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Renewable Energy Consumption, Trade Openness and Agricultural Productivity in Africa

Onyebuchi Iwegbu
Magister Scientiae

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Dissertation submitted to the Applied Economics Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Magister Scientiae*.

Adviser: Leonardo C. Borges Cardoso

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Assent:

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To God and to my parents.

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ABSTRACT

IWEGBU, Onyebuchi, M.Sc., Universidade Federal de Viçosa, August, 2024. **Renewable Energy Consumption, Trade Openness and Agricultural Productivity in Africa**. Adviser: Leonardo Chaves Borges Cardoso. Co-adviser: Mateus de Carvalho Reis Neves.

This study examines the relationship between renewable energy consumption, trade openness and agricultural productivity in Africa. Specifically, the study examines the intensity of the type of renewable energy consumed in Africa; investigates the effect of renewable energy consumption on agricultural productivity in Africa and analyse the effect of trade openness on agricultural productivity via the consumption of renewable energy in Africa. In achieving this, the System Generalized Methods of Moments (SYSGMM) estimation technique is employed while also checking the robustness of the result using the cross section augmented distributed lag model estimation technique. The result from the study shows that hydro and low carbon type of renewable energy accounts for over 90% of the renewable energy consumed in Africa between 2000 and 2020. Also, the result from the study shows that there is a positive and significant impact of renewable energy consumption on agricultural productivity in Africa. Trade openness and agricultural productivity have a positive relationship as trade openness facilitates the importation of machines that uses renewable energy in the agricultural value chain system. Thus, encouraging policy actions and the intensification of the use of renewable energy improves agricultural productivity in Africa. At regional level and in the long run, renewable energy consumption has a positive and significant effect on agricultural productivity only in Central and Southern region of Africa. Also, at the regional level, trade globalization has a positive and significant impact on agricultural productivity by enhancing the deployment of machines that uses renewable energy in the agricultural productivity in Central and Southern regions of Africa in the long run, and in the Eastern and Western regions of Africa in the short run. The use of renewable energy in the agricultural value-added space requires the deployment of new and innovative equipment which are mostly imported into Africa just like the processing and irrigation equipment; and these guarantees increase in agricultural productivity and efficiency. There is the need for respective governments of African economies and international development partners to provide finance for farmers which encouragesimportation of renewable energy enabled agricultural machineries used for processing, irrigation, packaging, refrigerating, transport system, storage, and

handling value chains to guarantee improved agricultural productivity.

Keywords: Agricultural Productivity; Renewable Energy Consumption; Trade Openness

RESUMO

IWEGBU, Onyebuchi, M.Sc., Universidade Federal de Viçosa, agosto de 2024. **Consumo de Energia Renovável, Abertura Comercial e Produtividade Agrícola na África**. Orientador: Leonardo Chaves Borges Cardoso. Coorientador: Mateus de Carvalho Reis Neves.

Este estudo examina a relação entre o consumo de energias renováveis, a abertura comercial e a produtividade agrícola em África. Especificamente, o estudo examina a intensidade do tipo de energia renovável consumida em África; investiga o efeito do consumo de energias renováveis na produtividade agrícola em África e analisa o efeito da abertura comercial na produtividade agrícola através do consumo de energias renováveis em África. Para conseguir isso, a técnica de estimativa de métodos generalizados de momentos do sistema (SYS-GMM) é empregada, ao mesmo tempo que verifica a robustez do resultado usando a técnica de estimativa do modelo de defasagem distribuída aumentada de seção transversal. O resultado do estudo mostra que as energias renováveis hidroeléctricas e de baixo carbono representam mais de 90% da energia renovável consumida em África entre 2000 e 2020. Além disso, o resultado do estudo mostra que há um impacto positivo e significativo das energias renováveis. consumo de energia na produtividade agrícola em África. A abertura comercial desempenha um papel positivo e significativo ao permitir o fluxo de máquinas utilizadas para a utilização de energias renováveis no sistema da cadeia de valor agrícola; encorajar as acções políticas e a intensificação da utilização de energias renováveis melhora a produtividade agrícola em África. A nível regional e a longo prazo, o consumo de energias renováveis tem um efeito positivo e significativo na produtividade agrícola apenas na região Central e Austral de África. Além disso, a nível regional, a globalização do comércio tem um impacto positivo e significativo na ajuda aos fluxos comerciais, o que aumenta a utilização de energias renováveis e aumenta a produtividade agrícola nas regiões Central e Austral de África, a longo prazo, e nas regiões Oriental e Ocidental de África. no curto prazo. A utilização de energias renováveis no espaço de valor acrescentado agrícola exige a implantação de equipamentos novos e inovadores que são maioritariamente importados para África, tais como equipamento de processamento e irrigação na produção agrícola, uma vez que estes garantem o aumento da produtividade e eficiência agrícola. Há anecessidade de os respectivos governos das economias africanas e dos parceiros internacionais de desenvolvimento capacitarem os agricultores, facilitando a importação de máquinas agrícolas habilitadas para energias renováveis e fornecerem os fundos básicos necessários para adquirir essas máquinas nas áreas de processamento, irrigação, embalagem, refrigeração, sistema de transporte, armazenamento e lidar com cadeias de valor para garantir maior produtividade agrícola.

Palavras-chave: Produtividade Agrícola; Consumo de Energia Renovável; Abertura Comercial

LIST OF ILLUSTRATIONS

LIST OF TABLES

LIST OF ACRONYMS AND ABBREVIATIONS

AEO	Africa Energy Outlook.
ASEAN	Association of Southeast Asian Nations.
CSA	Climate-Smart Agriculture.
FAO	Food and Agriculture Organisation.
GDP	Gross Domestic Product.
IEA	International Energy Agency.
IRENA	International Renewable Energy Agency.
OECD	Organisation for Economic Co-operation and Development.
SAFF	Sustainable Agriculture Finance Facility.
SDGs	Sustainable Development Goals.
TWh	Terawatt-hour.
UN	United Nations.
UNFCCC	United Nations Framework Convention on Climate Change.
WTO	World Trade Organisaiton.

LIST OF SYMBOLS

$	Dollar.
%	Percentage.

SUMMARY

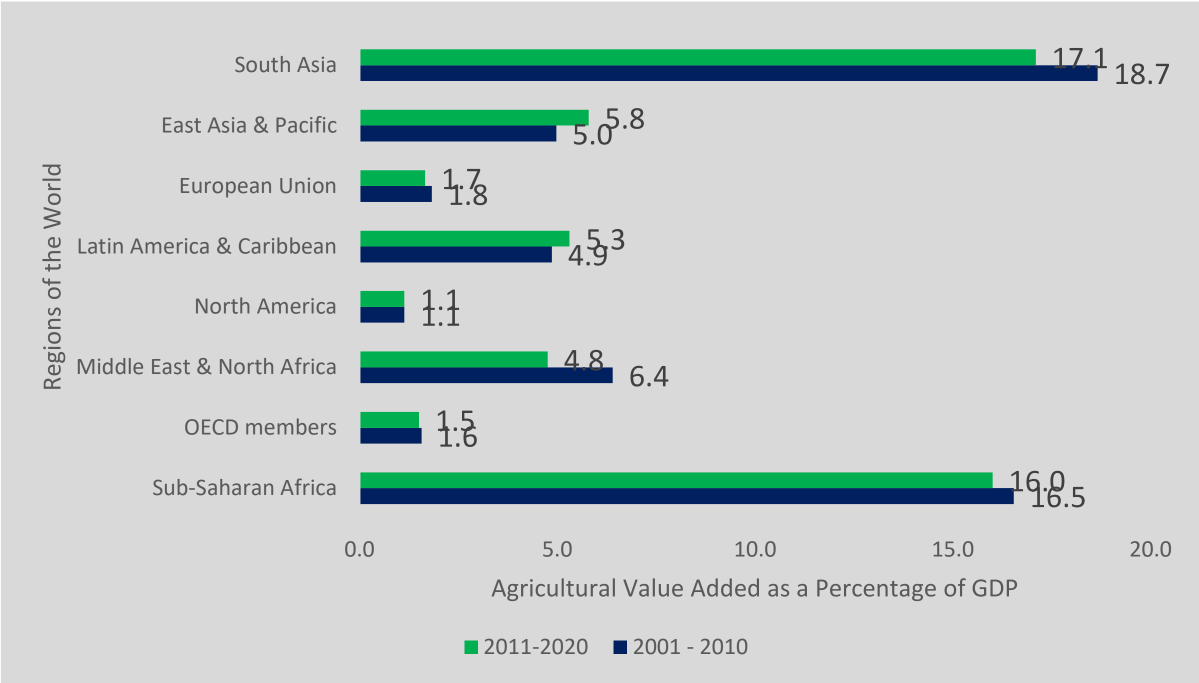
1. INTRODUCTION

This section introduces the theme of the study and thereafter, discusses the statement of the problem which also includes a background to how renewable energy consumption and trade openness affects agricultural productivity in Africa. The study investigates a link between renewable energy consumption and agricultural productivity. Also, how trade openness affects agricultural productivity and more importantly, how it affects the intensity to which renewable energy consumption affects agricultural productivity.

1.1. The Problem and its Background

Agriculture plays a significant role in economic growth and sustainable development of economies as it accounts for 4% of global gross domestic product; 25% of GDP in some least developing economies; 2 to 4 times more effective in increasing the income of the poorest when compared to other sectors; an efficient tool in ending extreme poverty; improve shared prosperity; feed projected 9.7 billion people by 2050; and improve food security for 80% of the world’s poor (World Bank, 2022a). It is one of the main reasons for human existence and does not only feed the population, but also provides raw materials to the industrial sector (Alston et al., 2009).

Figure 1. 1 - Regions' Agriculture Value Added (Share of GDP)



Source: World Bank (2022b)

In Africa, where the climatic condition and the natural habitat supports agriculture, it has continued to form the larger proportion of economic activities within the region as revealed from figure 1.1 which shows that apart from the South Asia, the Sub-Saharan Africa's agricultural contribution to GDP is the second largest for two decades. In the advanced economies, agriculture has contributed marginally to the economic growth process.

The increasing population growth rate of 2.71% within the region suggests that there is the need for the agricultural sector to increase its production capacity in order to feed them (The Economist, 2020). The agricultural sector in SSA accounts for the largest share of total employment. Between 2011 – 2020, the sector's employment share to total employment is 55%, this is 10 percentage points higher than the South Asia (World Bank, 2022b). Thus, agricultural productivity should be given greater attention. The growth in agricultural productivity suggests that there increase in labor productivity deployed in agricultural production. This can have an adverse effect on food insecurity due to the loss in labour income and consequently, increase in poverty. However, the deployment of innovative machines enhances the agricultural value chains which provides more employment opportunities for the masses (Hossain, 2008). Despite this, there are encouraging signs that African nations are once more recognizing the importance of agriculture as a key driver of growth, and not just growth but inclusive and more sustainable growth. The African Union's declaration of 2014 as the year of agriculture and food security in Africa is a testament to renewed commitment to this sector.

Globally, there has been the continuous increase in the demand for energy or energy use; this has been triggered by the continuous increase in population, advancement, and deployment of novel technologies in the production of goods and services (Nasreen & Anwar, 2014). In Africa, energy consumption increased by 155.6% between 1990 and 2019 (286.5TWh in 1990 and 732.4TWh in 2019) (IEA, 2022a) while that of the entire world increased by 129.7% between 1990 – 10,896.9TWh and 2019 – 25,027.3TWh (IEA, 2022b). Energy consumed in the Agricultural sector only accounted for 1.03% (2.95TWh) of total energy use in Africa in 1990 and this worsened to a meagre 0.84% (6.12TWh) in 2019 unlike the developed economies (OECD nations) in which energy consumed in agricultural sector accounted for 2.08% (758.94TWh) of the total in 1990 and remained 2.08% (914.1TWh) of the total in 2019) (IEA, 2022c).

Amongst other inputs required for agricultural production, energy consumption plays a significant role. With the mechanization of the sector, energy consumption is a vital component which contributes to agricultural productivity either directly or indirectly. The change in the pattern of agricultural production from human efforts to the use of machines directly requires significant quantum of energy for its successful operation (Kumar et al., 2018). Energy will be consumed directly while using tractors and it can also be used to heat or cool buildings, lighting on the farm, and indirectly in the fertilizers and chemicals produced off the farm (Schnepf, 2004). Thus, the quantum of energy used and that which is channeled to the agricultural sector is critical for growth and productivity of the sector. This presupposes that a significant relationship could exist between energy consumption and agricultural productivity. However, the type of energy use determines the efficiency of agriculture.

One of the global agenda of UN member countries is to achieve the 17 sustainable development goals (SDGs) by 2030. The second goal of this agenda seeks to "end hunger, achieve food security and improved nutrition and promote sustainable agriculture". The target 2.4 to be followed in achieving this goal is to "…ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality" (SDGs, 2022). UN posited that pursuing agricultural expansion is not only the target, but the pursuit of agricultural productivity, which is sustainable, environmentally friendly and improves social wellbeing. According to the agenda, only sustainable agricultural practices can end global hunger, achieve food security and improve nutrition.

Despite this target, Africa has been left behind in decreasing hunger and also poverty. Available data shows that about 38.9% of the populace are still leaving below US$1.90 per day compared to global average of 8.6% in 2018 while the prevalence of severe food insecurity in the population is 22.9% of the total population, unlike the global value of 9.5% for the same period (World Bank, 2022b). More also as will be later explored in the literature, agricultural productivity within the region has also been challenged by low returns on investment, greater risks of harvest failure due to technology adoption, imperfections in the market, knowledge deficit land grabbing and trade restrictions (Wiggins, 2015).

In pursuance of sustainable agriculture, developed economies have adopted the Climate-Smart Agriculture (CSA) system which seeks to achieve food security (Lipper et al., 2014). The CSA is poised with the objective of ensuring that farmers adopt integrated approaches that are sustainable and environmentally friendly; amongst which is the switch from dirty energy use to clean fuels and energy-efficient technology in agricultural production and at every agricultural value chain process (Vemeulen et al., 2012; CSA Guide, 2022; Lipper et al., 2014; Adeoye & Iwegbu, 2020). Also, renewable energy use will reduce environmental degradation thereby improve the environment and reduce the consequences of global warming on agricultural productivity. The implication of this is that SSA must begin to seek ways of using efficient energy sources in agricultural production, renewable energy is critical. Thus, the consumption of renewable energy consumption can be hypothesized to have significant impact on agricultural productivity.

The cost and scaling up of renewable energy remain massive, this has necessitated the continuous effort of development partners in ensuring that financial resources are provided towards the production of renewable energy and that farmers adopt environmentally friendly technology in agricultural production. The World Bank Group has continued to support these practices as they have committed US$8 billion in achieving CSA (World Bank, 2021). Brazil under the Integrated Crop-Livestock-

Forest (ILPF) program provided US$68 and US$62 million for the first two years as Sustainable Agriculture Finance Facility – SAFF (Embrapa, 2020).

Trade openness measures the extent to which an economy engages in trading activities with trading partners: this is a vital component that determines the extent of economic activities as well as agricultural productivity. Trade openness may affect agricultural production and its productivity via an increase in importation of machineries and capital equipment (Sadorsky,2012).

Available data from the FAO (2016) reveals that agricultural production improved consistently as the gross output in the sub-Saharan region increased from US$142 million in 2000 to US$225 million in 2016. Conversely, the sector has continued to experience a decline in foreign exchange earnings and merchandise export. The report by FAO (2016); WITS (2022) shows that the gross earnings in merchandise export in the region declined from 37.8% of GDP in 2008 to 24.3% of GDP in 2014 and further to 13.37% in 2019. Literature suggests that a major challenge to this declining nature of foreign exchange earnings from agricultural export which affects agricultural productivity has been attributed to the supply chain prevalent in the region. More notably, Ibrahim and Ajide (2020) asserted that too much of complications in trading because of various players involved, diverse standards, bureaucracy, protocols, high level of corruption and trade restrictions in most agricultural goods limit the extent of agricultural export in Africa. In light of the growing importance of trade, promoting measures that will ease trading, removal of restrictions, harmonizing nontariff barriers, improve custom modernization, reduce documents needed for exports, in a bid to engender and facilitate trade openness and globalization will certainly improve agricultural productivity within the region (Ibrahim et al, 2022). However, trade openness creates competitiveness which opens the economy to dumping with an adverse effect on the industrial sector. Despite this, the opportunity cost of trade liberalization in the agricultural sector is less compared to its gains in economies with much concentration on agriculture. The demand for agricultural produce by other countries will continue to lead to higher export and consequently affects agricultural productivity. This shows that trade openness can be hypothesized to have a significant effect on agricultural productivity.

Trade openness may also determine the extent of renewable energy consumed. Through trade openness and trade facilitation, developing economies can have access to renewable technology through importation which increases the consumption of renewable energy within Africa (Cole, 2006). Secondly, energy consumption can also affect trade openness; this is because energy serves as an important input used in production and with more consumption of it, output increases which then increases export (trade openness) (Nasreen & Anwar, 2014). Trade openness determines the extent to which agricultural products can be traded with other economies. Whichever way it is, trade openness will increase the intensity of the use of machines and the revenue from the sale of agricultural products. More importantly, as economies open their borders to trade, so also will the extent of energy use be affected within the agricultural sector. We therefore hypothesize that trade openness has a significant relationship with agricultural productivity and also determine the extent of renewable energy consumed for agricultural production.

1.2. Hypotheses

From the foregoing, this study tests the following alternative hypotheses:

H_1: Renewable energy consumption significantly affects agricultural productivity in Africa.

H_1: Trade openness has a significant mediating role in the renewable energy consumption – agricultural productivity nexus in Africa.

1.3. Primary Objective

The primary objective of this study is to examine the effect of renewable energy consumption and trade openness on agricultural productivity in Africa.

1.3.1. Specific Objectives

a) Examine the intensity of the type of renewable energy consumed in Africa.
b) Investigate the effect of renewable energy consumption on agricultural productivity in Africa.
c) Analyse the impact of trade openness on agricultural productivity via the consumption of renewable energy in Africa.

1.4. Justification of the Study

This study is justified by the urgent need to enhance agricultural productivity in Africa to address food security challenges and support sustainable economic growth. African agriculture faces significant productivity gaps due to limited access to modern energy sources and trade restrictions that hinder market access. Exploring the roles of renewable energy consumption and trade openness provides insights into pathways that can sustainably elevate agricultural output, reduce poverty, and foster resilience to climate change. Renewable energy offers a sustainable solution to power agricultural processes, while trade openness allows farmers to reach broader markets, enhancing income and productivity. By investigating these factors, this study can inform policies that support agricultural transformation, economic development, and environmental sustainability in Africa.

Renewable energy is critical in the agricultural sector. Conceptually, Dalberg (2018) noted that the productive use of solar energy can be deployed for irrigation, threshers, land preparation, mills, drying, chilling, night fishing, cold, milking, oil presses, egg incubators and electric fences. As innovation in solar-adapted agricultural equipment increases, economies in Africa and global donors such as World Bank have emphasized on the need to use such in engineering agricultural transformation to create value addition; enhance agro-processing; improve mechanization; and reduce post-harvest losses. To the best of our knowledge, there are scanty empirical evidence that has investigated how renewable energy consumption affects agricultural productivity in Africa. Thus, this study intends to provide empirical evidence to the growing debate.

Current energy debates emphasize on the need to develop and deploy sustainable energy driven machines in all sectors to protect the environment amidst the global climate change. This has been further reinforced by the United Nations Framework Convention on Climate Change (UNFCCC) with 198 countries agreeing to prevent dangerous human interference with the climate system. In this agreement, 48 African countries are signatories (UN, 1992). This study thus provides empirical evidence on how the use of renewable energy, a climate friendly energy source can affect the productivity of Africa’s Agricultural sector which create a unique set of impact mechanisms, creating multiplier effects on poverty reduction, income generation and growth in the real economy.

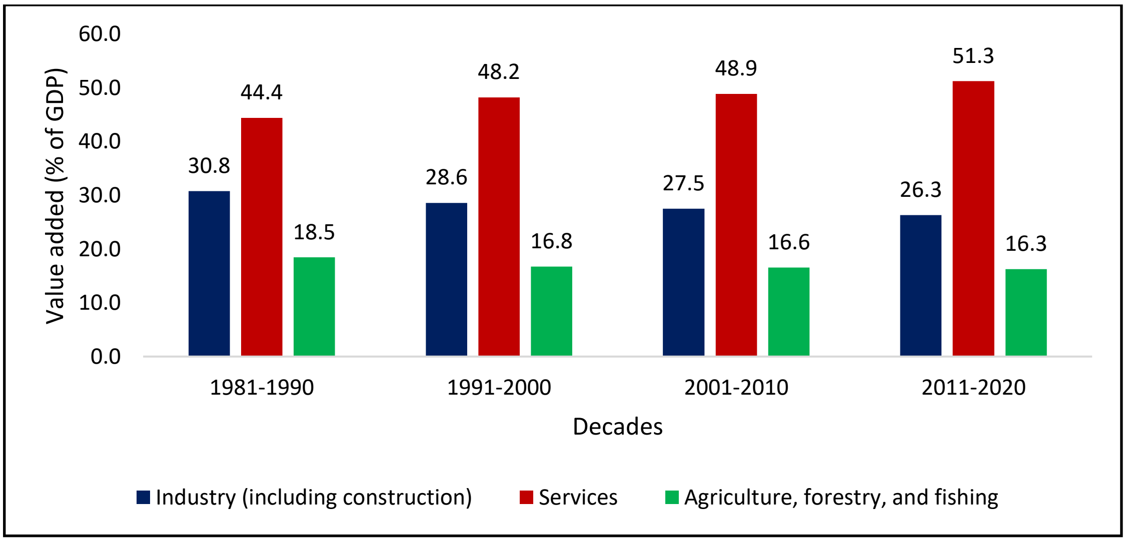
2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. A Review of Africa's Agricultural Sector and its Productivity

Agricultural productivity in Africa over the decades has been a major concern because of the intensive use of labour on the arable lands across the continent; another major reason for placing much emphasis on agricultural productivity in the region is because of its gradual decline in the past decades. Since the 2003 Maputo Declaration, agricultural growth and increase in productivity has become a major concern for policy makers at both country specific and the continent (Wiggins, 2015; Nwokoma et al, 2021). Another major reason for considering the productivity of the agricultural sector in Africa is because of its economic growth enhancing role. ACET (2014) noted that economic growth in Africa is largely due to primary production and increase in commodity price in the latter half of the 2000s with however, little changes in the structure of the economy.

As shown in figure 2.1, SSA economies is predominantly composed of the services sector since the last four decades by contributing an average of 44.4% between 1981 and 1990; and an increase to 51.3% between 2011 and 2020. However, despite the large arable land, agriculture has contributed a meagre 18.5% between 1981 and 1990 and further declined to 16.3% between 2011 and 2020 on average.

Figure 2. 1 - Structure of the Sub-Saharan Africa economies



Source: Author's sketch using data from World Bank (2022b)

Nin-Pratta and Fuglie (2013) explained that prior to the 1980s, agricultural productivity largely came from intensive use of land and labour, although other factors such as fertilizers, improved seedlings and energy use have contributed to productivity, it has remained relatively low and declined overtime. The report by ACET (2014) noted that the agricultural sector has witnessed slow productivity growth. Cereals production has grown far more slowly in Africa when compared to the industrialized part of Asia and Latin America. With respect to land productivity determining agricultural productivity, little emphasis can be placed in the case of Africa unlike Asia counterpart because Africa has a less densely settled parts than that of Asia. Despite this, Nin-Pratt and Fuglie (2013) documented that whether land or labour contributes to agricultural productivity in Africa, its growth has been modest since the 1990s. several studies have concluded that factor productivity growth emerges as an important driver of agricultural growth after the mid-1980s owing to policy reforms which promoted factor inputs needed for production. Future agricultural growth will increasingly depend on energy use deployed in machineries due to technological change, which will require greater investment in agricultural research and development, rural infrastructure, and education.

2.2. Challenges of Agricultural Productivity in Africa

Agricultural productivity in Africa has suffered many limitations and this has limited its growth; these will be examined in the points below.

2.2.1 Inadequate Technology Deployment

Inadequate deployment of technology used for local farming in Africa and in relation to the type of crops grown in the region has hampered agricultural productivity. In Africa, the farming system is dependent on rain feeds and thus, cultivation often occurs in semi-arid lands which breeds infertile soils thereby affecting productivity (Teye & Quarshie, 2022). These lands are in contrast to the well-irrigated alluvial floodplains for which the first round of improved Green Revolution crop varieties was bred. During the early stages of the Green Revolution, very little research was conducted by Africans on the wide variety of crops they produced such as roots and tubers and plantains, millets and sorghum. Thus, underinvestment in agricultural research and development due to inadequate fund limited the technological innovation that should have helped in improving Africa's agricultural productivity (Lipton, 2012). Although, substantial improvement has been made on techniques deployed in farming system (Larson et al., 2010; Nin-Pratt & Yu, 2010), empirical evidence through village surveys show that there exist large variations in yields from different farmers' fields which also corroborates to the fact that many farmers obtain lower yields than technically can be achieved in local conditions.

2.2.2 Low Returns on Earnings

For productivity to improve substantially, there is the need to intensify the deployment of inputs such as labour, energy use, irrigation and machinery. In some cases, this action pays-off as this will increase production; however, Africa is characterized with high transport costs thereby increasing the cost of external inputs, reduces output prices at the farm gate and directly reduces returns on investments (Cairns et al, 2021). Livingston et al. (2011) opined that average road transport costs are relatively high in Africa than Asia. In Uganda, Gollin and Rogerson (2014) found that a decline in rural transport costs significantly boosts agricultural productivity. Dercon et al. (2009) found that improved all-weather roads in the rural part of Ethiopia is a panacea for poverty reduction by almost 7% with consequential increase in consumption by 16%. Again, the huge tax on agricultural production in Africa between 1970s and 1980s negatively impacted on the returns on investment; however, after the economic reforms between 1980s and 1990s, the extent of the tax burden on investment opportunities in the agricultural sector declined (Benson & Mogues, 2018; Lloyd at al. 2009; Krueger & Valdés, 1991).

2.2.3 Adoption Risks

Technological adoption in a bid to improve agricultural productivity comes with significant risk and in most cases, risk averse farmers who prefers to produce crops that has lower mean returns but with lower variance compared to risk lovers prefers not to take risks, this leads to low returns and productivity. Substantial risks involved in agricultural production include risk of harvest failures which are occasionally caused by pests and diseases; bad weather; environmental impact due to the type of energy used; and crash in output prices (Guodaar et al., 2021). The risk averse farmers are reluctant in investing in better seed, improved energy use and fertilizer that would generally raise net returns, and a significant risk of harvest losses affects productivity

(Etwire et al, 2013). Empirical evidence of this factor is established in the findings of Dercon and Christiaensen (2011) who argued that Ethiopia farmers limited the use of fertilizer as there were notices of poor weather which led to poor harvests, reduction in consumption and ultimately, made net loss during sales.

2.2.4 Market Failures

Despite the existence of insurance markets for farmers to mitigate risks, market failure is often associated with risk loving farmers. The existence of imperfect rural market for inputs, non-existence of insurance or credit market affects agricultural productivity (Jones et al, 2022). The absence of information regarding agricultural products and services to bankers and suppliers results in market failure. More importantly, lack of information about farmers' character, competence and credit rating affects agricultural productivity and leads to costly information (Meyer, 2015). With these limitations associated with information, service providers in the agricultural sector cannot effectively provide services thereby limiting the potential demand (Poulton et al., 2006). As a result, many smallholder farmers cannot obtain inputs locally which are of good quality and at favourable price reflected in the costs of production and distribution margins (Omamo 2003).

Commercial and development banks in the rural areas in Africa have limited the provision of loans and credit facilities to farmers because such institution perceive many risks associated with their production process because of insufficient information relating to farmers' credit worthiness. Despite the growing deployment of technology in agricultural production, the unavailability of insurance and credit, and increase in risks associated with production threatens to trap many farmers in poverty and limits their productivity (Carter & Barrett, 2006).

2.2.5 Land Disputes

Many lands in Africa do not have legally defined property rights or formal titles as family land ownership system is mostly practiced in the rural settlements where agriculture is mostly practiced. For such rural farmers, the land they cultivate in are under some form of collective tenure system where farmers do not have permanent rights to the land and thus, they cultivate in them so long as they are resident but do not have the legal right to dispose off the land or transfer it (Berry, 1993). The unavailability of these well-defined property rights limits the ability of farmers to use the land as collateral in securing loans and credit facilities. Thus, many investors are constrained to provide credit facilities because of the fear of the inability to recoup their funds in the event of insolvency (Msokwe & Mbonile, 2021).

Empirical evidence that shows the extent to which collective tenure land system practiced in Africa affects agricultural productivity abounds. Some of the studies concluded that the collective land tenure system does not affect agricultural performance (Place & Hazell, 1993; Besley, 1995; Place & Otsuka, 2002; Mulungu & Myeya, 2018) while others found that the collective land tenure system negatively affects agricultural productivity (Goldstein & Udry, 2008; Deininger & Ali 2008; Msokwe & Mbonile, 2021). Despite these mixed findings, it can be argued that the degree of security attached to land ownership to a significantly affects productivity to an extent.

2.3. Poor Access to Energy Supply: The Role of Renewable Energy in Africa's Agricultural Productivity

Africa's population growth rate since 2000 on average was 2.5% each year and has grown faster than the rest of the world and more than twice the global rate. With more than 1.3 billion people as at 2020 accounting for about 20% of the world population and Egypt, Nigeria, Democratic Republic of Congo and Ethiopia accounting for 40% of the population, rapid demographic change will continue to drive the demand for energy (AEO, 2022). Further evidence shows that 750 million (55% of the entire population) people are living in rural areas as at 2020 making it one of the least urbanized parts of the world. These people face less access to basic services which includes energy, economic opportunities, and transport connections amongst others (Mapzen, 2017). AEO (2022) reveals that 565 million of Africans still do not have access to electricity and with most of them involved in rural agricultural activities, it becomes difficult to adopt energy-driven technologies which are needed to drive agricultural productivity. Although the energy demand in the agricultural sector accounts for less than 10% of total energy demand for productive uses, total energy consumption for productive uses across Africa is projected to rise by 33% between 2020 and 2030 making it important for energy demand to be readily available in the agricultural sector (AEO, 2022; Adenle, 2020). The poor supply of modern energy has limited the modernization of agriculture in staple food processing, conservation of cooked food, and animal house electrification (FEMA, 2006).

FEMA (2006) noted that increasing the traditional source of energy using the grid system to the rural areas is difficult because of the huge investment that is required in generation, transmission and distribution of the system to these areas. Also, because of the low density of people, it is difficult for these poor people to pay for a single-phased connection. For example, AEO (2022) reported that almost 45% of the population that had access to electricity in the sub-Saharan Africa were only via the grid connections while rural communities of more than 200 inhabitants are near a road, but more than 10km from a main grid, thus, the mini-grids system and stand-alone prevails in most of such situations. Out of the remaining that are gaining access to the stand-alone, 70% of them are renewables based and this is because of the continuous increase in the prices of diesel and other installation costs making renewable sources of energy an alternative and a cheaper source of energy. Furthermore, fall in relative costs and pro-usage policies enhances the use of renewables; this action has enhanced opportunities to exploit Africa's huge domestic potential for renewables. The continuous investment in renewable energy is expected to continue as the share of solar and wind to total power generation in Africa soars from 3% in 2020 to 27% in 2030 – close to levels in many parts of Europe today and this will be eight-times more than in 2020 (AEO, 2022).

Schützeichel (2017) noted that solar powered irrigation is very critical in promoting crop yields in Ghana and Kenya. Many of the small holder farmers were able to adopt the solar powered irrigation pump in resolving the frequent drought and unreliable rainfall experienced in Kenya. The use of renewable energy has helped small household farmers to gain access to mobile phones, TV and radio which provides crucial information in enhancing the delivery of better agricultural extension services and improved agricultural productivity for rural communities (Azimoh et al., 2015; Ulsrud et al., 2015; Schützeichel, 2017; Adenle, 2020).

2.4. Trade Openness in Enhancing Agricultural Productivity

In Africa, over 63% of the population lives in rural areas (World Bank, 2014) with most of them engaged in agriculture and manufacturing. Between 2011 – 2020, the sector's employment share to total employment is 55%, this is 10 percentage point higher than the South Asia (World Bank, 2022b). Thus, the agricultural sector is important in promoting employment and poverty reduction. Given the relevance of the sector, it is important that policies which can ensure its greater productivity are adopted. More notably, the sector's productivity is enhanced through increase in its local and international demand (Abizadeh & Pandey, 2009). Zahonogo (2016) noted that countries which are open to trade as well as promote policies which enhances trade relations are likely to perform better than others as trade relations ensures the export of own countries' products and easier importation of critical factor inputs needed for production. With many Africans engaged in agricultural activities Ibrahim et al. (2022) suggests that trade openness promote agricultural efficiency.

Trade openness guarantees the harmonization of nontariff barriers; promotion of port efficiency; upgrading of logistics and transport services; and ease of border crossing (Ibrahim et al., 2014). This was further demonstrated in the World Trade Organisation (WTO, 1994) Agreement on Agriculture (AoA) as they were committed in eliminating trade restrictions, distortions of inefficiency and thereby, double agricultural productivity (Sunge & Ngepah, 2020). More notably, Shu and Steinwender (2019) alluded to the fact that that international trade speeds up the rate of technological transfer and innovation which guarantees enhanced total factor productivity growth; this is further corroborated by Shaik and Miljkovic (2011); Hart et al. (2015) as they relate to trade policy and technical efficiency theories. According to Miljkovic et al. (2013), trade liberalization through increase in export of agricultural products increase farmers' income but can adversely affect the intensity of the deployment of technology towards enhancing productivity. As such, they concluded that trade liberalization does not promote agricultural productivity. In whichever form this is considered, FAO (2017) noted that through various regional bodies established in Africa (SADC, ECOWAS, COMESA, EAC), existing trade treaties has helped in expanding cross agricultural trade thereby improving the sharing of knowledge and technological transfers.

2.5. Theoretical Literature

Ayres and Warr (2009) noted that labour and capital are not sufficient in explaining growth as empirically proven using the US economy where the Solow residual accounted for 85% of output growth (Solow, 1956). Thus, the Neoclassical theory proposes that technological progress is critical and the only variable that explains growth. The consideration of energy use as a part of technology used in production gained much attention after the oil glut of 1973 – 1974 where economists were more interested in examining how energy consumption can affect the economy

(Streimikiene & Kasperowicz, 2016). Jorgenson (1984) thereafter introduced two more factors of production to the Neoclassical exposition, energy and materials. They argued that energy consumption is important in converting raw materials to final products and necessary in the agricultural value chain. This led to the wide acceptance that energy consumption plays a significant role in economic activities of which the agricultural sector is critical.

There are four hypotheses that have been tested in energy consumption cum economic growth relations which can also be used for the case of agricultural productivity for economies that largely depend on agricultural production. The growth hypothesis postulates that energy consumption causes improvement in economic activity (Tugcu et al., 2012). The neutrality hypothesis proposes that there is no causal relationship between economic activities and energy consumption (Menegaki, 2011). Thirdly, the conservation hypothesis states that a decrease in energy consumption will have little or no effect on economic activities (Sadorsky, 2009). The feedback hypothesis states that energy consumption increases economic activities and at the same time, economic activities increase energy consumption (Apergis & Payne, 2011).

2.6. Empirical Literature

Chopra et al. (2022) employed the Pooled Mean Group (PMG) estimation technique and the result shows that carbon emission is detrimental to agricultural productivity in the region. Also, natural resource rent negatively affects agricultural productivity while renewable energy consumption has a significant and positive effect on agricultural productivity. In this study, agricultural productivity was measured using the agricultural value added per capita. Chopra et al. (2022) corroborated the findings of Khan et al. (2020); Jebli et al. (2020) who noted that renewable energy consumption helps in reduction of environment degradation which positively enhances economic activities.

The empirical reviews provide a limited view of the complex relationships between renewable energy consumption, trade openness, and agricultural productivity. While some literature suggests potential positive links, the evidence is not conclusive, and further research is needed to fully understand these dynamics. Miljkovic et al. (2013) found no statistically significant impact of trade openness on technical efficiency in Brazilian agriculture, suggesting that trade liberalization might not necessarily translate into increased efficiency. They attribute this to the fact that primary markets for Brazilian agricultural commodities remain domestic, possibly due to protection from foreign competition. Conversely, Jebli et al. (2020) suggest a strong causal relationship between agricultural value added and trade openness in Tunisia. They argue that increasing international economic exchanges could provide new opportunities for the agricultural sector to develop and benefit from technology transfer, potentially leading to increased productivity. The contrasting findings from these studies underscore the complexity of the relationship between trade openness and agricultural productivity. Factors such as market dynamics, trade policies, and the nature of technology transfer likely play a role in determining the impact of trade liberalization on agricultural efficiency.

Considering the relationship between renewable energy and agricultural productivity, empirical reviews did not directly link renewable energy consumption to improved agricultural productivity. However, Jebli et al. (2020) advocate for increased renewable energy use in the agricultural sector, suggesting that it could enhance competitiveness in international markets while reducing pollution and mitigating climate change. Waheed et al. (2020) highlights the importance of renewable energy for reducing CO2 emissions in Pakistan, suggesting that increasing renewable energy usage can contribute to a less carbon-intensive agricultural sector. These benefits include reduced reliance on fossil fuels, soil contamination prevention, and potential cost savings. It is possible that these advantages could indirectly contribute to increased agricultural productivity, although this requires further investigation.

The existing literature focus on specific country contexts (Brazil, Tunisia, Pakistan) or specific sectors (e.g., solar energy); this limits the generalizability of their findings. Additionally, the reviews focus on the environmental benefits of renewable energy without directly quantifying its impact on agricultural productivity. Empirical studies should explore the specific mechanisms by which renewable energy adoption translates into enhanced agricultural output. For instance, studies could investigate how renewable energy impacts factors such as irrigation efficiency, input costs, and crop yields. Research should also consider the potential impact of renewable energy on agricultural labor productivity.

Gorjian et al. (2021) using case study method of investigation examined the consequences of deploying the Photovoltaic (PV) solar energy conversion technology with electric farm tractors and agricultural robots on sustainable farm production. The results from the findings show that its deployment guarantees sustainable powering of farm activities. However, it has suffered several challenges such as high initial costs and deficiencies in electricity storage technologies. In a related-research, Adenle (2020) conducted a meta-analysis in corroboration with expert interviews to understand the role of renewable energy sources like solar energy on Africa's sustainable development. The study found out that in Ghana, South Africa and Kenya, renewable energy sources are crucial for achieving sustainable development through enhanced delivery of improved agricultural extension services as well as improved agricultural productivity for the rural communities. More importantly, solar energy is largely deployed in Eastern Africa as it currently has 34% share of solar energy projects while the Western and Northern Africa are the least.

There is no empirical consensus on the impact of trade openness on agricultural productivity. Abizadeh and Pandey (2009) examined the effect of trade openness on the productivity of agricultural, industry and services sector for 20 OECD member countries between 1980 and 2000. Using the panel ordinary least squares, the result from the study shows that trade openness has a negative effect on agricultural productivity and industrial sector productivity. However, it has a positive impact on services sector productivity. World Bank (2019) in another related study on the market opportunity for productive use leveraging on solar energy in sub-Saharan Africa using case study style of investigation in Kenya, Zimbabwe and Cote d'Ivoire found that the use of solar energy in Zimbabwe was enhanced due to the 40% removal of import duty on solar products and this aided agricultural production. Although, the study noted that limited access to finance and land reforms have affected agricultural production, Iwegbu and de Mattos (2022) noted that the agricultural sector is enhanced among BRICS and WAMZ member countries through the provision of credit facilities in a well-developed financial system. In Cote d'Ivoire, the reduction of value added tax from 18% to 9% for solar products enhanced the use of solar energy. Also, the deployment of solar driven dryers could reduce losses and time spent in cassava and rice processing. In Kenya, the use of solar irrigation pumps is growing rapidly and this has affected agricultural efficiency. The result found that the use of horticulture irrigation which is solar driven caused 204% and 140% two-year returns on investment in Kenya and Zimbabwe respectively.

In a related research, Waheed et al. (2018) examined the impact of renewable energy consumption, forest cover and carbon emissions on Pakistan's agricultural productivity for the periods between 1990 to 2014. The study employed the Autoregressive Distributed Lag model estimation technique and the result from the study shows that renewable energy consumption and forest cover have negative effect on emissions while agricultural activities positively deepen the extent of emission. The study however did not examine the relationship between renewable energy consumption and agricultural productivity of which this study intends to provide empirical evidence on the study. In another related research, Jamil et al. (2016) noted that renewable energy deployment in the oil-rich Saudi Arabia has the capacity to reduce carbon emission thereby enhancing environmental quality.

The studies by Vural (2020) examined the relationship between non-renewable energy consumption, renewable energy consumption, trade and economic activities in eight Sub-Saharan countries. The result shows that trade and renewable energy consumption significantly increases and decreases carbon emissions respectively. Similarly, Zaman et al. (2022) used data spanning the period 1991 to 2015 for Pakistan economy to show that agricultural production, female employment, renewable energy consumption negatively influences carbon emission. The study employed the ARDL model in achieving the objective.

The study by Raeeni et al. (2019) examined how energy consumption affects the growth of Iranian agricultural sector and export. The study employed the granger causality tests and cointegration analysis to examine the objective. The result from the study shows that energy consumption has a uni-directional relationship with agricultural growth while there is no relationship between energy consumption and export of goods. Other studies that have also verified the direct relationship between energy consumption and economic growth also include Destek (2016); Streimikiene and Kasperowicz (2016); Altinay and Karagol, (2005); Lee and Chang (2008); Adebola (2011).

Empirical literature also exists on the impact of trade openness on agricultural performance. Milkovic et al. (2013) examined the impact of trade openness and technical efficiency on Brazilian agriculture. The study used the Stochastic Frontier Analysis (SFA) and the result from the study shows that trade openness does not significantly impact on the technical efficiency of Brazil’s agricultural sector because the increasing pressure with competition from Asia is limiting the enlarging of Brazil’s agricultural export.

The study by Nasreen and Anwar (2014) examined how trade openness could determine the extent of energy consumption in 15 Asian economies. The study employed fully modified ordinary least squares (FMOLS) estimation technique and the result shows that there is a significant impact of trade openness on energy consumption of 10 out of the 15 Asian countries examined.

Shuddhasattwa et al. (2015) examined the impact of trade openness and energy use on agricultural production of medium, low and high-income economies. The study employed the Polled Mean Group (PMG) analysis in estimating the result and the result found out that non-renewable energy consumption significantly affects pollution.

3. METHODOLOGICAL FRAMEWORK

3.1. Conceptual Framework

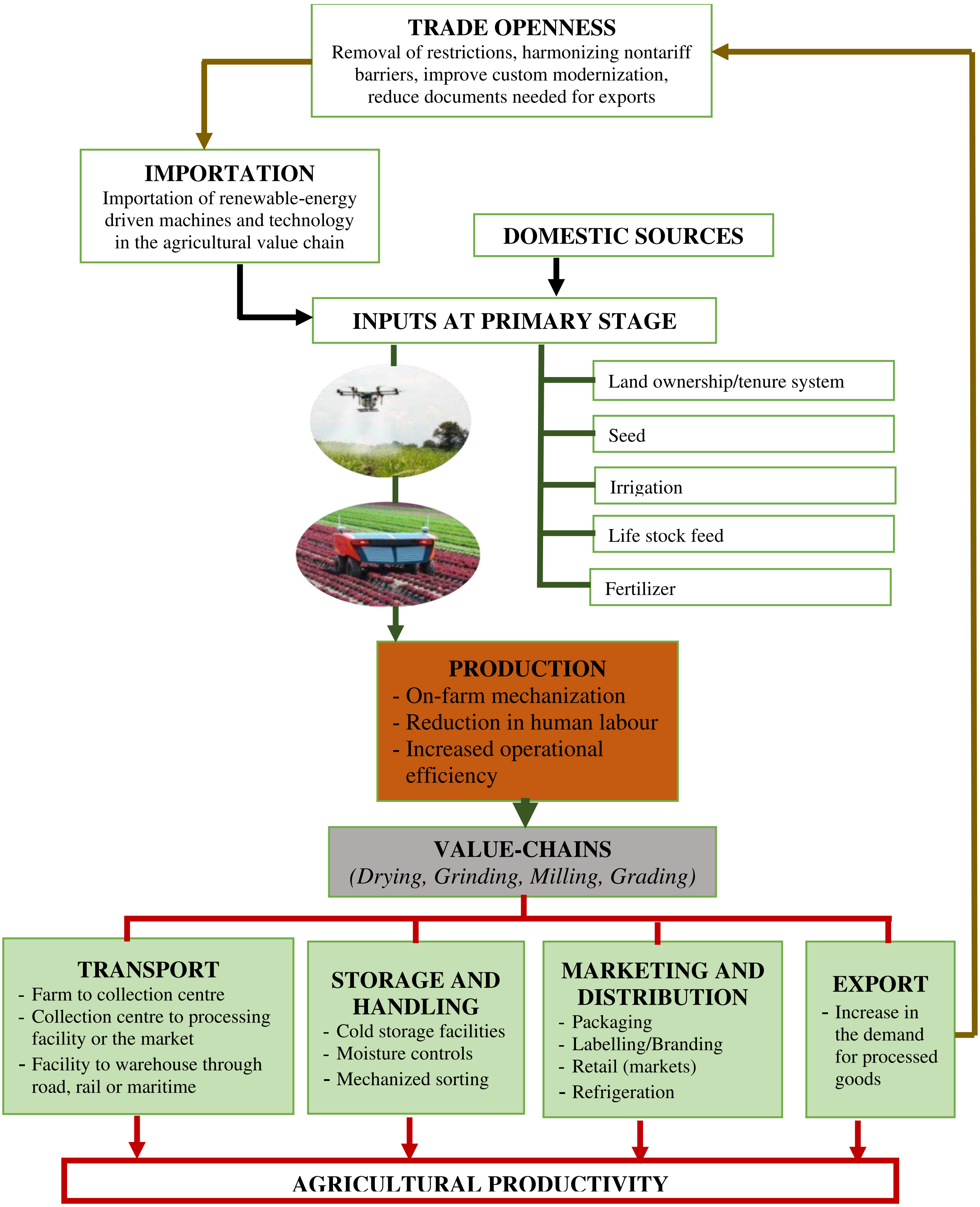
We adapt the conceptual framework of Taghizadeh-Hesary et al. (2019) who proposed that energy, especially renewable energy plays a critical role in the agri-food chain mechanism as it is relevant not only in the primary production stage, but in secondary activities such as drying, storage, transport, drying and distribution. The modification made in the framework proposes that due to the weak development of technology in Africa, trade openness strategies that allows the ease of importation of essential machineries, renewable-energy driven machines and technology into Africa promotes agricultural productivity. Also, through trade openness exportation of agricultural products becomes easier and will also enhance agricultural demand cum productivity.

Figure 3.1 shows that the removal of trade restrictions, harmonization of nontariff barriers, improving custom modernization and reduction of documents needed for exports enhances the importation of renewable-energy driven machines and technology in the agricultural value chain, this is used as an input and in the value-chain process post-primary stage. Other sources of input as shown in figure 3.1 comes from the domestic sources – land used in production, seed, life stock feed and the deployment of fertilizer. The deployment of renewable-energy driven machines increases the consumption of renewable energy. During the farming stage, solar powered irrigation systems are used for irrigation such as the Knowing Water Better (KnoWat) solar-powered irrigation system project deployed by FAO in Rwanda. The empirical evidence shows that the KnoWat was able to increase efficiency and reduce manual labour thereby supporting livelihoods in the district. (FAO, 2021).

In the post-cultivation era, different value-chain processes are employed in order to increase the productivity of the various agricultural products. For example, in Uganda, flour mill, grader/de-stoner, dal mill and dough mixer solar-powered food processing machines are deployed during grinding, drying and milling of agricultural products (SELCO Foundation, 2018). In Nepal, new micro hydropower plant has been deployed and this made it possible to open an agro-processing plant (World Bank, 2019); while in Kenya, the Solar-powered milling machines are deployed (Musinguzi, 2021). Renewable energy is also important in the transportation value chains that involves the conveying of agricultural products from the farm to the collection centre and to the processing facility. In the storage value chain process, solar-powered storage facilities which are energy efficient are employed in food preservation. An example of this is the solar-powered cold stores that are available in Kenya (GCCA, 2018).

The deployment of renewable energy efficiency machines cum renewable energy consumption in the transport; storage and handling; and marketing and distribution value chain enhances agricultural productivity. The easing of restrictions and increases in the demand for processed agricultural products lead to increase in export. Thus, the conceptual framework suggests that trade openness and renewable energy consumption affects agricultural output.

Figure 3. 1 - Renewable Energy, trade openness and agricultural productivity framework



Source: Adapted from IRENA (2021); GRDC (2020); Gorjian et al. (2021)

3.2. Theoretical Framework and Model Specification

The theoretical framework that supports this study is the Solow Neoclassical growth model. The core of the Solow model emphasizes that in the steady state, output per capita is exogenously determined by the growth rate level of technological progress and this is exogenously determined. Thus, the productivity of output is determined by technological progress. Consider a Cobb-Douglass production function where Y_t is output, K_t is capital, A_tL_t is effective labour, α and $1-\alpha$ are output elasticities of capital and labour respectively. Having the understanding that agricultural output is a component of the aggregate output. We make an assumption that the output (Y_t) can be replaced with agricultural output (AGR_t).

$$AGR_t = K_t^{\alpha}\left(A_tL_t\right)^{1-\alpha} \quad (3.1)$$

The starting point is to determine the key equation of the Solow model $(\dot{k})$. We assume that the initial levels of capital, labour and technical knowledge are taken as given and that labour and knowledge grows at a constant rate. The growth rates, *n* and *g* are exogenously determined. Following the basic fundamental macroeconomic identity which states that $Y(t)=C(t)+I(t)$, $C(t)$ is the consumption in time t and $I(t)$ is the investment in time t. We further specify that the private savings is defined as $S(t)=Y(t)-C(t)$. The simple assumption to make again is that private saving is proportional to income and so, we state that $S(t)=sY(t)$ and s is the marginal propensity to save $s\in(0,1)$. We substitute $Y(t)$ into $S(t)$, $S(t)=C(t)+I(t)-C(t)$ .We further assume that capital depreciates at a constant rate which is defined by δ. The gross investment is used to acquire new machines as well as to replace the depreciated capital. We thus have it that $I_t = K_t + \delta K_t$ and $K_t = I_t - \delta K_t$. The dynamic capital stock will be $\dot{K}_t = I_t - \delta K_t$. So, since we know the evolution of technology (g) and labour dynamics (n) which are exogenous, then we need to study the evolution of capital to determine how output is determined. Since the economy grows over time, we can then focus on the auxiliary variable capital stock per unit of effective labour κ than the unadjusted capital stock. Taking the log of both sides, the derivative of both sides with respect to time and some substitutions, the key equation of the Solow Model is defined as (see appendix 1 for mathematical derivation procedure):

$$\dot{\kappa}_t = s\kappa_t^{\alpha} - (n+g+\delta)\kappa_t \tag{3.2}$$

We can derive the steady-state level of capital stock per unit of effective labour (κ^*) recalling that at the steady state, $\kappa = \kappa^*; \dot{\kappa}_t = 0$. Substituting this (see appendix 2 for mathematical derivation procedure), we have it that:

$$\kappa^* = \left(\frac{n+g+\delta}{s}\right)^{\frac{1}{\alpha-1}} \tag{3.3}$$

With equation (3.10), we can then find the steady state level of output per unit of effective labour (y^*) which is a proxy to measure output productivity. At the steady state, $\kappa = \kappa^*; \dot{\kappa}_t = 0$ and $\kappa^* = \left(\frac{n+g+\delta}{s}\right)^{\frac{1}{\alpha-1}}$

$$y^* = \left(\frac{n+g+\delta}{s}\right)^{\frac{\alpha}{\alpha-1}} \tag{3.4}$$

Equation (3.4) is our equation of interest. The equation explains that output productivity is dependent on the growth rate of population, the growth rate of technological progress, the depreciation rate, output elasticities and the savings rate. Since agricultural output is a component of the aggregate output; having made an assumption that the output (Y_t) can be replaced with agricultural output (AGR_t), we can further extend the assumption that output productivity (y^*) can be replaced with the agricultural productivity ($agricpro$). Equation (3.4) therefore becomes:

$$agricpro = \left(\frac{n+g+\delta}{s}\right)^{\frac{\alpha}{\alpha-1}} \tag{3.5}$$

We propose that for investment to be beneficial to agricultural productivity, the investment growth rate must be able to at least cover the depreciation rate; and we then say that δ = investment growth rate (inv). We understand that technological progress can come in the form of the deployment of more efficient machines that are energy friendly as well as the use of renewable energy in farming and the value chain process (World Bank, 2019; SELCO Foundation, 2018). More convincingly, Chopra et al. (2022) have shown that renewable energy consumption guarantees improved agricultural productivity in the ASEAN countries and developing economies respectively. Thus, our interest with respect to the growth rate of technological progress is the extent of the consumption of renewable energy. Thus, we propose that g = renewable energy consumption (renegy). Let n = population growth rate (popgr), s = savings rate (sav); thus, a linear transformation of equation (3.5) is extended to become:

$$agricpro = f\left(renegy, popgr, sav, inv\right) \tag{3.6}$$

We further modify equation (3.6) by adapting the framework deployed by Hassine and Kandil (2009) who opined that agricultural productivity is enhanced through trade openness. Thus, equation (3.6) becomes:

$$agricpro = f\left(renegy, top, popgr, sav, inv\right) \tag{3.7}$$

However, we slightly differ from the model specified by Hassine and Kandil (2009) and adopting the framework of figure 3.1 to propose that the effectiveness of renewable energy consumption is enhanced through trade openness because the uniqueness of Africa is such that most of the technologies are imported and as such, removal of restrictions, harmonizing nontariff barriers and improvement of custom modernization will enhance the use of renewable energy in agricultural value chain. Thus, we introduce the interactive effect in equation (3.7) to become:

$$agricpro = f\left(renegy, top, popgr, sav, inv, top.renegy\right) \tag{3.8}$$

In ensuring a robust capturing of factors that determines agricultural productivity, we extend equation (3.8) by adapting the models as specified by Chopra et al. (2022); Echevarria (1998) by introducing fertilizer use $(fert)$, pesticide use $(pest)$, exchange rate $(exch)$, price level (prl), emissions (emi) and credit to agricultural sector $(creagr)$ to equation (3.16) and thus, this becomes:

$$agricpro = f\left(renegy, top, popgr, sav, inv, top.renegy, fert, pest, exch, prl, emi, creagr\right) \tag{3.9}$$

Bearing in mind that a panel study is been considered in this study, we modify equation (3.9) by writing them out explicitly in an econometric form to become:

$$\begin{aligned} agricpro_{i,t} &= \varphi_0 + \varphi_1 renegy_{i,t} + \varphi_2 top_{i,t} + \varphi_3 popgr_{i,t} + \varphi_4 sav_{i,t} + \varphi_5 inv_{i,t} \\ &\quad + \varphi_6 top_{i,t}.renegy_{i,t} + \varphi_7 fert_{i,t} + \varphi_8 pest_{i,t} + \varphi_9 exch_{i,t} + \varphi_{10} prl_{i,t} \\ &\quad + \varphi_{11} emi_{i,t} + \varphi_{12} creagr_{i,t} + \mu_{i,t} \end{aligned} \quad [1](3.10)$$

[1] Including both exchange rate and trade openness as independent variables is important because each impacts agricultural productivity in unique ways, even if related. Exchange rates influence the cost of agricultural imports and export competitiveness, while trade openness affects access to markets and resources with respect to imports and exports. Together, they provide a fuller picture of how currency value and market accessibility drive productivity in African agriculture.

Where $i = 1, 2, ... i$ (number of member countries) and $t = 1990, 1991, ..., 2020$. agricpro is agricultural productivity of country i at time t; top is trade openness of country i at time t; $renegy$ is renewable energy consumed of country i at time t and so on for other control variables.

3.3. Estimation Technique

To examine objectives two and three which is achieved by estimating equation (3.18), this study employs the System Generalised Methods of Moments (SYS-GMM) to estimate the equation as this resolves the issue of endogeneity. The SYS-GMM as developed by Arellano and Bover (1995) is used in estimating models in which there are large number of cross-sections (*i*) when compared to the individual time series (*t)*, that is, $i > N$; functional linear relationship has been established; the equation includes the lagged dependent variable; the explanatory variables are not entirely exogenous; the assumption of fixed effect is upheld; there is the presence of heteroscedasticity which is peculiar for a panel data and autocorrelation of order one with the individual country and not across the countries (Blundell & Bond, 1998; Arellano & Bover, 1995; Roodman, 2006). The SYS-GMM transforms the regressors through differencing and the use of a system of instrumental variables to guarantee efficiency and thereby creating a system of two equations called the system GMM. Roodman (2009) noted that the SYS-GMM is appropriate in resolving omitted variables bias. The transformation of equation (3.10) to conform to the SYS-GMM with lagged dependent variables is defined as:

$$\begin{aligned} agricpro_{i,t} = {} & \lambda_0 + \lambda_1 agricpro_{i,t-1} + \lambda_2 renegy_{i,t} + \lambda_3 top_{i,t} + \lambda_4 popgr_{i,t} + \lambda_5 sav_{i,t} + \lambda_6 inv_{i,t} \\ & + \lambda_7 top_{i,t}.renegy_{i,t} + \lambda_8 fert_{i,t} + \lambda_9 pest_{i,t} + \lambda_{10} exch_{i,t} + \lambda_{11} prl_{i,t} \\ & + \lambda_{12} emi_{i,t} + \lambda_{13} creagr_{i,t} + \mu_{i,t} \end{aligned} \tag{3.11}$$

with $agricpro_{i,t-p}; renegy_{i,t-p}; top_{i,t-p}; popgr_{i,t-p}; sav_{i,t-p}; inv_{i,t-p};\ fert_{i,t-p}; pest_{i,t-p}; exch_{i,t-p};$ $prl_{i,t-p}; emi_{i,t-p}; creagr_{i,t-p}$ as instruments.

3.4. Data description, treatment and sources

3.4.1. Data description

1. **Agricultural productivity measure**

The methodology used in determining output productivity is applied in measuring agricultural productivity. In standard economic literature, output productivity is measured using the total factor productivity (TFP). Total factor productivity is the ratio of total output to the two standard inputs used in production, labour employed and capital. TFP is the proportion of growth in output that is not explained by the two standard traditional measured inputs (Gordon, 2017; Sickles & Zelenyuk, 2019). Thus, agricultural productivity mirrored by the agricultural factor productivity is the proportion of agricultural output growth that is not explained by the two standard traditional measured inputs, capital and labour. Agricultural productivity is critical and used instead of growth in agricultural output because in the economic literature, Easterly and Levine (2001) empirically found out that for an average country, total factor productivity accounts for 60 percent of the growth of the output per capita. This implies that factors stimulating TFP shape the growth pattern of an economy and in the same vein, factors that drive agricultural productivity growth determine the growth of agricultural output. According to Comin (2006), the rate of total factor productivity growth can be estimated by subtracting the growth rates of capital and labour inputs from the growth rate of output.

We employ the standard Cobb-Douglass production function as used in Abizadeh and Pandey (2009) in constructing our agricultural productivity. We assume that the Cob-Douglas aggregate production function in the agricultural sector for country i at time t is defined as:

$$agric_{it} = agricpro_{it} K_{it}^{\alpha} L_{it}^{1-\alpha} \tag{3.12}$$

Where $agric$ is the agriculture, forestry, and fishing value added, K is the capital, L is the employment in agricultural sector, α and $1-\alpha$ are the capital and labour share of agricultural output respectively. From the equation, $agricpro$ is the traditional A in the production function, agricultural productivity. It therefore implies that from equation (3.12), we have it that:

$$agricpro_{it} = \frac{agric_{it}}{K_{it}^{\alpha} L_{it}^{1-\alpha}} \tag{3.13}$$

From equation (3.13), the determination of α and $1-\alpha$ helps us to solve for agricultural productivity. Gordon (2017) noted for US and other advanced economy, α and $1-\alpha$ are 30 percent and 70 percent respectively. However, considering that Africa are developing economies, the values of α and $1-\alpha$ will be determined from the model. Taking the log of both sides and separating, we have it that:

$$\ln agricpro_{it} = \ln agric_{it} - \alpha \ln K_{it} - (1-\alpha)\ln L_{it}$$

$$agricpro_{it} = \exp\left(\ln agric_{it} - \alpha \ln K_{it} - (1-\alpha)\ln L_{it}\right) \quad (3.14)$$

Equation (3.14) will be estimated for each respective economy.

2. Trade openness measure

The trade openness measure is adapted from the studies of Hassine and Kandi (2009); Ali et al. (2021) who used three different measures to proxy the degree of trade openness for each country, these are total agricultural trade, agricultural trade barriers and agricultural equipment imports. We shall limit our measure of trade openness (top) to the ratio of total agricultural trade (sum of agricultural imports – $agrimpt$ and export of agricultural commodities – $agrexp$) to agriculture, forestry, and fishing value added (agric). Thus, trade openness is defined as:

$$top_{it} = \frac{agrimpt_{it} + agrexp_{it}}{agric_{it}} \quad (3.15)$$

3. Renewable energy consumption measure

The data reported by IEA (2022c) shows the energy consumed by the agricultural sector, although, this is relatively low in relation to the total energy consumed in Africa. However, IRENA (2021) acknowledged that one of the challenges affecting renewable energy space in the agricultural sector is the paucity of data. As such, there is no time series data on total renewable energy use in the agricultural sector both from the International Energy Agency, International Renewable Energy Agency or Food and Agriculture Organisation of the UN as the total renewable energy consumed have not been disaggregated at sectoral level; but there are evidences of the deployment of renewable energy in agricultural sector of Africa (SELCO Foundation, 2018; Musinguzi, 2021; GCCA, 2018). More importantly, IRENA (2021) noted that many farmers in Africa are now resulting into the use of renewable energy machines and solar panels in farms and the agribusiness chain as the farmers who live in the rural areas are far from the national grid. As such, our measure of renewable energy consumed ($renegy$) is the share of renewable energy to total energy consumed in African countries, this corroborates with the measures adopted by Chopra et al. (2022) and Zaman et al. (2022). This measures the intensity of use of renewable energy to non-renewable energy. An increase in the share suggests that more of renewable energy is deployed across Africa than the other thereby promoting the actualization of the sustainable development goals.

Other variables employed and their appriori expectation are defined in tables 3.1 and 3.2.

Table 3. 1 - Data definition, measures and appriori expectation

S/N	Variable	Definition	Measure	Appriori expectation	Source	Literature
1	$agricpro_{m,i,t}$	Agricultural productivity	As defined in equation (3.22)	Dependent variable		Gordon (2017)
2	$inv_{m,i,t}$	Investment rate in agriculture	Gross fixed capital formation in Agriculture, Forestry and Fishing), Value US$ in millions	Positive	FAO (2022)	
3	$renegy_{m,i,t}$	Renewable energy consumption	Renewable energy consumption (% of total final energy consumption)	Positive	World Bank (2022b)	Chopra et al. (2022)
4	$popgr_{m,i,t}$	Population growth rate	Population growth (annual %)	Positive	World Bank (2022b)	
5	$sav_{m,i,t}$	Savings rate	Gross savings (% of GDP)	Positive	World Bank (2022b)	
6	$top_{m,i,t}$	Trade openness	As defined in equation (3.22)	Positive		(Sunge & Ngepah, 2020)
7	$fert_{m,i,t}$	Fertilizer use	Fertilizers use per value of agricultural production (kg/1000 Int.$; Nutrient nitrogen N	Positive	FAO (2022)	
8	$pest_{m,i,t}$	Pesticide use	Quantity of pesticides used in agriculture, Forestry and Fishing in tonnes	Positive	FAO (2022)	
9	$exch_{m,i,t}$	Exchange rate	Official exchange rate (LCU per US$, period average	Positive	World Bank (2022b)	
10	$prl_{m,i,t}$	Price level	Inflation, consumer prices (annual %)	Positive	World Bank (2022b)	
11	$emi_{m,i,t}$	Carbon emissions	Value of emissions (CO2) due to land use, farm gate, agri food system, and agricultural soil with LULUCF in kilotonnes	Negative	FAO (2022)	
12	$creagr_{m,i,t}$	Credit to the agricultural sector	Total credit to agricultural sector (2015 prices in US$ millions)	Positive	FAO (2022)	
13	K_{it}	Capital stocks in agriculture	Net capital stocks in Agriculture, Forestry and Fishing) Value (US$ millions)	Used in computation of agric. Productivity	FAO (2022)	Gordon (2017)

Note: $_{m,i,t}$ implies that it is the variable of country i in region m and at time t

Table 3. 2 - Continuation of data definition, measures and appriori expectation

S/N	Variable	Definition	Measure	Appriori expectation	Source	Literature
14	L_{it}	Employment in agriculture	Employment in Agriculture Total	Used in computation of agricultural productivity	World Bank (2022b)	Gordon (2017)
15	$agric_{it}$	Agriculture, forestry, and fishing value added	Gross value of Agricultural Production) (constant 2014-2016 thousand US$'000)	Used in computation of agricultural productivity	FAO (2022)	Hassine and Kandi (2009)
16	$agrimpt_{it}$	Agricultural imports	Value of Importation of agricultural products and machineries used in the agricultural sector in US$'000	Used in trade openness computation	FAO (2022)	Hassine and Kandi (2009)
17	$agrexp_{it}$	Export of agricultural commodities	Value of agricultural products exported in US$'000	Used in trade openness computation	FAO (2022)	Hassine and Kandi (2009)
18	$agricpro2_{it}$	agriculture, forestry, and fishing value added per worker.	As defined in equation (3.24)	Positive		Chopra et al. (2022)
19	$renegy2_{m,i,t}$	Total renewable energy consumed	Total renewable energy use (kg of oil equivalent) per $1,000 GDP	Positive	World Bank (2022b)	

Note: $_{m,i,t}$ implies that it is the variable of country i in region m and at time t

3.4.2. Data treatment

The type of renewable energy use for the whole African economy are retrieved for the purpose of achieving objective one. However, the share of renewable energy consumption to total energy consumed for each country, panel data is used to estimated objectives two and three.

The data retrieved covers the list of 54 African countries which are Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Ivory Coast, Djibouti, Egypt, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwana, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, and Zimbabwe. The scope will cover the regions between the period 2000 and 2020.

3.4.3. Robustness check

For robustness check, we adopted the measure used by Chopra et al. (2022) in determining agricultural productivity ($agricpro2_{it}$)in which agricultural productivity is agriculture, forestry, and fishing value added per worker. This is defined as:

$$agricpro2_{it} = \frac{agric_{it}}{L_{it}} \tag{3.16}$$

Another variant of renewable energy consumption is deployed in this study; this is the total renewable energy consumed ($renegy2$).

It is also important to investigate the objective of the study across different regions in Africa. For simplicity, the continent will be divided into five regions- Western Africa which is made up of sixteen countries (Benin, Burkina Faso, Cabo Verde, Cote'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone and Togo); Central Africa which is made up of nine countries (Angola, Cameroun, Central African Republic, Chad, Congo Democratic Republic, Congo Republic, Equatorial Guinea, Gabon and Sao Tome); Southern Africa which is made up of five countries (Botswana, Lesotho, Namibia, South Africa and Estwani); Northern Africa which is made up of six countries (Algeria, Egypt, Libya, Morocco, Sudan and Tunisia); Eastern Africa which is made up of eighteen countries (Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Seychelles, Somalia, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe). This division is so as to conform to the various economic blocs that are in Africa. With these groups, equation (3.10) will be modified to:

$$\begin{aligned} agricpro_{m,i,t} &= \varphi_0 + \varphi_1 renegy_{m,i,t} + \varphi_2 top_{m,i,t} + \varphi_3 popgr_{m,i,t} + \varphi_4 sav_{m,i,t} + \varphi_5 inv_{m,i,t} \\ &+ \varphi_6 top_{m,i,t}.renegy_{m,i,t} + \varphi_7 fert_{m,i,t} + \varphi_8 pest_{m,i,t} + \varphi_9 exch_{m,i,t} + \varphi_{10} prl_{m,i,t} \\ &+ \varphi_{11} emi_{m,i,t} + \varphi_{12} creagr_{m,i,t} + \mu_{m,i,t} \end{aligned} \tag{3.17}$$

Where $m = 1,2,3,4,5$ for the five regions, $i = 1,2,... i$ (number of member countries) and *t = 1990, 1991, …, 2020*. $agricpro$ is agricultural productivity of country *i* in region m and at time *t*; top is trade openness of country i in region m and at time t;

$renegy$ is renewable energy consumed of country i in region m and at time t and so on for other control variables. For each of the regions, the number of cross-sections are less than the independent country times series making the use of SYS-GMM inappropriate in estimating equation (3.13). Thus, the study will deploy the Cross-Section Augmented Distributed Lag (CS-DL) model in estimating each of the regions. The CS-DL as developed by Chudik et al. (2016) shows that the long run effect of explanatory variables on the dependent variable can be directly estimated both in the short run and in the long run. The CS-DL is an $ARDL(1,1)$ model and is suitable for estimating both short run and long run models. It is also suitable for estimating models that have series integrated at order $I(0)$ and order $I(1)$. The model in equation (3.17) is specified in the CS-DL form as:

$$\begin{aligned}\Delta agricpro_{m,i,t} &= \varsigma_0 + \varsigma_1 \Delta \sum_{i=1}^{p} renegy_{m,i,t-p} + \varsigma_2 \Delta \sum_{i=1}^{p} top_{m,i,t-p} + \varsigma_3 \Delta \sum_{i=1}^{p} popgr_{m,i,t-p} + \varsigma_4 \Delta \sum_{i=1}^{p} sav_{m,i,t-p} \\ &+ \varsigma_5 \Delta \sum_{i=1}^{p} inv_{m,i,t-p} + \varsigma_6 \Delta \sum_{i=1}^{p} top_{m,i,t-p}.renegy_{m,i,t-p} + \varsigma_7 \Delta \sum_{i=1}^{p} fert_{m,i,t-p} + \varsigma_8 \Delta \sum_{i=1}^{p} pest_{m,i,t-p} \\ &+ \varsigma_9 \Delta \sum_{i=1}^{p} exch_{m,i,t-p} + \varsigma_{10} \Delta \sum_{i=1}^{p} prl_{m,i,t-p} + \varsigma_{11} \Delta \sum_{i=1}^{p} emi_{m,i,t-p} + \varsigma_{12} \Delta \sum_{i=1}^{p} creagr_{m,i,t-p} + \varsigma_{13} ect_{t-1} \\ &+ \varsigma_{14} renegy_{m,i,t} + \varsigma_{15} top_{m,i,t} + \varsigma_{16} popgr_{m,i,t} + \varsigma_{17} sav_{m,i,t} + \varsigma_{18} inv_{m,i,t} + \varsigma_{19} top_{m,i,t}.renegy_{m,i,t} \\ &+ \varsigma_{20} fert_{m,i,t} + \varsigma_{21} pest_{m,i,t} + \varsigma_{22} exch_{m,i,t} + \varsigma_{23} prl_{m,i,t} + \varsigma_{24} emi_{m,i,t} + \varsigma_{25} creagr_{m,i,t} + \varepsilon_{m,i,t}\end{aligned} \quad (3.18)$$

Where ect is the error correction term; $\varsigma_1 \longrightarrow \varsigma_{12}$ are short run coefficients and $\varsigma_{14} \longrightarrow \varsigma_{25}$ are long run coefficients Before equation (3.26) is estimated, we employed the second-generation panel unit root test which allows for cross-sectional dependence as developed by Pesaran (2003). The M.H. Pesaran panel unit root test examines the stationarity of the variables at both level and first difference. Thereafter, the Kao (1999) cointegration test will be used to test for long run relationship associated with the regression before the model is then estimated.

4. PRESENTATION AND ANALYSIS OF RESULT

This section presents the results of the data analysed based on regression models specified in section three of this thesis. Prior to the estimation of the models, it is important to analyse the statistical properties of the variables by conducting descriptive statistics of the variables employed and correlation coefficient matrix. The equations and results are presented in a more readable format.

Figure 4. 1 - Africa's average agricultural productivity (2000-2020)

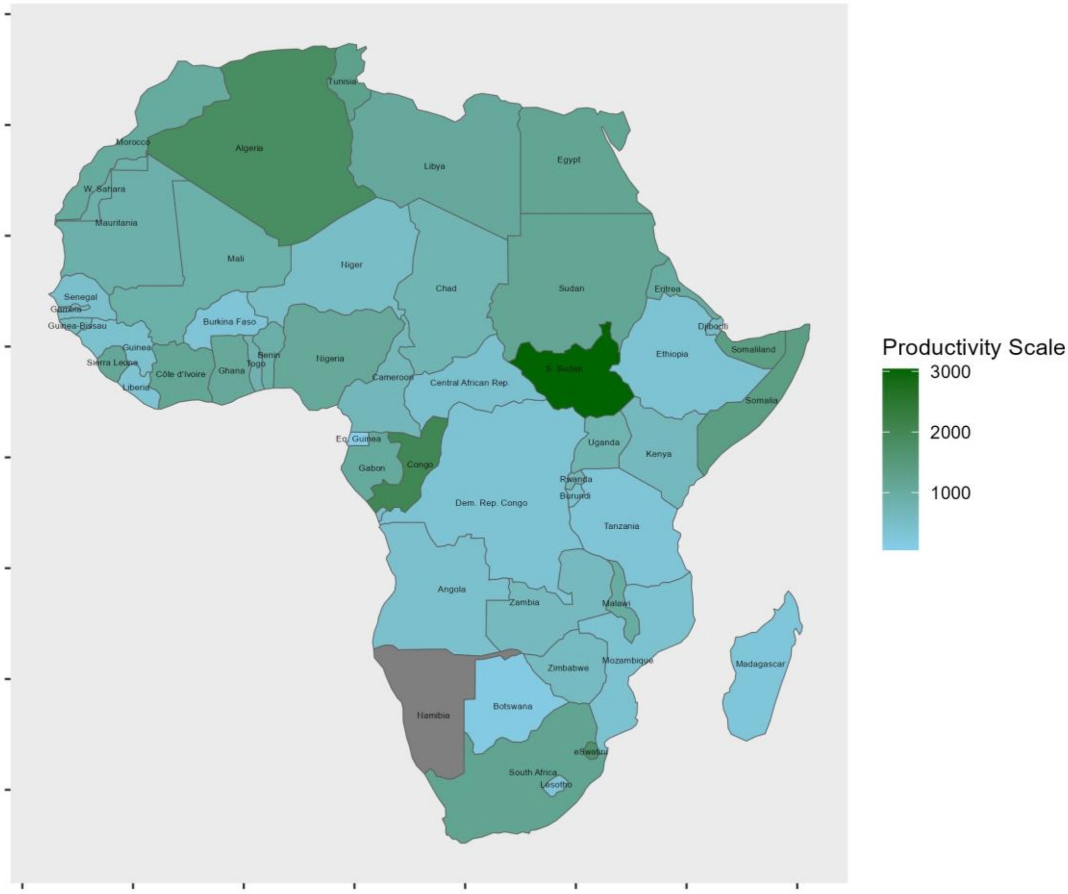


Figure 4.1 shows that Democratic Republic of Congo, South Sudan and Algeria are characterized with countries with higher level of productivity compared to other African counterparts. Nigeria, Ghana, Cote d'Ivoire, Sierra Leone, South Africa, Egypt and Sudan are among the group of countries with average level of productivity compared to others. Countries like Botswana, Lesotho, DRC, Senegal and Burkina Faso have averagely performed poorly in terms of their productivity over the 2 decades of investigation.

4.1. Descriptive and correlation results

This section presents the descriptive statistics of the variables employed for estimation at continent level and at regional level. Thereafter, the correlation matrix of the variables for Africa is presented.

Table 4. 1 - Descriptive statistics of the variables

	Entire African Continent				Eastern Africa	Western Africa	Central Africa	Southern Africa	Northern Africa
	Mean	Sd	Min	Max	Mean	Mean	Mean	Mean	Mean
lnagricpro	6.29	17.76	-47.31	80.19	11.13	1.05	5.32	12.76	-0.09
lnagricpro2	6.39	0.94	1.68	9.12	6.21	6.52	6.22	6.21	7.13
renegy	11.74	15.99	0.01	93.73	17.10	6.76	11.38	14.13	5.60
renegy2	81.11	107.67	0.08	634.96	113.96	60.62	88.67	63.97	27.25
lntop	3.82	1.24	0.64	7.84	3.60	3.63	3.71	5.22	4.13
popgr	2.37	0.95	-2.63	5.60	2.39	2.69	2.92	1.19	1.43
sav	18.53	11.41	-19.90	69.81	16.98	15.45	19.55	23.51	27.87
lninv	4.58	1.91	-1.26	9.96	4.35	4.66	4.05	4.19	6.55
fert	10.66	10.65	0.00	61.48	11.66	8.17	5.44	16.48	18.35
lnpest	5.69	2.78	-3.51	10.20	5.89	4.93	5.49	5.05	8.38
lnexch	4.84	2.94	-3.11	22.63	5.30	5.53	5.73	2.19	1.92
prl	9.55	31.77	-9.80	557.20	12.78	5.89	13.96	5.99	4.55
lnemi	9.34	1.87	4.05	13.32	9.06	8.79	9.72	9.59	11.13
lncreagr	7.79	2.01	0.69	11.74	8.05	7.05	7.46	8.37	9.55

Total observations for the entire continent are 1134, 399 for the Eastern, 336 for the Western, 189 for the Central, 105 for the Southern and 105 for the Northern regions of Africa.
Source: Author's computation using data from World Bank (2022); IEA (2022); FAO (2022).

The average value for agricultural productivity in Africa between the period 2000 and 2020 ranges between 47.3 and 80.19 with an average of 6.29 for the entire period, all in thousands of US dollars. Southern region of Africa has the highest agricultural productivity value, and this is followed by the Eastern region while Northern Africa has the lowest level of productivity. The Western region of Africa's productivity is far below the continent's average. Also, the result shows that on average, 11.74% of the total energy consumed in Africa comes from renewable sources for the period 2000 to 2020 with the Southern region of Africa having the largest share – 14.13% on average. Furthermore, the region (Eastern) with its largest share of energy from renewable sources has a very high productivity level while the country with the least consumption of renewable energy has the least productivity level (Northern Africa). This descriptive statistic augments the assertion that renewable energy consumption is related to agricultural productivity. Also, Tanzania which is in Eastern Africa has the highest share of renewable energy consumption of 93.73% while Botswana in the Southern region of Africa has the least share of renewable energy consumption. This suggests that strategies which are geared towards enhancing the overall deployment of renewable energy across the continent should be promoted.

The rate of change in agricultural trade openness on average for the continent is 3.82 and reached a peak of 7.84 while the least rate of change is 0.64. On average, 120.6% of the continent's agricultural output are traded in the international market either in the form of capital and raw material importation or in the form of primary and secondary agricultural product export. The share of agricultural output traded in the international market reached a peak of 25.8% by Equatorial Guinea in 2014 while the least traded in the continent was by South Sudan recording a meagre 1.9% in 2013.

Population growth rate in the continent has averaged 2.37% between the periods of 2000 and 2020 with the Central region experiencing the fastest growth rate of 2.92% on average while the Southern region who enjoys greater productivity and use of renewable energy has the least population growth rate on average of 1.19%. The gross savings ratio to GDP in the continent on average is 18.5% while it reached a maximum of 69.81%. Within the same scenario, the Western region of Africa has the lowest savings rate on average which is 15.45% while the Northern region of Africa has the highest which averaged 27.87%. On average and between 2000 and 2020, 10.66kg/1000 US$ of Nutrient Nitrogen N fertilizer was used while Zambia in 2016, used the highest quantity of 61.48kg/1000 US$. The Northern region of Africa were the highest users of fertilizer on average while the Central Africa are the lowest users. For pesticides, an average of 5.69 tonnes per annum is used in Africa between 2000 and 2020 and the Northern region again are the highest users of pesticides while the least was the Western region of Africa as they used 4.93 tonnes.

The volatility of exchange rate and level of prices have continued to be a major concern in Africa as the rate of change in the exchange rate rallied between (3.11) and 22.63 with the Eastern region mostly affected on average while the Northern region is the least. The inflation rate also revealed significant macroeconomic fluctuations in the region as the rate of inflation rallied between (9.8%) and 557.2% over a period of 21 years. Although the average inflation rate was 9.55% in the entire continent, the Central and the Eastern region maintained a double-digit inflation over the period. The rate of change in carbon emissions has continued to increase on average from 4.05 to 13.32 while the Democratic Republic of Congo in 2014 recorded the highest level of emission over the period of study, the country emitted CO2 of 606,761.9 kilotonnes which are due to land use, farm gate, agrifood system, and agricultural soil.

Table 4. 2a - Correlation matrix results

Variables	lnagricpro	lnagricpro2	(renegy)	renegy2	(lntop)	(popgr)	(sav)
lnagricpro	1.00						
lnagricpro2	-0.11***	1.00					
renegy	0.13***	0.10***	1.00				
renegy2	0.15***	-0.001	0.24***	1.00			
lntop	0.29***	-0.42***	-0.09***	-0.2***	1.00		
popgr	-0.11***	-0.01	0.06*	0.09***	-0.34***	1.00	
sav	-0.02	0.09***	0.07**	0.03	0.14***	-0.13***	1.00
lninv	-0.27***	0.40***	0.10***	0.16***	-0.36***	0.12***	0.13***
fert	0.11***	-0.001	-0.05	-0.1***	0.38***	-0.19***	0.15***
lnpest	-0.07**	0.20***	-0.04	0.08***	0.02	-0.03	-0.07**
lnexch	0.001	-0.08	0.14***	0.12***	-0.23***	0.31***	-0.4***
prl	0.02	-0.03	0.06*	0.12***	-0.09***	-0.02	-0.01
lnemi	-0.23***	0.18***	0.12***	0.21***	-0.24***	0.15***	0.15***
lncreagr	-0.05*	0.12***	-0.18***	0.05*	0.12***	-0.16***	0.04

***** implies that p<0.01 and significant at 1%, ** implies that p<0.05 and significant at 5%, * implies that p<0.1and significant at 10%**

Source: Author's computation using data from World Bank (2022); IEA (2022); FAO (2022)

Table 4. 2b - Continuation of correlation matrix results

Variables	(lninv)	(fert)	(lnpest)	(lnexch)	(prl)	lnemi	lncreagr
lnagricpro							
lnagricpro2							
renegy							
renegy2							
lntop							
popgr							
sav							
lninv	1.00						
fert	0.05*	1.00					
lnpest	0.29***	0.37***	1.00				
lnexch	-0.03	-0.17***	-0.1(	1.00			
prl	0.05	-0.02	0.07**	-0.02	1.00		
lnemi	0.78***	0.12***	0.38***	-0.02	0.11***	1.00	
lncreagr	0.34***	0.37***	0.19***	-0.20***	0.07**	0.21***	1.00

**** implies that p<0.01 and significant at 1%, ** implies that p<0.05 and significant at 5%, * implies that p<0.1and significant at 10%*

Source: Author's computation using data from World Bank (2022); IEA (2022); FAO (2022)

The correlation matrix result is presented in tables 4.2a and 4.2b. From the result, the highest degree of relationship among the explanatory variables is 0.78 and this is between the rate of change in carbon emissions and the rate of change in investment; this degree of relationship does not suggest perfect multicollinearity that can be said to be associated with the regression result. The result shows a positive relationship between renewable energy consumption and agricultural productivity over the period of study.

4.2. Intensity of the type of renewable energy consumed in Africa

In this section, a descriptive statistic on the various types of renewable energy consumed in Africa between 2000 and 2020 is conducted and presented in table 4.3 below.

Table 4. 3 - Renewable energy type in Africa (2000 – 2020)

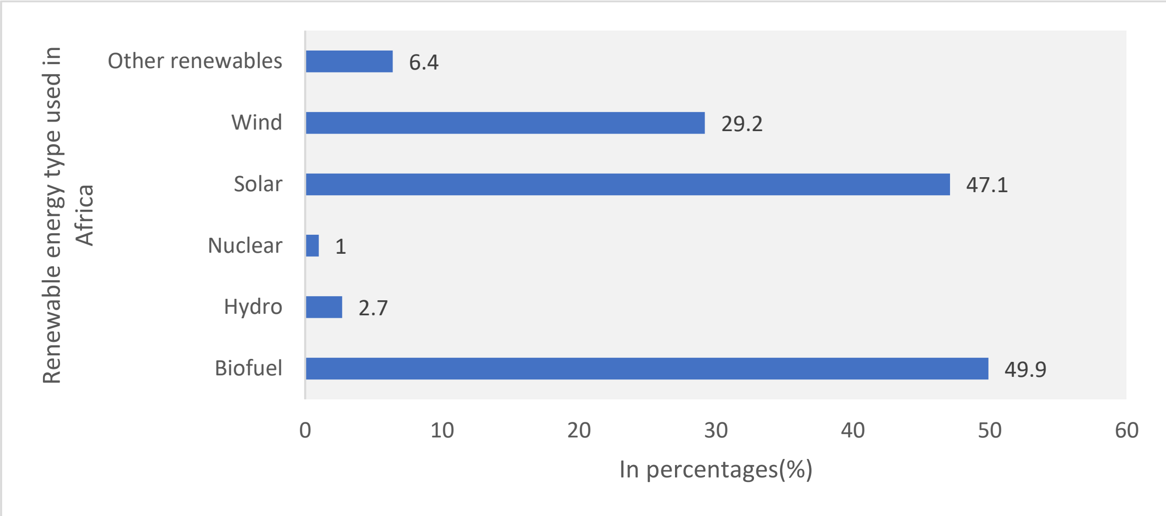
Renewable Energy Type (TWh/hr)	Mean	Standard deviation	Minimum	Maximum	Sum	Share to total renewables
Biofuel	0.48	0.25	0	0.86	10.18	0.14%
Hydro	275.64	41.36	209.02	351.75	5788.36	80.81%
Nuclear	33.47	3.05	26.8	38.39	702.83	9.81%
Solar	6.2	9.67	0.03	30.61	130.1	1.82%
Wind	13.37	16.36	0.49	53.76	280.76	3.92%
Other renewables	11.94	5.14	6.27	20.38	250.84	3.50%
Total renewables	341.1	70.86	251.98	495.18	7163.05	

Source: Author's computation using data from IRENA (2022)

From table 4.3, the result shows that the largest portion of renewable energy consumed in Africa is hydro as it accounts for 80.81% of the total renewables consumed between 2000 and 2020. The result shows that between 2000 and 2020, out of the 7,163.1TWh of renewables consumed, 5,788.36TWh was from hydro while the second largest renewables are 702.83TWh which is from nuclear sources. The result shows that the least type of renewables consumed in Africa is biofuels as 10.18TWh was consumed between 2000 and 2020, this accounted for 0.14% of the total renewables consumed. Notably, solar energy accounts for 1.82%, wind accounts for 3.92% while other forms of renewables account for 3.50% of total renewables. Thus, the result from table 4.3 shows that the most common form of renewables in

Africa are hydro renewables. It is further important for us to investigate the type of renewable energy that is gaining prominence in Africa in the past two decades, this can be deduced by calculating their growth rates and this is presented in figure 4.2.

Figure 4. 2 - Average growth rate of the types of renewables used in Africa (2000-2020)



Source: Author’s sketch using data from IRENA (2022)

From figure 4.2, the highest average annual growth rates on the type of renewable energy in Africa is that of biofuels, then followed by solar and then, wind energy. Figure 4.2 shows that between 2000 and 2020, the average annual growth rate in biofuels is 49.9%, then followed by solar (47.1%) and then, wind (29.2%). Thus, we can conclude that the fastest type of renewable energy that is dominating the renewable energy space in Africa are biofuels and then followed by solar and wind.

4.3. Effect of renewable energy and trade openness on agricultural productivity

This section presents the result of the system generalized methods of moments on the effect of renewable energy consumption on agricultural productivity and the role of trade openness, this is presented in table 4.5 below.

Table 4. 4 - SYS-GMM result

Variables	lnagricpro	lnagricpro	lnagricpro	lnagricpro2	lnagricpro2	lnagricpro2
$Lnagricpro_{t-1}$	0.9991***	0.9992***	0.9989***			
	(0.0005)	(0.00035)	(0.0003)			
Renewable energy consumption	0.0007**	0.0009***	-0.0061***	0.0013**	0.0008*	-0.0098***
	(0.0003)	(0.00028)	(0.002)	(0.001)	(0.0005)	(0.001)
Population growth rate	-0.0070*	-0.0095***	-0.0016	0.0125***	-0.0131***	-0.0008
	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)
Savings	0.0001	-0.0001	-0.00003	0.0011***	0.0002	0.0006**
	(0.0005)	(0.0004)	(0.00025)	(0.0003)	(0.0003)	(0.000)
Lnvestment	-0.0017	0.0037	0.0034	-0.0038	0.0162***	0.0182***
	(0.005)	(0.002)	(0.002)	(0.006)	(0.002)	(0.003)
Fertiliser use	-0.0022***	-0.0022***	-0.0016***	-0.0014**	0.000002	0.0006*
	(0.0005)	(0.0004)	(0.001)	(0.001)	(0.0004)	(0.0008)
Pesticide use	0.0062**	0.0044*	0.0055***	0.0229***	-0.0037	-0.0025*
	(0.002)	(0.002)	(0.001)	(0.005)	(0.003)	(0.001)
Exchnage rate	0.0049***	0.0039***	0.0032***	0.0016	-0.0002	0.0015**
	(0.001)	(0.001)	(0.00003)	(0.001)	(0.001)	(0.001)
Price level	0.0001*	0.0001***	0.000003	-0.00003	0.0001***	0.00018***
	(0.00003)	(0.00003)	(0.000)	(0.00004)	(0.00004)	(0.000)
Carbon emissions	-0.0244***	-0.0266***	-0.0230***	-0.0210***	-0.0109**	-0.0106**
	(0.006)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)
Credit to agricultrual sector	-0.0029	-0.0108***	-0.0051**	0.0043	-0.0275***	-0.0189***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)
Trade openness		0.0033	-0.0096		0.0350***	-0.0521***
		(0.006)	(0.007)		(0.006)	(0.004)
(renegy)(lntop)			0.0016***			0.0027***
			(0.0004)			(0.0003)
L.lnagricpro2				0.8435***	0.9072***	0.9125***
				(0.013)	(0.009)	(0.005)
Constant	0.2320***	0.2980***	0.2583***	0.9951***	1.0078***	0.9069***
	(0.055)	(0.054)	(0.044)	(0.063)	(0.092)	(0.057)
Observations	1,041	1,041	1,041	1,041	1,041	1,041
No. of countries	53	53	53	53	53	53
AR (1) Prob.	-4.4(0.000)	-4.4(0.000)	-4.4(0.000)	-4.2(0.000)	-4.2(0.000)	-4.3(0.000)
AR (2) Prob.	3.43(0.22)	5.44(0.72)	4.43(0.52)	4.55(0.61)	3.52(0.312)	3.50(0.31)
Hansen (Prob.)	42.6(0.100)	42.3(0.184)	24.4(0.496)	17.2(0.702)	22.97(0.463)	20.6(0.72)
Fisher (Prob)	0.000	0.000	0.000	0.000	0.000	0.000

******* *implies that p<0.01 and significant at 1%, ** implies that p<0.05 and significant at 5%, * implies that p<0.1and significant at 10%*

Source: Author's computation using data from World Bank (2022); IEA (2022); FAO (2022)

The result from table 4.4 shows the effect of renewable energy consumption on agricultural productivity. The first three columns show the effect of renewable energy consumption and trade openness on agricultural productivity using the residual of the Cobb-Douglas production function to measure agricultural productivity while the last three columns show the effect of renewable energy consumption and trade openness on agricultural productivity when measured using the agricultural value added per capita.

In the first column, the result shows the effect of renewable energy consumption while not considering the mediating role of trade openness. The result shows that there is a significant and positive effect of renewable energy consumption on agricultural productivity. This is evident as there is a positive coefficient between the share of renewable energy consumed and agricultural productivity. In the second column, the result shows that renewable energy continues to have a positive impact on agricultural productivity, however, trade openness does not have a significant impact. In the third column, the result shows that renewable energy consumption interacting with trade openness has a positive and significant effect on agricultural productivity. Thus, the result shows that trade openness has a significant mediating role in the renewable energy consumption and agricultural productivity nexus in Africa. This implies that trade policies that allow the transfer of machines and other material inputs which promote the use of renewable energy improve and affect agricultural productivity significantly. This result conforms to the findings of Chopra et al. (2022) whose study showed that renewable energy consumption has a significant and positive effect on agricultural productivity. This also corroborates with the findings of Khan et al. (2020); Jebli et al. (2020) who noted that renewable energy consumption helps in enhancing economic activities. This is evident as the use of renewable energy can be used to operate efficient irrigation systems; and provide a reliable and sustainable source of energy for irrigation, ensuring a consistent water supply to crops thereby improving its productivity.

Biofuel renewable energy is considered because biofuel crops, especially perennial ones, can be integrated into crop rotation systems which improve soil fertility and structure by preventing soil degradation and promoting nutrient cycling. This, in turn, can enhance the productivity of subsequent food crops. More importantly, biofuel crops can be grown on marginal lands that may not be suitable for food crop production. This allows for the productive use of land that might otherwise remain fallow or unused. Renewable energy here serves as an enhancer of agricultural technology and is particularly crucial in regions facing water scarcity or unreliable access to electricity. Many agricultural operations, especially in rural areas, may not have access to a reliable power grid. Renewable energy technologies will provide off-grid power solutions used in powering machinery, lighting, and refrigeration, thereby enhancing overall agricultural productivity.

Also, it helps farmers to reduce energy costs in the long run; this is because once the initial investment in renewable energy infrastructure is made, ongoing operational costs are often lower compared to conventional energy sources. These cost savings can be significant for agricultural businesses, leading to increased profitability. Renewable uses help in mitigating climate change, promote soil health, biodiversity, and overall ecosystem resilience. Renewable energy use helps in precision farming, sensor technologies, and data analytics which enhances decision-making processes, optimize resource use, and improve overall farm management.

In the same vein, the fourth column shows the effect of renewable energy consumption on agricultural productivity which is measured using the agricultural value added per capita. The result shows that renewable energy has a positive and significant effect on agricultural productivity. In the fifth column, trade openness improves agricultural productivity, and this was further strengthened when it was interacted with renewable energy consumption in the sixth column, this conforms to the result we have in the third column. This suggests that among the two measures of agricultural productivity, trade agreements, and policies which promote agricultural trade relations and the flow of renewable energy related materials in the agricultural sector, improves its productivity. Put in another form, combined policies on trade openness and the use of renewable energy in the agricultural sector improve agricultural productivity.

We shall interpret other variables using the results in the third and sixth column for robustness analysis. The result shows that population growth rate negatively and significantly affects agricultural productivity using the two measures. This implies that the increase in population growth poses a negative effect on the productivity of the agricultural sector in Africa. Conscious effort must be made in controlling population. As at 2022, the UN confirmed that the world population has reached 8 billion and Africa region is growing three times faster than the global average which further opines that by 2070, it will become the most populous place globally, surpassing Asia (Guardian, 2022). The result also shows that savings have a negative impact on the first measure of agricultural productivity, however, when measured using agricultural value added per capita, savings rate has a positive and significant impact on agricultural productivity.

Other results from the estimation show that the rate of change in investment has a positive impact on the two measures of agricultural productivity while fertilizer use does not improve the first measure of productivity but does for the second measure. Conversely, the rate of change in the amounts of pesticides used significantly and positively enhances agricultural productivity using the first measure, however, this does not for the second measure. Interestingly, exchange rate depreciation or devaluation improves agricultural productivity using the two measures. We note here that the depreciation of the exchange rate makes local goods cheaper and promotes the demand for agricultural products from foreign buyers. The inflation rate also surprisingly positively improves agricultural productivity using the two measures.

It is also worth noting that carbon emissions negatively affect agricultural productivity as presented in the third and sixth column of the results in table 4.4. The implication of these results is that increases in carbon emissions negatively affect agricultural productivity and the reduction in carbon emission can be made feasible by switching more from the nonrenewable energy sources to renewable energy source. The credit to the agricultural sector in enhancing investment within the sector does not show a promising positive effect. Rather, the flow into the sector has negatively impacted agricultural productivity.

The post-diagnostic test results shows that in the entire six equations presented in table 4.5, the null hypothesis of no autocorrelation of order one is rejected for the six models as the probability of the AR(1) test for serial correlation are all less than 10%. Thus, there is serial correlation of order one associated with the regression result; this is expected as the SYS-GMM with the lagged dependent variable included expects some level of first order serial correlation. However, there should not be serial correlation of higher order associated with the regression result and this was validated by the AR(2) process in which we fail to reject the null hypothesis of serial correlation of higher order associated with the regression result as their probabilities are all statistically insignificant and greater than 10%. The Hansen chi-square statistics examines the null hypothesis that the instruments used in the estimation are purely exogenous and the result reported in table 3.5 shows that for the six models, we fail to reject the null hypothesis of the Hansen test and we therefore conclude that the instruments used in estimation are purely exogenous. The F Fisher test examines the overall best fit of the regression line and the result shows that we reject the null hypothesis, and we accept the alternative and conclude that the regression lines are robust.

4.4. Effect of renewable energy and trade openness on agricultural productivity at regional level

Here, we examine the effect of renewable energy and trade openness on agricultural productivity across the five regions in Africa, the Eastern, Western, Central, Northern and Southern regions of Africa. The purpose of conducting this analysis is to determine if renewable energy and trade openness have unique effect on agricultural productivity across regions or otherwise. Before estimating this result, we acknowledge that the number of cross sections in each region are lower than the individual time series and thus, employ the Cross-Section Augmented Distributed Lag (CS-DL) model in estimating each of the regions. Before its estimation, it is important that we conduct the Hausman random test, the unit root test and the cointegration test of the models to ensure that the results are robust and free from the basic econometrics errors.

4.4.1. Hausman random effect test

The result of the Hausman H test for the five equations shows that we reject the null hypothesis that the random effect model is appropriate and accept the alternative hypothesis and we conclude that the fixed effect model is more appropriate. Thus, we shall be estimating the models in conformity with the fixed effect.[2]

4.4.2. Panel unit root test

This section presents the unit root test result of the series employed in the regional estimation. The unit root test is conducted in order to ensure that there is long run stability and that the series are free from unit root problem. The result of the panel unit root test is presented in table 4.5 below.

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[2] The Hausman H random effect test examines the null hypothesis that the random effect model is appropriate and should be sued as against the alternative hypothesis of choosing the fixed effect as appropriate; the test can be approximated to the chi-square test statistics.

Table 4. 5 - Pesaran panel unit root test result

	At level		**First difference**			**At level**		**First difference**		
Variable	Z[t-bar]	p-value	Z[t-bar]	p-value	Con.	Z[t-bar]	p-value	Z[t-bar]	p-value	Con.
	Eastern African Region					**Western African Region**				
Lnagricpro	-2.29	0.535	-3.22***	0.000	I(1)	-2.56	0.146	-3.32***	0.000	I(1)
Renegy	7.38	1.000	-4.21***	0.000	I(1)	-1.74	0.993	-2.84**	0.014	I(1)
Popgr	-4.63***	0.000	–	–	I(0)	-3.79***	0.000	–	–	I(0)
Sav	-1.52	1.000	-3.88***	0.000	I(1)	-2.05	0.872	-2.83**	0.015	I(1)
Lninv	-3.14***	0.000	–	–	I(0)	-2.39	0.362	-3.22***	0.000	I(1)
Fert	-2.25**	0.013	–	–	I(0)	-1.94	0.219	-3.84***	0.000	I(1)
Lnpest	-1.34	0.967	-2.04*	0.096	I(1)	-2.44***	0.000	–	–	I(0)
Lnexch	-2.22	0.673	-2.75**	0.022	I(1)	-2.75**	0.029	–	–	I(0)
Prl	-1.38	1.000	-3.48***	0.000	I(1)	-2.46	0.258	-3.40***	0.000	I(1)
Lnemi	1.49	0.932	-1.93**	0.027	I(1)	2.47	0.993	-3.49***	0.000	I(1)
Lncreagr	-3.14***	0.001	–	–	I(0)	-3.23***	0.000	–	–	I(0)
Lntop	-2.09	0.845	-3.12***	0.000	I(1)	-2.54	0.166	-3.65***	0.000	I(1)
lntop.renegy	5.76	1.000	-6.35***	0.000	I(1)	-1.89	0.965	-3.40***	0.000	I(1)
	Central Africa region					**Southern African region**				
Lnagricpro	-2.26	0.570	-4.11***	0.000	I(0)	-2.21	0.591	-4.45***	0.000	I(0)
Renegy	-1.90	0.905	-3.3***	0.001	I(1)	-1.67	0.939	-4.37***	0.000	I(1)
Popgr	-4.71***	0.000	–	–	I(0)	-4.01***	0.000	–	–	I(0)
Sav	-0.84	1.000	-3.95***	0.000	I(1)	-2.60	0.243	-3.45***	0.005	I(1)
Lninv	-2.80*	0.057	–	–	I(0)	-4.52***	0.000	–	–	I(0)
Fert	-1.80	0.451	-3.34***	0.000	I(1)	-1.50	0.723	-3.58***	0.000	I(1)
Lnpest	-2.29*	0.051	–	–	I(0)	-0.91	0.975	-2.55**	0.035	I(1)
Lnexch	-1.23	1.000	-2.75*	0.084	I(1)	-2.47	0.349	-3.31**	0.011	I(1)
Prl	-4.15***	0.000	–	–	I(0)	-3.44***	0.003	–	–	I(0)
Lnemi	-2.98**	0.015	–	–	I(0)	-1.494	0.975	-5.13***	0.000	I(1)
Lncreagr	-1.76	0.958	-3.98***	0.000	I(1)	-2.85*	0.098	-3.54***	0.003	I(1)
Lntop	-2.37	0.429	-3.04**	0.012	I(1)	-2.53	0.298	-3.37***	0.008	I(1)
lntop.renegy	-1.85	0.933	-3.70***	0.000	I(1)	-1.78	0.900	-3.57***	0.002	I(1)
	Northern African region									
Lnagricpro	-2.75	0.144	-3.25**	0.016	I(1)					
Renegy	-0.90	1.000	-2.95**	0.041	I(1)					
Popgr	-4.01***	0.000	–	–	I(0)					
Sav	-1.86	0.851	-4.71***	0.000	I(1)					
Lninv	-1.48	0.978	-3.13**	0.031	I(1)					
Fert	-2.41*	0.068	–	–	I(0)					
Lnpest	-1.39	0.800	-3.01*	0.053	I(1)					
Lnexch	-0.46	1.000	-3.11**	0.034	I(1)					
Prl	-2.54	0.294	-3.83***	0.000	I(1)					
Lnemi	-1.82	0.880	-5.19***	0.000	I(1)					
Lncreagr	-1.93	0.791	-3.27**	0.015	I(1)					
Lntop	-2.67	0.192	-3.87***	0.000	I(1)					
lntop.renegy	-1.19	0.997	-3.47***	0.000	I(1)					

*** implies that p<0.01 and significant at 1%, ** implies that p<0.05 and significant at 5%, * implies that p<0.1and significant at 10%. At level, number of observations for Eastern region is 361 and at first difference, observation is 342. At level, number of observations for Western region is 304 and at first difference, observation is 288. At level, number of observations for the Central region is and at first difference, observation is 288. At level, the number of observations for Southern region is 95 and at first difference, observation is 90. At level, the number of observations for the Northern region is 95 and at first difference, observation is 90.

Source: Author’s computation using data from World Bank (2022); IEA (2022); FAO (2022)

The Pesaran panel unit root test result is presented in table 4.5 for the entire regions in the continent. The result shows that in the Eastern region of the continent, four of the variables (population growth rate, investment, fertilizer and credit to the agricultural sector) employed are stationary at level as their probability values at level are less than 10%. However, the remaining nine variables are stationary at first difference. In the Western African region, the result shows that also, four of the variables (population growth rate, pesticide use, exchange rate and credit to the agricultural sector) employed are stationary at level as their probability values at level are less than 10%. In the Central region of Africa, five of the variables (population growth rate, investment, pesticide use, price level and carbon emission) employed are stationary at level as the probabilities at level are all less than 10%. However, the remaining variables are stationary at first difference. In the Southern Africa region, only three variables (population growth rate, investment and price level) are stationary at level while other variables are stationary at first difference. In the Northern African region, only two variables (population growth rate and fertilizer use) are stationary at level while others are stationary at first difference.

4.4.3. Kao panel cointegration test

Since not all the variables are stationary at level, it is important to conduct a cointegration test in order determine the existence of long run relationship thereby establishing a cointegration associated with the regression models. The Kao residual cointegration method is employed with the result presented in table 4.6.

Table 4. 6 - Kao cointegration test result

Parameter	Eastern Region stat.	Western Region stat.	Central region stat.	Southern region stat.	Northern region stat.
No. of panels	19	16	9	5	4
Avg. no. of periods	18.6	18.6	18	19	19
Modified Dickey-Fuller t statistics	-7.78*** (0.000)	-7.37*** (0.000)	-6.88*** (0.000)	-4.98*** (0.000)	-5.76*** (0.000)
Dickey-fuller t statistics	-8.72*** (0.000)	-6.61*** (0.004)	-7.12*** (0.000)	-3.47*** (0.000)	-5.17*** (0.000)
Augmented Dickey-fuller t statistics	-5.24*** (0.000)	-268*** (0.000)	-3.98*** (0.000)	-1.73** (0.042)	-3.06*** (0.001)

*Using the Newey-West lags selection *** implies that p<0.01 and significant at 1%, ** implies that p<0.05 and significant at 5%, * implies that p<0.1and significant at 10%*

Source: Author's computation using data from World Bank (2022); IEA (2022); FAO (2022)

The result from table 4.6 shows that we reject the null hypothesis that there is no cointegration using the Dickey-Fuller, modified Dickey-Fuller and the Augmented Dickey-Fuller t statistics; this is because the probability values are all less than 10%. Thus, we have established that cointegration exist in the five models. The next step is to present the regression results of the five regions.

4.4.4. Cross-Section Augmented Distributed Lag (CS-DL) regression result

Table 4. 7 - Long run results

Variables	**Eastern Africa**	**Western Africa**	**Central Africa**	**Southern Africa**	**Northern Africa**
Renewable energy	0.0022	0.0143	0.0208**	0.0167***	-0.0202
	(0.005)	(0.014)	(0.010)	(0.001)	(0.055)
Population growth rate	-0.0020	-0.0612**	0.0132	-0.0251	-0.0796
	(0.015)	(0.031)	(0.027)	(0.049)	(0.051)
Savings	-0.0018	0.0010	0.0036*	0.0028	-0.0008
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Investment	0.0266*	0.0175	-0.0316	0.1012***	0.0041
	(0.016)	(0.024)	(0.033)	(0.035)	(0.034)
Fertiliser use	0.0005	-0.0016	-0.0101	0.0033**	-0.0054**
	(0.002)	(0.003)	(0.007)	(0.002)	(0.003)
Pesticide use	-0.0055	0.0038	0.0127	0.0420*	0.0180
	(0.011)	(0.014)	(0.021)	(0.023)	(0.042)
Exchnage rate	-0.0057*	-0.0302	-0.0223	-0.0081	0.0289
	(0.003)	(0.037)	(0.042)	(0.044)	(0.039)
Price level	0.0004	-0.0064**	-0.0012	-0.0017	-0.0004
	(0.000)	(0.003)	(0.001)	(0.003)	(0.003)
Carbon emissions	0.0530***	-0.0469	0.1089*	-0.2044	-0.0224
	(0.020)	(0.049)	(0.056)	(0.152)	(0.086)
Credit to agricultural sector	-0.0150	-0.0048	0.0850**	0.0114	0.0083
	(0.017)	(0.019)	(0.038)	(0.027)	(0.052)
Trade openess	-0.0401	-0.1559***	0.0505	0.1594***	-0.1504
	(0.025)	(0.052)	(0.039)	(0.060)	(0.109)
(lntop)(renegy)	0.0001	-0.0055	0.0040*	0.0038*	0.0037
	(0.001)	(0.004)	(0.002)	(0.002)	(0.011)
Constant	7.1591***	1.4125***	3.1608***	16.3900***	1.3820*
	(0.552)	(0.305)	(0.549)	(2.723)	(0.817)

***** implies that p<0.01 and significant at 1%, ** implies that p<0.05 and significant at 5%, * implies that p<0.1and significant at 10%*

Source: Author's computation using data from World Bank (2022); IEA (2022); FAO (2022)

Table 4. 8 - Short run results

Variables	Eastern Africa	Western Africa	Central Africa	Southern Africa	Northern Africa
ECT	-0.6528***	-0.6124***	-0.7430***	-1.1139***	-0.8606***
	(0.049)	(0.054)	(0.085)	(0.148)	(0.125)
Δrenegy	0.0027	-0.0399***	-0.0101***	-0.0114	-0.0360
	(0.004)	(0.012)	(0.0008)	(0.014)	(0.035)
Δpopgr	0.0025	0.0800***	-0.0130	-0.5114***	-0.1296
	(0.009)	(0.029)	(0.065)	(0.103)	(0.132)
Δsav	0.0002	0.0002	-0.0009**	-0.0017	-0.0022*
	(0.001)	(0.001)	(0.0002)	(0.002)	(0.001)
Δlninv	0.0420*	0.1405***	0.0770	0.0017	0.0638*
	(0.022)	(0.045)	(0.055)	(0.039)	(0.037)
Δfert	-0.0058***	-0.0006	0.0005***	-0.0024	0.0045**
	(0.001)	(0.002)	(0.0006)	(0.002)	(0.002)
Δlnpest	0.0160	0.0007	0.0122	-0.0087	-0.0281
	(0.014)	(0.008)	(0.052)	(0.032)	(0.041)
Δlnexch	-0.0146***	0.2571***	0.1425	0.0935	-0.0231
	(0.005)	(0.078)	(0.095)	(0.084)	(0.034)
Δprl	-0.0002	0.0020	0.0003	0.0011	0.0014
	(0.000)	(0.001)	(0.000)	(0.002)	(0.002)
Δlnemi	0.0568**	0.0444	-0.0554	0.0881	0.1541
	(0.026)	(0.034)	(0.058)	(0.130)	(0.099)
Δlncreagr	-0.0722**	-0.0043	-0.0125	0.0175	-0.1829*
	(0.028)	(0.016)	(0.013)	(0.032)	(0.104)
Δlntop	-0.0072	-0.2073***	-0.1179***	-0.1171*	-0.1978**
	(0.020)	(0.037)	(0.034)	(0.068)	(0.079)
Δ(lntop)(renegy)	0.0018**	0.0105***	0.0024	0.0025	0.0082
	(0.001)	(0.003)	(0.002)	(0.003)	(0.007)

**** implies that p<0.01 and significant at 1%, ** implies that p<0.05 and significant at 5%, * implies that p<0.1and significant at 10%*

Source: Author's computation using data from World Bank (2022); IEA (2022); FAO (2022)

The purpose of estimating the results in tables 4.9 and 4.10 is to examine the effect of renewable energy consumption and trade openness on agricultural productivity across the five regions in Africa. The result shows that in the long run, renewable energy consumption only has significant and positive impact on agricultural productivity of the Central and Southern regions of Africa while it has a positive impact on that of the Eastern and Western regions, however, this is not statistically significant. When we interact renewable energy consumption and trade openness in the long run, the result shows that the agricultural productivity of the Central and Southern regions of Africa will significantly improve; although, the interaction effect positively enhances the agricultural productivity of the Eastern and Northern regions, this is not statistically significant. Thus, the implication of this is that in the long run, trade globalization strategies directed at promoting the flow of renewable energy enabled machines significantly improve agricultural productivity in the Central and Southern regions of Africa.

In the short run, the result shows that renewable energy consumption and the interaction with trade openness significantly improves agricultural productivity in the Western and Eastern regions of Africa. Without the interaction, the result shows that renewable energy consumption on its own does not significantly improve agricultural productivity in these regions; however, with trade globalization, there are more opportunities which the agricultural sector has in the Eastern and Western Africa in boosting her productivity through increase in renewable consumption.

The result also shows that the population growth rate has a negative impact on the extent of agricultural productivity across the five regions in Africa. The savings rate only has a positive and significant impact on agricultural productivity in the Central region while domestic investment only significantly and positively increases the productivity of the Eastern and Southern regions of Africa.

4.5. Robustness check

The preceding analysis examined the effect of renewable energy consumption and trade openness on agricultural productivity in Africa as a whole and at regional level using the two measures of agricultural productivity while renewable energy consumption was captured using the share of renewable energy to total energy consumption and this implies that our result explains what happens to agricultural productivity when more of renewable energy is used in the energy consumption mix. Let us now examine this relationship using the amount of renewable energy consumed as a variable; this is presented in table 4.9.

Table 4. 9 - SYS-GMM result using quantity of renewable energy consumed

Variables	lnagricpro	lnagricpro	lnagricpro	lnagricpro2	lnagricpro2	lnagricpro2
l.lnagricpro	0.9989***	0.9989***	0.9990***			
	(0.00037)	(0.00026)	(0.00023)			
renegy2	0.0002***	-0.0002***	0.0002***	-0.000012	-0.00008***	0.0008***
	(0.00002)	(0.00002)	(0.00044)	(0.00002)	(0.00002)	(0.0002)
Population growth rate	-0.0011	-0.0040	-0.0033	-0.0038	-0.0124***	-0.0098***
	(0.005)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)
Savings	0.0002	-0.0001	-0.00005	0.0007**	0.0003	0.00009
	(0.0004)	(0.00024)	(0.0002)	(0.00029)	(0.0002)	(0.0002)
Investment	-0.0024	-0.0005	0.000018	0.0026	0.0148***	0.0107***
	(0.005)	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)
Fertilisr use	-0.0020***	-0.0009*	-0.0010**	-0.0005	0.0015***	0.0016***
	(0.0005)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.0003)
Pesticide use	0.0066***	0.0029	0.0014	0.0140***	-0.0016	-0.0050**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Exchnage rate	0.0068***	0.0049***	0.0035***	-0.0001	-0.0019**	-0.0042***
	(0.00045)	(0.00043)	(0.00047)	(0.001)	(0.001)	(0.001)
Price level	0.0001***	0.0001***	0.00004**	-0.0001**	0.00006	-0.00003
	(0.00004)	(0.00002)	(0.00002)	(0.00004)	(0.00004)	(0.00004)
Carbon emission	-0.0189***	-0.0139***	-0.0140***	-0.0293***	-0.0104**	-0.0016
	(0.005)	(0.005)	(0.004)	(0.006)	(0.004)	(0.004)
Credit to agricultural sector	-0.0057	-0.0012	0.0032	0.0037	-0.0088***	-0.0084***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Trade openness		-0.0236***	0.0263***		-0.0356***	0.0532***
		(0.005)	(0.004)		(0.005)	(0.006)
(renegy2)(lntop)			0.000035***			0.00019***
			(0.000013)			(0.00003)
l.lnagricpro2				0.8818***	0.9107***	0.8965***
				(0.008)	(0.008)	(0.007)
constant	0.2026***	0.2275***	0.2128***	0.9156***	0.8357***	0.9572***
	(0.038)	(0.038)	(0.027)	(0.058)	(0.076)	(0.070)
Observations	1,036	1,036	1,036	1,036	1,036	1,036
No. of countries	53	53	53	53	53	53
AR (1) Prob.	-4.4(0.00)	-4.4(0.00)	-4.4(0.000)	-4.2(0.000)	-4.2(0.000)	-4.2(0.000)
AR (2) Prob.	2.44(0.02)	2.42(0.02)	2.42(0.02)	2.56(0.010)	2.6(0.011)	2.55(0.011)
Hansen (Prob.)	40.6(0.14)	43.2(0.16)	41.8(0.311)	37.65(0.23)	43.78(0.15)	23.59(0.54)
Fisher (Prob)	0.000	0.000	0.000	0.000	0.000	0.000

**** implies that p<0.01 and significant at 1%, ** implies that p<0.05 and significant at 5%, * implies that p<0.1and significant at 10%*

Source: Author's computation using data from World Bank (2022); IEA (2022); FAO (2022)

The result from table 4.11 in relations to the effectiveness of trade openness and renewable energy consumption on agricultural productivity is in tandem with the result obtained while renewable energy was measured using the share of renewables to total energy consumed as presented in table 4.5. In essence, the result still shows that renewable energy consumption interacting with trade openness has significant and positive effect on agricultural productivity. The implication of this is that trade openness has a significant mediating role in the renewable energy consumption and agricultural productivity nexus in Africa. The result in the third and sixth column suggests that trade openness strategies that are channeled towards the deployment of renewable energy-based technologies and machines in the agricultural sector guarantees the sector's productivity growth.

5. SUMMARY OF FINDINGS, CONCLUSION AND POLICY RECOMMENDATION

5.1 Summary of findings

This study investigates the effect of renewable energy consumption and trade openness on agricultural sector productivity in Africa between the period 2000 and 2020. The study hypothesizes that renewable energy consumption has significant impact on agricultural productivity and trade openness has a significant mediating role in the renewable energy consumption – agricultural productivity nexus in Africa. The specific objectives studied in this research are to examine the intensity of the type of renewable energy consumed in Africa, investigate the effect of renewable energy consumption on agricultural productivity in Africa and analyse the impact of trade openness on agricultural productivity via the consumption of renewable energy in Africa.

To implement the objectives, data were retrieved from the respective international organizations' databases while the system generalized methods of moments estimation technique was employed to investigate the effect of trade openness and renewable energy consumption on agricultural productivity in Africa as a whole while. The continent was also divided into regions- Eastern, Western, Central, Southern and Northern regions and the cross section augmented distributed lag model estimation techniques were employed to examine the objectives at regional level.

The study found that the Southern region of Africa has the highest agricultural productivity value, and this is followed by the Eastern region while Northern Africa has the lowest level of productivity. On average, 11.74% of the total energy consumed in Africa comes from renewable sources for the period 2000 to 2020. Considering the regional averages, the Southern region of Africa has the largest share of renewable energy consumed, accounting for 14.13% on average. Furthermore, the Southern region of Africa is the region with the largest share of energy from renewable sources cum productivity level in the agricultural sector. The Northern region of Africa is characterized with the least consumption of renewable energy and least productivity level. Hydro form of renewable energy account for 80.81% of the total renewable energy consumed in Africa while biofuel is the least, accounting for 0.14%. Biofuels and solar renewables are the fastest type of renewable energy that is dominating the renewable energy space in Africa with an average annual growth rate of 49.9% and 47.1% respectively between 2000 and 2020.

There is a positive and significant effect of renewable energy consumption on agricultural productivity in Africa. Trade openness plays a positive and significant role in enabling the inflow of machines deployed towards utilization of renewable energy in the agricultural value chain system; encouraging the policy actions and the intensification of the use of renewable energy improves agricultural productivity in Africa. At regional level and in the long run, renewable energy consumption has a positive and significant effect on agricultural productivity only in Central and Southern region of Africa. Also, at the regional level, trade globalization has a positive and significant effect in aiding trade flows which enhances the use of renewable energy and ultimately enhances agricultural productivity in Central and Southern regions of Africa in the long run and in the Eastern and Western regions of Africa in the short run.

Irrespective of the policy targeted at switching from non-renewables to renewables while maintaining the level of energy consumed or targeted at enhancing the deployment of renewables irrespective of the extent of non-renewables, renewable energy consumption will always have positive and significant effect in enhancing agricultural productivity.

5.2. Conclusion

The study examined the intensity of the type of renewable energy consumed in Africa, the effect of renewable energy consumption on agricultural productivity and analysed the impact of trade openness on agricultural productivity via the consumption of renewable energy in Africa. The key estimation techniques deployed are descriptive statistics, system generalized methods of moments and the cross sectional augmented distributed lag model. It can be concluded from the study that the Southern region of Africa has the highest level of agricultural productivity and renewable energy use while the Northern region of Africa has the lowest on both considerations. The share of renewable energy to total energy consumed in Africa has remained relatively low.

The renewable energy space has been dominated by hydro renewables in the past two decades. However, biofuels and solar renewables are gaining prominence as they are the fastest renewable energy type currently deployed with average annual growth rates above 45% for both. Renewable energy consumption shows a promising mark in improving the productivity level of the agricultural sector in Africa. At the same instance, trade openness is very significant in enabling the flow of agricultural products and the transfer of machines which supports the use of renewable energy in the agricultural sector. The improvement of this trade policy objective which intensifies the use of renewable energy improves agricultural productivity in Africa.

At the regional level, and in the long run, renewable energy consumption has a positive and significant effect on agricultural productivity in the Central and Southern region of Africa. Trade globalization policies as explained earlier which intensifies trade flows and the use of renewable energy compatible machines enhances agricultural productivity in Central and Southern regions of Africa in the long run and the Eastern and Western regions of Africa in the short run. Irrespective of the policy targeted at switching energy types or absolutely intensifying the use of renewable energy, they both have positive and significant effect in enhancing agricultural productivity in Africa as a whole.

5.3. Policy Recommendations

The major conclusion drawn from this study is that renewable energy consumption has a significant and positive impact on agricultural productivity in Africa as a continent, although at regional level, it has varying long run and short run positive effect. Also, trade openness is significant in enhancing the deployment of renewable energy technologies in the agricultural space which significantly improves productivity. To this end, the following recommendations should be considered to enhance the effectiveness of trade openness and renewable energy on agricultural productivity in Africa.

African policymakers should prioritize investments in renewable energy infrastructure tailored to rural and agricultural communities. This includes expanding access to solar, wind, and biogas energy sources, which can provide reliable power for irrigation, processing, and storage, reducing post-harvest losses. By fostering partnerships between governments, private sectors, and international development agencies, funding can be directed to build resilient and sustainable energy systems in rural areas, boosting agricultural output. Additionally, implementing training programs on renewable energy use and maintenance will equip farmers with the skills to harness these technologies, fostering self-sufficiency and supporting sustainable agricultural practices.

To capitalize on the positive effect of trade openness on agricultural productivity, policies should focus on reducing barriers to agricultural trade across African countries, as well as on the global stage. Streamlining cross-border regulations, enhancing logistics networks, and supporting compliance with international standards can facilitate the movement of agricultural products and inputs. Furthermore, expanding export incentives and ensuring that small-scale farmers have access to trade opportunities will help maximize agricultural productivity. A framework that promotes both domestic and international trade can attract foreign investment, fostering technological advancements and increasing productivity. By improving trade policies and facilitating access to global markets, Africa can create a robust agricultural sector that leverages both renewable energy and open trade.

The use of renewable energy in the agricultural value-added space requires the deployment of new and innovative equipment such as processing and irrigation equipment in agricultural production as this guarantee an increase in agricultural productivity and efficiency. The machines and appliances are quite expensive and to utilize more of renewable energy requires investments in innovation that test and deploy technological solutions adapted to the needs of various agricultural value chains. It therefore presupposes that dedicated high-risk innovation funds is required as well as partnerships between local technology and suppliers towards this space.

Not only in the provision of technical expertise, in cases where the machines are developed abroad, there is the need for funds, favourable import policies and grant of credit facilities to import them and be used in the agricultural space. The government can provide agriculture loans at a very low interest rate and charge them to procure energy friendly and more optimized machines needed in the agricultural value chain. The study further recommends that in order to optimize the use of renewable energy in the agricultural value space, there is the need for respective governments of African economies and international development partners to empower farmers by facilitating importation of renewable energy enabled agricultural machineries and provide the base funds needed to procure these machineries across the processing, irrigation, packaging, refrigerating, transport system, storage, and handling value chains to guarantee improved agricultural productivity.

More importantly, renewable energy has been sparsely adopted by rural farmers across the continent although there is a fast adoption rate on the use of solar and biofuels. Many of them are not aware of the available energy friendly and saving instrument which can enhance their efficiency. The massive awareness through World Bank assisted projects across Africa as seen in the literature reviewed in this study have helped to an extent, a lot still needs to be done. There is a need for more collaboration in creating awareness of the available renewable energy machines that can be used in the agricultural space in Africa. Such awareness should expose the farmers to the skills needed for installation, maintenance and operation of the renewable energy enabled machines. Also, integrating renewable energy into the existing agricultural practices requires, especially the manual one additional capacity building such as how to handle drip irrigation systems. Even training and capacity building is required on the skills needed to access markets for new products and higher yields for existing products. Despite the efforts by FAO, World Bank, IMED Foundations, more is needed within the agricultural space in Africa.

Attention must also be placed on designing trade policies that encourage the flow of agricultural products across Africa as well as easing the importation of energy-friendly machines needed in the agricultural space. To achieve this, the agricultural value chain system must be optimized in Africa to improve the value of agricultural products which become suitable for sale at the international market.

5.4. Contribution to knowledge

To the best of our knowledge, this study is the first to examine the effect of renewable energy consumption on agricultural productivity in Africa. It is also among the first to establish the trade openness-renewable energy consumption linkage in Africa. Not only did the study examine the consequences in Africa as a whole, it provides empirical evidence across the major regions in Africa who have overtime, developed regional policies which tries to see how each can efficiently harness their potentials towards achieving sustainable development and shared objectives.

5.5. Suggestions for further studies

The research has established that renewable energy consumption improves agricultural productivity. It is recommended that further studies should design framework in resolving adoption issues and capacity building towards the utilization of renewable energy compatible machines across Africa especially in the rural areas, this will guarantee full blown utilization of renewable energy in agricultural production in Africa.

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APPENDICES

Appendix 1: Key Equation of the Solow Model

$$\kappa_t = \frac{K_t}{A_t L_t} \tag{3.8}$$

From equation (3.8), we take the log of both sides and we can therefore state that

$\ln(\kappa_t) = \ln \frac{K_t}{A_t L_t}$ taking the logarithm rule,

$$\ln(\kappa_t) = \ln K_t - \ln A_t - \ln L_t$$

The next thing to do is to take the derivative of both sides with respect to time. Thus, we have it that:

$$\frac{\delta \ln(\kappa_t)}{\delta t} = \frac{\left[\ln(K_t) - \ln(A_t) - \ln(L_t)\right]}{\delta t}$$

$$\frac{\delta \ln(\kappa_t)}{\delta t} = \frac{\delta \ln(K_t)}{\delta t} - \frac{\delta \ln(A_t)}{\delta t} - \frac{\delta \ln(L_t)}{\delta t}$$

Applying the quotient rule

$$\frac{\delta \ln(K_t)}{\delta t} = \frac{\delta \ln(K_t)}{\delta t} \cdot \frac{\delta k_t}{\delta t}$$

Given that $\frac{\delta k_t}{\delta t} = \dot{k}_t$ then we have it that

$$\frac{\delta \ln(K_t)}{\delta t} = \frac{\delta \ln(K_t)}{\delta t} \cdot \frac{\delta K_t}{\delta t} = \frac{1}{K_t} . \dot{K}_t = \frac{\dot{K}_t}{K_t} = \hat{k}_t$$

Thus, we can seldom say that

$$\frac{\dot{\kappa}_t}{\kappa_t} = \frac{\dot{K}_t}{K_t} - \frac{\dot{A}_t}{A_t} - \frac{\dot{L}_t}{L_t}$$

But

$$\hat{L}(t) = \frac{\dot{L}(t)}{L(t)} = n$$

$$\hat{A}(t) = \frac{\dot{A}(t)}{A(t)} = g$$

$$\frac{\dot{\kappa}_t}{\kappa_t} = \frac{\dot{K}_t}{K_t} - g - n$$

$$\frac{\dot{\kappa}_t}{\kappa_t} = \frac{\dot{K}_t}{K_t} - (g + n)$$

Recall that $\dot{K}_t = sY_t - \delta K_t$ before equation (3.7),

$$\frac{\dot{\kappa}_t}{\kappa_t} = \frac{(sY_t - \delta K_t)}{K_t} - (g+n)$$

Multiply through by κ_t and we have this as

$$\dot{\kappa}_t = \frac{(sY_t - \delta K_t)}{K_t}.\kappa_t - (g+n)\kappa_t$$

Recall that $\kappa_t = \frac{K_t}{A_t L_t}$ from equation (3.8),

$$\dot{\kappa}_t = \frac{(sY_t - \delta K_t)}{K_t}.\frac{K_t}{A_t L_t} - (g+n)\kappa_t$$

$$\dot{\kappa}_t = \frac{(sY_t - \delta K_t)}{A_t L_t} - (g+n)\kappa_t$$

$$\dot{\kappa}_t = \frac{sY_t}{A_t L_t} - \frac{\delta K_t}{A_t L_t} - (g+n)\kappa_t$$

Also, we know that $\kappa_t = \frac{K_t}{A_t L_t}$, thus,

$$\dot{\kappa}_t = \frac{sY_t}{A_t L_t} - \delta\kappa_t - (g+n)\kappa_t$$

$$\dot{\kappa}_t = \frac{sY_t}{A_t L_t} - (n+g+\delta)\kappa_t$$

The output per effective labour is given as $\frac{Y_t}{A_t L_t} = \frac{1}{A_t L_t}.\left(K_t\right)^{\alpha}.\left(A_t L_t\right)^{1-\alpha}$ and because of the property of constant returns to scale,

$$\frac{Y_t}{A_t L_t} = \left(\frac{K_t}{A_t L_t}\right)^{\alpha}\left(\frac{A_t L_t}{A_t L_t}\right)^{1-\alpha} = \kappa_t^{\alpha}$$

Thus,

$$\dot{\kappa}_t = s\kappa_t^{\alpha} - (n+g+\delta)\kappa_t$$ **Key Equation of the Solow Model**

Appendix 2: Derivation of the steady-state level of capital stock per unit of effective labour

To find the steady-state level of capital stock per unit of effective labour (κ^*)

Recall that the key equation of the Solow model is defined as $\dot{\kappa}_t = s\kappa^{\alpha} - (n+g+\delta)\kappa_t$

At the steady state, $\kappa = \kappa^*; \dot{\kappa}_t = 0$

Thus, substitute $\dot{\kappa}_t = 0$ in the key equation of the Solow model

$$0 = s\left(\kappa^*\right)^{\alpha} - (n+g+\delta)\left(\kappa^*\right)$$

$$s\left(\kappa^*\right)^{\alpha} = (n+g+\delta)\left(\kappa^*\right)$$

$$\left(\kappa^*\right)^{\alpha} = \frac{(n+g+\delta)\left(\kappa^*\right)}{s}$$

$$\frac{\left(\kappa^*\right)^{\alpha}}{\left(\kappa^*\right)} = \frac{(n+g+\delta)}{s}$$

$$\left(\kappa^*\right)^{\alpha-1} = \frac{(n+g+\delta)}{s}$$

$$\kappa^* = \left(\frac{n+g+\delta}{s}\right)^{\frac{1}{\alpha-1}}$$

Appendix 3: Descriptive statistics of variables used in the model for whole of Africa

	count	sum_w	mean	var	sd	min	max	sum
lnagricpro	1134	1134	6.288447		17.76179	-47.30744	80.18775	7131.099
lnagricpro2	1134	1134	6.389839		.9375677	1.680715	9.12071	7246.077
renegy	1133	1133	11.74067		15.98527	.01	93.73	13302.18
renegy2	1128	1128	81.11097		107.6653	.0807174	634.9637	91493.18
lntop	1134	1134	3.824793		1.238772	.6448822	7.840627	4337.315
popgr	1134	1134	2.367077		.9536439	-2.628656	5.604992	2684.266
sav	1129	1129	18.52787		11.41361	-19.90298	69.80782	20917.97
lninv	1134	1134	4.582629		1.913526	-1.263935	9.961684	5196.702
fert	1134	1134	10.65525		10.65245	0	61.48	12083.05
lnpest	1134	1134	5.691748		2.780028	-3.506558	10.19828	6454.442
lnexch	1134	1134	4.837787		2.937878	-3.112977	22.62881	5486.051
prl	1134	1134	9.545105		31.77452	-9.797647	557.2018	10824.15
lnemi	1123	1123	9.336973		1.866058	4.049957	13.31589	10485.42
lncreagr	1103	1103	7.792979		2.013659	.6931472	11.74087	8595.655

Appendix 4: correlations result

Pairwise correlations

Variables	(lnagricpro)	(lnagricpro2)	(renegy)	(renegy2)	(lntop)	(popgr)	(sav)	
lnagricpro	1.000							
lnagricpro2	-0.111***	1.000						
renegy	0.127***	0.098***	1.000					
renegy2	0.145***	-0.001	0.242***	1.000				
lntop	0.287***	-0.422***	-0.087***	-0.188***	1.000			
popgr	-0.114***	-0.013	0.057*	0.085***	-0.336***	1.000		
sav	-0.017	0.087***	0.071**	0.029	0.137***	-0.129***	1.000	
lninv	-0.265***	0.398***	0.102***	0.155***	-0.357***	0.119***	0.125***	
fert	0.112***	-0.001	-0.047	-0.099***	0.384***	-0.191***	0.146***	
lnpest	-0.072**	0.203***	-0.035	0.083***	0.022	-0.028	-0.067**	0
lnexch	0.000	-0.027	0.136***	0.123***	-0.234***	0.314***	-0.348***	
prl	0.024	-0.025	0.057*	0.117***	-0.094***	-0.016	-0.009	
lnemi	-0.234***	0.175***	0.121***	0.214***	-0.237***	0.152***	0.154***	0
lncreagr	-0.052*	0.124***	-0.178***	0.051*	0.120***	-0.160***	0.042	0

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Appendix 5: Descriptive statistics at regional levels

Eastern Africa

	count	sum_w	mean	var	sd	min	max	sum
lnagricpro	399	399	11.13244		24.31664	-47.30744	80.18775	4441.845
lnagricpro2	399	399	6.212095		1.162981	1.680715	9.12071	2478.626
renegy	398	398	17.10453		20.36663	.62	93.73	6807.602
renegy2	393	393	113.9627		133.5689	1.109109	634.9637	44787.33
lntop	399	399	3.595539		1.37704	.6448822	7.737496	1434.62
popgr	399	399	2.389247		.986061	-2.628656	5.604992	953.3095
sav	399	399	16.98455		8.508136	-4.619157	45.21787	6776.837
lninv	399	399	4.35357		1.919483	-1.263935	7.866209	1737.074
fert	399	399	11.66036		11.48709	.01	61.48	4652.483
lnpest	399	399	5.894247		3.147736	-3.506558	10.17477	2351.805
lnexch	399	399	5.297356		3.851618	-3.112977	22.62881	2113.645
prl	399	399	12.78276		38.36933	-8.237845	557.2018	5100.32
lnemi	394	394	9.061862		1.798554	5.104463	13.01573	3570.374
lncreagr	398	398	8.050961		1.684661	4.75359	11.63036	3204.283

Western

	count	sum_w	mean	var	sd	min	max	sum
lnagricpro	336	336	1.052002		13.1904	-30.38426	21.50492	353.4727
lnagricpro2	336	336	6.518948		.4952395	5.179591	7.458604	2190.367
renegy	336	336	6.758424		6.660662	.01	37.852	2270.83
renegy2	336	336	60.6238		59.01467	2.313144	344.6564	20369.6
lntop	336	336	3.631593		.8069356	1.668528	5.038714	1220.215
popgr	336	336	2.688664		.5940004	1.09448	5.363031	903.391
sav	336	336	15.44951		11.06809	-19.90297	50.65045	5191.035
lninv	336	336	4.660531		1.761406	1.654867	9.961684	1565.939

fert	336	336	8.166337		7.991433	0	38.40909	2743.889
lnpest	336	336	4.927875		2.079811	.0953102	9.482335	1655.766
lnexch	336	336	5.533523		1.935156	-.6071178	9.193187	1859.264
prl	336	336	5.886516		6.654558	-3.502586	41.5095	1977.87
lnemi	330	330	8.793658		1.535966	5.158481	12.17866	2901.907
lncreagr	336	336	7.046907		1.849868	1.386294	11.24446	2367.761

Central

	count	sum_w	mean	var	sd	min	max	sum
lnagricpro	189	189	5.322084		10.77965	-12.73676	21.5606	1005.874
lnagricpro2	189	189	6.22456		1.024013	3.204421	7.735664	1176.442
Renegy	189	189	11.38281		16.73499	.05	65.84	2151.351
renegy2	189	189	88.67113		101.1864	2.638387	409.6268	16758.84
lntop	189	189	3.709967		1.487096	1.568781	7.840627	701.1838
popgr	189	189	2.92163		.8321279	.2596476	4.654917	552.1881
sav	189	189	19.547		12.45055	3.453187	57.85012	3694.383
lninv	189	189	4.051702		1.840737	-.9597386	6.965027	765.7718
fert	189	189	5.444874		8.388495	0	35.56409	1029.081
Lnpest	189	189	5.487796		2.631359	-.1392621	9.290777	1037.193
lnexch	189	189	5.727153		1.287192	2.076709	7.523547	1082.432
prl	189	189	13.96421		52.72821	-8.97474	513.9068	2639.236
lnemi	189	189	9.721655		2.01688	4.049957	13.31589	1837.393
lncreagr	180	180	7.461522		2.366148	.6931472	11.58286	1343.074

Southern

	count	sum_w	mean	var	sd	min	max	sum
lnagricpro	105	105	12.75704		6.079869	3.883041	18.90026	1339.489
lnagricpro2	105	105	6.213756		.9250425	4.332964	7.504879	652.4443
renegy	105	105	14.13264		16.29705	.01	54.37	1483.927
renegy2	105	105	63.96781		117.4343	2.405236	586.2352	6716.62
lntop	105	105	5.215219		.8585203	3.828811	7.176451	547.598
popgr	105	105	1.18857		.6632023	-.6163564	2.197416	124.7998
sav	105	105	23.50739		9.925712	3.850888	47.64428	2468.276
lninv	105	105	4.189668		1.895918	.9707308	7.768965	439.9151
fert	105	105	16.4793		9.310788	.18	46.6	1730.327
lnpest	105	105	5.046122		3.02283	-1.203973	10.19828	529.8428
lnexch	105	105	2.185867		.3122947	1.54625	2.801556	229.516
prl	105	105	5.994702		3.973108	-9.616154	33.81258	629.4437
lnemi	105	105	9.588814		2.258674	6.647879	13.279	1006.825
lncreagr	105	105	8.365728		1.501687	4.682131	10.708	878.4014

Northern

	count	sum_w	mean	var	sd	min	max	sum

lnagricpro	105	105	-.091254	10.14734	-12.92838	12.23153	- 9.581672
lnagricpro2	105	105	7.125698	.2374798	6.593433	7.776146	748.1983
renegy	105	105	5.604474	6.987879	.05	29.15478	588.4698
renegy2	105	105	27.24564	78.02358	.0807174	516.6139	2860.792
lntop	105	105	4.130458	.4863291	3.311307	5.220881	433.6981
popgr	105	105	1.434071	.4272672	.5489261	2.267954	150.5774
sav	100	100	27.87439	14.91971	.3984882	69.80782	2787.439
lninv	105	105	6.552398	1.127137	3.293668	8.043889	688.0018
fert	105	105	18.35495	12.01305	.49	49.39	1927.27
lnpest	105	105	8.379383	.9269901	6.475387	9.620063	879.8352
lnexch	105	105	1.916135	1.603715	-.6690604	6.518332	201.1941
prl	105	105	4.545521	4.879604	-9.797647	29.50661	477.2797
lnemi	105	105	11.13259	.7834129	9.866399	12.49382	1168.922
lncreagr	84	84	9.549247	2.280901	5.595681	11.74087	802.1367

Appendix 6: Hausman Test

Eastern Africa

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 34.88
Prob>chi2 = 0.0054

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Western Africa

Test: Ho: difference in coefficients not systematic

chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 22.49
Prob>chi2 = 0.0324

Central Africa

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 166.88
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)

Southern Africa

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 91.33
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)

Northern Africa

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 70.90
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)

Appendix 7: Panel unit root test result

Eastern Africa

. do "C:\Users\Buchi\AppData\Local\Temp\STD40f8_000000.tmp"

. **Panel Unit Root Test By Pesaran**
. pescadf lnagricpro, lags(1) trend nodemean

Pesaran's CADF test for lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,21) Obs = 361
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.291	-2.630	-2.720	-2.880	0.089	0.535

. pescadf d.lnagricpro, lags(1) trend nodemean

Pesaran's CADF test for D.lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,20) Obs = 342
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.220	-2.630	-2.730	-2.920	-4.056	0.000

. pescadf renegy, lags(1) trend nodemean

```
Pesaran's CADF test for renegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
panel is unbalanced, only standarized Ztbar statistic can be calculated

Z[t-bar] test, (N,T1-T19) = (19, 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 20
21 21)
Obs = 360     Augmented by 1 lags (average)

   Z[t-bar]  P-value
   7.378    1.000

. pescadf d.renegy, lags(0) trend

Pesaran's CADF test for D.renegy
Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend
panel is unbalanced, only standarized Ztbar statistic can be calculated

Z[t-bar] test, (N,T1-T19) = (19, 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 19
20 20)
Obs = 360     Augmented by 0 lags (average)

   Z[t-bar]  P-value
  -4.209    0.000

. pescadf popgr, lags(1) trend nodemean

Pesaran's CADF test for popgr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,21)        Obs = 361
Augmented by 1 lags (average)

   t-bar     cv10     cv5      cv1   Z[t-bar]    P-value
  -4.630   -2.630   -2.720   -2.880  -10.873     0.000

. pescadf sav, lags(1) trend nodemean

Pesaran's CADF test for sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,21)        Obs = 361
Augmented by 1 lags (average)

   t-bar     cv10     cv5      cv1   Z[t-bar]    P-value
  -1.515   -2.630   -2.720   -2.880    3.724     1.000
```

```
. pescadf d.sav, lags(1) trend nodemean

Pesaran's CADF test for D.sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,20)        Obs = 342
Augmented by 1 lags (average)

   t-bar     cv10      cv5      cv1   Z[t-bar]    P-value
  -3.877   -2.630    -2.730    -2.920   -6.890     0.000

. pescadf lninv, lags(1) trend nodemean

Pesaran's CADF test for lninv
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,21)        Obs = 361
Augmented by 1 lags (average)

   t-bar     cv10      cv5      cv1   Z[t-bar]    P-value
  -3.143   -2.630    -2.720    -2.880   -3.903     0.000

. pescadf fert, lags(1) notrend nodemean

Pesaran's CADF test for fert
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (19,21)        Obs = 361
Augmented by 1 lags (average)

   t-bar     cv10      cv5      cv1   Z[t-bar]    P-value
  -2.245   -2.110    -2.200    -2.380   -2.226     0.013

. pescadf lnpest, lags(1) notrend nodemean

Pesaran's CADF test for lnpest
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (19,21)        Obs = 361
Augmented by 1 lags (average)

   t-bar     cv10      cv5      cv1   Z[t-bar]    P-value
  -1.342   -2.110    -2.200    -2.380    1.834     0.967

. pescadf d.lnpest, lags(1) notrend nodemean
```

Pesaran's CADF test for D.lnpest
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (19,20)   Obs = 342
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.035	-2.100	-2.210	-2.400	-1.302	0.096

. pescadf lnexch, lags(1) trend nodemean

Pesaran's CADF test for lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,21)   Obs = 361
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.215	-2.630	-2.720	-2.880	0.447	0.673

. pescadf d.lnexch, lags(1) trend nodemean

Pesaran's CADF test for D.lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,20)   Obs = 342
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.745	-2.630	-2.730	-2.920	-2.007	0.022

. pescadf prl, lags(1) trend nodemean

Pesaran's CADF test for prl
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,21)   Obs = 361
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.378	-2.630	-2.720	-2.880	4.369	1.000

. pescadf d.prl, lags(1) trend nodemean

Pesaran's CADF test for D.prl

Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,20)   Obs = 342
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.484	-2.630	-2.730	-2.920	-5.196	0.000

. pescadf lnemi, lags(1) trend nodemean

Number of gaps in sample: 1
sample may not contain gaps

Pesaran's CADF test for lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
panel is unbalanced, only standarized Ztbar statistic can be calculated

Z[t-bar] test, (N,T1-T19) = (19, 16 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21)
Obs = 354   Augmented by 1 lags (average)

Z[t-bar]	P-value
1.489	0.932

. pescadf d.lnemi, lags(1) trend nodemean

Number of gaps in sample: 1
sample may not contain gaps

Pesaran's CADF test for D.lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
panel is unbalanced, only standarized Ztbar statistic can be calculated

Z[t-bar] test, (N,T1-T19) = (19, 14 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20)
Obs = 334   Augmented by 1 lags (average)

Z[t-bar]	P-value
-1.926	0.027

. pescadf lncreagr, lags(1) trend nodemean

Pesaran's CADF test for lncreagr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
panel is unbalanced, only standarized Ztbar statistic can be calculated

Z[t-bar] test, (N,T1-T19) = (19, 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 20 21 21)
Obs = 360 Augmented by 1 lags (average)

```
  Z[t-bar]  P-value
 -3.141    0.001
```

. pescadf lntop, lags(1) trend nodemean

Pesaran's CADF test for lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,21) Obs = 361
Augmented by 1 lags (average)

```
  t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
 -2.093   -2.630   -2.720   -2.880   1.015     0.845
```

. pescadf d.lntop, lags(1) trend nodemean

Pesaran's CADF test for D.lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (19,20) Obs = 342
Augmented by 1 lags (average)

```
  t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
 -3.119   -2.630   -2.730   -2.920  -3.620     0.000
```

. pescadf lntoprenegy, lags(1) trend nodemean

Pesaran's CADF test for lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
panel is unbalanced, only standarized Ztbar statistic can be calculated

Z[t-bar] test, (N,T1-T19) = (19, 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 21 20 21 21)
Obs = 360 Augmented by 1 lags (average)

```
  Z[t-bar]  P-value
  5.757    1.000
```

. pescadf d.lntoprenegy, lags(0) trend nodemean

Pesaran's CADF test for D.lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

panel is unbalanced, only standarized Ztbar statistic can be calculated

Z[t-bar] test, (N,T1-T19) = (19, 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 19 20 20)
Obs = 360   Augmented by 0 lags (average)

Z[t-bar]	P-value
-6.349	0.000

Western Africa

. do "C:\Users\Buchi\AppData\Local\Temp\STD40f8_000000.tmp"

. **Panel Unit Root Test By Pesaran**
. pescadf lnagricpro, lags(1) trend nodemean

Pesaran's CADF test for lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)   Obs = 304
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.555	-2.630	-2.720	-2.880	-1.054	0.146

. pescadf d.lnagricpro, lags(1) trend nodemean

Pesaran's CADF test for D.lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,20)   Obs = 288
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.321	-2.630	-2.730	-2.920	-4.121	0.000

. pescadf renegy, lags(1) trend nodemean

Pesaran's CADF test for renegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)   Obs = 304
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.742	-2.630	-2.720	-2.880	2.445	0.993

. pescadf d.renegy, lags(0) trend

Pesaran's CADF test for D.renegy
Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,20)   Obs = 304
Augmented by 0 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.836	-2.630	-2.730	-2.920	-2.202	0.014

. pescadf popgr, lags(1) trend nodemean

Pesaran's CADF test for popgr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)   Obs = 304
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.793	-2.630	-2.720	-2.880	-6.377	0.000

. pescadf sav, lags(1) trend nodemean

Pesaran's CADF test for sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)   Obs = 304
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.046	-2.630	-2.720	-2.880	1.134	0.872

. pescadf d.sav, lags(1) trend nodemean

Pesaran's CADF test for D.sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,20)   Obs = 288
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.831	-2.630	-2.730	-2.920	-2.182	0.015

. pescadf lninv, lags(1) trend nodemean

Pesaran's CADF test for lninv

Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)   Obs = 304
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.392	-2.630	-2.720	-2.880	-0.354	0.362

. pescadf d.lninv, lags(1) trend nodemean

Pesaran's CADF test for D.lninv
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,20)   Obs = 288
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.220	-2.630	-2.730	-2.920	-3.721	0.000

. pescadf fert, lags(1) notrend nodemean

Pesaran's CADF test for fert
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (16,21)   Obs = 304
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.938	-2.110	-2.200	-2.380	-0.777	0.219

. pescadf d.fert, lags(1) notrend nodemean

Pesaran's CADF test for D.fert
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (16,20)   Obs = 288
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.835	-2.100	-2.210	-2.400	-8.257	0.000

. pescadf lnpest, lags(1) notrend nodemean

Pesaran's CADF test for lnpest
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

```
t-bar test, N,T = (16,21)        Obs = 304
Augmented by 1 lags (average)

    t-bar     cv10      cv5       cv1   Z[t-bar]    P-value
   -2.440   -2.110    -2.200    -2.380   -2.844     0.002

. pescadf lnexch, lags(1) trend nodemean

Pesaran's CADF test for lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)        Obs = 304
Augmented by 1 lags (average)

    t-bar     cv10      cv5       cv1   Z[t-bar]    P-value
   -2.752   -2.630    -2.720    -2.880   -1.900     0.029

. pescadf prl, lags(1) trend nodemean

Pesaran's CADF test for prl
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)        Obs = 304
Augmented by 1 lags (average)

    t-bar     cv10      cv5       cv1   Z[t-bar]    P-value
   -2.461   -2.630    -2.720    -2.880   -0.648     0.258

. pescadf d.prl, lags(1) trend nodemean

Pesaran's CADF test for D.prl
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,20)        Obs = 288
Augmented by 1 lags (average)

    t-bar     cv10      cv5       cv1   Z[t-bar]    P-value
   -3.398   -2.630    -2.730    -2.920   -4.427     0.000

. pescadf lnemi, lags(1) trend nodemean

Pesaran's CADF test for lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
panel is unbalanced, only standarized Ztbar statistic can be calculated
```

```
Z[t-bar] test, (N,T1-T16) = (16, 21 21 20 21 21 16 21 21 21 21 21 21 21 21 21 21)
Obs = 298     Augmented by 1 lags (average)

   Z[t-bar]  P-value
   2.469    0.993

. pescadf d.lnemi, lags(1) trend nodemean

Pesaran's CADF test for D.lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
panel is unbalanced, only standarized Ztbar statistic can be calculated

Z[t-bar] test, (N,T1-T16) = (16, 20 20 19 20 20 15 20 20 20 20 20 20 20 20 20 20)
Obs = 282     Augmented by 1 lags (average)

   Z[t-bar]  P-value
  -3.492    0.000

. pescadf lncreagr, lags(1) trend nodemean

Pesaran's CADF test for lncreagr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)        Obs = 304
Augmented by 1 lags (average)

   t-bar     cv10     cv5      cv1   Z[t-bar]    P-value
  -3.227   -2.630   -2.720   -2.880   -3.943     0.000

. pescadf lntop, lags(1) trend nodemean

Pesaran's CADF test for lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)        Obs = 304
Augmented by 1 lags (average)

   t-bar     cv10     cv5      cv1   Z[t-bar]    P-value
  -2.536   -2.630   -2.720   -2.880   -0.970     0.166

. pescadf d.lntop, lags(1) trend nodemean

Pesaran's CADF test for D.lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,20)        Obs = 288
```

Augmented by 1 lags (average)

```
   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -3.649  -2.630   -2.730   -2.920  -5.420     0.000
```

. pescadf lntoprenegy, lags(1) trend nodemean

Pesaran's CADF test for lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,21)   Obs = 304
Augmented by 1 lags (average)

```
   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -1.890  -2.630   -2.720   -2.880   1.806     0.965
```

. pescadf d.lntoprenegy, lags(0) trend nodemean

Pesaran's CADF test for D.lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (16,20)   Obs = 304
Augmented by 0 lags (average)

```
   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -3.396  -2.630   -2.730   -2.920  -4.421     0.000
```

.
end of do-file
Central Africa
. do "C:\Users\Buchi\AppData\Local\Temp\STD40f8_000000.tmp"

. **Panel Unit Root Test By Pesaran**
. pescadf lnagricpro, lags(2) trend nodemean

Pesaran's CADF test for lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)   Obs = 162
Augmented by 2 lags (average)

```
   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -2.255  -2.730   -2.860   -3.100   0.177     0.570
```

. pescadf d.lnagricpro, lags(1) trend nodemean

Pesaran's CADF test for D.lnagricpro

```
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,20)          Obs = 162
Augmented by 1 lags (average)

   t-bar     cv10      cv5       cv1   Z[t-bar]    P-value
  -4.113   -2.740    -2.880    -3.150   -5.445     0.000

. pescadf renegy, lags(1) trend nodemean

Pesaran's CADF test for renegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)          Obs = 171
Augmented by 1 lags (average)

   t-bar     cv10      cv5       cv1   Z[t-bar]    P-value
  -1.904   -2.730    -2.860    -3.100    1.310     0.905

. pescadf d.renegy, lags(0) trend

Pesaran's CADF test for D.renegy
Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,20)          Obs = 171
Augmented by 0 lags (average)

   t-bar     cv10      cv5       cv1   Z[t-bar]    P-value
  -3.287   -2.740    -2.880    -3.150   -2.992     0.001

. pescadf popgr, lags(1) trend nodemean

Pesaran's CADF test for popgr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)          Obs = 171
Augmented by 1 lags (average)

   t-bar     cv10      cv5       cv1   Z[t-bar]    P-value
  -4.713   -2.730    -2.860    -3.100   -7.751     0.000

. pescadf sav, lags(1) trend nodemean

Pesaran's CADF test for sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
```

```
t-bar test, N,T = (9,21)        Obs = 171
Augmented by 1 lags (average)

   t-bar    cv10    cv5     cv1   Z[t-bar]   P-value
  -0.839  -2.730  -2.860  -3.100   4.746     1.000

. pescadf d.sav, lags(1) trend nodemean

Pesaran's CADF test for D.sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,20)        Obs = 162
Augmented by 1 lags (average)

   t-bar    cv10    cv5     cv1   Z[t-bar]   P-value
  -3.954  -2.740  -2.880  -3.150  -4.971     0.000

. pescadf lninv, lags(1) trend nodemean

Pesaran's CADF test for lninv
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)        Obs = 171
Augmented by 1 lags (average)

   t-bar    cv10    cv5     cv1   Z[t-bar]   P-value
  -2.801  -2.730  -2.860  -3.100  -1.583     0.057

. pescadf fert, lags(1) notrend nodemean

Pesaran's CADF test for fert
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (9,21)        Obs = 171
Augmented by 1 lags (average)

   t-bar    cv10    cv5     cv1   Z[t-bar]   P-value
  -1.799  -2.210  -2.330  -2.570  -0.122     0.451

. pescadf d.fert, lags(1) notrend nodemean

Pesaran's CADF test for D.fert
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (9,20)        Obs = 162
```

```
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -3.335  -2.210   -2.340   -2.600  -4.676    0.000

. pescadf lnpest, lags(1) notrend nodemean

Pesaran's CADF test for lnpest
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (9,21)        Obs = 171
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -2.288  -2.210   -2.330   -2.570  -1.632    0.051

. pescadf lnexch, lags(1) trend nodemean

Pesaran's CADF test for lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)        Obs = 171
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -1.229  -2.730   -2.860   -3.100   3.486    1.000

. pescadf d.lnexch, lags(1) trend nodemean

Pesaran's CADF test for D.lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,20)        Obs = 162
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -2.745  -2.740   -2.880   -3.150  -1.380    0.084

. pescadf prl, lags(1) trend nodemean

Pesaran's CADF test for prl
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)        Obs = 171
Augmented by 1 lags (average)
```

```
   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -4.152  -2.730   -2.860   -3.100   -5.942     0.000

. pescadf lnemi, lags(1) trend nodemean

Pesaran's CADF test for lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)        Obs = 171
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -2.984  -2.730   -2.860   -3.100   -2.173     0.015

. pescadf lncreagr, lags(1) trend nodemean

Pesaran's CADF test for lncreagr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,20)        Obs = 162
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -1.756  -2.740   -2.880   -3.150    1.724     0.958

. pescadf d.lncreagr, lags(0) trend nodemean

Pesaran's CADF test for D.lncreagr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,19)        Obs = 162
Augmented by 0 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -3.980  -2.740   -2.880   -3.150   -5.003     0.000

. pescadf lntop, lags(1) trend nodemean

Pesaran's CADF test for lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)        Obs = 171
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -2.365  -2.730   -2.860   -3.100   -0.179     0.429
```

```
. pescadf d.lntop, lags(1) trend nodemean

Pesaran's CADF test for D.lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,20)         Obs = 162
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -3.039   -2.740   -2.880   -3.150   -2.253     0.012

. pescadf lntoprenegy, lags(1) trend nodemean

Pesaran's CADF test for lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,21)         Obs = 171
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -1.845   -2.730   -2.860   -3.100    1.501     0.933

. pescadf d.lntoprenegy, lags(0) trend nodemean

Pesaran's CADF test for D.lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (9,20)         Obs = 171
Augmented by 0 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -3.701   -2.740   -2.880   -3.150   -4.220     0.000
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Southern Africa

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. **Panel Unit Root Test By Pesaran**
. pescadf lnagricpro, lags(2) trend nodemean

Pesaran's CADF test for lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)         Obs = 90
Augmented by 2 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
```

```
  -2.214  -2.730   -2.860   -3.100   0.230    0.591

. pescadf d.lnagricpro, lags(1) trend nodemean

Pesaran's CADF test for D.lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)        Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -4.446  -2.740   -2.880   -3.150  -4.794     0.000

. pescadf renegy, lags(1) trend nodemean

Pesaran's CADF test for renegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -1.667  -2.730   -2.860   -3.100   1.546     0.939

. pescadf d.renegy, lags(0) trend

Pesaran's CADF test for D.renegy
Cross-sectional average in first period extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)        Obs = 95
Augmented by 0 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -4.365  -2.740   -2.880   -3.150  -4.617     0.000

. pescadf popgr, lags(1) trend nodemean

Pesaran's CADF test for popgr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -4.005  -2.730   -2.860   -3.100  -4.076     0.000
```

```
. pescadf sav, lags(1) trend nodemean

Pesaran's CADF test for sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5     cv1  Z[t-bar]   P-value
  -2.600  -2.730  -2.860  -3.100  -0.697    0.243

. pescadf d.sav, lags(1) trend nodemean

Pesaran's CADF test for D.sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)        Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5     cv1  Z[t-bar]   P-value
  -3.445  -2.740  -2.880  -3.150  -2.578    0.005

. pescadf lninv, lags(1) trend nodemean

Pesaran's CADF test for lninv
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5     cv1  Z[t-bar]   P-value
  -4.515  -2.730  -2.860  -3.100  -5.303    0.000

. pescadf fert, lags(1) notrend nodemean

Pesaran's CADF test for fert
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5     cv1  Z[t-bar]   P-value
  -1.504  -2.210  -2.330  -2.570   0.590    0.723

. pescadf d.fert, lags(1) notrend nodemean
```

```
Pesaran's CADF test for D.fert
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (5,20)        Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -3.583  -2.210   -2.340   -2.600  -4.022     0.000

. pescadf lnpest, lags(1) notrend nodemean

Pesaran's CADF test for lnpest
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -0.910  -2.210   -2.330   -2.570   1.959     0.975

. pescadf d.lnpest, lags(1) trend nodemean

Pesaran's CADF test for D.lnpest
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)        Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -1.548  -2.740   -2.880   -3.150   1.621     0.947

. pescadf lnexch, lags(1) trend nodemean

Pesaran's CADF test for lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -2.471  -2.730   -2.860   -3.100  -0.388     0.349

. pescadf d.lnexch, lags(1) trend nodemean

Pesaran's CADF test for D.lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
```

```
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)        Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -3.311  -2.740   -2.880   -3.150  -2.283    0.011

. pescadf prl, lags(1) trend nodemean

Pesaran's CADF test for prl
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -3.438  -2.730   -2.860   -3.100  -2.713    0.003

. pescadf lnemi, lags(1) trend nodemean

Pesaran's CADF test for lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -1.494  -2.730   -2.860   -3.100   1.961    0.975

. pescadf d.lnemi, lags(0) trend nodemean

Pesaran's CADF test for D.lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)        Obs = 95
Augmented by 0 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -5.128  -2.740   -2.880   -3.150  -6.305    0.000

. pescadf lncreagr, lags(1) trend nodemean

Pesaran's CADF test for lncreagr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend
```

t-bar test, N,T = (5,21) Obs = 95
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.848	-2.730	-2.860	-3.100	-1.293	0.098

. pescadf d.lncreagr, lags(1) trend nodemean

Pesaran's CADF test for D.lncreagr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20) Obs = 90
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.541	-2.740	-2.880	-3.150	-2.793	0.003

. pescadf lntop, lags(1) trend nodemean

Pesaran's CADF test for lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21) Obs = 95
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.530	-2.730	-2.860	-3.100	-0.529	0.298

. pescadf d.lntop, lags(1) trend nodemean

Pesaran's CADF test for D.lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20) Obs = 90
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.370	-2.740	-2.880	-3.150	-2.414	0.008

. pescadf lntoprenegy, lags(1) trend nodemean

Pesaran's CADF test for lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21) Obs = 95
Augmented by 1 lags (average)

```
  t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
 -1.776  -2.730    -2.860    -3.100    1.284     0.900
```

. pescadf d.lntoprenegy, lags(0) trend nodemean

Pesaran's CADF test for D.lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)   Obs = 95
Augmented by 0 lags (average)

```
  t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
 -3.573  -2.740    -2.880    -3.150   -2.862     0.002.
```

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Northern Africa

. do "C:\Users\Buchi\AppData\Local\Temp\STD40f8_000000.tmp"

. **Panel Unit Root Test By Pesaran**
. pescadf lnagricpro, lags(1) trend nodemean

Pesaran's CADF test for lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)   Obs = 95
Augmented by 1 lags (average)

```
  t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
 -2.752  -2.730    -2.860    -3.100   -1.062     0.144
```

. pescadf d.lnagricpro, lags(1) trend nodemean

Pesaran's CADF test for D.lnagricpro
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)   Obs = 90
Augmented by 1 lags (average)

```
  t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
 -3.251  -2.740    -2.880    -3.150   -2.150     0.016
```

. pescadf renegy, lags(1) trend nodemean

Pesaran's CADF test for renegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)   Obs = 95
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-0.902	-2.730	-2.860	-3.100	3.385	1.000

. pescadf d.renegy, lags(0) trend nodemean

Pesaran's CADF test for D.renegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)   Obs = 95
Augmented by 0 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-0.952	-2.740	-2.880	-3.150	2.940	0.998

. pescadf popgr, lags(1) trend nodemean

Pesaran's CADF test for popgr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)   Obs = 95
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-4.008	-2.730	-2.860	-3.100	-4.083	0.000

. pescadf sav, lags(1) trend nodemean

Pesaran's CADF test for sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)   Obs = 90
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.863	-2.740	-2.880	-3.150	1.042	0.851

. pescadf d.sav, lags(1) trend nodemean

Pesaran's CADF test for D.sav
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,19)   Obs = 85
Augmented by 1 lags (average)

```
   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -4.708  -2.740   -2.880   -3.150  -5.280     0.000

. pescadf lninv, lags(1) trend nodemean

Pesaran's CADF test for lninv
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)         Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -1.476  -2.730   -2.860   -3.100   2.005     0.978

. pescadf d.lninv, lags(1) trend nodemean

Pesaran's CADF test for D.lninv
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)         Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -3.125  -2.740   -2.880   -3.150  -1.870     0.031

. pescadf fert, lags(1) notrend nodemean

Pesaran's CADF test for fert
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (5,21)         Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
  -2.408  -2.210   -2.330   -2.570  -1.493     0.068

. pescadf lnpest, lags(1) notrend nodemean

Pesaran's CADF test for lnpest
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (5,21)         Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]    P-value
```

```
  -1.394  -2.210   -2.330   -2.570   0.843    0.800

. pescadf d.lnpest, lags(1) trend nodemean

Pesaran's CADF test for D.lnpest
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)         Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -3.009  -2.740   -2.880   -3.150  -1.615    0.053

. pescadf lnexch, lags(1) trend nodemean

Pesaran's CADF test for lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)         Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -0.463  -2.730   -2.860   -3.100   4.441    1.000

. pescadf d.lnexch, lags(1) trend nodemean

Pesaran's CADF test for D.lnexch
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)         Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -3.107  -2.740   -2.880   -3.150  -1.832    0.034

. pescadf prl, lags(1) trend nodemean

Pesaran's CADF test for prl
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)         Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5      cv1   Z[t-bar]   P-value
  -2.535  -2.730   -2.860   -3.100  -0.541    0.294
```

```
. pescadf d.prl, lags(1) trend nodemean

Pesaran's CADF test for D.prl
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)        Obs = 90
Augmented by 1 lags (average)

   t-bar    cv10     cv5     cv1   Z[t-bar]    P-value
  -3.829  -2.740  -2.880  -3.150  -3.430     0.000

. pescadf lnemi, lags(1) trend nodemean

Pesaran's CADF test for lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)        Obs = 95
Augmented by 1 lags (average)

   t-bar    cv10     cv5     cv1   Z[t-bar]    P-value
  -1.820  -2.730  -2.860  -3.100   1.177     0.880

. pescadf d.lnemi, lags(0) trend nodemean

Pesaran's CADF test for D.lnemi
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)        Obs = 95
Augmented by 0 lags (average)

   t-bar    cv10     cv5     cv1   Z[t-bar]    P-value
  -5.187  -2.740  -2.880  -3.150  -6.435     0.000

. pescadf lncreagr, lags(1) trend nodemean

Pesaran's CADF test for lncreagr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (4,21)        Obs = 76
Augmented by 1 lags (average)

   t-bar    cv10     cv5     cv1   Z[t-bar]    P-value
  -1.934  -2.730  -2.860  -3.100   0.809     0.791

. pescadf d.lncreagr, lags(1) notrend nodemean
```

Pesaran's CADF test for D.lncreagr
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant

t-bar test, N,T = (4,20)   Obs = 72
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.258	-2.210	-2.340	-2.600	0.916	0.820

. pescadf lntop, lags(1) trend nodemean

Pesaran's CADF test for lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)   Obs = 95
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-2.672	-2.730	-2.860	-3.100	-0.870	0.192

. pescadf d.lntop, lags(1) trend nodemean

Pesaran's CADF test for D.lntop
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,20)   Obs = 90
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-3.871	-2.740	-2.880	-3.150	-3.523	0.000

. pescadf lntoprenegy, lags(1) trend nodemean

Pesaran's CADF test for lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated
Deterministics chosen: constant & trend

t-bar test, N,T = (5,21)   Obs = 95
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.188	-2.730	-2.860	-3.100	2.698	0.997

. pescadf d.lntoprenegy, lags(1) notrend nodemean

Pesaran's CADF test for D.lntoprenegy
Cross-sectional average in first period not extracted and extreme t-values truncated

Deterministics chosen: constant

t-bar test, N,T = (5,20)   Obs = 90
Augmented by 1 lags (average)

t-bar	cv10	cv5	cv1	Z[t-bar]	P-value
-1.467	-2.210	-2.340	-2.600	0.571	0.716.

end of do-file

Appendix 8: Individual Country Estimation of Productivity

Country	Dependent variable	capital (lnK)	Std. err(K)	Labour (lnL)	Std.err (L)	Constant	Std.err	Obs.	R2	Adj. R2
Algeria	lnalgagric	0.095	(0.239)	1.543**	(0.610)	-3.426	(4.512)	21	0.903	0.893
Angola	lnangagric	0.371***	(0.072)	0.950***	(0.235)	-1.472	(2.618)	21	0.925	0.917
Benin	lnbenagric	-0.262	(0.244)	1.744***	(0.587)	0.959	(4.023)	21	0.865	0.850
Botswana	lnbotagric	-0.021	(0.250)	0.018	(0.786)	18.500***	(6.415)	21	0.001	-0.110
Burkina Faso	lnbukagric	0.282**	(0.106)	0.855*	(0.434)	2.133	(4.984)	21	0.813	0.792
Burundi	lnburagric	-0.115	(0.078)	1.208***	(0.202)	5.157**	(1.905)	21	0.832	0.813
Cabo Verde	lncabagric	-0.068	(0.200)	-0.074	(0.640)	21.311***	(4.277)	21	0.113	0.015
Cameroon	lncamagric	0.492**	(0.176)	1.077**	(0.378)	-5.579*	(2.736)	21	0.937	0.930
Central African Republic	lncafagric	0.183***	(0.053)	0.189	(0.271)	13.954***	(2.906)	21	0.878	0.865
Chad	lnchaagric	0.129	(0.137)	1.345**	(0.470)	-1.289	(4.519)	21	0.898	0.886
Comoros	lncomagric	0.044**	(0.015)	0.271***	(0.033)	14.249***	(0.277)	21	0.925	0.917
Congo, Rep.	lncongagric	0.051	(0.049)	1.148***	(0.106)	4.468***	(0.800)	21	0.969	0.965
Côte d'Ivoire	lncotagric	-0.292***	(0.088)	2.660***	(0.222)	-12.446***	(1.843)	21	0.967	0.963
Democratic Republic of the Congo	lndrcagric	-0.022	(0.124)	2.107***	(0.240)	-12.479**	(4.836)	21	0.811	0.790
Djibouti	lndjiagric	0.141*	(0.075)	-0.382	(0.315)	20.275***	(2.754)	21	0.183	0.092
Egypt	lnegyagric	-0.012	(0.056)	0.767***	(0.194)	11.313***	(2.075)	21	0.881	0.868
Equatorial Guinea	lnequagric	-0.273***	(0.064)	0.013	(0.234)	21.349***	(1.862)	21	0.895	0.883
Eritrea	lneriagric	-0.062	(0.114)	0.877**	(0.375)	9.792**	(3.562)	21	0.460	0.399
Eswatini	lneswagric	0.163***	(0.029)	0.774***	(0.102)	6.955***	(1.084)	21	0.911	0.901
Ethiopia	lnethagric	-0.335***	(0.094)	2.207***	(0.188)	-7.713***	(1.385)	21	0.981	0.979
Gabon	lngabagric	-0.025	(0.023)	0.680***	(0.033)	11.606***	(0.467)	21	0.966	0.962

Gambia	lngamagric	0.376	(0.221)	-0.261	(0.216)	15.618***	(2.784)	21	0.139	0.044
Ghana	lnghaagric	0.116**	(0.053)	1.345***	(0.131)	-1.268	(1.157)	21	0.976	0.973
Guinea	lnguiagric	0.004	(0.042)	1.703***	(0.106)	-4.626***	(0.832)	21	0.992	0.991
Guinea-Bissau	lngubagric	0.224	(0.264)	0.239	(0.663)	12.287***	(4.035)	21	0.718	0.686
Kenya	lnkenagric	-0.371***	(0.113)	1.983***	(0.350)	-1.594	(3.345)	21	0.923	0.914
Lesotho	lnlesagric	-0.029	(0.083)	0.152	(0.463)	17.549***	(4.942)	21	0.007	-0.104
Liberia	lnlibagric	-0.063	(0.055)	0.527***	(0.166)	13.759***	(1.396)	21	0.723	0.692
Libya	lnlbyagric	-0.005	(0.026)	0.645***	(0.082)	12.169***	(1.180)	21	0.782	0.758
Madagascar	lnmadagric	0.319***	(0.083)	0.281***	(0.080)	10.373***	(1.082)	21	0.878	0.865
Malawi	lnmalagric	0.214	(0.156)	2.040***	(0.232)	-13.686***	(2.519)	21	0.920	0.912
Mali	lnmaliagric	0.405***	(0.126)	0.091	(0.517)	12.398**	(5.433)	21	0.956	0.951
Mauritania	lnmauagric	-0.128**	(0.059)	1.222***	(0.134)	6.375***	(0.740)	21	0.973	0.970
Mauritius	lnmaragric	0.033	(0.084)	-0.690	(0.484)	28.107***	(4.830)	21	0.295	0.217
Morocco	lnmoragric	0.192	(0.264)	1.935*	(1.113)	-12.692	(12.021)	21	0.832	0.813
Mozambique	lnmozagric	0.134	(0.130)	1.068**	(0.423)	2.029	(4.481)	21	0.807	0.785
Namibia	lnnamagric	0.066	(0.067)	0.069	(0.072)	16.807***	(1.892)	21	0.076	-0.026
Niger	lnnigagric	-0.104	(0.121)	2.173***	(0.219)	-10.010***	(1.910)	21	0.940	0.934
Nigeria	lnngragric	0.064	(0.118)	1.119	(0.776)	3.244	(10.833)	21	0.832	0.813
Rwanda	lnrwaagric	0.453	(0.323)	-1.286	(1.068)	32.607***	(10.082)	21	0.145	0.050
Sao Tome and Principe	lnsaoagric	-0.035	(0.039)	0.060	(0.213)	17.303***	(1.693)	21	0.198	0.109
Senegal	lnsenagric	-0.166	(0.261)	2.880***	(0.668)	-18.556***	(5.921)	21	0.757	0.730
Seychelles	lnseyagric	-0.313***	(0.093)	-0.108	(0.138)	23.692***	(3.423)	21	0.511	0.457
Sierra Leone	lnsieagric	-0.413	(0.319)	4.103***	(1.129)	-29.853**	(10.931)	21	0.663	0.626
Somalia	lnsomagric	-0.033	(0.037)	-0.048	(0.075)	22.957***	(1.713)	21	0.042	-0.064
South Africa	lnsafagric	-0.083	(0.075)	1.309***	(0.150)	3.969*	(1.989)	21	0.852	0.836
South Sudan	lnssuagric	-0.180	(0.540)	-3.543***	(0.495)	79.976***	(19.839)	21	0.962	0.958
Sudan	lnsudagric	0.205***	(0.065)	4.116***	(0.346)	-47.191***	(6.887)	21	0.973	0.970
Togo	lntogagric	0.167***	(0.056)	0.853***	(0.115)	5.482***	(0.755)	21	0.978	0.975
Tunisia	lntunagric	-0.115	(0.137)	2.173***	(0.408)	-7.811*	(3.993)	21	0.785	0.762
Uganda	lnugaagric	-0.379	(0.226)	0.663	(0.388)	20.412***	(1.850)	21	0.140	0.044
Zambia	lnzamagric	-0.061	(0.066)	2.219***	(0.258)	-11.159***	(2.948)	21	0.913	0.904
Zimbabwe	lnzimagric	-0.042	(0.043)	0.297	(0.479)	18.226**	(7.061)	21	0.052	-0.053
Tanzania	lntanagric	0.357*	(0.197)	0.575	(0.722)	4.985	(7.903)	21	0.936	0.929

Appendix 9: Raw Result of Productivity Estimation

```
. do "C:\Users\Buchi\AppData\Local\Temp\STD3f50_000000.tmp"
. *Regress agricultural productivity equation**
. reg lnalgagric lnalgk lnalgl

      Source |       SS           df       MS      Number of obs   =        21
```

```
-------------+------------------------------   F(2, 18)       =     84.11
       Model |  1.98609079         2  .993045396   Prob > F       =    0.0000
    Residual |  .212519505        18  .011806639   R-squared      =    0.9033
-------------+------------------------------   Adj R-squared  =    0.8926
       Total |   2.1986103        20  .109930515   Root MSE       =    .10866

------------------------------------------------------------------------------
  lnalgagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnalgk |   .0947631   .2390812     0.40   0.696    -.4075278    .5970541
      lnalgl |   1.543482   .6098944     2.53   0.021     .2621415    2.824823
       _cons |  -3.425827   4.511815    -0.76   0.458     -12.9048    6.053143
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnangagric lnangk lnangl

      Source |       SS           df       MS      Number of obs   =        21
-------------+------------------------------   F(2, 18)       =    111.03
       Model |  3.46986856         2  1.73493428   Prob > F       =    0.0000
    Residual |  .281271451        18  .015626192   R-squared      =    0.9250
-------------+------------------------------   Adj R-squared  =    0.9167
       Total |  3.75114001        20     .187557   Root MSE       =      .125

------------------------------------------------------------------------------
  lnangagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnangk |   .3712613    .072422     5.13   0.000     .2191084    .5234142
      lnangl |   .9498319   .2346208     4.05   0.001      .456912    1.442752
       _cons |  -1.471569   2.617708    -0.56   0.581    -6.971169     4.02803
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnbenagric lnbenk lnbenl

      Source |       SS           df       MS      Number of obs   =        21
-------------+------------------------------   F(2, 18)       =     57.73
       Model |  .889670113         2  .444835056   Prob > F       =    0.0000
    Residual |  .138709644        18  .007706091   R-squared      =    0.8651
-------------+------------------------------   Adj R-squared  =    0.8501
```

```
      Total |  1.02837976       20  .051418988   Root MSE      =   .08778

------------------------------------------------------------------------------
  lnbenagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnbenk |  -.2615949   .2436819    -1.07   0.297    -.7735515    .2503617
     lnbenl |   1.743959   .5872035     2.97   0.008     .5102907    2.977628
      _cons |   .9594349   4.022796     0.24   0.814    -7.492147    9.411017
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnbotagric lnbotk lnbotl

     Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    0.01
      Model |  .00092102        2  .00046051           Prob > F      =  0.9883
   Residual |  .705673413      18  .039204078          R-squared     =  0.0013
-------------+------------------------------           Adj R-squared = -0.1097
      Total |  .706594433      20  .035329722          Root MSE      =    .198

------------------------------------------------------------------------------
  lnbotagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnbotk |  -.0208971   .2503715    -0.08   0.934    -.5469082     .505114
     lnbotl |   .0178548   .7856876     0.02   0.982    -1.632813    1.668523
      _cons |    18.4996   6.415222     2.88   0.010     5.021716    31.97748
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnbukagric lnbukk lnbukl

     Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   39.10
      Model |  1.26461336       2  .632306679          Prob > F      =  0.0000
   Residual |  .291074082      18  .016170782          R-squared     =  0.8129
-------------+------------------------------           Adj R-squared =  0.7921
      Total |  1.55568744      20  .077784372          Root MSE      =   .12716

------------------------------------------------------------------------------
  lnbukagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

```
-------------+----------------------------------------------------------------
      lnbukk |   .2818481   .1060472     2.66   0.016     .0590513     .504645
      lnbukl |   .8554279   .4339123     1.97   0.064    -.0561879    1.767044
       _cons |   2.132717   4.983961     0.43   0.674    -8.338197    12.60363
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnburagric lnburk lnburl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   44.54
       Model |  .711674048     2  .355837024           Prob > F      =  0.0000
    Residual |  .143813567    18  .007989643           R-squared     =  0.8319
-------------+------------------------------           Adj R-squared =  0.8132
       Total |  .855487616    20  .042774381           Root MSE      =  .08938

------------------------------------------------------------------------------
  lnburagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnburk |  -.1150025   .0782536    -1.47   0.159    -.2794073    .0494023
      lnburl |   1.207928   .2018174     5.99   0.000     .7839255    1.631931
       _cons |   5.156618   1.904904     2.71   0.014     1.154564    9.158672
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lncabagric lncabk lncabl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    1.15
       Model |  .029777925     2  .014888963           Prob > F      =  0.3389
    Residual |  .233090842    18  .012949491           R-squared     =  0.1133
-------------+------------------------------           Adj R-squared =  0.0148
       Total |  .262868767    20  .013143438           Root MSE      =   .1138

------------------------------------------------------------------------------
  lncabagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lncabk |  -.0679351   .1998603    -0.34   0.738    -.4878259    .3519558
      lncabl |  -.0738774   .6402325    -0.12   0.909    -1.418956    1.271201
       _cons |   21.31126   4.277371     4.98   0.000     12.32483    30.29768
```

```
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lncamagric lncamk lncaml

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =  132.96
       Model |  2.15637394     2  1.07818697           Prob > F      =  0.0000
    Residual |  .145958548    18  .008108808           R-squared     =  0.9366
-------------+------------------------------           Adj R-squared =  0.9296
       Total |  2.30233249    20  .115116625           Root MSE      =  .09005

------------------------------------------------------------------------------
  lncamagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lncamk |   .4924622   .1760835     2.80   0.012     .1225244       .8624
      lncaml |   1.076963    .378154     2.85   0.011     .2824904    1.871435
       _cons |  -5.578553   2.735942    -2.04   0.056    -11.32655     .169448
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lncafagric lncafk lncafl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =   64.99
       Model |  .136569151     2  .068284576           Prob > F      =  0.0000
    Residual |  .018912251    18  .001050681           R-squared     =  0.8784
-------------+------------------------------           Adj R-squared =  0.8648
       Total |  .155481403    20   .00777407           Root MSE      =  .03241

------------------------------------------------------------------------------
  lncafagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lncafk |   .1829538   .0531918     3.44   0.003      .071202    .2947056
      lncafl |   .1893204   .2713823     0.70   0.494    -.3808327    .7594735
       _cons |   13.95408   2.906465     4.80   0.000     7.847826    20.06034
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
```

```
> nd
testt.xml
dir : seeout

. reg lnchaagric lnchak lnchal

     Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   79.06
      Model |  1.86301526     2  .931507629           Prob > F      =  0.0000
   Residual |  .212085262    18  .011782515           R-squared     =  0.8978
-------------+------------------------------           Adj R-squared =  0.8864
      Total |  2.07510052    20  .103755026           Root MSE      =  .10855

------------------------------------------------------------------------------
  lnchaagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnchak |   .1290276   .1369024     0.94   0.358    -.1585937     .416649
      lnchal |    1.34535   .4704071     2.86   0.010     .3570612    2.333638
       _cons |  -1.288514   4.519417    -0.29   0.779    -10.78346    8.206428
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lncomagric lncomk lncoml

     Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =  111.57
      Model |  .077442775     2  .038721388           Prob > F      =  0.0000
   Residual |  .006247211    18  .000347067           R-squared     =  0.9254
-------------+------------------------------           Adj R-squared =  0.9171
      Total |  .083689986    20  .004184499           Root MSE      =  .01863

------------------------------------------------------------------------------
  lncomagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lncomk |   .0440771   .0154791     2.85   0.011     .0115567    .0765976
      lncoml |   .2706024   .0331657     8.16   0.000     .2009239    .3402809
       _cons |    14.2491   .2772359    51.40   0.000     13.66665    14.83155
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout
```

```
. reg lncongagric lncongk lncongl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =  277.70
       Model |  .920972836     2  .460486418           Prob > F      =  0.0000
    Residual |  .029847954    18  .00165822            R-squared     =  0.9686
-------------+------------------------------           Adj R-squared =  0.9651
       Total |  .95082079     20  .04754104            Root MSE      =  .04072

------------------------------------------------------------------------------
 lncongagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lncongk |   .0513466   .0486898     1.05   0.306    -.0509469    .1536402
     lncongl |    1.14788   .1060959    10.82   0.000     .9249803    1.370779
       _cons |   4.468446   .8000428     5.59   0.000     2.787619    6.149274
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lncotagric lncotk lncotl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =  259.79
       Model |  1.19775738     2  .598878691           Prob > F      =  0.0000
    Residual |  .041493913    18  .002305217           R-squared     =  0.9665
-------------+------------------------------           Adj R-squared =  0.9628
       Total |  1.2392513     20  .061962565           Root MSE      =  .04801

------------------------------------------------------------------------------
  lncotagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lncotk |  -.2918577   .0876089    -3.33   0.004    -.4759171   -.1077983
      lncotl |    2.65973   .2216438    12.00   0.000     2.194073    3.125386
       _cons |  -12.44647   1.843429    -6.75   0.000    -16.31937    -8.57357
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lndrcagric lndrck lndrcl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   38.70
```

```
       Model |  2.02767155     2  1.01383578   Prob > F      =  0.0000
    Residual |  .471590186    18  .026199455   R-squared     =  0.8113
-------------+------------------------------   Adj R-squared =  0.7903
       Total |  2.49926174    20  .124963087   Root MSE      =  .16186

------------------------------------------------------------------------------
  lndrcagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lndrck |   -.021782   .1243035    -0.18   0.863    -.282934     .23937
      lndrcl |   2.107229   .2396187     8.79   0.000    1.603809    2.610649
       _cons |  -12.47908   4.836143    -2.58   0.019   -22.63944   -2.318722
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lndjiagric lndjik lndjil

      Source |       SS       df       MS      Number of obs =      21
-------------+------------------------------   F(2, 18)      =    2.02
       Model |  .040234854     2  .020117427   Prob > F      =  0.1619
    Residual |  .179432484    18  .009968471   R-squared     =  0.1832
-------------+------------------------------   Adj R-squared =  0.0924
       Total |  .219667338    20  .010983367   Root MSE      =  .09984

------------------------------------------------------------------------------
  lndjiagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lndjik |   .1407715   .0751989     1.87   0.078   -.0172156    .2987586
      lndjil |  -.3822186   .3152399    -1.21   0.241   -1.044513    .2800757
       _cons |   20.27491   2.753876     7.36   0.000    14.48923    26.06059
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnegyagric lnegyk lnegyl

      Source |       SS       df       MS      Number of obs =      21
-------------+------------------------------   F(2, 18)      =   66.63
       Model |  .186714989     2  .093357494   Prob > F      =  0.0000
    Residual |  .025219316    18  .001401073   R-squared     =  0.8810
-------------+------------------------------   Adj R-squared =  0.8678
       Total |  .211934305    20  .010596715   Root MSE      =  .03743
```

```
------------------------------------------------------------------------------
  lnegyagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnegyk |  -.0121231   .0560128    -0.22   0.831    -.1298017    .1055555
      lnegyl |    .767028   .1940068     3.95   0.001     .3594348    1.174621
       _cons |   11.31272   2.074793     5.45   0.000     6.953739     15.6717
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnequagric lnequk lnequl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   76.32
       Model |  1.4793646     2  .739682299           Prob > F      =  0.0000
    Residual |  .174462387    18  .009692355           R-squared     =  0.8945
-------------+------------------------------           Adj R-squared =  0.8828
       Total |  1.65382699    20  .082691349           Root MSE      =  .09845

------------------------------------------------------------------------------
  lnequagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnequk |  -.2726257   .0644971    -4.23   0.001    -.4081291   -.1371223
      lnequl |   .0125259   .2343965     0.05   0.958     -.479923    .5049748
       _cons |   21.34889   1.861752    11.47   0.000     17.43749    25.26029
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lneriagric lnerik lneril

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    7.65
       Model |  .190329075     2  .095164538           Prob > F      =  0.0039
    Residual |  .223841925    18  .012435663           R-squared     =  0.4595
-------------+------------------------------           Adj R-squared =  0.3995
       Total |     .414171    20   .02070855           Root MSE      =  .11152

------------------------------------------------------------------------------
  lneriagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
     lnerik |  -.0624016   .1143221    -0.55   0.592    -.3025835    .1777803
     lneril |   .8773984   .3748572     2.34   0.031     .0898527    1.664944
      _cons |   9.791892   3.561889     2.75   0.013     2.308641    17.27514
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10) addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lneswagric lneswk lneswl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =   92.31
       Model |  .156026652     2  .078013326           Prob > F      =  0.0000
    Residual |  .015212662    18  .000845148           R-squared     =  0.9112
-------------+------------------------------           Adj R-squared =  0.9013
       Total |  .171239314    20  .008561966           Root MSE      =  .02907

------------------------------------------------------------------------------
  lneswagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lneswk |   .1632307   .0291391     5.60   0.000     .1020117    .2244496
      lneswl |   .7742795   .1024944     7.55   0.000     .5589467    .9896123
       _cons |   6.954586   1.083728     6.42   0.000     4.677759    9.231413
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10) addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnethagric lnethk lnethl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =  460.75
       Model |  2.18371274     2  1.09185637           Prob > F      =  0.0000
    Residual |  .042655082    18  .002369727           R-squared     =  0.9808
-------------+------------------------------           Adj R-squared =  0.9787
       Total |  2.22636782    20  .111318391           Root MSE      =  .04868

------------------------------------------------------------------------------
  lnethagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnethk |  -.3349413   .0939051    -3.57   0.002    -.5322286    -.137654
      lnethl |   2.206867   .1883529    11.72   0.000     1.811152    2.602582
       _cons |  -7.713379   1.385124    -5.57   0.000    -10.62342    -4.80334
------------------------------------------------------------------------------
```

```
. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lngabagric lngabk lngabl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =  257.11
       Model |  .31341544      2  .15670772            Prob > F      =  0.0000
    Residual |  .010970927    18  .000609496           R-squared     =  0.9662
-------------+------------------------------           Adj R-squared =  0.9624
       Total |  .324386367    20  .016219318           Root MSE      =  .02469

------------------------------------------------------------------------------
  lngabagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lngabk |  -.0253793   .0234391    -1.08   0.293     -.074623    .0238644
      lngabl |   .6798527   .0333627    20.38   0.000     .6097603     .749945
       _cons |   11.60562   .4673614    24.83   0.000     10.62373    12.58751
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lngamagric lngamk lngaml

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    1.46
       Model |  .050854837     2  .025427418           Prob > F      =  0.2592
    Residual |  .314196341    18  .017455352           R-squared     =  0.1393
-------------+------------------------------           Adj R-squared =  0.0437
       Total |  .365051178    20  .018252559           Root MSE      =  .13212

------------------------------------------------------------------------------
  lngamagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lngamk |   .3759217    .220591     1.70   0.106    -.0875228    .8393663
      lngaml |  -.2605901   .2157198    -1.21   0.243    -.7138006    .1926204
       _cons |   15.61788   2.783711     5.61   0.000     9.769515    21.46623
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
```

testt.xml
dir : seeout

. reg lnghaagric lnghak lnghal

```
      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =  366.79
       Model |  1.37714547     2  .688572735           Prob > F      =  0.0000
    Residual |  .033791407    18   .0018773            R-squared     =  0.9761
-------------+------------------------------           Adj R-squared =  0.9734
       Total |  1.41093688    20  .070546844           Root MSE      =  .04333

------------------------------------------------------------------------------
  lnghaagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnghak |   .1163839   .0530929     2.19   0.042     .0048398     .227928
      lnghal |   1.344951   .1305632    10.30   0.000     1.070648    1.619254
       _cons |  -1.268149   1.156694    -1.10   0.287    -3.698272    1.161974
------------------------------------------------------------------------------
```

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10) addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnguiagric lnguik lnguil

```
      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      = 1118.47
       Model |  1.39675772     2   .69837886           Prob > F      =  0.0000
    Residual |  .011239264    18  .000624404           R-squared     =  0.9920
-------------+------------------------------           Adj R-squared =  0.9911
       Total |  1.40799698    20  .070399849           Root MSE      =  .02499

------------------------------------------------------------------------------
  lnguiagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnguik |    .003845   .0415901     0.09   0.927    -.0835326    .0912225
      lnguil |   1.703162   .1060194    16.06   0.000     1.480423      1.9259
       _cons |  -4.626321   .8317524    -5.56   0.000    -6.373768   -2.878874
------------------------------------------------------------------------------
```

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10) addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lngubagric lngubk lngubl

```
      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =   22.89
       Model |  .36779959     2  .183899795            Prob > F      =  0.0000
    Residual |  .14460398    18  .008033554            R-squared     =  0.7178
-------------+------------------------------           Adj R-squared =  0.6864
       Total |  .51240357    20  .025620178            Root MSE      =  .08963

------------------------------------------------------------------------------
  lngubagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lngubk |   .2237809   .2644705     0.85   0.409     -.331851    .7794129
     lngubl |    .238621   .6629482     0.36   0.723    -1.154182    1.631424
      _cons |   12.28722   4.034776     3.05   0.007     3.810471    20.76397
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnkenagric lnkenk lnkenl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =  107.85
       Model |  .604446796     2  .302223398           Prob > F      =  0.0000
    Residual |  .050440678    18   .00280226           R-squared     =  0.9230
-------------+------------------------------           Adj R-squared =  0.9144
       Total |  .654887475    20  .032744374           Root MSE      =  .05294

------------------------------------------------------------------------------
  lnkenagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnkenk |  -.3705789   .1132259    -3.27   0.004    -.6084577   -.1327001
     lnkenl |   1.982532   .3498324     5.67   0.000     1.247562    2.717503
      _cons |  -1.594233   3.345245    -0.48   0.639    -8.622332    5.433866
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnlesagric lnlesk lnlesl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =    0.06
       Model |  .000684306     2  .000342153           Prob > F      =  0.9404
```

```
   Residual |  .099918286        18  .005551016   R-squared      =   0.0068
-------------+----------------------------------   Adj R-squared   =   -0.1036
      Total |  .100602592        20   .00503013   Root MSE       =   .07451

------------------------------------------------------------------------------
  lnlesagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnlesk |   -.028924   .0833641    -0.35   0.733    -.2040656    .1462176
      lnlesl |   .1516533    .462751     0.33   0.747    -.8205506    1.123857
       _cons |   17.54931   4.941648     3.55   0.002     7.167295    27.93133
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnlibagric lnlibk lnlibl

      Source |       SS          df       MS      Number of obs   =        21
-------------+----------------------------------   F(2, 18)        =     23.46
       Model |  .088724337         2  .044362168   Prob > F        =    0.0000
   Residual |  .034034226        18   .00189079   R-squared       =    0.7228
-------------+----------------------------------   Adj R-squared   =    0.6919
      Total |  .122758563        20  .006137928   Root MSE        =    .04348

------------------------------------------------------------------------------
  lnlibagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnlibk |  -.0625599   .0549432    -1.14   0.270    -.1779912    .0528715
      lnlibl |   .5271605   .1659578     3.18   0.005     .1784962    .8758249
       _cons |   13.75867   1.396449     9.85   0.000     10.82484     16.6925
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnlbyagric lnlbyk lnlbyl

      Source |       SS          df       MS      Number of obs   =        21
-------------+----------------------------------   F(2, 18)        =     32.24
       Model |  .072662542         2  .036331271   Prob > F        =    0.0000
   Residual |  .020283185        18  .001126844   R-squared       =    0.7818
-------------+----------------------------------   Adj R-squared   =    0.7575
      Total |  .092945727        20  .004647286   Root MSE        =    .03357
```

```
------------------------------------------------------------------------------
  lnlbyagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnlbyk |  -.0050614   .0260477    -0.19   0.848    -.0597856    .0496629
      lnlbyl |   .6449338   .0824567     7.82   0.000     .4716987    .8181689
       _cons |   12.16946   1.180403    10.31   0.000     9.689523    14.64939
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnmadagric lnmadk lnmadl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =   65.04
       Model |  .279771987     2  .139885993           Prob > F      =  0.0000
    Residual |  .038712496    18  .002150694           R-squared     =  0.8784
-------------+------------------------------           Adj R-squared =  0.8649
       Total |  .318484483    20  .015924224           Root MSE      =  .04638

------------------------------------------------------------------------------
  lnmadagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnmadk |   .3190502   .0825998     3.86   0.001     .1455143     .492586
      lnmadl |   .2810714   .0799153     3.52   0.002     .1131756    .4489672
       _cons |   10.37252   1.081643     9.59   0.000      8.10007    12.64496
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnmalagric lnmalk lnmall

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =  104.13
       Model |  3.53660649     2  1.76830324           Prob > F      =  0.0000
    Residual |  .305661713    18  .016981206           R-squared     =  0.9204
-------------+------------------------------           Adj R-squared =  0.9116
       Total |   3.8422682    20   .19211341           Root MSE      =  .13031

------------------------------------------------------------------------------
  lnmalagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnmalk |   .2137598   .1558014     1.37   0.187    -.1135667    .5410863
```

```
     lnmall |   2.040016   .2318764     8.80   0.000     1.552862     2.52717
      _cons |  -13.68553   2.519243    -5.43   0.000    -18.97827    -8.392799
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnmaliagric lnmalik lnmalil

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =  194.95
       Model |  2.08009648     2  1.04004824           Prob > F      =  0.0000
    Residual |  .096029122    18  .005334951           R-squared     =  0.9559
-------------+------------------------------           Adj R-squared =  0.9510
       Total |  2.17612561    20   .10880628           Root MSE      =  .07304

------------------------------------------------------------------------------
 lnmaliagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnmalik |   .4050231   .1256011     3.22   0.005      .141145    .6689013
     lnmalil |    .091335    .516657     0.18   0.862     -.994121    1.176791
       _cons |   12.39824   5.432516     2.28   0.035     .9849496    23.81153
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnmauagric lnmauk lnmaul

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =  325.40
       Model |  .444846209     2  .222423104           Prob > F      =  0.0000
    Residual |  .012303854    18  .000683547           R-squared     =  0.9731
-------------+------------------------------           Adj R-squared =  0.9701
       Total |  .457150062    20  .022857503           Root MSE      =  .02614

------------------------------------------------------------------------------
  lnmauagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnmauk |  -.1283558   .0593476    -2.16   0.044    -.2530405   -.0036711
      lnmaul |    1.22205   .1341784     9.11   0.000     .9401512    1.503948
       _cons |   6.374554   .7398412     8.62   0.000     4.820206    7.928903
------------------------------------------------------------------------------
```

```
. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnmaragric lnmark lnmarl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =    3.77
       Model |  .024105276     2  .012052638           Prob > F      =  0.0428
    Residual |   .05750712    18   .00319484           R-squared     =  0.2954
-------------+------------------------------           Adj R-squared =  0.2171
       Total |  .081612396    20   .00408062           Root MSE      =  .05652

------------------------------------------------------------------------------
  lnmaragric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnmark |   .0331647   .0841247     0.39   0.698    -.1435747    .2099042
       lnmarl |  -.6896141   .4835307    -1.43   0.171    -1.705474    .3262462
       _cons |   28.10667   4.829832     5.82   0.000     17.95957    38.25377
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnmoragric lnmork lnmorl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =   44.54
       Model |  .884466139     2  .442233069           Prob > F      =  0.0000
    Residual |  .178731752    18  .009929542           R-squared     =  0.8319
-------------+------------------------------           Adj R-squared =  0.8132
       Total |  1.06319789    20  .053159895           Root MSE      =  .09965

------------------------------------------------------------------------------
  lnmoragric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnmork |   .1915138   .2636137     0.73   0.477    -.3623181    .7453457
      lnmorl |   1.935316   1.112808     1.74   0.099    -.4026067    4.273239
       _cons |  -12.69209   12.02128    -1.06   0.305    -37.94787    12.56368
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
```

```
dir : seeout

. reg lnmozagric lnmozk lnmozl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =   37.56
       Model |  .864920123     2  .432460062           Prob > F      =  0.0000
    Residual |   .20725244    18  .011514024           R-squared     =  0.8067
-------------+------------------------------           Adj R-squared =  0.7852
       Total |  1.07217256    20  .053608628           Root MSE      =   .1073

------------------------------------------------------------------------------
  lnmozagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnmozk |   .1339379   .1304061     1.03   0.318    -.1400352     .407911
      lnmozl |   1.068108   .4230827     2.52   0.021     .1792442    1.956972
       _cons |   2.029346   4.481075     0.45   0.656    -7.385042    11.44373
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnnamagric lnnamk lnnaml

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =    0.75
       Model |  .004462965     2  .002231482           Prob > F      =  0.4887
    Residual |  .053895391    18  .002994188           R-squared     =  0.0765
-------------+------------------------------           Adj R-squared = -0.0261
       Total |  .058358356    20  .002917918           Root MSE      =  .05472

------------------------------------------------------------------------------
  lnnamagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnnamk |   .0657787   .0665111     0.99   0.336    -.0739559    .2055133
      lnnaml |   .0690919   .0720542     0.96   0.350    -.0822884    .2204721
       _cons |   16.80711   1.891644     8.88   0.000     12.83291     20.7813
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnnigagric lnnigk lnnigl
```

```
      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =  141.50
       Model |  3.32835216     2  1.66417608           Prob > F      =  0.0000
    Residual |  .211694644    18  .011760814           R-squared     =  0.9402
-------------+------------------------------           Adj R-squared =  0.9336
       Total |   3.5400468    20   .17700234           Root MSE      =  .10845

------------------------------------------------------------------------------
   lnnigagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnnigk |  -.1041031   .1212477    -0.86   0.402    -.3588351    .1506288
      lnnigl |   2.173448   .2191407     9.92   0.000     1.713051    2.633846
       _cons |  -10.01026   1.910323    -5.24   0.000     -14.0237   -5.996819
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnngragric lnngrk lnngrl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   44.42
       Model |   .54559078     2   .27279539           Prob > F      =  0.0000
    Residual |  .110539127    18  .006141063           R-squared     =  0.8315
-------------+------------------------------           Adj R-squared =  0.8128
       Total |  .656129907    20  .032806495           Root MSE      =  .07836

------------------------------------------------------------------------------
   lnngragric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnngrk |   .0639162   .1179501     0.54   0.595    -.1838877    .3117201
      lnngrl |   1.118938   .7758424     1.44   0.166    -.5110466    2.748922
       _cons |   3.244331   10.83284     0.30   0.768    -19.51463    26.00329
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnrwaagric lnrwak lnrwal

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    1.53
       Model |  .053585847     2  .026792924           Prob > F      =  0.2438
    Residual |  .315591795    18  .017532878           R-squared     =  0.1451
```

```
-------------+------------------------------   Adj R-squared  =   0.0502
       Total |  .369177643     20  .018458882   Root MSE      =   .13241

------------------------------------------------------------------------------
  lnrwaagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnrwak |   .4526833   .3231709     1.40   0.178    -.2262736     1.13164
      lnrwal |  -1.285864   1.068181    -1.20   0.244    -3.530029    .9583011
       _cons |   32.60699   10.08179     3.23   0.005     11.42593    53.78805
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnsaoagric lnsaok lnsaol

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    2.22
       Model |  .008766091     2  .004383046           Prob > F      =  0.1373
    Residual |  .03551545     18  .001973081           R-squared     =  0.1980
-------------+------------------------------           Adj R-squared =  0.1088
       Total |  .044281541    20  .002214077           Root MSE      =  .04442

------------------------------------------------------------------------------
  lnsaoagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnsaok |  -.0345152     .03858    -0.89   0.383    -.1155687    .0465383
      lnsaol |        .06    .213467     0.28   0.782    -.3884774    .5084774
       _cons |   17.30346   1.693226    10.22   0.000     13.74613     20.8608
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnsenagric lnsenk lnsenl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   28.06
       Model |  2.71488614     2  1.35744307           Prob > F      =  0.0000
    Residual |  .870879656    18  .048382203           R-squared     =  0.7571
-------------+------------------------------           Adj R-squared =  0.7301
       Total |  3.58576579    20   .17928829           Root MSE      =  .21996

------------------------------------------------------------------------------
```

```
  lnsenagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       lnsenk |  -.1659752   .2606696    -0.64   0.532    -.7136218    .3816713
       lnsenl |   2.879932   .6681166     4.31   0.000     1.476271    4.283593
        _cons |   -18.5564    5.92104    -3.13   0.006    -30.99604   -6.116752
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnseyagric lnseyk lnseyl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    9.42
       Model |  .203388893     2  .101694446           Prob > F      =  0.0016
    Residual |  .194255696    18  .010791983           R-squared     =  0.5115
-------------+------------------------------           Adj R-squared =  0.4572
       Total |  .397644588    20  .019882229           Root MSE      =  .10388

------------------------------------------------------------------------------
  lnseyagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       lnseyk |  -.3129385   .0931506    -3.36   0.003    -.5086406   -.1172365
       lnseyl |  -.1076884    .138499    -0.78   0.447    -.3986641    .1832873
        _cons |   23.69216   3.422823     6.92   0.000     16.50108    30.88325
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnsieagric lnsiek lnsiel

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   17.72
       Model |   2.5878918     2   1.2939459           Prob > F      =  0.0001
    Residual |  1.31443462    18  .073024145           R-squared     =  0.6632
-------------+------------------------------           Adj R-squared =  0.6257
       Total |  3.90232641    20  .195116321           Root MSE      =  .27023

------------------------------------------------------------------------------
  lnsieagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       lnsiek |   -.412941    .318808    -1.30   0.212    -1.082732    .2568497
       lnsiel |   4.102679   1.129025     3.63   0.002     1.730686    6.474672
```

```
     _cons |  -29.85342   10.93081    -2.73   0.014    -52.8182   -6.888627
------------------------------------------------------------------------------
```

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnsomagric lnsomk lnsoml

```
      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18) =    0.39
       Model |  .001508182     2  .000754091           Prob > F      =  0.6799
    Residual |  .034429166    18  .001912731           R-squared     =  0.0420
-------------+------------------------------           Adj R-squared = -0.0645
       Total |  .035937348    20  .001796867           Root MSE      =  .04373

------------------------------------------------------------------------------
  lnsomagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnsomk |  -.0331367   .0373259    -0.89   0.386    -.1115556    .0452822
      lnsoml |  -.0478397   .0754224    -0.63   0.534    -.2062963     .110617
       _cons |   22.95704   1.713318    13.40   0.000     19.35749    26.55659
------------------------------------------------------------------------------
```

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnsafagric lnsafk lnsafl

```
      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18) =   51.95
       Model |  .375670673     2  .187835337           Prob > F      =  0.0000
    Residual |  .065086063    18  .003615892           R-squared     =  0.8523
-------------+------------------------------           Adj R-squared =  0.8359
       Total |  .440756737    20  .022037837           Root MSE      =  .06013

------------------------------------------------------------------------------
  lnsafagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnsafk |  -.0828995   .0751827    -1.10   0.285    -.2408526    .0750535
      lnsafl |   1.309078   .1496608     8.75   0.000     .9946523    1.623504
       _cons |   3.969434   1.989088     2.00   0.061    -.2094847    8.148354
------------------------------------------------------------------------------
```

```
. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnssuagric lnssuk lnssul

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =  228.19
       Model |  10.430375      2  5.2151875            Prob > F      =  0.0000
    Residual |  .411389686    18  .022854983           R-squared     =  0.9621
-------------+------------------------------           Adj R-squared =  0.9578
       Total |  10.8417647    20  .542088235           Root MSE      =  .15118

------------------------------------------------------------------------------
  lnssuagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnssuk |  -.1798581   .5398753    -0.33   0.743    -1.314094    .9543779
      lnssul |  -3.542942    .495428    -7.15   0.000    -4.583798   -2.502086
       _cons |   79.97618   19.83924     4.03   0.001     38.29549    121.6569
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnsudagric lnsudk lnsudl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =  326.98
       Model |  3.71870766     2  1.85935383           Prob > F      =  0.0000
    Residual |  .102355166    18  .005686398           R-squared     =  0.9732
-------------+------------------------------           Adj R-squared =  0.9702
       Total |  3.82106283    20  .191053142           Root MSE      =  .07541

------------------------------------------------------------------------------
  lnsudagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnsudk |   .2048352   .0651896     3.14   0.006      .067877    .3417934
      lnsudl |   4.116251   .3459473    11.90   0.000     3.389443    4.843059
       _cons |  -47.19067   6.886509    -6.85   0.000    -61.65869   -32.72265
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
```

```
dir : seeout

. reg lntogagric lntogk lntogl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =  397.94
       Model |  .841644522     2  .420822261           Prob > F      =  0.0000
    Residual |  .019035038    18  .001057502           R-squared     =  0.9779
-------------+------------------------------           Adj R-squared =  0.9754
       Total |   .86067956    20  .043033978           Root MSE      =  .03252

------------------------------------------------------------------------------
  lntogagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lntogk |   .1674168   .0557077     3.01   0.008     .0503793    .2844544
      lntogl |   .8526865   .1152605     7.40   0.000     .6105331     1.09484
       _cons |   5.482434   .7554666     7.26   0.000     3.895258    7.069611
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lntunagric lntunk lntunl

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(  2,    18) =   32.94
       Model |  .443975341     2   .22198767           Prob > F      =  0.0000
    Residual |  .121310902    18  .006739495           R-squared     =  0.7854
-------------+------------------------------           Adj R-squared =  0.7616
       Total |  .565286243    20  .028264312           Root MSE      =  .08209

------------------------------------------------------------------------------
  lntunagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lntunk |  -.1147426   .1367985    -0.84   0.413    -.4021456    .1726604
      lntunl |   2.172597   .4079023     5.33   0.000     1.315626    3.029568
       _cons |  -7.811299   3.992503    -1.96   0.066    -16.19924    .5766397
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnugaagric lnugak lnugal
```

```
      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    1.46
       Model |   .02242693     2  .011213465           Prob > F      =  0.2584
    Residual |  .138218925    18  .007678829           R-squared     =  0.1396
-------------+------------------------------           Adj R-squared =  0.0440
       Total |  .160645854    20  .008032293           Root MSE      =  .08763

------------------------------------------------------------------------------
  lnugaagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnugak |  -.3792049   .2256309    -1.68   0.110    -.8532379    .0948282
      lnugal |   .6625137   .3880239     1.71   0.105    -.1526943    1.477722
       _cons |    20.4121   1.850277    11.03   0.000     16.52482    24.29939
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnzamagric lnzamk lnzaml

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =   94.98
       Model |  2.45966261     2   1.2298313           Prob > F      =  0.0000
    Residual |  .233058736    18  .012947708           R-squared     =  0.9134
-------------+------------------------------           Adj R-squared =  0.9038
       Total |  2.69272134    20  .134636067           Root MSE      =  .11379

------------------------------------------------------------------------------
  lnzamagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnzamk |  -.0605085   .0655998    -0.92   0.369    -.1983286    .0773117
      lnzaml |   2.219129   .2581172     8.60   0.000     1.676844    2.761413
       _cons |  -11.15853   2.948135    -3.78   0.001    -17.35233   -4.964726
------------------------------------------------------------------------------

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lnzimagric lnzimk lnziml

      Source |       SS       df       MS              Number of obs =      21
-------------+------------------------------           F(2, 18)      =    0.49
       Model |  .021633989     2  .010816994           Prob > F      =  0.6192
    Residual |  .395491425    18  .021971746           R-squared     =  0.0519
```

```
-------------+----------------------------------   Adj R-squared   =  -0.0535
       Total |  .417125413        20  .020856271   Root MSE        =   .14823

------------------------------------------------------------------------------
  lnzimagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnzimk |  -.0418608   .0427196    -0.98   0.340    -.1316113    .0478897
      lnziml |   .2973679   .4793095     0.62   0.543     -.709624     1.30436
       _cons |   18.22621    7.06124     2.58   0.019     3.391095    33.06132
------------------------------------------------------------------------------
```

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10) addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. reg lntanagric lntank lntanl

```
      Source |       SS           df       MS      Number of obs   =        21
-------------+----------------------------------   F(2, 18)        =    131.39
       Model |  2.07259291         2  1.03629645   Prob > F        =    0.0000
    Residual |  .141965432        18  .007886968   R-squared       =    0.9359
-------------+----------------------------------   Adj R-squared   =    0.9288
       Total |  2.21455834        20  .110727917   Root MSE        =    .08881

------------------------------------------------------------------------------
  lntanagric |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lntank |   .3572234   .1974346     1.81   0.087    -.0575713    .7720181
      lntanl |   .5754973   .7223051     0.80   0.436    -.9420094    2.093004
       _cons |   4.985053   7.903422     0.63   0.536    -11.61942    21.58953
------------------------------------------------------------------------------
```

. outreg2 using testt, bdec(3) tdec(3) rdec(3) adec(3) alpha (0.01, 0.05, 0.10) addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
testt.xml
dir : seeout

. end of do-file

Appendix 11: GMM Estimated Result

. xtabond2 lnagricpro l.lnagricpro renegy popgr sav lninv fert lnpest lnexch prl lnemi lncreagr, gmm(l.lnagricpro l(0/1).re
> negy l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest l(0/1).lnexch l(0/1).prl l(0/1).lnemi l(0/1).lncreagr
> , collapse lag(1 1)) iv(l.lnagricpro, eq(diff)) twostep small orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed, perm.

```
Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                  Number of obs      =      1041
Time variable : b                        Number of groups   =        53
Number of instruments = 44                  Obs per group: min =        12
F(11, 52)     =  5.40e+06                             avg =     19.64
Prob > F      =     0.000                             max =        20
------------------------------------------------------------------------------
  lnagricpro |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lnagricpro |
         L1. |   .9991098   .0004681  2134.34   0.000     .9981705    1.000049
             |
      renegy |   .0007194   .0003199     2.25   0.029     .0000776    .0013613
       popgr |  -.0070499   .0041807    -1.69   0.098     -.015439    .0013393
         sav |   .0000527   .0004622     0.11   0.910    -.0008748    .0009802
       lninv |  -.0017411   .0048005    -0.36   0.718    -.0113741    .0078919
        fert |  -.0021541   .0004824    -4.47   0.000    -.0031221    -.001186
      lnpest |    .006221   .0023344     2.66   0.010     .0015367    .0109052
      lnexch |   .0049477   .0005049     9.80   0.000     .0039346    .0059607
         prl |   .0000577    .000031     1.86   0.069    -4.57e-06      .00012
       lnemi |  -.0244308   .0056741    -4.31   0.000    -.0358167    -.013045
    lncreagr |  -.0029066   .0034741    -0.84   0.407    -.0098778    .0040647
       _cons |   .2320252   .0554112     4.19   0.000     .1208344     .343216
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv fert
    L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi lncreagr
    L.lncreagr) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv fert
    L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi lncreagr
    L.lncreagr) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.35  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   3.43  Pr > z =  0.215
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(32)    = 354.43  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(32)    =  42.58  Prob > chi2 =  0.100
  (Robust, but weakened by many instruments.)
```

```
Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(11)   =  11.20  Prob > chi2 =  0.427
    Difference (null H = exogenous): chi2(21)   =  31.38  Prob > chi2 =  0.068
  iv(L.lnagricpro, eq(diff))
    Hansen test excluding group:     chi2(31)   =  38.73  Prob > chi2 =  0.160
    Difference (null H = exogenous): chi2(1)    =   3.85  Prob > chi2 =  0.050


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro l.lnagricpro renegy popgr sav lninv fert lnpest lnexch prl lnemi
lncreagr lntop, gmm(l.lnagricpro l(0
> /1).renegy l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest l(0/1).lnexch
l(0/1).prl l(0/1).lnemi l(0/1).ln
> creagr l(0/1).top, collapse lag(1 1)) iv(l.lnagricpro, eq(diff)) twostep small orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                      Number of obs      =      1041
Time variable : b                               Number of groups   =        53
Number of instruments = 48                      Obs per group: min =        12
F(12, 52)     =  5.82e+06                                      avg =     19.64
Prob > F      =     0.000                                      max =        20
------------------------------------------------------------------------------
  lnagricpro |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lnagricpro |
         L1. |   .9992065   .0003474  2876.57   0.000     .9985095    .9999036
             |
      renegy |    .000868   .0002757     3.15   0.003     .0003149    .0014212
       popgr |  -.0094985   .0034978    -2.72   0.009    -.0165174   -.0024796
         sav |  -.0000741   .0003655    -0.20   0.840    -.0008075    .0006593
       lninv |   .0037095   .0022977     1.61   0.112    -.0009011    .0083201
        fert |  -.0021826   .0004267    -5.12   0.000    -.0030388   -.0013263
      lnpest |   .0044246   .0022288     1.99   0.052    -.0000479     .008897
      lnexch |   .0038658   .0005931     6.52   0.000     .0026757    .0050559
         prl |   .0000833   .0000289     2.89   0.006     .0000254    .0001413
       lnemi |  -.0266231   .0044401    -6.00   0.000    -.0355328   -.0177134
    lncreagr |  -.0108208   .0025939    -4.17   0.000    -.0160258   -.0056159
       lntop |   .0032901   .0057966     0.57   0.573    -.0083417    .0149218
       _cons |   .2979992   .0541722     5.50   0.000     .1892946    .4067038
------------------------------------------------------------------------------
```

```
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv fert
    L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi lncreagr
    L.lncreagr top L.top) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv fert
    L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi lncreagr
    L.lncreagr top L.top) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.35  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   5.44  Pr > z =  0.715
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(35)   = 383.08  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(35)   =  42.34  Prob > chi2 =  0.184
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(12)   =  16.22  Prob > chi2 =  0.181
    Difference (null H = exogenous): chi2(23)   =  26.12  Prob > chi2 =  0.295
  iv(L.lnagricpro, eq(diff))
    Hansen test excluding group:     chi2(34)   =  37.30  Prob > chi2 =  0.320
    Difference (null H = exogenous): chi2(1)    =   5.05  Prob > chi2 =  0.025


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro l.lnagricpro renegy popgr sav lninv fert lnpest lnexch prl lnemi
lncreagr lntop c.renegy#c.lntop, gmm
> (l.lnagricpro l(0/1).renegy l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest
l(0/1).lnexch l(0/1).prl l(0/1
> ).lnemi l(0/1).lncreagr l(0/1).top l(0/1).c.renegy#c.top, collapse lag(1 1))
iv(l.lnagricpro, eq(diff)) twostep small ort
> hog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.
```

```
Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                      Number of obs      =      1041
Time variable : b                            Number of groups   =        53
Number of instruments = 52                      Obs per group: min =        12
F(13, 52)     =  3.80e+07                              avg =     19.64
Prob > F      =     0.000                              max =        20
------------------------------------------------------------------------------
     lnagricpro |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
     lnagricpro |
           L1. |   .9988813   .0002646  3775.47   0.000     .9983504    .9994122
               |
        renegy |  -.0060914   .0016075    -3.79   0.000    -.0093171   -.0028656
         popgr |  -.0015961   .0032452    -0.49   0.625     -.008108    .0049159
           sav |  -.0000338   .0002534    -0.13   0.894    -.0005423    .0004747
         lninv |    .003449   .0024326     1.42   0.162    -.0014324    .0083304
          fert |  -.0015534    .000504    -3.08   0.003    -.0025648    -.000542
        lnpest |   .0055108   .0012309     4.48   0.000     .0030407    .0079808
        lnexch |   .0031786   .0004909     6.48   0.000     .0021935    .0041636
           prl |   .0000336    .000026     1.29   0.202    -.0000186    .0000858
         lnemi |  -.0230066   .0044769    -5.14   0.000    -.0319902   -.0140229
      lncreagr |  -.0051319   .0023241    -2.21   0.032    -.0097954   -.0004683
         lntop |  -.0096377   .0067456    -1.43   0.159    -.0231737    .0038983
               |
c.renegy#c.lntop |   .0016121    .000389     4.14   0.000     .0008315    .0023926
               |
         _cons |    .258265   .0442193     5.84   0.000     .1695324    .3469976
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv fert
    L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi lncreagr
    L.lncreagr top L.top c.renegy#c.top cL.renegy#c.top) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv fert
    L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi lncreagr
    L.lncreagr top L.top c.renegy#c.top cL.renegy#c.top) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.38  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   4.43  Pr > z =  0.515
------------------------------------------------------------------------------
```

```
Sargan test of overid. restrictions: chi2(38)   = 380.38  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(38)   =  43.42  Prob > chi2 =  0.251
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(13)   =  19.01  Prob > chi2 =  0.123
    Difference (null H = exogenous): chi2(25)   =  24.40  Prob > chi2 =  0.496
  iv(L.lnagricpro, eq(diff))
    Hansen test excluding group:     chi2(37)   =  36.43  Prob > chi2 =  0.496
    Difference (null H = exogenous): chi2(1)    =   6.99  Prob > chi2 =  0.008


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro2 l.lnagricpro2 renegy popgr sav lninv fert lnpest lnexch prl
lnemi lncreagr, gmm(l.lnagricpro2 l(0/1)
> .renegy l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest l(0/1).lnexch
l(0/1).prl l(0/1).lnemi l(0/1).lncre
> agr, collapse lag(1 1)) iv(l.lnagricpro2, eq(diff)) twostep small orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                      Number of obs      =      1041
Time variable : b                               Number of groups   =        53
Number of instruments = 44                      Obs per group: min =        12
F(11, 52)     = 212543.10                                      avg =     19.64
Prob > F      =     0.000                                      max =        20
------------------------------------------------------------------------------
 lnagricpro2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 lnagricpro2 |
         L1. |   .8435463   .0126445    66.71   0.000     .8181734    .8689193
             |
      renegy |    .001313   .0005576     2.35   0.022     .0001942    .0024318
       popgr |   .0124633   .0046041     2.71   0.009     .0032245     .021702
         sav |    .001075   .0002891     3.72   0.000     .0004949    .0016551
       lninv |  -.0038301   .0061942    -0.62   0.539    -.0162597    .0085994
        fert |  -.0013586   .0006323    -2.15   0.036    -.0026274   -.0000898
      lnpest |   .0229307    .005083     4.51   0.000      .012731    .0331304
      lnexch |   .0015828   .0009819     1.61   0.113    -.0003876    .0035531
         prl |  -.0000349   .0000352    -0.99   0.326    -.0001057    .0000358
```

```
       lnemi |  -.0210335   .0060443    -3.48   0.001    -.0331623   -.0089046
    lncreagr |    .004333   .0038445     1.13   0.265    -.0033815    .0120475
       _cons |   .9950748   .0629847    15.80   0.000     .8686868    1.121463
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro2
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro2 renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro2 renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.22  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   4.55  Pr > z =  0.611
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(32)   = 100.42  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(32)   =  31.86  Prob > chi2 =  0.474
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(11)   =  14.72  Prob > chi2 =  0.196
    Difference (null H = exogenous): chi2(21)   =  17.15  Prob > chi2 =  0.702
  iv(L.lnagricpro2, eq(diff))
    Hansen test excluding group:     chi2(31)   =  31.43  Prob > chi2 =  0.445
    Difference (null H = exogenous): chi2(1)    =   0.44  Prob > chi2 =  0.508


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro2 l.lnagricpro2 renegy popgr sav lninv fert lnpest lnexch prl
lnemi lncreagr lntop, gmm(l.lnagricpro2
> l(0/1).renegy l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest l(0/1).lnexch
l(0/1).prl l(0/1).lnemi l(0/1)
> .lncreagr l(0/1).top, collapse lag(1 1)) iv(l.lnagricpro2, eq(diff)) twostep small orthog
```

Favoring space over speed. To switch, type or click on mata: mata set matafavor speed, perm.

```
Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                      Number of obs      =      1041
Time variable : b                               Number of groups   =        53
Number of instruments = 48                      Obs per group: min =        12
F(12, 52)     = 308033.32                                      avg =     19.64
Prob > F      =     0.000                                      max =        20
------------------------------------------------------------------------------
 lnagricpro2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 lnagricpro2 |
         L1. |     .90718    .008582   105.71   0.000     .8899588    .9244011
             |
      renegy |   .0007809   .0004529     1.72   0.091    -.0001279    .0016897
       popgr |   -.013087   .0035356    -3.70   0.001    -.0201816   -.0059924
         sav |   .0002336   .0003441     0.68   0.500    -.0004568    .0009241
       lninv |   .0161539   .0023596     6.85   0.000     .0114191    .0208887
        fert |   .0000176   .0004238     0.04   0.967    -.0008328    .0008679
      lnpest |  -.0036766   .0025509    -1.44   0.156    -.0087954    .0014422
      lnexch |  -.0002254   .0010044    -0.22   0.823    -.0022408      .00179
         prl |   .0001495   .0000431     3.47   0.001      .000063     .000236
       lnemi |  -.0108969   .0051789    -2.10   0.040    -.0212891   -.0005048
    lncreagr |  -.0275377   .0039535    -6.97   0.000    -.0354711   -.0196044
       lntop |   .0350295   .0064268     5.45   0.000    -.0479258   -.0221331
       _cons |   1.007764   .0917834    10.98   0.000     .8235873    1.191941
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro2
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro2 renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr top L.top) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro2 renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr top L.top) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.20  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   3.52  Pr > z =  0.312
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(35)   = 213.52  Prob > chi2 =  0.000
```

```
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(35)   =  43.04  Prob > chi2 =  0.165
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(12)   =  20.07  Prob > chi2 =  0.066
    Difference (null H = exogenous): chi2(23)   =  22.97  Prob > chi2 =  0.463
  iv(L.lnagricpro2, eq(diff))
    Hansen test excluding group:     chi2(34)   =  39.33  Prob > chi2 =  0.244
    Difference (null H = exogenous): chi2(1)    =   3.71  Prob > chi2 =  0.054


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro2 l.lnagricpro2 renegy popgr sav lninv fert lnpest lnexch prl
lnemi lncreagr lntop c.renegy#c.lntop, g
> mm(l.lnagricpro2 l(0/1).renegy l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert
l(0/1).lnpest l(0/1).lnexch l(0/1).prl l(
> 0/1).lnemi l(0/1).lncreagr l(0/1).top l(0/1).c.renegy#c.top, collapse lag(1 1))
iv(l.lnagricpro2, eq(diff)) twostep small
>  orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                 Number of obs      =      1041
Time variable : b                       Number of groups   =       53
Number of instruments = 52                 Obs per group: min =        12
F(13, 52)     =  1.03e+07                              avg =     19.64
Prob > F      =     0.000                              max =        20
------------------------------------------------------------------------------
    lnagricpro2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
    lnagricpro2 |
            L1. |    .912522    .004721   193.29   0.000     .9030487    .9219953
                |
         renegy |  -.0097708   .0013062    -7.48   0.000    -.0123918   -.0071498
          popgr |   -.000816   .0028372    -0.29   0.775    -.0065092    .0048772
            sav |   .0005653    .000264     2.14   0.037     .0000355    .0010952
          lninv |   .0182197   .0031042     5.87   0.000     .0119907    .0244488
           fert |   .0006156   .0003456     1.78   0.081    -.0000779    .0013092
         lnpest |  -.0025035   .0014927    -1.68   0.100    -.0054988    .0004919
         lnexch |   .0014787   .0006992     2.11   0.039     .0000756    .0028818
```

```
         prl |  .0000679   .0000248    2.74   0.008    .0000182   .0001177
        lnemi |  -.0105717   .0041413   -2.55   0.014   -.0188818  -.0022617
      lncreagr |   -.018878   .0029953   -6.30   0.000   -.0248886  -.0128674
        lntop |  -.0520947   .0038291  -13.61   0.000   -.0597783  -.0444111
              |
c.renegy#c.lntop |    .002711   .0003213    8.44   0.000    .0020663    .0033557
              |
        _cons |   .9069375   .0570874   15.89   0.000    .7923831    1.021492
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro2
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro2 renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr top L.top c.renegy#c.top cL.renegy#c.top) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro2 renegy L.renegy popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr top L.top c.renegy#c.top cL.renegy#c.top) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.25  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   3.50  Pr > z =  0.313
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(38)   = 215.68  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(38)   =  42.85  Prob > chi2 =  0.271
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(13)   =  22.26  Prob > chi2 =  0.052
    Difference (null H = exogenous): chi2(25)   =  20.60  Prob > chi2 =  0.715
  iv(L.lnagricpro2, eq(diff))
    Hansen test excluding group:     chi2(37)   =  41.51  Prob > chi2 =  0.281
    Difference (null H = exogenous): chi2(1)    =   1.35  Prob > chi2 =  0.246


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout
```

.
end of do-file

Appendix 10: Robustness result

```
. do "C:\Users\Buchi\AppData\Local\Temp\STD40f8_000000.tmp"

. **System GMM estimation using the second measure of renewable energy**
. xtabond2 lnagricpro l.lnagricpro renegy2 popgr sav lninv fert lnpest lnexch prl lnemi
lncreagr, gmm(l.lnagricpro l(0/1).r
> enegy2 l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest l(0/1).lnexch
l(0/1).prl l(0/1).lnemi l(0/1).lncrea
> gr, collapse lag(1 1)) iv(l.lnagricpro, eq(diff)) twostep small orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                      Number of obs      =      1036
Time variable : b                            Number of groups   =        53
Number of instruments = 44                      Obs per group: min =        12
F(11, 52)     =  6.84e+06                                      avg =     19.55
Prob > F      =     0.000                                      max =        20
------------------------------------------------------------------------------
  lnagricpro |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lnagricpro |
         L1. |    .998871   .0003668  2722.94   0.000     .9981349    .9996071
             |
     renegy2 |  .0001786   .0000228     7.85   0.000    -.0002243    -.000133
       popgr |  -.0010884   .0045923    -0.24   0.814    -.0103036    .0081269
         sav |   .0001775   .0003865     0.46   0.648     -.000598    .0009531
       lninv |  -.0024103   .0052399    -0.46   0.647     -.012925    .0081044
        fert |   -.002034   .0004532    -4.49   0.000    -.0029433   -.0011246
      lnpest |   .0065968   .0019774     3.34   0.002      .002629    .0105647
      lnexch |   .0067593   .0004511    14.99   0.000     .0058542    .0076645
         prl |   .0001212   .0000382     3.18   0.003     .0000446    .0001978
       lnemi |  -.0188996   .0052568    -3.60   0.001    -.0294482    -.008351
    lncreagr |  -.0057345   .0043194    -1.33   0.190     -.014402    .0029331
       _cons |   .2025796   .0379565     5.34   0.000     .1264142     .278745
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr) collapsed
```

```
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.35  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   2.44  Pr > z =  0.015
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(32)   = 348.71  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(32)   =  40.59  Prob > chi2 =  0.142
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(11)   =  11.56  Prob > chi2 =  0.398
    Difference (null H = exogenous): chi2(21)   =  29.03  Prob > chi2 =  0.113
  iv(L.lnagricpro, eq(diff))
    Hansen test excluding group:     chi2(31)   =  33.02  Prob > chi2 =  0.369
    Difference (null H = exogenous): chi2(1)    =   7.57  Prob > chi2 =  0.006


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro l.lnagricpro renegy2 popgr sav lninv fert lnpest lnexch prl lnemi
lncreagr lntop, gmm(l.lnagricpro l(
> 0/1).renegy2 l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest l(0/1).lnexch
l(0/1).prl l(0/1).lnemi l(0/1).
> lncreagr l(0/1).lntop, collapse lag(1 1)) iv(l.lnagricpro, eq(diff)) twostep small orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                      Number of obs      =      1036
Time variable : b                               Number of groups   =        53
Number of instruments = 48                      Obs per group: min =        12
F(12, 52)     =  1.40e+07                                      avg =     19.55
Prob > F      =     0.000                                      max =        20
------------------------------------------------------------------------------
  lnagricpro |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
 lnagricpro |
        L1. |  .9988858  .0002649 3770.38  0.000   .9983542   .9994175
            |
    renegy2 | -.0001627   .0000191   -8.51  0.000  -.0002011  -.0001244
      popgr | -.0039694  .0029508   -1.35  0.184  -.0098905   .0019518
        sav | -.0000694  .0002409   -0.29  0.775  -.0005527    .000414
      lninv |  -.000486   .002303   -0.21  0.834  -.0051073   .0041353
       fert | -.0009081  .0005194   -1.75  0.086  -.0019504   .0001342
     lnpest |  .0028758  .0025249    1.14  0.260  -.0021907   .0079424
     lnexch |  .0049337  .0004323   11.41  0.000   .0040662   .0058012
        prl |   .000076  .0000219    3.47  0.001    .000032   .0001199
      lnemi | -.0139162  .0046516   -2.99  0.004  -.0232503  -.0045821
   lncreagr | -.0011986  .0030092   -0.40  0.692   -.007237   .0048399
      lntop | -.0235827   .004639   -5.08  0.000  -.0328915   -.014274
      _cons |  .2275004  .0376237    6.05  0.000   .1520029   .3029979
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr lntop L.lntop) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr lntop L.lntop) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.35  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   2.42  Pr > z =  0.016
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(35)   = 411.14  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(35)   =  43.23  Prob > chi2 =  0.160
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(12)   =  17.42  Prob > chi2 =  0.135
    Difference (null H = exogenous): chi2(23)   =  25.81  Prob > chi2 =  0.310
  iv(L.lnagricpro, eq(diff))
    Hansen test excluding group:     chi2(34)   =  36.09  Prob > chi2 =  0.371
    Difference (null H = exogenous): chi2(1)    =   7.14  Prob > chi2 =  0.008
```

```
. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro l.lnagricpro renegy2 popgr sav lninv fert lnpest lnexch prl lnemi
lncreagr lntop c.renegy2#c.lntop, g
> mm(l.lnagricpro l(0/1).renegy2 l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert
l(0/1).lnpest l(0/1).lnexch l(0/1).prl l(
> 0/1).lnemi l(0/1).lncreagr l(0/1).lntop l(0/1).c.renegy2#c.lntop, collapse lag(1 1))
iv(l.lnagricpro, eq(diff)) twostep s
> mall orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                  Number of obs      =      1036
Time variable : b                           Number of groups   =        53
Number of instruments = 52                  Obs per group: min =        12
F(13, 52)     =  8.92e+08                                  avg =     19.55
Prob > F      =     0.000                                  max =        20
------------------------------------------------------------------------------
      lnagricpro |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
      lnagricpro |
             L1. |   .9989736   .0002264  4412.92   0.000     .9985194    .9994279
                 |
         renegy2 |   .0002199   .0000439     5.00   0.000     -.000308   -.0001317
           popgr |  -.0032918   .0024652    -1.34   0.188    -.0082385    .0016549
             sav |  -.0000497    .000157    -0.32   0.753    -.0003648    .0002653
           lninv |    .000018   .0017448     0.01   0.992    -.0034833    .0035192
            fert |  -.0010336   .0005061    -2.04   0.046    -.0020492   -.0000179
          lnpest |   .0014059   .0023003     0.61   0.544      -.00321    .0060217
          lnexch |   .0034673    .000469     7.39   0.000     .0025262    .0044083
             prl |   .0000363   .0000175     2.07   0.044     1.08e-06    .0000715
           lnemi |  -.0140327   .0040738    -3.44   0.001    -.0222073   -.0058581
         lncreagr |   .0031501   .0023873     1.32   0.193    -.0016403    .0079405
           lntop |   .0263082   .0039575     6.65   0.000    -.0342495   -.0183669
                 |
c.renegy2#c.lntop |   .0000349   .0000127     2.75   0.008     9.46e-06    .0000603
                 |
           _cons |   .2128139   .0271263     7.85   0.000      .158381    .2672467
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
```

```
    FOD.L.lnagricpro
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr lntop L.lntop c.renegy2#c.lntop cL.renegy2#c.lntop)
    collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr lntop L.lntop c.renegy2#c.lntop cL.renegy2#c.lntop)
    collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.35  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   2.42  Pr > z =  0.015
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(38)   = 415.56  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(38)   =  41.76  Prob > chi2 =  0.311
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(13)   =  19.38  Prob > chi2 =  0.112
    Difference (null H = exogenous): chi2(25)   =  22.38  Prob > chi2 =  0.614
  iv(L.lnagricpro, eq(diff))
    Hansen test excluding group:     chi2(37)   =  37.71  Prob > chi2 =  0.437
    Difference (null H = exogenous): chi2(1)    =   4.05  Prob > chi2 =  0.044


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro2 l.lnagricpro2 renegy2 popgr sav lninv fert lnpest lnexch prl
lnemi lncreagr, gmm(l.lnagricpro2 l(0/1
> ).renegy2 l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest l(0/1).lnexch
l(0/1).prl l(0/1).lnemi l(0/1).lnc
> reagr, collapse lag(1 1)) iv(l.lnagricpro2, eq(diff)) twostep small orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                      Number of obs      =      1036
```

```
Time variable : b                          Number of groups   =       53
Number of instruments = 44                     Obs per group: min =        12
F(11, 52)     = 200036.11                              avg =     19.55
Prob > F      =     0.000                             max =       20
------------------------------------------------------------------------------
 lnagricpro2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 lnagricpro2 |
         L1. |   .8818445   .0075225   117.23   0.000     .8667495    .8969395
             |
     renegy2 |   -.000012   .0000167    -0.72   0.477    -.0000455    .0000216
       popgr |  -.0037734   .0044176    -0.85   0.397     -.012638    .0050911
         sav |   .0006593   .0002886     2.28   0.026     .0000803    .0012384
       lninv |   .0026352   .0052371     0.50   0.617    -.0078738    .0131443
        fert |  -.0004522   .0006326    -0.71   0.478    -.0017216    .0008172
      lnpest |   .0140348   .0032525     4.32   0.000     .0075082    .0205614
      lnexch |  -.0000915   .0007647    -0.12   0.905     -.001626     .001443
         prl |  -.0000769   .0000361    -2.13   0.038    -.0001494   -4.41e-06
       lnemi |  -.0293258   .0055536    -5.28   0.000      -.04047   -.0181816
    lncreagr |   .0036759   .0028964     1.27   0.210    -.0021362     .009488
       _cons |   .9155963   .0583689    15.69   0.000     .7984706    1.032722
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro2
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro2 renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro2 renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.20  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   2.56  Pr > z =  0.010
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(32)   = 121.59  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(32)   =  37.65  Prob > chi2 =  0.226
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(11)   =  20.59  Prob > chi2 =  0.038
```

```
  Difference (null H = exogenous): chi2(21)   =  17.06  Prob > chi2 =  0.708
 iv(L.lnagricpro2, eq(diff))
  Hansen test excluding group:     chi2(31)   =  36.69  Prob > chi2 =  0.222
  Difference (null H = exogenous): chi2(1)    =   0.96  Prob > chi2 =  0.326


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro2 l.lnagricpro2 renegy2 popgr sav lninv fert lnpest lnexch prl
lnemi lncreagr lntop, gmm(l.lnagricpro2
>  l(0/1).renegy2 l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert l(0/1).lnpest l(0/1).lnexch
l(0/1).prl l(0/1).lnemi l(0/
> 1).lncreagr l(0/1).lntop, collapse lag(1 1)) iv(l.lnagricpro2, eq(diff)) twostep small
orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: countrynum                   Number of obs      =      1036
Time variable : b                        Number of groups   =        53
Number of instruments = 48                   Obs per group: min =        12
F(12, 52)     = 701072.61                                avg =     19.55
Prob > F      =     0.000                                max =        20
------------------------------------------------------------------------------
 lnagricpro2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 lnagricpro2 |
         L1. |   .9107251   .0079599   114.41   0.000     .8947524    .9266978
             |
     renegy2 |  -.0000809   .0000239    -3.38   0.001    -.0001289   -.0000329
       popgr |  -.0124388   .0036461    -3.41   0.001    -.0197552   -.0051223
         sav |   .0003139    .000246     1.28   0.208    -.0001797    .0008075
       lninv |   .0147801   .0046614     3.17   0.003     .0054263    .0241339
        fert |   .0015474   .0004766     3.25   0.002     .0005911    .0025037
      lnpest |  -.0016135    .002759    -0.58   0.561    -.0071498    .0039228
      lnexch |  -.0018793   .0007934    -2.37   0.022    -.0034713   -.0002872
         prl |   2.27e-06   .0000402     0.06   0.955    -.0000784     .000083
       lnemi |  -.0104427   .0040496    -2.58   0.013    -.0185689   -.0023165
    lncreagr |  -.0087823   .0032062    -2.74   0.008    -.0152159   -.0023487
       lntop |   -.035643   .0047225    -7.55   0.000    -.0451194   -.0261665
       _cons |   .8356998   .0758409    11.02   0.000      .683514    .9878857
------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.
```

```
Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro2
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro2 renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr lntop L.lntop) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro2 renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr lntop L.lntop) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.21  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   2.55  Pr > z =  0.011
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(35)   = 280.53  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(35)   =  43.78  Prob > chi2 =  0.147
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(12)   =  22.74  Prob > chi2 =  0.030
    Difference (null H = exogenous): chi2(23)   =  21.05  Prob > chi2 =  0.578
  iv(L.lnagricpro2, eq(diff))
    Hansen test excluding group:     chi2(34)   =  40.72  Prob > chi2 =  0.199
    Difference (null H = exogenous): chi2(1)    =   3.06  Prob > chi2 =  0.080


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

. xtabond2 lnagricpro2 l.lnagricpro2 renegy2 popgr sav lninv fert lnpest lnexch prl
lnemi lncreagr lntop c.renegy2#c.lntop,
>  gmm(l.lnagricpro2 l(0/1).renegy2 l(0/1).popgr l(0/1).sav l(0/1).lninv l(0/1).fert
l(0/1).lnpest l(0/1).lnexch l(0/1).prl
>  l(0/1).lnemi l(0/1).lncreagr l(0/1).lntop l(0/1).c.renegy2#c.lntop, collapse lag(1 1))
iv(l.lnagricpro2, eq(diff)) twost
> ep small orthog
Favoring space over speed. To switch, type or click on mata: mata set matafavor
speed, perm.

Dynamic panel-data estimation, two-step system GMM
```

```
---------------------------------------------------------------------------
Group variable: countrynum                  Number of obs      =     1036
Time variable : b                       Number of groups   =       53
Number of instruments = 52                  Obs per group: min =       12
F(13, 52)     =  2.26e+06                              avg =     19.55
Prob > F      =     0.000                              max =       20
--------------------------------------------------------------------------------
     lnagricpro2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+--------------------------------------------------------------
     lnagricpro2 |
             L1. |   .8964841   .0073754   121.55   0.000     .8816843    .9112839
                 |
         renegy2 |   .0007876   .0001716     4.59   0.000    -.0011319   -.0004433
           popgr |  -.0098387   .0033982    -2.90   0.006    -.0166576   -.0030198
             sav |   .0000967   .0002063     0.47   0.641    -.0003171    .0005106
           lninv |   .0106991   .0039537     2.71   0.009     .0027654    .0186328
            fert |   .0015567   .0002906     5.36   0.000     .0009735    .0021398
          lnpest |  -.0049834   .0024221    -2.06   0.045    -.0098437    -.000123
          lnexch |  -.0041979   .0005628    -7.46   0.000    -.0053273   -.0030684
             prl |  -.0000324   .0000385    -0.84   0.404    -.0001096    .0000448
           lnemi |  -.0015804   .0038643    -0.41   0.684    -.0093346    .0061738
        lncreagr |  -.0083657   .0026144    -3.20   0.002    -.0136119   -.0031195
           lntop |    .053196   .0060825    -8.75   0.000    -.0654014   -.0409907
                 |
c.renegy2#c.lntop |    .000192   .0000334     5.75   0.000      .000125     .000259
                 |
           _cons |   .9572043   .0701401    13.65   0.000      .816458    1.097951
--------------------------------------------------------------------------------
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for orthogonal deviations equation
  Standard
    FOD.L.lnagricpro2
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L.(L.lnagricpro2 renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr lntop L.lntop c.renegy2#c.lntop cL.renegy2#c.lntop)
    collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.lnagricpro2 renegy2 L.renegy2 popgr L.popgr sav L.sav lninv L.lninv
    fert L.fert lnpest L.lnpest lnexch L.lnexch prl L.prl lnemi L.lnemi
    lncreagr L.lncreagr lntop L.lntop c.renegy2#c.lntop cL.renegy2#c.lntop)
    collapsed
---------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -4.22  Pr > z =  0.000
Arellano-Bond test for AR(2) in first differences: z =   2.55  Pr > z =  0.011
---------------------------------------------------------------------------
```

```
Sargan test of overid. restrictions: chi2(38)   = 275.77  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(38)   =  47.73  Prob > chi2 =  0.134
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(13)   =  24.14  Prob > chi2 =  0.030
    Difference (null H = exogenous): chi2(25)   =  23.59  Prob > chi2 =  0.543
  iv(L.lnagricpro2, eq(diff))
    Hansen test excluding group:     chi2(37)   =  43.97  Prob > chi2 =  0.200
    Difference (null H = exogenous): chi2(1)    =   3.75  Prob > chi2 =  0.053


. outreg2 using testt, bdec(4) tdec(4) rdec(4) adec(4) alpha (0.01, 0.05, 0.10)
addstat(Adj. R-squared, e(r2_a)) excel appe
> nd
check eret list for the existence of e(r2_a)
testt.xml
dir : seeout

.
```