Agricultural Productivity, Economic Growth & Human Development in Sub-Saharan Africa: A Least Squares Dummy Variables (LSDV) Approach

Abigail Lindner Azaria Wagner

Abstract: Researchers have established over the past couple of decades the importance of agricultural research and development and agricultural productivity for economic growth and poverty reduction. Poverty is often judged in these studies with poverty rates, but this statistic represents only a small part of human socioeconomic well-being. While agricultural R&D and productivity may indeed reduce poverty, we wish to investigate whether they also have a significant effect on composite human development, as measured by the United Nations' Human Development Index (HDI). We use least squares dummy variable estimations and a causal chain model on a panel of 27 countries in Sub-Saharan Africa (SSA) to assess the impact of agricultural growth on economic growth and human development. With an elasticity of 0.00315 for human development, agricultural growth is determined to have a significant but small effect on human development, while life expectancy and education outcomes are deemed significant and more impactful. Our findings suggest that policymakers should focus on improving the health and education of their countries rather than on boosting the economy to better support human development.

1 Introduction

As the first of their Sustainable Development Goals, the United Nations declares the common humanitarian aim to eliminate poverty worldwide. In the 2019 Sustainable Development Goals Report, the organization celebrates that the global population in poverty dropped from 36% in 1999 to 16% in 2010 to 10% in 2015. Growth has expanded especially in Eastern Asia, while over half of the remaining 736 million people living on less than $1.90 a day in 2015 were in Sub-Saharan Africa (SSA) [70].

Support for and alleviation of the sufferings of the poor has captured the energies of many men and women through history. In the past fifty or sixty years, public perception of poverty has shifted from its old view about the impossibility of eradication and even the necessity of it for economic advancement to a newer view about the necessity of its eradication and its restriction on economic advancement [58]. Researchers and policymakers have proposed many factors to "best" confront the poverty question. In the developed West, there is particular interest in addressing the poor populations in developing countries. The aid that Britain, Germany, and France provided their colonies in Asia, Africa, and Latin America for infrastructure pre-independence continued post-independence, some out of sympathetic humanitarian feelings and much, during the World War, from political motivation.

The power of economic growth in poverty reduction is well recognized [1, 44, 48, 59]. Post-world wars the emphasis in development was placed on industry and agriculture was neglected, but the example of Asia during the Green Revolution, when rural technology transfers boosted the agricultural productivity of the nations, fueled interest in agricultural research and development as a means by which to spur developing economies and reduce poverty in the '70s and '80s. In the last decade there has been a resurgence in research interest for the agricultural sector for economic development and, subsequently, poverty reduction.

Numerous country case studies and cross-country evaluations support the view that agricultural research and productivity contribute more greatly to overall economic growth than industrial productivity and improve the conditions of the poor in developing countries. In much of SSA, the agricultural sector continues to account for a significant part of the GDP in the region. McKinsey & Company reported that 60% of the SSA population works on smallholder farms whose agricultural output generates 23% of the region's GDP [32]. For comparison, in 2018 the value added of the agricultural sector as a percentage of GDP in the Europe Union was a mere 1.1%. Thus, it is has been supposed that agricultural development can play an important role in economic growth and poverty reduction in SSA, and recent research supports this belief [2, 26, 66]. Though the sector accounted for less of the country's GDP in 2011 than services, CGIAR estimates that it contributed over 50% when one accounts for the linkages between agriculture, agro-based industries, and the service sector.

Our interest is whether this agricultural growth that has had such positive and significant effects on economic growth and poverty reduction has the same impact on composite human development, as measured by the United Nations Development Programme's (UNDP) Human Development Index (HDI), compared to other factors such as education.

Past research on the agricultural sector in SSA has used time series data for individual countries or for a panel of countries. Using a panel of countries provides a more complete picture of the growth circumstances in the developing countries of the continent, but complications of country heterogeneity arise. Being interested in long-term effects, we circumvent this heterogeneity complication by using least squares dummy variable (LSDV) estimations on a panel of 27 countries from 1990 to 2019 to measure the impact of agricultural growth on aggregate economic growth and human development. We take advantage of cross-country data on agricultural factors, employment, GDP, and population from the World Bank, data on agricultural research and development spending from the Agricultural Science and Technology Indicators (ASTI) of the International Food Policy Research Institute (IFPRI), and data on education and health from the United Nations Human Development Data for paneled regression analyses.

The next section describes the main literature to date on agricultural productivity and economic growth in individual and aggregated countries in the developing world and the factors that contribute to human development. The third section is an overview of the analytical frameworks used to determine correlation between the variables. The fourth section details the collection, preparation, and use of the data. The fifth section presents the main results from the analyses and the last section discusses the implications of these results.

2 Literature review

Impact of agricultural growth on economic growth

Research to improve food production has operated according to one or more of four mechanisms: 1) intensification of a single farm component, 2) addition of a productive element to a farm system, 3) improved use of resources to increase crop intensity, and 4) improved per hectare yield of staples through introduction of regenerative elements and locally-appropriate crop varieties and animal breeds [53].

In China from 1981 to 2001, after the Green Revolution when technologies with pro-growth mechanisms of the aforementioned ilk migrated to the country, de Janvry & Sadoulet (2010) calculated that a 1% increase in agricultural growth contributed, directly and indirectly, 0.45% to aggregate growth and 2.24% to poverty reduction, compared to the respective 0.92% and 2.85% statistics for a 1% increase in non-agricultural growth [22]. Considering that the agricultural sector constituted less than a one-quarter share of the Chinese economy over this time period, the similarities in poverty effects between the agricultural and the non-agricultural speaks to the strength of research- and technology-supported agriculture in reducing poverty.

This effect of the agricultural sector on the aggregate economy was also observed by Datt & Ravallion (1996, 1998) in India, Woden (1999) in Bangladesh, and Thorbecke & Jung (1996) in Indonesia. In each instance, growth in agricultural input and small-scale industries reduced poverty, but growth in manufacturing did not [23, 24, 73, 68]. Cross-country examinations commonly find a greater increase in the poor's income and the reduction of poverty by agricultural growth than in industrial output because industrial output is urban-based, while agricultural growth is rural-based, and the majority of the poor live in rural regions. Considering just GDP, according to Gallup et al. (1997) a 1% increase in agricultural GDP boosts manufacturing GDP by 1.16% and service GDP by 0.79% while the incomes of the poorest quintile increase 1.61% [30].

That agricultural growth has greater poverty-reducing effects than non-agricultural growth has also been demonstrated through scenario simulations. Diao, Hazell & Thurlow (2010) used Economy-Wide Multi-Market (EMM) and computable general equilibrium (CGE) models to examine the relative contribution of agriculture to poverty reduction and growth in six African countries – Ethiopia, Ghana, Kenya, Uganda, and Zambia – and found that for all countries the poverty headcount five years forward from the research would be lower under agricultural-led development scenarios versus non-agricultural-led development scenarios [26]. For Kenya, which had a baseline of 46.2% poverty, the difference was between 36.0% and 44.1%. The authors of this paper concluded that agriculture can generate greater employment and incomes among the poor and facilitate greater broad-based growth for the poor and non-poor than industry.

The next section details why material improvements benefit both the agricultural rural and the industrial urban – the entire economy – when research and development boosts agricultural productivity, but the impact of industrial productivity is limited to the urban.

Regarding the impact of agricultural productivity on poverty headcount: Based on over 100 pooled observations from Africa, Asia, Latin America, the Caribbean, and other regions with transitional economies, Thirtle, Lin & Piesse (2003) calculated that a mere 1% increase in agricultural productivity would reduce the population in poverty by over 6 million in Africa and Asia and would cost research investments of $119 per capita of the poor in Africa and $179 per capita of the poor in Asia [66].

More recently, Alene & Coulibaly (2009), in determining the marginal impact of agricultural productivity elasticity with agricultural research, per capita income effect on productivity change, and poverty effect on per capita income change, estimated that a 1% change in agricultural productivity raises GDP per capita by 0.95%, indicating the poverty-reducing effects of agriculture on GDP per capita [2]. Cervantes-Godoy & Dewbre (2010) agree, based on a multiple regression analysis of 25 countries, that increases in agricultural GDP influence poverty levels more than increases in non-agricultural GDP [18].

Agriculture and economy linkages

Researchers have proposed several reasons for the benefits of agricultural growth to aggregate economic growth. Alene & Coulibaly (2009) note that agricultural research, and subsequent agricultural growth, benefits the poor directly by raising incomes and/or home consumption; and indirectly by lowering food prices and through production and consumption linkages [2]. Production linkages include upstream farm demand for inputs and services to support agriculture and downstream farm demand for processing, storage, and transport of farm outputs, while consumption links concern the ability of farm laborers to spend their incomes, which agricultural innovations have increased, to grow the local rural economy [67].

According to Hazell & Haddad (2001), agricultural growth improves the overall economy by supplying basic foods, raw materials, and exports; releasing labor and capital to the non-food sector; giving greater purchasing power to the poor; and creating a nascent rural market for manufacturing [35]. The second and fourth points speak to the domino effect of agricultural growth in the economy. Increased productivity in this sector achieves two main advancements: 1) more efficient farming technologies allow some farm laborers to move out of agriculture into higher-paying non-agricultural work, and 2) increased agricultural productivity leads to increased demand for manufacturing services and food processing factories.

Mellor (1999) suggested that real wages rise consistently with agricultural growth, suggesting that agricultural growth has an employment multiplier, which measures the number of direct, indirect, or induced jobs created or lost in an area [46]. If agriculture creates more jobs directly in its sector by yield-promoting technologies and indirectly through increased demand for work in other sectors, it can be said that agricultural growth helps to reduce poverty through greater employment economy-wide.

While theoretically this view on agricultural productivity and job creation makes sense, Schneider & Gugerty (2011) are careful to note that technology may reduce or increase employment and wages depending on its effects [61]. For example, if the technology is labor-saving, production costs will decrease and profits will rise but output may not change and employment would thus reduce. Alternatively, if the technology instead raises yields, output and employment will increase, but not necessarily profits. For far-reaching economic impact, increased yields seem to pack the most punch, though the environmental impact may be less positive depending on implementation.

In East Asia, there is an inverse relationship between rising yields and poverty, indicating that high-yield, versus labor-saving or land expansion, technologies have the greater positive effect on employment and wages [22]. This conclusion is supported by the findings of Thirtle, Irz, Lin & Wiggins (2001), wherein a 1% increase in yield had –0.91 poverty elasticity. In other words, in their cross-sectional regression analyses increasing yield 1% reduced poverty by 0.91% - nearly 1 to 1 [67].

Impact of agricultural and economic growth on human development

The research on the impact of agricultural growth, or economic growth in general, on human development is considerably less than that on agricultural growth on economic growth. Self & Grabowski (2007) is one study that addressed the role of the agricultural sector in economic growth and human development [63]. Specifically, the researchers investigated agricultural modernization by technology and productivity, treating HDI as the dependent variable, in 89 countries through Africa, Latin America, the Middle East, Europe, and elsewhere. To account for region heterogeneity, dummy variables were added for Asia, Latin America, and SSA. By their regressions, a 1% increase in agriculture total factor productivity leads to a 0.013% increase in HDI.

According to the International Food Policy Research Institute, while agriculture has the most direct link to the first Millennium Development Goal regarding the eradication of poverty and hunger that the United Nations proposed to accomplish by 2015, the sector impacts all eight through various economic, education, and health linkages [60]. From a practical point of view, Welch & Graham (1998) address the problem of micronutrient malnutrition in which agriculture aimed at quantity over quality, so that populations eat foods that do not meet daily nutritional requirements [72]. This has a direct effect on human health and productivity. They see an improvement in sustainable, healthful food production as a key to stimulating human health, livelihood, and well-being.

Considering economic growth in general, Ranis, Stewart & Ramirez (2000) studied how it and human development reinforce one another such that poor performance in economic growth prompts poor performance in human development and vice versa, and likewise for strong performance in economic growth [56]. To look at a specific example, in the "Chain A" connecting economic growth to human development, the resources of the economy are employed and spent on goods such as basic education, food, and primary health care that promote human development; in the "Chain B" connecting human development to economic growth, the overall well-being of a people determines their quality of labor and innovative capacity. Ranis (2004) further explores these linkages [54].

Boozer, Ranis, Stewart & Suri (2003), building on the work of Ranis, Stewart & Ramirez (2000) on virtuous, vicious, human development-lopsided, and economic growth-lopsided cycles, use infant mortality to measure human development and per capita real income growth for economic growth to assess the long-term cycles of developing countries from 1960 to 2001 [13]. A virtuous cycle is characterized by high human development and high economic growth; a vicious cycle, low human development and low economic growth; human development-lopsided, strong Chain A but weak Chain B; and economic growth-lopsided, strong Chain B but weak Chain A. They determined that SSA, along with South Asia, are stuck in a vicious cycle. Closer inspection of Chain B revealed to them that promotion of human development levels early in a country's progression must precede acceleration of growth; the strength of economic growth on human development, Chain A, varies due to structural and policy factors and is lower in SSA.

For a country to move from a vicious cycle, a human development-lopsided cycle, or an economic-development lopsided cycle to a virtuous cycle, Ranis & Stewart (2006) emphasize improvements in human development over improvements in economic growth, suggesting that human development has a greater effect on economic growth than economic growth on human development [55]. Our aim in this paper will be to assess this later direction.

Background to the Human Development Index

GDP and poverty rate are common metrics for country progress, but they do not provide a holistic picture of this. They are based on income levels, but human well-being extends beyond economics. Concerning the poverty rate, its use in analyses for SSA is limited because of the paucity of data on poverty levels in Africa. The most complete source we found for individual country data is the World Bank's PovcalNet, but availability varied from country to country. For example, Madagascar and Mauritania have seven data points starting in 1993 and 1987, respectively, while Benin and the Central Africa Republic have only three starting in 2003 and 1992. Zimbabwe has only two: 2011 and 2017. The World Bank acknowledges that these huge data gaps have "stunted poverty-fighting efforts" in the past [74].

Moreover, the single poverty rate or poverty headcount (as a percentage of population) statistic can skew the reality. Since the mid-1980s to the 2010s the poverty levels in most of the 27 African countries in our panel have declined, but the actual headcount has increased. For example, in Tanzania the poverty rate as determined by a 2011 PPP$1.90 a day cutoff was 72.06% in 1991 and 49.08% in 2017, but the number in poverty had grown from about 19.5 million to over 27.5 million. Christensen, Ojomo & Dillon (2019) observe that the per capita income of Burundi, the Central African Republic, Gambia, Malawi, and other SSA countries has declined from the 1960s to 2015 [19].

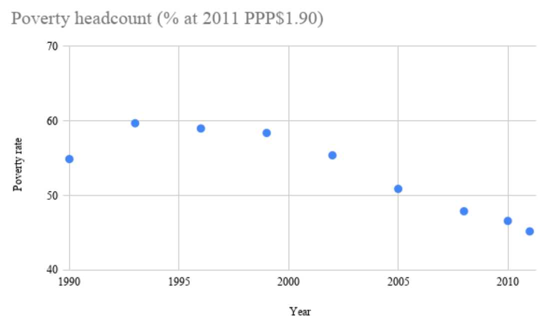


Figure 1: Poverty Rate in Sub-Saharan Africa (2011 PPP$1.90 a day)
Source: World Bank World Development Indicators

Despite these conflicting findings, Chen & Ravallion (2007), while acknowledging the rising poverty counts, are encouraged by signs of progress in the Sub-Saharan Africa region, and other developing regions outside China, that have spurred proportionate rates of decline in poverty since 2000 [17]. It is inaccurate, then, to say that the policies implemented in these countries in the last couple of decades have had no impact on poverty levels. Nevertheless, the poverty rate statistic is insufficient for reflecting the overall well-being of a country's people.

Poverty is a multidimensional phenomenon that transcends measures of income. Non-income social indicators are just as important if not more important than income-based economic indicators in measuring human development and poverty [9]. In Bangladesh, Bhuiya et al. (2007) created a multidimensional measure of poverty that brought the variables of education, health, food, housing, clothing, and social participation together, defining poverty as inadequate fulfillment of these needs [12].

The motivation of Bhuiya et al. (2007) in creating a new, more holistic measure of poverty echoes the efforts of the UNDP in creating the Human Development Index. The developers of this index understood that private incomes "fail to capture even some very basic instrumental features of the standard of living in developing countries", such as lifespan, infant mortality, illiteracy, hunger, and personal liberty [7]. The UNDP first used the HDI in the 1990 Human Development Report. It seeks to emphasize the people of a country and their capability, not just their economy, by gathering data on three broad categories of life: health, education, and standard of living. The first HDI used data on life expectancy at birth, the literacy rate, and the logarithm of the gross national product (GNP). As of July 2020, the main variable for health was still life expectancy; for education, mean years of schooling and expected years of schooling had replaced literacy rate; and for standard of living, gross national income (GNI) per capita took the place of GNP.

HDI is calculated by the sum of the indices derived from the data for these three categories. As described by Anand & Sen (1994), the HDI H_j for country j is calculated by

$$H_j = \frac{1}{3}\sum_{i=1}^{3} H_{ij}, \tag{1}$$

where $H_{ij} = \frac{X_{ij} - \min_k(X_{ik})}{\max_k(X_{ik}) - \min_k(x_{ik})}$ is the i^{th} variable's contribution to the HDI for country i and X_{ij} is the attainment level in the X_i dimension, $i = 1, 2, 3$. After all the countries for which sufficient data have had their HDI calculated, the UNDP ranks the countries into Very High Human Development, High Human Development, Medium Human Development, and Low Human Development. The maximum score is 1, indicating the highest possible level of human development, and the minimum possible score is 0. As of 2018, 19 of the countries in our 27-country SSA panel ranked in Low Human Development. Six - Cameroon, Eswatini, Ghana, Kenya, Zambia, and Zimbabwe - attained Medium Human Development. Only Botswana and South Africa had indices - 0.728 and 0.705, respectively - placing them in the High Human Development category. No African country has yet achieved Very High Human Development by the UNDP's HDI standards.

The choice of variables in the HDI is based on research on what sectors of human life have the greatest impact on community well-being. A brief description of the relevance of mean and expected years of schooling, life expectancy, GNP/GNI/GDP per capita, and the discarded but still important IMR follow.

Mean and expected years of schooling: Mean years of schooling measures the average number of years of education that a country's population aged 25 and over has completed, while expected years of schooling measures the number of years that a two-year-old may expect to attend school based on current enrollment rates in the different grades. For an example, in 2018 the mean years of schooling in the United States was 13.4 and the expected years of schooling was 16.3. Those statistics in Kenya are 6.6 and 11.1.

It is important to note that increasing rates of student enrollment and anticipated student enrollment are not themselves determinants of improved human development. The quality of the education matters. Spaull (2015) reiterates the findings of other researchers that a low-quality education becomes a poverty trap and may be worse than no education [65]. Where the education quality is high in SSA, Asongu & Odhiambo (2018) detected a positive effect on mobile phone penetration - the introduction and use of new technologies, which has been suggested as an important means by which developing countries may "catch up" to developed countries [8, 45].

In our regressions, expected years of schooling was selected as an independent variable rather than mean years of schooling or both HDI education indices, since the mean years of schooling concerns current conditions and expected years of schooling concerns future improvement (or deprivation).

Life expectancy: Life expectancy measures the total number of years a person is expected to live based on the time of their birth, current age, and demographic factors like income level and gender. The HDI uses life expectancy at birth (LEB). From 2000 to 2016 humans globally have enjoyed an increase in LEB of 5.5 years. LEB growth plateaued in SSA in the 1990s because of the HIV/AIDS pandemic, but has since risen from about 50.5 in 2000 to a little over 61 in 2016.

That increased longevity should indicate overall human improvement should be obvious. It signals that the medical resources, and people's access to them, have increased, which improved infrastructure (roads, buildings) would have to precede. Cervellati & Sunde (2005) have indicated strong interplay between life expectancy, technological advancement, and human capital formation - that is, the acquisition of persons with the specialized skills to develop a country's economic and political spheres [16]. Increased longevity increases opportunities for a person to develop their skills and innovate in their lifetime, creating technologies to extend the lifespans of others who may repeat this process.

GNP/GNI/GDP per capita: Gross national product (GNP), gross national income (GNI), and gross domestic product (GDP) all serve the same purpose: to reflect the economic growth of a nation. They differ in the goods and services that they include. GNP, the first economic measure that the HDI used, estimates the total value of all final goods and services produced by a country's residents (i.e. not through foreigners in the country). GNI extends further than GNP by including the product of a country's citizens who live abroad. GDP is part of GNI; it tracks the total goods and services from within a country's borders. Table 1 below, outlining the differences between these economic measures, is reproduced from Amadeo (2020) [6].

In our regressions, we use GDP, as the value added to the economy of agriculture and other sectors is recorded in terms of percent GDP.

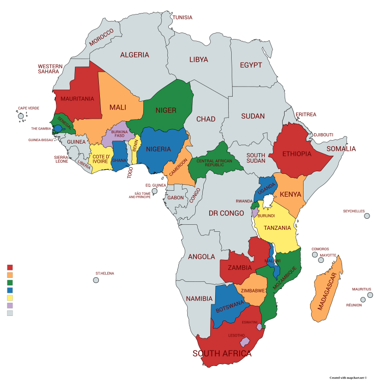
Infant mortality rate: IMR counts the number of deaths of children before age 1 out of every 1,000 live births. In their *State Infant Mortality (SIM) Toolkit*, the Centers for Disease Control and Prevention, the Association of Maternal & Child Health Programs, and the National March of Dimes regarded IMR as a crude indicator of overall community health [64].

High IMRs are often linked to poor neonatal care, early pregnancy, lower education levels, and lack of resources or lack of access to resources due to poverty, all of which serve to dampen human development [37]. When it had been part of the HDI, Lee et al. (1997) found that HDI powerfully predicted 85% to 92% of the variation in a country's IMR [41]. Alijanzadeh, Asefzadeh & Zare (2016) recognize IMR as a vital index for health standards and social inequality and one of the best indicators of healthcare inequities [4].

3 Data

Country panel

Our research began with Kenya, whose poverty rate of 35.5% in 2015-2016 was the lowest in East Africa and lower than the SSA regional average based on a 2011 PPP$1.90 per day cutoff. According to the World Bank, from a GDP of $12.705 billion in current monies in 2000, Kenya grew to $87.908 billion in 2018 – a nearly 700% increase. Moreover, Kenya rose from an HDI of 0.467 in 1990 to an HDI of 0.579 in 2018, an increase of about 24%. What has influenced this economic and human development improvement? To test the hypothesis that agricultural development significantly and positively affects human development in addition to economic growth, just as much as or more than other factors in SSA, we evaluate 27 countries scattered through the region, mirrored off the panel that Alene & Coulibaly (2009) compiled based on data availability [2]. These are Benin, Botswana, Burkina Faso, Burundi, Cameroon, the Central African Republic, Cote d'Ivoire, Eswatini (Swaziland), Ethiopia, Gambia, Ghana, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe.



These 27 countries are spread over all the U.N. subregions of Africa other than Northern Africa, which is not part of SSA. Based on the WeForum stages of economic development, in 2018 the majority of these countries were factor-driven and none had yet grown beyond efficiency-driven. Moreover, almost all of them have Global Competitive Indices below 4 as of 2019 [75, 76]. A factor-driven economy depends on unskilled labor and natural resources, while an efficiency-driven economy is driven by education, efficient goods, labor, financial, and domestic or foreign markets, and the ability to use technologies.

That all but six of the countries (Botswana and Nigeria are in transition between factor-driven and efficiency-

Income earned by:	GDP	GNI	GNP
Residents in country	C+I+G+X	C+I+G+X	C+I+G+X
Foreigners in country	Includes	Includes if spent in country	Excludes all
Residents out of country	Excludes	Includes if remitted back	Includes all
Foreigners out of country	Excludes	Excludes	Excludes
C=Consumption, I=Investment	G=Government spending	X = Exports-Imports	

Table 1: Comparison of GDP, GNI & GNP

driven, Eswatini and South Africa are efficiency-driven, and WeForum Global Competitiveness data was not available for the Central African Republic and Nigeria) are factor-driven suggests that the agricultural sector accounts for a large part of the labor output of the country, so technological and financial investments in it are expected to boost the overall economy more than investments in the industrial sector and, through the linkages discussed above, provide greater opportunities for the improvement of the education and health parameters of human development. In fact, for all the selected countries but Botswana, Lesotho, and South Africa, from 1990 to 2018 the agricultural sector covered an average 10% or more of the country's GDP, and for twelve of them that statistic is between 25% and 35%.

Variables

Data was collected for the period from 1990 to 2019. The data and sources of all the variables considered are detailed in Table 2 in Appendix A. All but five data sets have at least one country whose values went to 2018 or 2019. (1) The poverty headcount (%) for individual countries from PovcalNet is scattered; some countries have only two data points since the late 1980s or early 1990s while others have five or more. (2) The poverty headcount ratio data for the SSA region from PovcalNet has 2010 as its last data point. (3) The tractors data from the World Bank is scattered. For some countries, the most recent data comes from the 1980s. (2) The total agricultural R&D spending from IPFRI provides data through 2016. (4) The literacy rate data among the population aged 15 and over from the World Bank is scattered similar to the poverty headcount (%) data.

The data was organized and reformatted in Microsoft Excel before being analyzed in R. The choice of variables was guided by the research of Alene & Coulibaly (2009), Janvrey & Sadoulet (2010), Rao, Coelli & Alauddin (2014), Thirtle, Lin & Piesse (2003), and Thirtle, Irz, Lin & Wiggins (2001) [2, 22, 57, 66, 67]. The end R data frame had 29 variable columns in addition to "Country" and "Year", some of which were not used because of lack of sufficient data or significance. The details of the variable columns are described in Table 3 in Appendix B.

Panel unit root tests

A common assumption of regression analyses is the stationarity of the dependent and independent variables and the error term. Stationarity implies constant moments and joint moments such that the statistical properties of a given variable stay the same over time. For example, the mean of variable X has constant mean μ, not function-defined mean $\mu(t)$ [3]. The error term is the difference between the expected value of the independent variable brought about by the dependent variables and the observed value of the independent variable. Because we assume that the error term of a regression model is a white noise process, a subsequent assumption of stationarity holds.

To test the stationarity of the variables related to agricultural productivity, GDP, and poverty, we apply the Im-Pesaran-Shin (IPS) unit root test for heterogeneous patterns, first proposed by Im, Pesaran & Shin (2003) [40]. IPS uses averages of the likelihood ratio and augmented Dickey-Fuller tests to test the null hypothesis $H_0 : \beta_i = 0 \forall i$ against the alternative hypotheses $H_1 : \beta_i < 0, i = 1, 2, \ldots, N_1$ and $\beta_i = 0, i = N_1 + 1, N_2 + 2, \ldots, N$, i.e. all the individual series have unit roots while none or only some of the individual series have unit roots. IPS was used in exclusion of the Levin-Lin-Chu Unit-Root Test, the Panel Augmented Dickey-Fulley Test, and other well-known unit root tests after the example of Bangake & Eggoh (2012), who used a Pooled Mean Group cointegration technique for their analysis of savings and investment in 37 African countries [10]. The unit root tests were run through the **plm** package in R, with *pmax*=15 and individual lag length determined by Akaike Information Criteria (AIC).

The variables tested were Ag.employ, Ag.land, Ag. exports, Ag.val.added, Cereal.prod, Fertilizer, RD.spending for agricultural development; Ag.val.added, Gov.expend, Industry.val.added, Labor.force, and Natl.invest for economic growth; and GDP.per.cap, IMR, Life.expect, School.mean, and School.expect for human development. Separate unit root tests were conducted for each group. The divisions above will be further explained in Methods.

The null hypothesis of non-stationarity is rejected by calculating the p-value and comparing it to a critical value. We chose $p = 0.05$. Summaries of the IPS unit root tests are in Table 4 in Appendix C. Due to detected non-stationarity of Ag.land, Ag.land.per (the percentage of the total land area that is put to agricultural use) is used for the regression analysis work instead.

4 Methods

Least squares dummy variable (LSDV) model

One challenge of dynamic country panel data is the unrecognized country heterogeneity. Dynamic data panel models have the number of time series observations, T, relatively large and of the same order of magnitude as the number of groups, N. These panels arise most often in cross-country analyses. In the majority of applications, the parameters of interest are the long run effects and the speed of adjustment to the long run, such as the effect, in our study, that agriculture has on poverty over a long period of time in a panel of African countries.

There are two main procedures used for these panels. At one end, separate equations can be estimated for each group and the distribution of the estimated coefficients across groups can be examined. This is the mean of the estimates, called the Mean Group Estimator (MGE). The MGE will produce consistent estimates of the average of the parameters. This estimator, however, does not take account of the fact that certain parameters may be the same across groups. The traditional pooled estimators are at the other end. Here the intercepts are allowed to differ across groups while all other coefficients and error variances are constrained to be the same. This is the approach used by Ogunlesi, Bokana, Okoye & Loy in their analysis of agricultural productivity [49].

As noted before, the 27 countries in this study have different GDPs and economic compositions. Moreover, they are located in different parts of Africa and operate under different forms of government. Though agricultural R&D spending and development has been shown to grow economies and reduce poverty in countries as economically strong as South Africa and in countries less economically well-to-do as Madagascar, these country differences likely have an impact on the independent and dependent variables that we are studying.

There are many reasons to expect the long-term equilibrium relationships between variables to have similarities across groups, including budgets, the selling and buying of currency or goods, and the influence of common technology. Reasoning that short-run dynamics and error variances should be the same tends to be less compelling. However, as we are concerned with the long-term impacts of agricultural productivity on economic growth and economic growth on human development, we do not need to explore the specifics of the short-run dynamics. Thus, we employ the traditional pooled estimator wherein the intercepts differ but the coefficients and variances stay the same; in particular, the least square dummy variable (LSDV) model.

LSDV is a variation of a fixed effects (FE) model. In a fixed model, all model parameters are non-random quantities and time-invariant variables - in our case, Country - are controlled. This contrasts with a random effects (RE) model, which determines that some or all of the model parameters are random and includes the effects of time-invariant variables. The choice between an FE and an RE model is often determined, alongside understanding of specific data dynamics, with a Durbin-Wu-Hausman test based on Hausman (1978) or a Mundlak test based on Mundlak (1978), though Clark & Linzer have, by simulations, shown the Hausman test to be an unnecessary and insufficient statistic for the choice [20, 34, 47]. An alternative, is the within-between (WB) model, whose mechanics are based on RE but whose treatment of variable means is based on FE in an effort to marry the precision and flexibility of RE to the unbiasedness of FE [27].

Suppose we have the basic linear regression equation $Y_{it} = X_{it}\beta + \alpha_i + \epsilon_{it}$, where i is the number of individuals (e.g. countries), t stands for a unit of time, Y_{it} is the dependent variable for individual i at time t, X_{it} is an $N \times 1$ vector of the independent variables for Y_{it} (N the number of independent variables), α_i is a group specific constant term that varies for each i, and ϵ_{it} is the typical error term. Averaging this equation over time and centering it yields the LSDV estimation of the original model, as below:

$$y_{it} - \overline{y_t} = (X_{it} - \overline{X}_l)^I \beta + (\epsilon_{it} - \overline{\epsilon}_l)$$

where $\overline{x}_l$ is the mean of the x_{it} from $t = 1$ to $t = T$ and $\overline{\epsilon}_l$ is the mean of the ϵ_{it} likewise calculated. The individual effect terms α_i are calculated from $\overline{X}_l$ and the standardized error for each individual from the modified equation above [50].

We selected the FE, LSDV estimator for our study. There is a precedent for the use of LSDV in analyses with country panels focused on economic growth in SSA in the work of Basu & Guariglia (2007) on investment and growth, Pamuk, Bulte & Adekunle (2014) on innovation systems and agricultural technology adoption, Asongu & Odhiambo (2019) on education, information technology, and human development, and others [8, 11, ?, 51]. The appropriateness of FE over RE was further confirmed using the **phtest** through the **plm** package of R, a Hausman test for panel models. The null hypothesis H_0 of the test is that the unique errors are uncorrelated with the regressors, which would make RE a suitable choice. The alternative hypothesis H_a, accepted if the p-value is significant ($p < 0.05$) states that the unique errors are correlated, leaning in favor of FE.

An LSDV estimator includes an indicator dummy variable for each panel unit, minus 1 to avoid the dummy variable trap. The inclusion of these dummy variables accounts for the country heterogeneity, absorbing the effects particular to each country, that regular ordinary least squares (OLS) regression misses. The image below from Oscar Torres-Reyna (2010) at Princeton University illustrates the effect of these dummy variables on the graphical representation of the estimation [69].

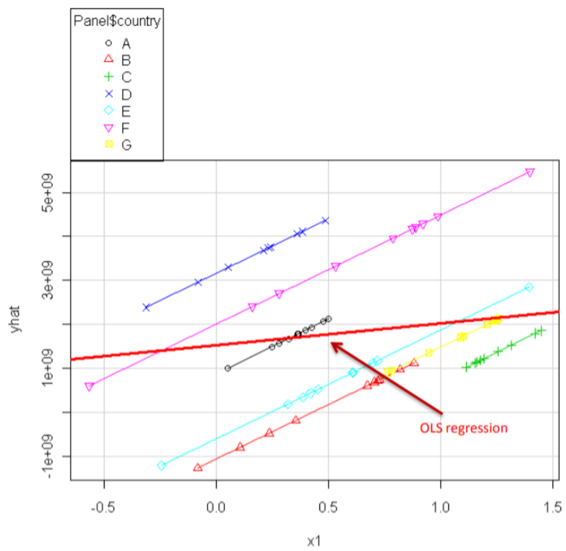


Figure 2: LDSV vs OLS

As the figure shows, a simple OLS regression on the panel data that Torres-Reyna used generated a single red line starting at the $1 \cdot 10^9$ y-intercept. When dummy variables for the seven countries A, B, C, D, E, F, and G were added in the LSDV estimation, all the countries assumed the same slope, steeper than in the OLS regression, but started at different x-y positions.

Model specification

Based on diagnostic plots to detect non-linear relationships, normality, homoskedasticity, and influential cases, it was determined that arranging models with the natural logarithms of each variable, instead of the variables as they were, yielded models that better fit the data. We defined a system of agriculture value added (agricultural growth), GDP (overall economic growth), and HDI (human development) equations as follows with t representing year t. This structure is based on the system of equations from Alene & Coulibaly (2009) and the causal chain model from Thirtle, Lin & Piesse (2003) [2, 66].

$$\begin{aligned}\ln[Ag.val.added]_t = {} & \alpha_{AE}\ln[Ag.employ]_t \\ & + \alpha_{AX}\ln[Ag.exports]_t \\ & + \alpha_{AL}\ln[Ag.land.per]_t \\ & + \alpha_{CP}\ln[Cereal.production]_t \\ & + \alpha_{FE}\ln[Fertilizer]_t \\ & + \alpha_{RD}\ln[RD.spending]_t \end{aligned} \tag{2}$$

$$\begin{aligned}\ln[GDPpercapita]_t = {} & \beta_{AV}\ln[Ag.val.added]_t \\ & + \beta_{GE}\ln[Gov.expend]_t \\ & + \beta_{IV}\ln[Industry.val.added]_t \\ & + \beta_{LF}\ln[Labor.force]_t \end{aligned} \tag{3}$$

$$\begin{aligned}\ln[HDI]_{i,t} = {} & \phi_{GC}\ln[GDPpercapita]_t \\ & + \phi_{IM}\ln[IMR]_t \\ & + \phi_{LE}\ln[Life.expect]_t \\ & + \phi_{SC}\ln[School.expect]_t \end{aligned} \tag{4}$$

A Farrar-Glauber test, based on the work of Farrar & Glauber (1967), was performed on each part of the system to check for multicollinearity [29]. The Farrar-Glauber test is a collection of three tests to detect 1) the existence and severity of multicollinearity based on a Chi-square test, 2) the location of multicollinearity based on an F test, and 3) the pattern of multicollinearity based on a t-test. We used the process outlined by Ghosh (2017) [31], with the **mctest** and **ppcor** packages from R. The results of the first and second tests appear in Appendix D.

We determined multicollinearity by using the Variance Inflation Factors (VIF) method. VIF, calculated by taking $\frac{1}{1-R^2}$ for each of the $k-1$ indepedent variable equations, measures the degree to which multicollinearity, if present, increases the variance of the regression coefficient. A VIF greater than 10 or lower than 0.1 often suggests a problem of high multicollinearity [38]. Opinions about the maximum acceptable VIF value vary and depend on what the researchers know about the data and circumstances being evaluated. We decided to reject variables with VIFs above 10, according to the generally accepted view [28, 77].

Due to detected multicollinearity between Industry.val.added and Natl.Invest in economic growth, Natl.Invest was removed. A second round of the Farrar-Glauber test was run on the economic growth model after removing Natl.invest. No multicollinearity was detected then. The statistics in Appendix D display this second round of results.

5 Results

Linear regressions were carried out in R using the **stats** package. LSDV was implemented by adding a factor *Country* to the independent variables in the formula for agricultural growth, economic growth, and human development. To avoid the dummy variable trap whereby the independent variables become so collinear as to render the OLS unsolvable, we subtract one *Country* dummy. The results of the regressions are displayed in Table 5. The coefficients for the *Country* variables were excluded for the sake of conserving space and of presenting only the relevant information.

Agricultural Growth

Variable:	Coefficient Estimate:
log(Ag.employ)	-0.59294***
log(Ag.exports)	0.09446***
log(Ag.land)	3.30131***
log(Cereal.production)	0.35526***
log(Fertilizer)	0.0204839
log(RD.spending)	0.21610*

Economic Growth

Variable:	Coefficient Estimate:
log(Ag.val.added)	0.35255***
log(Industry.val.added)	0.36386***
log(Gov.expend)	0.03119**
log(Labor.force)	-0.05130***

Human Development

Variable:	Coefficient Estimate:
log(GDP.per.cap)	0.002414
log(IMR)	-0.077226***
log(Life.expect)	0.634790***
log(School.expect)	0.283374***

*** Significant at 0.001 level
** Significant at 0.01 level
* Significant at 0.05 level

Table: **LSDV Estimation Results**

Two variables worth immediately noting in agricultural growth are Ag.employ and Ag.land. These variables measure the population engaged in agricultural work and the square kilometers of the country's total land area that has been dedicated to agricultural cultivation. The independent variable in this first LSDV estimation, Ag.val.added or agricultural value added, describes the net output of the agricultural sector, which includes forestry, fishing, crop cultivation, and livestock production. Should output not change, it makes sense that a 1% increase in agricultural employment should result in a 0.59% decrease in agricultural value added; this would imply decreased agricultural productivity.

That a 1% increase in the land cultivated for agriculture should result in so large an increase in agricultural value added - over 3 times as much - accords with the observation by Deininger et al. (2011) that much of the agricultural growth in SSA in the past couple of decades has resulted from land expansion and not cultivation intensity, which is more costly and time-consuming [25]. However, as Goedde (2019) noted, Africa has little land remaining to which farmers can expand, and increased productivity and agricultural intensification must be a primary goal of workers in SSA moving forward [32, 36]. The significant value for Cereal.production, the total metric tons of cereal crops produced in a country, of 0.36 reflects the importance of land yield intensification.

Agricultural research and development, represented in the analyses as RD.spending, aims to measure created and implemented technologies in SSA to increase productivity and further grow this sector. The elasticity of 0.22 for agricultural R&D spending is lower than those found by Alene & Coulibaly (2009) and Thirtle, Lin & Piesse (2003), which may be the result of not introducing lagged values into our model [2, 66]. However, the result is still significant and relatively high. A major element of technological advancement by R&D is agricultural machinery, tracked by the World Bank as the number of tractors in a country, but due to low data availability we were unable to include this variable in our model. We were able to include fertilizer, a common input heralded as a technology to boost agricultural productivity in SSA, but our LSDV estimations suggest otherwise. The increase in agricultural value added by fertilizer is less than 0.1% and, moreover, insignificant. Liverpool-Tasie et al. (2015) at the World Bank suggest, based on their investigation of Nigeria, that the low profitability of fertilizer inputs in SSA are due to low marginal physical product and high transportation costs [42].

Moving to economic growth, the agricultural and industrial sectors appear to have near-equal impact, at increases in GDP per capita of 0.35% and 0.36% accompanying 1% increases in either sector. Considering that industry accounts for a greater part of the GDPs of most of the countries in our panel (exceptions include Burundi, Ethiopia, Mali, and Niger, whose average agricultural sector compositions of GDP from 1990 to 2018 are over 35%), the similar elasticities on overall economic growth point to the linkages that Alene & Coulibaly (2009), Hazell & Haddad (2001), and Mellor (1999) considered and that were detailed in a previous section [2, 35, 46].

Government expenditure includes current expenditures for governmental purchases of goods and services and contributions to national defense and security. The impact is significant at the 0.001 level, but not as considerable as value added in the agricultural and industrial sectors. The 0.05% decrease in GDP per capita that accompanies a 1% increase in the labor force should not imply that SSA should aim to discourage labor participation, resulting in unemployment that would undoubtedly lower the levels of human development in the countries. The interpretation is similar to that of employment in the agricultural growth estimations discussed above. It makes sense that more workers in the labor force, implying growing population, should reduce GDP per capita. This realization only illuminates the need for greater productivity in the individual sectors of the GDP, particularly agriculture and industry in our case.

Regarding human development as the UNDP measures it with the HDI, GDP has a surprisingly small impact based on our LSDV estimations - insignificant, in fact. The greater and significant coefficient estimates of 0.63 and 0.28 for life expectancy (Life.expect) and expected years of schooling (School.expect) indicate that addressing the health and educational deficiencies of a country will more greatly enhance the overall well-being of its population than increasing its people's economic statuses.

An additional OLS regression was carried out for human development that includes School.mean, the second variable used to calculate the Education Index of HDI. The results are below.

Human Development

Variable:	Coefficient Estimate:
log(GDP.per.cap)	0.008886**
log(IMR)	-0.011121
log(Life.expect)	0.643007***
log(School.expect)	0.118479***
log(School.mean)	0.240245***

*** Significant at 0.001 level
** Significant at 0.01 level

Here, the effect of IMR is still negative (an increase in IMR decreases HDI) but non-significant, while the effect of GDP per capita is still small at 0.009 but significant at the 0.01 level. Life expectancy still has the largest impact, followed by mean years of schooling and expected years of schooling. If the value added of the agricultural sector to GDP is 0.35 and the elasticity of GDP per capita growth on human development is 0.009, then the impact of 1% growth in the agricultural sector on human development is a mere 0.00315%; the impact of 1% growth in the industrial sector is not much more at 0.00324%. Here, we assume independence of Ag.val.added, and Industry.val.added to GDP.per.cap after the example of Alene & Coulibaly (2009) [2]. Moreover, a Pearson's chi-squared test using the **stats** package in R was run to verify independence under the null hypothesis H_0: The variables are independent and the alternative hypothesis H_a: The variables are dependent. A p-value less than 0.05 indicates independence. Testing GDP.per.cap, Ag.val.added, and Industry.val.added yields a p-value less than $2.2 \cdot 10^{-16}$.

6 Conclusion and implications

In this paper we assessed the impact of agricultural growth in Sub-Saharan Africa (SSA), measured by agricultural value added, on economic growth and human development, measured by GDP per capita and the United Nations' Human Development Index (HDI), respectively, using a dynamic cross-sectional panel of 27 countries from 1990 to 2019 selected based on the example of Alene & Coulibaly (2009) and data availability [2]. We used least squares dummy variable estimations to control for country heterogeneity in our regressions and, after the method of Thirtle, Lin & Piesse (2003), a causal chain model to capture the impact of agricultural growth on economic growth and human development.

The results first showed that agricultural growth does have a significant impact on economic growth, equal to industrial growth despite the latter sector often accounting for a larger portion of a country's GDP. Specifically, a 1% in increase in agricultural value added leads to an increase of 0.35% in GDP per capita; in industry value added, an increase of 0.36%. However, the result was not the same for human development, where a 1% increase in GDP per capita would lead, after including the mean years of schooling in addition to the expected years of schooling in the estimation, a 0.009% increase in human development as represented by the HDI. This calculates to a 0.00315% increase in human development with a 1% increase in agricultural value added and a 0.00324% increase in human development with a 1% increase in industry value added. This lesser importance of economic development on human development relates to the findings of Boozer, Ranis, Stewart & Suri (2003) that the Chain B from human development to economic growth is not as strong in SSA as in other developing countries [13].

Of the independent variables evaluated, life expectancy had the largest human development elasticity; a 1% increase in life expectancy leads to a 0.64% increase in human development. The second and third largest were mean years of schooling and expected years of schooling - 0.24% and 0.12%. The implication is that health and education have greater significance on human development than income or national production. This accords with the thinking of the Universal Health Coverage Coalition that formed after the United Nations launched their sustainable development goals for 2030. The economists in this coalition believe that the policymakers should prioritize better health to achieve higher levels of development [62, 71]. Longer lifespans are achieved by improved health, which is brought to a country through education and training, new technologies, and infrastructure that gives people access to medical services - all factors that contribute to the healthy development of communities.

A focus on health for human development in the modern age may be traced to the Declaration of Alma-Ata by the International Conference on Primary Health Care in Kazakhstan in September 1978. This declaration called for an affirmation of health as a human right, a recognition that without protection of health economic and social development cannot be sustained, and the mobilization of governments, international organization, agencies, and health workers to support the introduction, development, and maintenance of primary health care worldwide in order that all people have an acceptable level of health by 2000. Almost two decades after this “deadline”, the goal has not been achieved, but the theory that health plays a major role in advancing developing countries has not disappeared. Crafts (1997) notes that the improvement in living standards and mortality from 1870 to 1950 have been the result largely not of income increases but of scientific advancement and better health provision, with only about a quarter of the decline in mortality attributable to income [21].

The question in the twenty-first century becomes, by what means does health enhance human development? What role should education play; is it a precedent for improved health or does improved health facilitate greater educational outcomes? Another line of inquiry worth investigating is whether economic growth, while not directly boosting human development, might have some significant impact on the growth of a country’s health sector in SSA.

For further exploration of the link between agricultural and economic growth and human development, the link between economic growth and health, and/or the link between health and human development in SSA, a pooled mean group (PMG) estimation as proposed by Pesaran, Shin & Smith (1999) is worth considering in favor of least square dummy variables estimation [52]. Zaman et al. (2019) used this technique to investigate the growth-inequality-poverty triangle across 124 countries [78]. It has also been useful in finance research [15, 43]. Examination of what health policies countries with high HDI have implemented, and whether these policies prompted the improvement of human development or the improvement of human development allowed for the implementation of these policies may be helpful in determining the approaches that policymakers should consider for SSA. Further exploration of the strength of relationship from human development to economic growth after the research of Ranis, Stewart & Ramirez (2000) and Boozer, Ranis, Stewart & Suri (2003) is another possible line of study to delve deeper into the results of this paper [13, 56].

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A Data Names and Sources

Variable	Source
Agriculture, forestry, and fishing, value added (current US$)	World Bank*
Agricultural land (sq. km)	World Bank*
Agricultural machinary, tractors	World Bank***
Agricultural raw materials exports (% of merchandise exports)	World Bank*
Arable land (hectares)	World Bank*
Cereal production (metric tons)	World Bank*
Employment in agriculture (% of total employment) (modeled ILO estimate)	World Bank*
Employment in industry (% of total employment) (modeled ILO estimate)	World Bank*
Expected years of schooling (years)	United Nations*
Fertilizer consumption (kilograms per hectare of arable land)	World Bank*
GDP (current US$)	World Bank*
General government final consumption expenditure (% of GDP)	World Bank*
GNI (current US$)	World Bank*
Gross capital formation (current US$)	World Bank*
Headcount(%) *(individual countries)*	PovcalNet***
Human Development Index	United Nations*
Industry (including construction) value added (current US$)	World Bank*
Labor force, total	World Bank*
Land area (sq. km)	World Bank*
Life expectancy at birth, total (years)	World Bank**
Literacy rate, adult total (% of people ages 15 and above)	World Bank***
Mean years of schooling (years)	United Nations*
Merchandise exports (current US$)	World Bank*
Mortality rate, infant (per 1,000 live births)	World Bank*
Persistence to last grade of primary, female (% of cohort)	World Bank***
Population ages 0-14 (% of total population)	World Bank*
Population, total	World Bank
Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population) *(aggregate SSA)*	PovcalNet***
Rural population	World Bank*
Total agricultural R&D spending (2011 PPP$)	ASTI through IFPRI**

Table 2: **Original data variables**
*Data from 1990-2018 or 1990-2019 **Data ends before 2019 ***Data is scattered

B Dataframe Variables

Column Name	Units	Calculation
Ag.employ	People	Divided ”Employment in agriculture (% of total employment)” by 100 and multiplied the result by ”Labor force, total”
Ag.exports	Current US$	Divided ”Agricultural raw materials exports (% of merchandise exports)” by 100 and multiplied the result by ”Merchandise exports (current US$)”
Ag.land	Square kilometers	(no change) ”Agricultural land (sq. km)”
Ag.land.per	% total land area	Divided ”Ag.land” by ”Land area (sq. km)”
Ag.val.added	Current US$	(no change) ”Agriculture, forestry, and fishing, value added (current US$)
Cereal.prod	Metric tons	(no change) ”Cereal production (metric tons)”
Fertilizer	Kilograms	Converted ”Fertilizer consumption (kilograms per hectare of arable land)” to $\frac{kg}{km^2}$ by multiplying the values by $\frac{1}{100}$ and then found total kg
GDP	Current US$	(no change) ”GDP (current US$)”
GDP.per.cap	Current US$/Person	Divided ”GDP (current US$) by ”Population, total”
GNI	Current US$	(no change) ”GNI (current US$)”
GNI.per.cap	Current US$	Divided ”GNI (current US$)” by ”Population, total”
Gov.expend	Current US$	Divided ”General government final consumption expenditure (% of GDP)” by 100 and multiplied by ”GDP (current US$)”
HDI	index	(no change) ”Human Development Index”
Industry.employ	People	Divided ”Employment in industry (% of total employment)” by 100 and multiplied the result by ”Labor force, total”
Industry.val.added	Current US$	(no change) ”Industry (including construction, value added (current US$)
Labor.force	People	(no change) ”Labor force, total”
Land.area	Square kilometers	(no change) ”Land area (sq. km)”
Life.expect	Years	(no change) ”Life expectancy at birth, total (years)”
Literacy	People	Calculated total literate population from ”Population ages 0-14 (% of total population), ”Population, total”, and ”Literacy rate, adult total (% of people ages 15 and above”)
IMR	Infants per 1,000	(no change) ”Mortality rate, infant (per 1,000 live births)
Natl.invest	Current US$	(no change) ”Gross capital formation (current US$)”
Population	People	(no change) ”Population, total”
Poverty (%)	People	(no change) ”Headcount (%) *individual countries*
RD.spending	2011 PPP$	(no change) ”Total agricultural R&D spending (2011PPP$)”
Rural.pop	People	Divided ”Rural population (% of total population)” by 100 and multiplied the result by ”Population, total”
School.complete	%	(no change) ”Persistence to last grade of primary, female (% of cohort)”
School.expect	Years	(no change) ”Expected years of schooling (years)”
School.mean	Years	(no change) ”Mean years of schooling (years)”
Tractors	Unit item	(no change) ”Agricultural machinery, tractors”

Table 3: **Calculation & Organization of Dataframe Variable Columns**

C Im-Pesaran-Shin Unit Root Tests Results

Agriculture Value Added variables		
Overall T-bar statistic: -6.68 (-7.618)	*Overall p-value*: 0	
Variables	**T-bar**	**P-value**
Ag.employ	-3.61	$5.48 \cdot 10^{-3}$
Ag.exports	-6.00	$1.63 \cdot 10^{-7}$
Ag.land	-2.10	$2.44 \cdot 10^{-1}$
(Ag.land.per)	(-4.09)	$(1.01 \cdot 10^{-3})$
Ag.val.added	-3.58	$6.19 \cdot 10^{-3}$
Fertilizer	-5.21	$8.51 \cdot 10^{-6}$
RD.spending	-2.96	$3.88 \cdot 10^{-2}$
GDP variables		
Overall T-bar statistic: -10.085	*Overall p-value*: 0	
Variables	**T-bar**	**P-value**
Ag.val.added	-5.03	$1.91 \cdot 10^{-5}$
GDP.per.cap	-5.60	$1.29 \cdot 10^{-6}$
Gov.expend	-3.89	$2.09 \cdot 10^{-3}$
Industry.val.added	5.54	$1.75 \cdot 10^{-6}$
Labor.force	-4.63	$1.15 \cdot 10^{-4}$
Natl.invest	-5.83	$3.96 \cdot 10^{-7}$
Human Development variables		
Overall T-bar statistic: -9.979	*Overall p-value*: 0	
Variables	**T-bar**	**P-value**
GDP.per.cap	-5.53	$1.47 \cdot 10^{-6}$
HDI	-5.16	$9.61 \cdot 10^{-6}$
IMR	-6.36	$6.44 \cdot 10^{-9}$
Life.expect	-7.22	$7.98 \cdot^{-11}$
School.expect	-4.30	$4.31 \cdot 10^{-4}$
School.mean	-5.42	$2.64 \cdot 10^{-6}$

Table 4: **T-Bars and P-Values of IPS Tests**

D Farrar-Glauber Tests

1 $-->$ COLLINEARITY is detected by the test
0 $-->$ COLLINEARITY is not detected by the test

	MC Results	Detection
Determinant $\|X'X\|$:	0.0982	0
Farrar Chi-Square:	657.2923	1
Red Indicator:	0.3919	0
Sum of Lambda Inverse:	12.8594	0
Theil's Method	-1.4128	0
Conditions Number:	72.6975	1

Table 5: **Agricultural Growth Overall Multicollinearity Diagnostics**

	MC Results	Detection
Determinant $\|X'X\|$:	0.1404	0
Farrar Chi-Square:	1389.7854	1
Red Indicator:	0.4869	0
Sum of Lambda Inverse:	12.1297	0
Theil's Method	-0.4311	0
Conditions Number:	103.5747	1

Table 6: **Economic Growth Overall Multicollinearity Diagnostics**

	MC Results	Detection
Determinant $\|X'X\|$:	0.1835	0
Farrar Chi-Square:	1247.7688	1
Red Indicator:	0.5127	1
Sum of Lambda Inverse:	9.4177	0
Theil's Method	-0.6866	0
Conditions Number:	189.4183	1

Table 7: **Infant Mortality Rate Overall Multicollinearity Diagnostics**

	VIF	Detection
log(Ag.employ)	1.8268	0
log(Ag.exports)	2.6238	0
log(Ag.land.per)	1.4828	0
log(Cereal.prod)	2.9002	0
log(Fertilizer)	1.1165	0
log(RD.spending)	2.9093	0

Table 8: **Agricultural Growth All Individual Multicollinearity Diagnostics, VIF Method**

	VIF	Detection
log(Ag.val.added)	5.3151	0
log(Gov.expend)	1.1159	0
log(Industry.val.added)	2.3514	0
log(Labor.force)	3.3472	0

Table 9: **Economic Growth All Individual Multicollinearity Diagnostics**

	VIF	Detection
log(GDP.per.cap)	1.4579	0
log(IMR)	3.5630	0
log(Life.expect)	2.6722	0
log(School.expect)	1.7247	0

Table 10: **Human Development All Individual Multicollinearity Diagnostics**