP per capita, PPP (constant 1995 international $) |  | GDP5 | GNI per capita, Atlas method (current US$) 2018 file |
| GDP6 | GDP per capita, PPP (current international $) 2004 file |  | GDP6 | GNI per capita (constant 2010 US$) 2018 file |
| GDP7 | GNI per capita, PPP (current international $) 2004 file |  | GDP7 | GNI per capita, PPP (current international $) 2018 file |
| GDP8 | GDP per capita (constant 2000 US$) 2009 file |  | GDP8 | GNI per capita, PPP (constant 2011 international $) 2018 file |
| GDP9 | GDP per capita, PPP (current international $) 2009 file |  | GDP9 | [2014 GDP published by IMF in October 2015 IMF-2015](https://en.wikipedia.org/wiki/List_of_IMF_ranked_countries_by_GDP" \l "cite_note-3) |
| GDP10 | GDP per capita, PPP (constant 2005 international $) 2009 file |  | GDP10 | [2014 GDP published by IMF in October 2015](https://en.wikipedia.org/wiki/List_of_IMF_ranked_countries_by_GDP" \l "cite_note-3) |
| GDP11 | GNI per capita, Atlas method (current US$) 2009 file |  |  |  |
| GDP12 | GNI per capita, PPP (current international $) 2009 file |  |  | Estimators for Tertiary Education for the year 2000 |
| GDP13 | GDP per capita (current US$) 2015 file |  | Ter1 | School enrollment, tertiary (% gross) file 2004 |
| GDP14 | GDP per capita (constant 2005 US$) 2015 file |  | Ter2 | School enrollment, tertiary (% gross) file 2009 |
| GDP15 | GDP per capita, PPP (constant 2011 international $) 2015 file |  | Ter3 | School enrollment, tertiary (% gross) file 2015 |
| GDP16 | GDP per capita, PPP (current international $) 2015 file |  | Ter4 | School Enrollment file lee lee |
| GDP17 | GNI per capita, Atlas method (current US$) 2015 file |  |  | Estimators for Tertiary Education for the year 2007 |
| GDP18 | GNI per capita (constant 2005 US$) 2015 file |  | Ter1 | School enrollment, tertiary (% gross) file 2015 |
| GDP19 | GNI per capita, PPP (constant 2011 international $) 2015 file |  | Ter2 | School enrollment, tertiary (% gross) file 2019 |
| GDP20 | GNI per capita, PPP (current international $) 2015 file |  | Ter3 | School enrollment, tertiary (% gross) file 2021 |
|  | Estimators for GDP for the year 2007 |  |  | Estimators for Tertiary Education for the year 2014 |
| GDP1 | GDP per capita (current US$) 2015 file |  | Ter1 | School enrollment, tertiary (% gross) file 2018 |
| GDP2 | GDP per capita (constant 2005 US$) 2015 file |  | Ter2 | School enrollment, tertiary (% gross) file 2019 |
| GDP3 | GDP per capita, PPP (constant 2011 international $) 2015 file |  | Ter3 | School enrollment, tertiary (% gross) file 2023 |
| GDP4 | GDP per capita, PPP (current international $) 2015 file |  |  |  |
| GDP5 | GNI per capita, Atlas method (current US$) 2015 file |  |  | Estimators for Secondary Education for the year 2000 |
| GDP6 | GNI per capita (constant 2005 US$) 2015 file |  | Sec1 | School enrollment, secondary (% gross) file 2004 |
| GDP7 | GNI per capita, PPP (current international $) 2015 file |  | Sec2 | School enrollment, secondary (% gross) file 2009 |
| GDP8 | GNI per capita, PPP (constant 2011 international $) 2015 file |  | Sec3 | School enrollment, secondary (% gross) file 2015 |
| GDP9 | GDP per capita (current US$) 2015 file |  | Sec4 | School Enrollment file lee lee |
| GDP10 | GDP per capita (constant 2010 US$) 2015 file |  |  | Estimators for Secondary Education for the year 2007 |
| GDP11 | GDP per capita, PPP (current international $) 2015 file |  | Sec1 | School enrollment, secondary (% gross) file 2015 |
| GDP12 | GDP per capita, PPP (constant 2017 international $) 2015 file |  | Sec2 | School enrollment, secondary (% gross) file 2019 |
| GDP13 | GNI per capita, Atlas method (current US$) 2015 file |  | Sec3 | School enrollment, secondary (% gross) file 2021 |
| GDP14 | GNI per capita (constant 2010 US$) 2015 file |  |  | Estimators for Secondary Education for the year 2014 |
| GDP15 | GNI per capita, PPP (current international $) 2015 file |  | Sec1 | School enrollment, secondary (% gross) file 2018 |
| GDP16 | GNI per capita, PPP (constant 2017 international $) 2015 file |  | Sec2 | School enrollment, secondary (% gross) file 2019 |
|  |  |  | Sec3 | School enrollment, secondary (% gross) file 2023 |