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Carbon emissions, climate change, and Nigeria's agricultural productivity

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ABSTRACT

This paper examined the impact of climate change through the carbon emissions channel on agricultural productivity in Nigeria. It adopted the transposed second-generation environmental Kuznets curve model, which defined growth (agricultural productivity) as a function of climate change. Data from world development indicators between 1960 and 2019 were utilized to examine the impact of climate change on agricultural productivity. The paper employed the bound test (ARDL) method. The result showed the existence of a long-run relationship between carbon emissions (proxy by CO_2 emissions and CO_2 intensity) and agricultural productivity (proxy by Agric.GDP, crop production index, and food production index) in Nigeria. The speed of adjustments is between 34% and 80%. Thus, a change in CO_2 emissions and intensity affects Agric.GDP differently, but CO_2 emissions and intensity negatively impacted crop and food production in Nigeria. The result implies that carbon emissions and carbon intensity cause decline and generates a dampening threat to Nigeria's agricultural productivity through physical risk channels. By extension, the study concludes that carbon emission causes climate vulnerability that affects agricultural yields, production, and productivity. Carbon emissions results in low agricultural productivity which in turn disrupt food security as well as distort the poverty reduction strategy in the country. This study, therefore, recommends an equitable implementation of carbon pricing, adoption of mitigation policies, promotion of effective and efficient environmental laws, and the implementation of an appropriate abatement policy that jointly optimizes environmental stability and growth targets of the sustainable development goals.

Keywords: carbon emissions, agricultural productivity, sustainable development goals, climate vulnerability

INTRODUCTION

Agricultural productivity could be conceptualized through the productivity lenses defined in Hallegatte et al. (2018). The agricultural sector (productivity) plays a key role in supplying resources that meets man's domestic and industrial needs. Agricultural productivity remains a significant channel for enhancing food security and zero-poverty targets (AGRA, 2014; Alkire et al., 2014; Hoda et al., 2017; Munang & Andrews, 2014; Reddy, 2012). It is based on the foregoing imperatives that this study seeks to unravel the impact of climate change on agricultural productivity. However, one of the short-coming in the literature is that the direction of causation between agricultural productivity and climate change is unclear, arising from unbalanced and skewed geographical issues (Al-Amin et al., 2013; Nonan & Bedamatta, 2012). Also, the nexus between climate change and disaggregated agricultural sectors is still in the early stage and a subject of debate considering the policy's inconclusiveness on what mitigation policy should be appropriate for the global economy. This is largely so because existing studies such as; the water-energy-food nexus in Asia-Pacific (Barnosky et al., 2013), environmental security, climate change and competition for water, energy, and land (Godfray et al., 2010), and regional scale examination of climate change, water, energy, and food (Liu, 2014) and Sub-Saharan perspectives of climate change and agricultural nexus (Phiiri et al., 2016) informs the study of many gaps that need considerations especially as it patterns to the disaggregating agricultural sector. Other issues such as divergent geographical conditions, irregular environmental regulations, and unbalanced mitigation laws consistently provide the basis for further examination of issues.

Agricultural productivity is at the center of the climate change debate because, scientific predictions have revealed that climatic phenomena such as tropical storms, floods, droughts, water security, typical cyclones, rising tide, warming seas, coral bleaching, melting glaciers, heat waves, etc are increasing at an increasing as well as transmit physical risks that affect the structural and social dynamics of human development (Carvajal-Velez, 2007). The emerging trends in climatic changes show that flooding, rising temperature, and appreciable sea level in Africa is a threat to the long-term growth of the sector. These physical risks are a manifestation of the evolving concern on the long-term impact of greenhouse gas (GHG) emissions (IPCC, 2014). GHG emissions properties affect both the human and non-human components that make up the agricultural system (Tol, 2009). Eckstein et al. (2021) state that climate variability causes socio-economic consequences through the manifestations of extreme volatility in climate weather conditions. This weather volatility produces weather shocks (Devereux, 2007), generates climate change that boosts biotic stress such as insects (pests) and weed growth, creates a decline in soil beneficial microbes, and threaten pollinator (Shahzad et al., 2021).

Severe environmental disruptions affect agricultural performance because climate change and agriculture have a causal link. The agricultural sector and global food insecurity therefore deeply correlate with climate instability (Saina et al., 2013). For example, dynamic movement in the glacier called glacier melting and retreating have serious implications for the water content and water supply for irrigation and hydropower generation (Oerlemans, 2005).

An evidential issue of rising sea temperature in oceans is coral bleaching. According to Reaser et al. (2000), coral bleaching is a water-damaging situation that potentially threatens the entire coral reefs which provide support mechanisms to the marine organism. Coastal ecosystem degradation e.g., wetlands and coral reefs have serious implications for the entire composition of the agriculture system and productivity. Also, in terms of flooding, Nordhaus (2006) asserts that the consequences of flooding affect national economies. European Academics' Science Advisory Council posits that the incidence of flooding has grown by 50% in the past decades and more still occurring at a rate four times higher than it was twenty years ago. Climate variability causes vulnerability in food security and generates agricultural losses due to flooding.

There are predictions that the average global temperature will heat up from 0.9 °C to 1.5 °C by 2050 and could be higher based on the desertification indicator (Arora, 2019). Since global temperatures have risen substantially over the years, many environmental diseases caused by extreme weather e.g., cold spells and heat waves affect the attitude, topography, and cause environmental disturbance on yields, and portend serious threats to livestock.

The implosive dangers due to the inestimable effect of climate change remain a major policy problem because it could cause development reversal through famine due to agricultural yield and food value chain disasters. Based on the annual report by *Weather*, *Climate*, and *Catastrophe Insight*, natural disaster costs to the global economy between 2016 and 2018 increased from $200 billion per year to $225 billion per year. Similarly, the *2020 World Food Program report*, *Global Assessment of Land Degradation and Improvement*, and *United Nations Environment Program* have jointly estimated that crop yield per hectare is significantly slower than the population growth, a quarter of the land area globally is degraded due to anthropogenic activities and climate change, and more than 600 million hectares of farmland have become infertile due to drought and desertification, respectively.

On the other hand, the agricultural sector through fertilizer utilization and fossil-fuel uses results in carbon emissions (sub-specie of GHGs) which aggravate global warming that stimulates climate change trends that generate climate variability. With an estimated world population of 9.7 billion people per thousand by 2050, pressure on agricultural land to meet the growing demand for food production becomes a policy dilemma. Two paradoxes exist in the nexus surrounding carbon emission and climate change and on the other hand agricultural productivity and food security (supply). First, is the increasing impact of the anthropogenic manipulation of natural resources that eventually accentuates global warming. Due to the unexaggerated rising demand for food caused by the growing population, policymakers have proposed and utilized an unprecedented agrochemical practice, expansive water exploitation, and livestock generation. These practices have aggravated the GHG trends arising from over-exploitation (Arora, 2019).

Second, human activities on the farms affect the weather and temperature conditions that in turn damages human directly through the utility function and indirectly through productivity channels. Agriculture and food processing account for 19%-29% of global anthropogenic GHG emissions, emitting 9,800-16,900 megatons of carbon dioxide equivalent (Vermeulen et al., 2012). Also, stimulating mechanized farming and other measures to accelerate crop production produce radioactive effects and anthropogenic changes in atmospheric composition which in turn increase CO_2 concentration and GHG emissions (Milly et al., 2002). Scientifically, carbon emission spillover is observed through human activities on the farm. A notable effect of carbon emission is the carbon concentration that aggravates climate change problems. Thus, climate change causes climate vulnerability that disrupts the ecosystem and makes economic interactions susceptible to the (Hallegate et al., 2018; Hertel & Rosch, 2010) as well as dampen long-run food security. The concern on the nature of climate pattern which generates high temperature and flooding enthrones factors that affect food security as well as cause developmental trauma through increasing agricultural (food) prices, the aggregate decline in calories, crop losses, and water contaminations (Pacetti et al., 2017). This scenario creates social tension, threatens social survival, impedes sustainability, and threatens climate change adaption (mitigation) strategies (Adger, 2006; Smit & Wandel, 2006).

In **Figure 1**, Sullivan and Byambaa (2013) showed a geographical climate vulnerability index. However, in **Figure 2** GermanWatch shows graphical representations of the global climate risk index between 2000 and 2019. Both **Figure 1** and **Figure 2** provide overwhelming problems for the global community.

Climate change and the agricultural sector nexus have been extended in Hallegatte et al. (2018). Carbon emissions, climate change, and agricultural linkage cause associated damages in it goal 1 and goal 2 of the SDGs. One could recall that goal 1 of the UN's 17 sustainable development goals

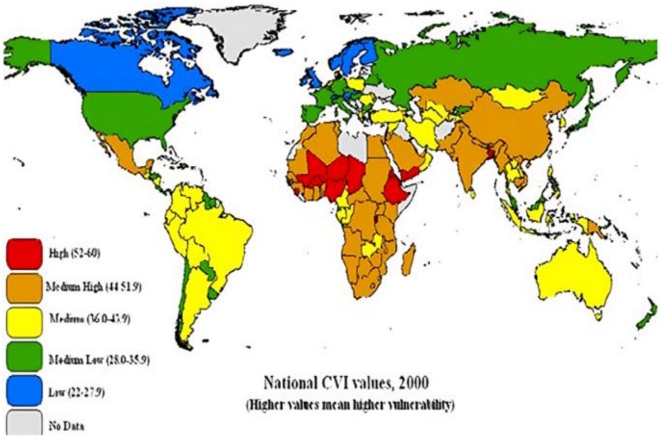

Figure 1. Climate vulnerability index (Sullivan & Byambaa, 2013)

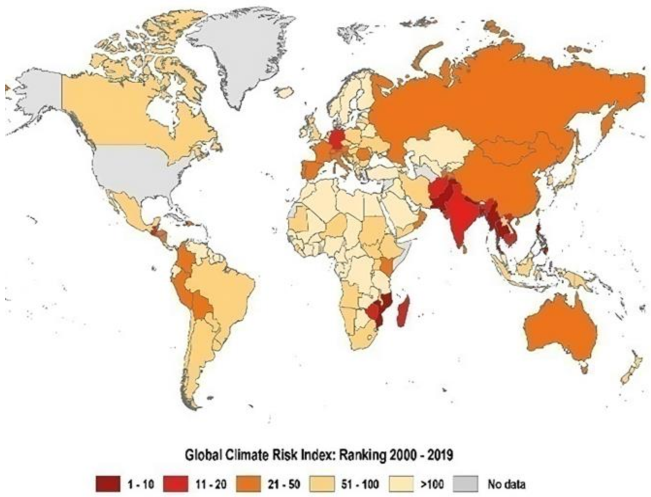

Figure 2. Global climate risk index (Eckstein et al., 2021)

(SDGs) is zero poverty and goal 2 of the SDGs is to end hunger, achieve food security, improve nutrition, and promote sustainable agriculture. But climate change impedes SDGs such that higher climate variability leads to higher flooding, higher flooding leads to food insecurity, and food insecurity, in turn, and food insecurity causes instability that increases poverty incidences (De Silva & Kawaski, 2018). From the graphical representation, the African region has moved from the medium in 2000 (Sullivan and Byambaa, 2013) to the range of 21%-100% between 2000 and 2019 (GermanWatch, 2020).

Given the precarious narrative of climate change presented above, climate change could limit food supply and disrupt the food system (food quality, food availability, and food value chain) with long-term implications for poverty reduction. Since, agriculture positively affects food supply it causes inestimable problems for global poverty reduction strategy (PSR) (Hallegatte et al., 2018).

Policymakers in Sub-Saharan Africa are seriously concerned about zero poverty (goal 1) and zero hunger (goal 2) targets. Poverty and hunger targets are complex and self-propagating with lack of employment (income) as the common denominator (Leichenko & Silva, 2014). World Bank (2021) posited that global extreme poverty rose in 2020 due to the COVID-19 pandemic. Extreme poverty hovers between 9.1% and 9.4% of the world's population in 2020. According to Khoday and Ali (2018), one-third of the global population are poor or near-poor and faces consistent threats to survival.

On the other hand, the progress to achieve zero-hunger 2030 targets has come under heavy disruption, between 720 million and 811 million individuals experienced hunger in 2020. This is an addition of 118 million individuals to the numerical incidence experienced in 2019. UN (2021) showed that between 2019 and 2020, the prevalence of undernourishment moved from 8.4% in 2019 to 9.9% in 2020. The total number of undernourished is put at 768 million in 2020. Sadly, the decomposition of these numbers showed that 282 million live in Africa, 418 million reside in Asia, and 60 million reside in Latin America. Thus, between 2019 and 2020, an additional 46 million, 57 million, and 14 million hungry people were added to the numbers in Africa, Asia, and the Caribbean, respectively. Statistically, 2.37 billion suffered food insufficiency in 2020. This number rose by an additional 320 million within one year. This staggering data have also translated to a stunting growth scenario in affected economies. About 149.2 million, which is about 22.0% of children under the age of five years globally are affected by the disturbing global food system. Additionally, FAO (2021) forecasted that about 660 million people could face hunger in 2030. The effect of changing climate hazards and other exposures connote that the world's poverty rate could be about 7% or more by 2030. About 132 million poor people globally dwell in areas with high flood risk.

Climate variability leads to lower resilience for low-income countries in managing future shocks and diminished shared prosperity (Olsson et al., 2014, Skoufias, 2012; The Fifth Assessment Report, 2015). Thus, climate change can push between 68 million and 132 million into income-related poverty by 2030. On the whole, the forces of climate change continue to trigger cycles of higher income inequality, and lower social mobility, and disrupt labor productivity through low agricultural yield and sectoral downturns.

FAO (2021, p. 1) attests that "the world is at a critical juncture." World Bank (2021, p. 1) stipulates that "there are high tendencies that climate change, conflicts, and structural economic shocks, etc will constitute devastating cost as well as disrupt long-run economic trajectory if left untreated." The reports by FAO (2021) and World Bank (2021) jointly incentivize the rationale to reconsider the climate change and agricultural nexus. Climate change via its climate vulnerability channels enforces its impact on poverty and hunger through agricultural and financial system channels.

Scholars are deeply overwhelmed about the direction of causality, shock, long-run impact, and risks permeating the linkage between climate change, agricultural output, financial risk, and poverty (hunger). This is because of the existence of variations in the regional weather pattern and differences in topography. Due to policy inconsistencies inherent in estimating the impact of changing climate patterns on economic activities, this study would be limited to climate change and global agricultural productivity in Nigeria.

The significance of this study is largely connected with the observable policy inconsistencies disrupting policy actions to de-trend the impact of climate change and the several limitations frustrating PSR and structural adjustments in economic patterns to boost economic activity.

From previous studies, the disaggregated agricultural examination is under-reported in the carbon emission, climate change, and agricultural productivity nexus. Hence, this paper seeks to examine the impact of climate change on disaggregated agricultural productivity. This paper estimates the impact of carbon emission (a proxy for climate change) on agricultural productivity (proxy by agricultural contribution to GDP). Furthermore, it is against this backdrop this paper investigates the impact of climate change on crop production and food production in Nigeria. The motivating questions therefore becomes whether carbon emissions (climate change) impede agricultural growth in Nigeria (Africa). Does climate intensity affect AgricGDP? Specifically, what is the impact of carbon emission on agricultural contribution to GDP (AgricGDP), food production, and crop production?

This paper is divided into five sections namely, introduction, literature review, data and methodology, results and discussion, and conclusion and recommendation.

LITERATURE REVIEW

In a broad term, the intricate nexus underpinning climate change and agricultural productivity could be viewed from the following linkages. Firstly, climate change affects agricultural productivity through direct channels (e.g., unpredictable weather patterns, high temperatures, flooding) and indirect channels (e.g., physical risk on loans, financial shock: distort equilibrium interest rate). Secondly, low agricultural productivity yields affect climate change through direct channels (hunger, insecurity, and inequality) and indirect channels (deviant behavior towards mitigation and adaptation). Thirdly, agricultural productivity directly affects poverty incidence (e.g., low crop yield and low employment channels) and climate change (e.g., generation of carbon dioxide in the application of fertilizer and use of heavy-duty equipment). Fourthly, GHG emission control policy set limits on sectoral (agricultural) productivity by altering the energy mix (fossil-fuel use) that affect agricultural yields (employment of inputs) which causes a decline in agricultural yields which results in unemployment and low calorie (De Silva & Kawaski, 2018; Hertel & Rosch, 2010; Pacetti et al., 2017). Fifthly, transmission effects emanating from climate change to agricultural output can be deduced from the development reversal channels. Low agricultural productivity causes poverty, hunger, inequality, unemployment, and insecurity which threatens and disrupts economic activities due to cut-back (shutdown) in agricultural-related economic activities (United Nations Department of Economic and Social Affairs, 2016).

Specifically, Hallegatte et al. (2018) identified prices, assets, productivity, and opportunities channels as permissible paths to measure climate change's impact on poverty. According to Hallegatte et al. (2018) "the link between poverty and climate vulnerability goes two ways namely, climate change is one major driver of people's vulnerability to climate-related shocks and stressors, and this vulnerability subjectively set people in poverty." Moser (2008) suggests that health shocks are the prominent channels in why people fall into poverty. The assessment of shock waves using Hallegatte et al. (2016) perspective aligns with Krishna (2006) that poverty shocks are generated directly or indirectly from the environment and climate. One of the causes of climate-related shock that causes poverty is natural risks e.g., the drought that makes an investment in agribusiness risky and causes depletion of natural capital, fiscal shocks, and misallocation of funds (Elbers et al., 2007). On the other hand, Barbier and Hochard (2018) demonstrate that cities with poor biophysical settings or lack of market access have a lower elasticity of poverty reduction to growth. Thus, inclusive and robust economic growth is required to attain overall poverty reduction. Stern's (2006) report complements the World Bank's study of 2008 that focused on the potential impacts of climate variability on poverty and development. The linkage between climate variability and human development is captured in Carvajal-Velez (2007), IPCC (2015), United Nations Economic Commission for Africa (2010), and World Bank (2003).

Theoretical Literature

Analytically, the environmental Kuznets curve (EKC) is employed to estimate the relationship between pollution and income per capita. The leading critiques of the EKC have argued that the econometric framework of EKC is subjective (Arrow et al., 1995; Copeland & Taylor, 2004; Stern, 1998). Dasgupta (2002) argued that EKC is monotonic. There are two perspectives to this argument namely new toxics and race-to-the-bottom scenarios. The new toxics scenario posits that EKC does not hold for new toxics e.g., carcinogenic chemicals, and carbon dioxide. On the other hand, the race to the bottom scenario asserts that EKC is inconsistent because of the outsourcing operation by developed countries in which they outsource dirty production to developing countries thereby making it increasingly difficult for emissions to be reduced. The revised EKC further argued that arising from inevitable technological changes, EKC shows a downward curve behavior shifting to the left (Stern, 2004). Stern (2004) contends that the proximate causes that define the EKC relationship are namely, the scale effect (expansion), the changes in economic structure or product mix, changes in the technological state, different industrial pollution, and changes in input mix.

In a similar vein, scholars try to decompose pollution, a major issue in the EKCs. Selden and Song (1994) estimated EKCs using four-dimensional series namely SO_2, NO_x, SPM, and CO_2. Shafik and Bandyopadhyay (1992) studied EKC from 10 indicators. Grossman and Krueger (1991) estimated EKCs using SO_2, dark matter (fine smoke), and suspended particles (SPM). In a related development, pollution was decomposed into local pollution and global pollution in the study of EKC (Lopez, 1994). According to Lopez (1994), local pollution is amenable to EKC rather than global pollution. Also, pollution generated from consumption rather than production was considered in a study such as McConnel (1997).

Empirically, the EKC is conceptualized in the literature from two generations of analysis. Firstly, first-generation EKC (FGEKC) conceptualized a two-phased dimension: increasing and decreasing functional relationship between income inequality and economic development expansion over time

(Kuznets, 1955). Secondly, FGEKC estimated that income inequality first rises and then falls as economies develop. In the second generation, the concept of EKC (SGEKC) further hypothesized a two-dimensional relationship between pollution events and economic growth per capita (Grossman & Krueger, 1991; Shafik & Bandyopadhyay, 1992).

The apparent difference between FGEKC and SGEKC is the attention placed on income inequality (FGEKC) and GDP per capita (SGEKC). The underpinning argument anchored in both FGEKC and SGEKC is that pollution is a sub-specie of development. Based on development realities, EKC argued that greater economic activity constitutes a task to environmental quality through technology-pollution channels. The SGEKC, therefore, views the scale effect as the core explanatory variable on the relationship between environmental pollution and income per capita. Within the SGEKC, two methodological frontiers exist that decomposed the two-dimensional EKC into a square-EKC model and a cubic-EKC model. The SGEKC model estimated a functional relationship between environmental pollution and quadratic (or cubic) GDP per capita.

The apriori expectation for the quadratic GDP per capita and cubic GDP per capita is given as $\beta_2\rho^2<0$ and $\beta_3\rho^3>0$, where $\beta_i\rho^i$ is parameter, GDP per capita, and i=2, 3, respectively. These signs connote a decreasing (economies of scale) and an increasing (diseconomies of scale) pattern in the relationship between environmental pollution and GDP per capita.

Theoretically, the behavior of the relationship between climate change (environmental pollution) as a function of quadratic GDP per capita ($\beta_2\rho<0^2$) is found to be an inverted U-shaped i.e., based on the quadratic school of thought. Various degrees of EKC exist in the literature. The cubic school of thought ($\beta_3\rho^3>0$) viewed the functional relationship between environmental pollution and cubic GDP per capita as an N-shaped (Grossman & Krueger, 1991). Panayotou's (1993) finding is consistent with the inverted U-shaped of the SGEKC. Panayotou (1993) argued that higher levels of development, coupled with investment and enforcement of environmental regulations result in levelling-off and the gradual decline of environmental degradation. The implication of the inverted U-shaped is that in the infant stage of economic growth, degradation, and pollution increase, and after a certain period high-income levels of economic growth leads to environmental improvement (Stern, 2004).

Empirical Literature

Early studies on climate change on productivity are traceable to Cline (1992), Fankhauser (1995), Nordhaus (1991), Titus (1992), and Tol (2002). Studies on how weather (climate change) retards economic development have evolved from per capita income and temperature studies (Nordhaus, 2006) to biodiversity and ecosystem (Champ et al., 2003) to institutional response (Easterly & Levine, 2003) to question about annual growth rate (Fankhauser & Tol, 2005) to induced-conflict due to scarcity (Salehyan, 2008; Zhang et al., 2007) to trade and development (Hubler, 2016). Climate change and poverty are inextricably intertwined (McCarthy, 2020) and flow intertemporally (Hallegatte et al., 2016). Climate change aggravates poverty through direct channels e.g., high temperatures, extreme rainfall, and natural disasters (Aragie, 2013), indirect channels e.g., transitory-demand and supply shocks, and immediate channels e.g., financial shock and agricultural price shock, and the feedback consequences of poverty impede environment quality.

The general impact of climate change on agricultural productivity can be deduced from the fact that the different patterns of rainfall cause variability in the flood. The evaluation utilized a comprehensive hydrologic and hydraulic model (Hettiarachchi et al., 2018). Also, the forecast of rainfall-driven flood risk, principally accounted for by climate change is captured in Kundzewicz et al. (2013). The result of the study is consistent with the IPCC SREX assessment. The study showed distinguished two major floodings such as flash flooding and urban flooding are caused by climate change, but the nature of rainfall is connected to the detailed nature, magnitude, or frequency of climate change. Vermeulen et al. (2012) found a bi-causality between food systems and climate change. The core drivers in this bi-causality are the prevailing social conditions.

Schreider et al. (2000) in a study titled "climate change impacts on urban flooding" explained that GCMs' slab model showed that between 2030 and 2070 climate change might cause less significant urban flood damage. On the contrary, the stochastic weather generator technique found that the higher the CO_2 concentration the higher the damage. Also, the study utilized the hydrological model to estimate the CO_2 and flood relationship. The study found that doubling CO_2 conditions cause a positive impact on flooding though the result varies from place to place.

Milly et al. (2002) identified radioactive anthropogenic climate change and flood risk causality through the intensification of the global water cycle. The study concludes that the flood trend is continuously based on the climate change impact using both stream flow measurement and numerical simulations of the anthropogenic climate changes. Flood affects daily calorie consumption by approximately 60 kcal. Flood brings about an increase in the deficiency level of iron, vitamin A, and vitamins C by 11%, 12%, and 27%, respectively. The risk of exposure to natural disasters leads to a decline in income by 3%, drives 3% of the household to poverty, and causes significantly lower diet quality and quantity with difficult consumption coping strategies (Oskorouchi & Sousa-Poza, 2021). Dorward and Kydd (2002) posit that erratic rainfall lowers the productivity of rural economies through a decline in returns on investment, distortions of investment by increasing investment hazard, and discouraging investment due to the risk-averse nature of investors.

Experiences of global warming caused by climate change portend a threat to poverty reduction strategies through the associated economic agents' exposure to shocks, uncertainty, and risks. More troubling is the depleting global dimension of climate change. Smith et al. (2021) link the climate-poverty nexus through conflicts by their impact on retarding political, economic, and social conditions. Therefore, climate-conflict linkage creates a pervasive and stimulant nexus that cause poverty. Scholars are unanimous on the noticeable causality existing between consequences of climate variability-global warming and flooding-food insecurity. The dimension of this logic underpinning this causality exposes the climate-flood risk-poverty causality to further studies based on the emerging reality of climate change (GHG emission) incidences.

The emerging trends show that flooding, rising temperature, and appreciable sea level are perceptibly related to the impact of GHG emissions. GHG emissions properties affect both the human and non-human components that make up the agricultural system (Tol, 2009). This is because exposure, susceptibility, and management of climate hazards depend on the prevailing structural inequalities governing the societal arrangement (World Economic and Social Survey, 2016). Economists have linked carbon emission control policy to causing poverty because of the significant impact carbon emission control policy has on the global energy mix used for generating power for the industries that contribute to GDP. So, at the end thereof, a carbon emission reversal policy on the energy mix transmits productivity shocks that affect poverty reduction strategies and widen inequality gaps through GDP and FDI inflow. This implies that carbon emission policy causes productivity shock and income shock that worsen poverty (Hallegatte et al., 2016) and inequality indices (Islam & Winkel, 2017).

On the other hand, high poverty and inequality threaten mitigation and adaptation (Hallegate et al., 2018) that could seamlessly lead to climate vulnerability reversal (Geoff et al., 2008). The task of reducing climate change and poverty jointly is at the center of development discourse. Two important poverty reduction strategies adopted by low-income countries are by improving and accelerating inclusiveness. The negative link between poverty and carbon emission control policy explains the analytical framework for this study. Carbon emissions and incomes differ between high-income countries and low-income countries in terms of industrial contribution to GDP. Carbon per person and per ecological emission is driven by income concentration, with the concentration of income potentially being a threat to mitigation, compliance, adaptation, and enforcement (Caron & Fally, 2018). The literature shows an increasing functional relationship between emission and income inequality through differential exposure and vulnerability. However, the net increase in emissions remains in contention in the literature arising from rising emission-rising income in a developed country and rising emission-lowering income in developing countries as well as defined by poor people's emissions higher than the decrease of consumption by rich people. The empirical link shows that emissions increase more slowly than income in most developed and middle-income countries.

According to Guterres (2021), "climate shocks and the COVID-19 pandemic are increasing threat to humanity." The compounding forces of COVID-19 crisis, conflict, and climate variability e.g., GHG emission CO2concentration proxy by flooding and temperature impact negatively on poverty reduction strategy (World Bank, 2020). By this reality, the socio-economic consequences of climate hazards typify that the dimension of climate variability manifests in many ways through increased volatility of extreme weather events (Eckstein et al., 2021). Devereux (2007) posits that extreme weather event produces weather shock that triggers a sequence of entitlement failure. The new realm of global food insecurity caused by factors not limited to climate variability (Saina et al., 2013) calls for action to avoid developmental reversal due to climate hazards.

Also, another dimension of poverty is hunger. Hunger's resistance to policy sequencing targeted at rationalizing global resources is the most profound moral contradiction of our age (Cohen, 1995). Guterres (2021) contends that over 30 million people are 'just one step away from a declaration of famine. Bucher (2021) people are being starved. Beasley (2021) the head of the World Food Program (2020, 2021) estimates over 16 million people in Yemen are now plagued with crisis levels of hunger. In 2020, one in nine people were estimated to be hungry or undernourished while 149 million children under the age of five years are still affected by stunting globally (Global Nutrition Report, 2020). At the end of 2020, over 88 million people suffered acute hunger due to unpredictable dynamism. Between 2018 and 2019, the incidence of undernourished people due to food insecurity grew by 10 million, and there are nearly 60 million more undernourished people now in 2014. Much more, over 690 million people still go hungry which is 8.9 percent of people globally. UN report identified conflict as a major driver of hunger (Action Against Hunger, 2020). Conflict is to a large extent influenced by climate variability (Burrows & Kinney, 2016; Smith et al., 2021). Conflict (insecurity) e.g., Boko Haram affects agricultural productivity by causing desertion of farmland. Flooding, therefore, becomes a threat to the achievement of SDGs to end poverty (Del Ninno et al., 2003). The consequences of flooding affect national economies (Nordhaus, 2006) and labor market (Mueller & Quisumbing, 2011), which drives upward the trend of poverty (Del Silva & Kawasaki, 2018). Another paradox aside from the climate change-poverty causality is the revelation that agriculture and food processing account for 19%-29% of global anthropogenic GHG emissions, emitting 9,800-16,900 megatons of carbon dioxide equivalent (Vermeulen et al., 2012). Thus, the policy impact to stimulate mechanized farming and other measures to reduce poverty produce radioactive effects and anthropogenic changes in atmospheric composition which in turn increases CO_2 concentration and GHG emission (Milly et al., 2002).

Climate variability causes vulnerability in food security and generates agricultural losses due to flooding. This scenario creates social tension, threatens social survival, impedes sustainability, and threatens climate change adaption (mitigation) strategies (Adger, 2006; Smit & Wandel, 2006). In terms of hampering adaptation, the inestimable food insecurity-poverty-generated phenomenon crashes socio-economic policy on inclusiveness (D'Souza & Jolliffe, 2012, 2013) as more and more people become economically disadvantaged due to the vulnerability of climate variability (Oskorouchi & Sousa-Posa, 2021). Climate variability increases flooding and hence poverty. Scholars have become aggressive in the questions on the causal link existing between climate diffusion and poverty. One of its kind is the food insecurity (shortages) caused by the change in statistical properties of weather events and flooding.

DATA AND METHODOLOGY

Data sourced from World Development Indicators was employed for this study. This study adopts a quasi-experimental research design. ARDL method was utilized to account for time-varying impacts of climate variability (proxy by CO_2 emission and CO_2 intensity) on Agricultural GDP (AgricGDP), food production index (FOODPI), and crop production index (CROPI) in Nigeria. From the literature, poverty is linked with climate variability through drought, flood, extreme temperature index, desertification, etc., which causes a decline in crop yield as well as causes investment risk in the agribusiness outlook. Hence, employment falls and inflation grew which cripples' income and standard of living thereby leading to poverty.

Model Specification

Based line model is obtained from the EKC model. For clarity, EKC is therefore decomposed into FGEKC (first generation EKC) and SGEKC (second generation EKC).

The FGEKC is given, as follows:

Inequality=f (economic development) (1)

However, the SGEKC states that

Pollution=f (quadratic or cubic GDP per capita) (2)

The standard SGEKC regression conceptualized by Grossman and Krueger (1995) is given, as follows:

$$\left(\frac{E}{P}\right)_{it} = \alpha_i + \gamma_t + \beta_1 In\left(\frac{GDP}{P}\right)_{it} + \beta_2 In\left(\frac{GDP}{P}\right)^2_{it} + \varepsilon_{it} \quad (3)$$

where E is emission, P is population, GDP is gross domestic product, In indicates natural logarithm, and α_i, γ_t represent intercept parameters, which vary across countries or region i and years t. The prevailing assumption is that emissions per capita may differ over countries at any particular income level (Stern, 2004). The turning point where emissions or concentration are at maximum is given, as follows:

$$\tau = exp\left(\frac{-\beta_1}{2\beta_2}\right) \quad (4)$$

Based on the warning issued by UN Secretary-General Antonio Guterres (2020), this study undertook modifications in the baseline model EKC by transposing the SGEKC i.e., interchanging the LHS and RHS function in the SGEKC. The modified SGEKC does not consider the quadratic changes in the regressors. This is because, only one type of growth (GDP) i.e., agricultural contribution to GDP (Agric. GDP) is considered in this study. Hence,

Agric.Producitivty = f (Carbon emissions) (5)

where agricultural productivity is proxy by Agric.GDP, as follows:

$$Agric.GDP_t = f\ (CO_2Emissions_{t,\mu_t}) \quad (6)$$

where *CO_2 Emissions* and *intensity* is proxy by carbon emissions:

$$Agric.GDP_t = f\ (CO_2Intensity_{t,\mu_t}) \quad (7)$$

$$Agric.GDP_t = \alpha_1 + \beta_2 CO_2EM_t + \beta_3 FCPL_t + \beta_4 TLF_t + \beta_5 RINT_t + \beta_6 INF_t + \beta_7 PMCL_t + \beta_8 AVDPW_t + \mu_t \quad (8)$$

$$Agric.GDP_t = \alpha_1 + \beta_2 CO_2INT_t + \beta_3 FCPL_t + \beta_4 TLF_t + \beta_5 RINT_t + \beta_6 INF_t + \beta_7 PMCL_t + \beta_8 AVDPW_t + \mu_t \quad (9)$$

$$FoodPI_t = \alpha_1 + \beta_2 CO_2INT_t + \beta_3 INFLA_t + \beta_4 AVDPW_t + \beta_5 FERTCONS_t + \beta_6 POP_t + \beta_7 EMPLAGR_t + \beta_8 ARABLAND_t + \mu_t \quad (10)$$

$$CropPI_t = \alpha_1 + \beta_2 CO_2INT_t + \beta_3 INFLA_t + \beta_4 AVDPW_t + \beta_5 FERTCONS_t + +\beta_6 EMPLAGR_t + \beta_7 ARABLAND_t + \mu_t \quad (11)$$

where Agric.GDP is agriculture contribution to GDP, CROPPI is crop production index, FOODPI is food production index, CO_2EM is CO_2 emissions<0, CO_2INT is CO_2 intensity<0, FCPL is fertilizer consumption per land>0, TLF is total labor force>0, RINT is real interest<0, INF is inflation>0, PMCLis permanent crop land>0, AVDPW is agricultural value added per worker>0, FERTCONS is fertilizer consumption>0, EMPLAGR is employment in agriculture>0, ARABLAND is arable land>0, α_i is constant, and $\mu_{it}$is stochastic term, t=1, 2, ... (**Appendix A**).

RESULTS AND DISCUSSION

Table 1 shows the regression results for model 8-11. From model 8, there is a long relationship between CO_2 emission, CO_2 intensity, FOODPI, CROPPI, and Agric.GDP in Nigeria. The value of the F-test is greater than the upper and lower bound tests. The result implies that climatic effects could disrupt agricultural production and in turn, agricultural mechanizations could spur climate change stress. The co-integration between CO_2 emission and Agric.GDP is 62.09% and the impact of CO_2 emission is infinitesimally positive and significant at 5%.

The result shows that a 1% change in inflation and real interest significantly impact Agric.GDP by 19.3% and 18.2%, respectively. But the result shows that fertilizer consumption per land and permanent cropland negatively impact Agric.GDP. Thus, a one percent change in fertilizer consumption per land and permanent cropland, Agric.GDP by 14.1% and 351%, respectively. There are mixed findings on the impact of carbon emissions and carbon intensity on Agric.GDP. But the manifestation of the negative impact of carbon emissions on crop and food production index shows the effect of climate change on agricultural productivity. The result could be due to the deteriorating effect of insecurity and activities of oil spillage on agricultural land.

In model 9, CO_2 intensity has a negative and non-significant impact on Agric.GDP. The speed of adjustment between CO_2 intensity is 34.4% and there is an existence of a long-run relationship that implies that CO_2 intensity and emission could produce long-run vulnerability in the long-run for the agricultural sector. Unlike in model 8, in model 10, CO_2 emission has a significant and long-run negative impact on the food production index with an 85% speed of adjustment. Also, model 11, shows that CO_2 emission has a long-run negative and significant impact on crop production index with a 51% speed of adjustment. Except for model 8, model 10, and model 11, the result showed the impact of CO_2 emission on Agric.GDP conforms to economic interpretation. This implies that CO_2 emissions impede agricultural productivity.

CO_2 emissions (a proxy for carbon emissions) through their direct impact on unpredictable rainfall, drought, and flood, distort agricultural productivity which cripples poverty reduction strategies through employment channels, and inflicts more hunger by causing food deterioration and famine.

Table 1. Regression results for model 8-11

	AGRIC.GDP	AGRIC.GDP	FOODPI	CROPPI
CO_2_EMISSIONS	0.000109 (0.0035)		-0.000445 (0.0091)	-0.000307 (0.0032)
CO_2_INTENSITY		-4.252292 (0.4257)		
FERTCONSPERLAND	-0.141517 (0.0064)	-0.073640 (0.2642)		
TLABOFORCE	2.59E-06 (0.0006)	2.33E-06 (0.0000)		
REALINTR_	0.181539 (0.0008)	0.243086 (0.0000)		
INFLA	0.192971 (0.0007)	0.159270 (0.0000)	-0.030082 (0.1818)	-0.123854 (0.0018)
PERMANENT_CROPLAND	-3.510377 (0.0060)	-6.580449 (0.0007)		
AGRVADPERWORKER	0.013327 (0.0005)	0.015291 (0.0000)	-0.001526 (0.4731)	-0.004652 (0.3700)
FERTILIZERCONS			0.006298 (0.0173)	0.001077 (0.5274)
POPLA			-4.46E-05 (0.0536)	
EMPLOYAGRIC			7.705042 (0.0364)	12.64157 (0.0001)
ARABLE_LAND			0.412030 (0.3132)	2.199790 (0.0004)
R-squared	0.999961	0.988754	0.999986	0.999423
Adjusted R-squared	0.999516	0.975259	0.999888	0.998462
F-statistic-Prob (F-statistic)	2246.820 (0.0004)	73.26830 (0.0000)	10214.84 (0.00009)	1039.841 (0.0000)
CointEq (-1)	-0.620985 (0.0001)	-0.343589 (0.0000)	-0.859938 (0.0001)	-0.512220 (0.0000)
Jarque-Bera	0.53226 (0.7663)	1.33780 (0.5122)	1.45843 (0.48228)	0.538007 (0.76414)
Breusch-Godfrey serial correlation LM test	0.3155	0.1655	0.0533	0.0778
Heteroskedasticity test: Breusch-Pagan-Godfrey	0.4351	0.2298	0.9324	0.2772
Ramsey RESET test	0.3327	0.2387	0.1799	0.8841

Note. Source: Computed by the authors from EViews 9

In the North-East, the direct link between climate change and the declining water volume in Lake Chad, thus, throw-up famine, hunger, and poverty due to the impact of drying Lake Chad on the agricultural lifecycle.

Nigeria's 33.3% unemployment rate could be indirectly linked to CO_2 emission impact on agricultural productivity which consistently and persistently disrupts the supply chain and crop yield that creates low employability in the sector. The result confirms previous studies e.g., Devereux (2007) and Dorward and Kydd (2002) that climate change has a disruptive impact on agriculture which in turn complicate and distort poverty reduction strategies. The negative relationship between climate change and agricultural productivity implies that the higher the climate change variability to lower the agricultural yields. Hence, lower agricultural yields thereby lead to a decline in employment and income which in turn cause poverty reduction risk. Also, the implications of this connote that economic interaction faces serious disruption as carbon emissions has continuously been emitted into space. Thus, the interplay of economic variables that enable economic growth, therefore, the potential of the economy to achieve SDGs goal 1 and goal 2 tends to be susceptible.

CONCLUSION AND RECOMMENDATION

This study is premised on the nexus between carbon emissions and agricultural productivity. The term productivity is defined based on Hallegatte et al. (2018). Therefore, there is a long-run linkage between carbon emissions and the intensity of agricultural productivity in Eq. (8-11). The study finds indirectly that poverty and food shortage (insecurity) is probable in the long run. Climate change caused by irredeemable and irreversible carbon emissions generates physical risks that disrupt agricultural-related activities.

From the results in **Table 1**, carbon emissions produce a long-run threat to agricultural-related economic activities in Nigeria which in turn affect food security and zero-hunger and poverty targets. That is, carbon emission causes climate change which generates climate vulnerability in the ecosystem and creates biotic stresses that increase pests and cause a decline in soil fertility (Shahzad et al., 2021). Climate vulnerability includes and is not limited to the unpredicted properties of weather events, flooding, and health-related issues that have been found to affect poverty by lowering productivity and GDP per capita through depressed crop yields link to rising sea levels, heat waves, super storms, and transitory risks. Also, through transitory risks the mitigation of emissions leads to a decline in firms engaged in agricultural value chain activities that in turn bring about negative growth hence poverty.

The overarching problem is that firms in the agricultural sector are affected by the externality effect of carbon emissions (CO_2 and pollution) and GHG emissions (global warming) that first cause climate change which disrupts crop yield as well as causes an inevitable transfer of earned income from investment on assets to CO_2-health-related diseases. And cause low investment in the sector cause low productivity. These two issues thereby cause a decline in the income-earning channel of the economic agents which disrupts the acquisition of new assets, new hiring, and hence poverty. The government should adopt strategies that will progressively reduce GHGs emissions and set GHGs codes and standards for industrial and household activities. Secondly, externality cause low investment arising from risks and hazards in the sector. Low investment tends to affect productivity.

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APPENDIX A

Model 1

Table A1.

Dependent variable: AGRICGDP				
Method: ARDL				
Date: 03/26/22 Time: 13:37				
Sample (adjusted): 1993 2018				
Included observations: 26 after adjustments				
Maximum dependent lags: 2 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (2 lags, automatic): CO_2_EMISSION				
FERTCONSPERLAND TLABOFORCE REALINTR_ INFLA				
PERMANENT_CROPLAND AGRVADPERWORKER				
Fixed regressors: C				
Number of models evaluated: 4,374				
Selected Model: ARDL (2, 2, 2, 2, 2, 2, 2, 2)				
Variable	Coefficient	Standard error	t-Statistic	Prob.*
AGRICGDP (-1)	0.122929	0.042330	2.904092	0.1009
AGRICGDP (-2)	0.256086	0.031570	8.111753	0.0149
CO2_EMISSION	0.000109	6.45E-06	16.88435	0.0035
CO2_EMISSION (-1)	9.39E-05	7.72E-06	12.16427	0.0067
CO2_EMISSION (-2)	9.34E-05	5.56E-06	16.79976	0.0035
FERTCONSPERLAND	-0.141517	0.011400	-12.41420	0.0064
FERTCONSPERLAND (-1)	-0.126891	0.011785	-10.76678	0.0085
FERTCONSPERLAND (-2)	-0.398836	0.025084	-15.90022	0.0039
TLABOFORCE	2.59E-06	6.48E-08	40.02323	0.0006
TLABOFORCE (-1)	6.29E-07	1.50E-07	4.203296	0.0522
TLABOFORCE (-2)	-2.06E-06	1.21E-07	-17.10785	0.0034
REALINTR_	0.181539	0.004984	36.42493	0.0008
REALINTR_ (-1)	0.113014	0.011385	9.926871	0.0100
REALINTR_ (-2)	-0.053084	0.006568	-8.081838	0.0150
INFLA	0.192971	0.004992	38.65630	0.0007
INFLA (-1)	0.098368	0.008979	10.95516	0.0082
INFLA (-2)	-0.029573	0.004431	-6.674539	0.0217
PERMANENT_CROPLAND	-3.510377	0.272256	-12.89368	0.0060
PERMANENT_CROPLAND (-1)	-2.582966	0.466668	-5.534916	0.0311
PERMANENT_CROPLAND (-2)	0.487154	0.382032	1.275167	0.3303
AGRVADPERWORKER	0.013327	0.000297	44.83236	0.0005
AGRVADPERWORKER (-1)	-0.007610	0.000708	-10.74692	0.0085
AGRVADPERWORKER (-2)	-0.012721	0.000808	-15.74764	0.0040
C	-14.80878	2.030246	-7.294083	0.0183
R-squared	0.999961	Mean dependent var		24.82605
Adjusted R-squared	0.999516	S.D. dependent var		3.956536
S.E. of regression	0.087022	Akaike info criterion		-2.764109
Sum squared resid	0.015146	Schwarz criterion		-1.602789
Log likelihood	59.93341	Hannan-Quinn criter.		-2.429691
F-statistic	2246.820	Durbin-Watson stat		3.094835
Prob (F-statistic)	0.000445			
*Note. p-values and any subsequent tests do not account for model selection.				

Table A2.

ARDL Error Correction Regression				
Dependent Variable: D (AGRICGDP)				
Selected Model: ARDL (2, 2, 2, 2, 2, 2, 2, 2)				
Case 2: Restricted constant and no trend				
Date: 03/26/22 Time: 13:39				
Sample: 1960 2020				
Included observations: 26				
ECM regression				
Case 2: Restricted constant and no trend				
Variable	Coefficient	Standard error	t-Statistic	Prob.
D (AGRICGDP (-1))	-0.256086	0.010324	-24.80544	0.0016
D (CO_2_EMISSION)	0.000109	1.73E-06	63.00476	0.0003
D (CO_2_ EMISSION (-1))	-9.34E-05	1.92E-06	-48.62530	0.0004
D (FERTCONSPERLAND)	-0.141517	0.002946	-48.04334	0.0004
D (FERTCONSPERLAND (-1))	0.398836	0.004836	82.47287	0.0001
D (TLABOFORCE)	2.59E-06	1.62E-08	160.5668	0.0000
D (TLABOFORCE (-1))	2.06E-06	3.94E-08	52.34308	0.0004
D (REALINTR_)	0.181539	0.001342	135.2589	0.0001
D (REALINTR_ (-1))	0.053084	0.001792	29.63091	0.0011
D (INFLA)	0.192971	0.001045	184.6506	0.0000
D (INFLA (-1))	0.029573	0.001255	23.56773	0.0018
D (PERMANENT_CROPLAND)	-3.510377	0.081651	-42.99222	0.0005
D (PERMANENT_CROPLAND (-1))	-0.487154	0.080370	-6.061393	0.0262
D (AGRVADPERWORKER)	0.013327	5.34E-05	249.4968	0.0000
D (AGRVADPERWORKER (-1))	0.012721	0.000305	41.68778	0.0006
CointEq (-1)*	-0.620985	0.006030	-102.9741	0.0001
R-squared	0.999946	Mean dependent var		0.033947
Adjusted R-squared	0.999864	S.D. dependent var		3.339598
S.E. of regression	0.038917	Akaike info criterion		-3.379493
Sum squared resid	0.015146	Schwarz criterion		-2.605280
Log likelihood	59.93341	Hannan-Quinn criter.		-3.156548
Durbin-Watson stat	3.094835			
*p-value incompatible with t-bounds distribution				
F-bounds test		Null hypothesis: No levels relationship		
Test statistic	Value	Signif.	I (0)	I (1)
F-statistic	235.6369	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9

Table A3.

ARDL Long Run Form and Bounds Test				
Dependent Variable: D (AGRICGDP)				
Selected Model: ARDL (2, 2, 2, 2, 2, 2, 2, 2)				
Case 2: Restricted Constant and No Trend				
Date: 03/26/22 Time: 13:39				
Sample: 1960 2020				
Included observations: 26				
Conditional Error Correction Regression				
Variable	Coefficient	Standard error	t-Statistic	Prob.
C	-14.80878	2.030246	-7.294083	0.0183
AGRICGDP (-1)*	-0.620985	0.021734	-28.57213	0.0012
CO2_EMISSION (-1)	0.000296	1.28E-05	23.14348	0.0019
FERTCONSPERLAND (-1)	-0.667243	0.039167	-17.03595	0.0034
TLABOFORCE (-1)	1.16E-06	6.49E-08	17.89132	0.0031
REALINTR_ (-1)	0.241469	0.012551	19.23874	0.0027
INFLA (-1)	0.261765	0.008084	32.37902	0.0010
PERMANENT_CROPLAND (-1)	-5.606188	0.376338	-14.89669	0.0045
AGRVADPERWORKER (-1)	-0.007003	0.000267	-26.25974	0.0014
D (AGRICGDP (-1))	-0.256086	0.031570	-8.111753	0.0149
D (CO2_EMISSION)	0.000109	6.45E-06	16.88435	0.0035
D (CO2_EMISSION (-1))	-9.34E-05	5.56E-06	-16.79976	0.0035
D (FERTCONSPERLAND)	-0.141517	0.011400	-12.41420	0.0064
D (FERTCONSPERLAND (-1))	0.398836	0.025084	15.90022	0.0039
D (TLABOFORCE)	2.59E-06	6.48E-08	40.02323	0.0006
D (TLABOFORCE (-1))	2.06E-06	1.21E-07	17.10785	0.0034
D (REALINTR_)	0.181539	0.004984	36.42493	0.0008
D (REALINTR_ (-1))	0.053084	0.006568	8.081838	0.0150
D (INFLA)	0.192971	0.004992	38.65630	0.0007
D (INFLA (-1))	0.029573	0.004431	6.674539	0.0217
D (PERMANENT_CROPLAND)	-3.510377	0.272256	-12.89368	0.0060
D (PERMANENT_CROPLAND (-1))	-0.487154	0.382032	-1.275167	0.3303
D (AGRVADPERWORKER)	0.013327	0.000297	44.83236	0.0005
D (AGRVADPERWORKER (-1))	0.012721	0.000808	15.74764	0.0040
* p-value incompatible with t-Bounds distribution.				
Levels Equation				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Standard error	t-Statistic	Prob.
CO2_EMISSION	0.000477	2.86E-05	16.67564	0.0036
FERTCONSPERLAND	-1.074491	0.069853	-15.38226	0.0042
TLABOFORCE	1.87E-06	1.43E-07	13.02860	0.0058
REALINTR_	0.388849	0.019052	20.41024	0.0024
INFLA	0.421533	0.015483	27.22535	0.0013
PERMANENT_CROPLAND	-9.027901	0.781882	-11.54638	0.0074
AGRVADPERWORKER	-0.011277	0.000618	-18.26230	0.0030
C	-23.84726	3.659644	-6.516277	0.0227
EC = AGRICGDP - (0.0005*CO_2_EMISSION-1.0745*FERTCONSPERLAND+0.0000*TLABOFORCE + 0.3888*REALINTR_ + 0.4215*INFLA-9.0279				
*PERMANENT_CROPLAND-0.0113*AGRVADPERWORKER-23.8473)				
F-bounds test		Null hypothesis: No levels relationship		
Test statistic	Value	Signif.	I (0)	I (1)
			Asymptotic: n=1,000	
F-statistic	235.6369	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9
Actual sample size	26		Finite sample: n=35	
		10%	2.196	3.37
		5%	2.597	3.907
		1%	3.599	5.23
			Finite sample: n=30	
		10%	2.277	3.498
		5%	2.73	4.163
		1%	3.864	5.694

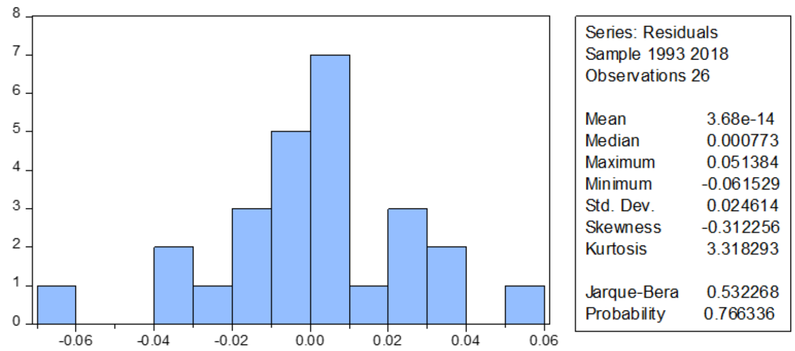

Table A4.

Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	3.421185	Prob. F (1,1)	0.3155	
Obs*R-squared	20.11922	Prob. Chi-Square (1)	0.0000	
Test Equation:				
Dependent Variable: RESID				
Method: ARDL				
Date: 03/26/22 Time: 13:40				
Sample: 1993 2018				
Included observations: 26				
Presample missing value lagged residuals set to zero.				
Variable	Coefficient	Standard error	t-Statistic	Prob.
AGRICGDP (-1)	-0.000585	0.028472	-0.020561	0.9869
AGRICGDP (-2)	0.005735	0.021458	0.267244	0.8338
CO2_EMISSION	-1.57E-06	4.42E-06	-0.355472	0.7826
CO2_EMISSION (-1)	6.90E-06	6.39E-06	1.079211	0.4758
CO2_EMISSION (-2)	2.60E-06	3.99E-06	0.650061	0.6330
FERTCONSPERLAND	0.008326	0.008891	0.936461	0.5209
FERTCONSPERLAND (-1)	-0.001922	0.007994	-0.240413	0.8498
FERTCONSPERLAND (-2)	-0.006538	0.017237	-0.379299	0.7692
TLABOFORCE	3.02E-08	4.66E-08	0.649072	0.6335
TLABOFORCE (-1)	-3.66E-08	1.03E-07	-0.356625	0.7819
TLABOFORCE (-2)	4.66E-08	8.49E-08	0.549096	0.6803
REALINTR_	-0.002784	0.003674	-0.757581	0.5873
REALINTR_ (-1)	-0.000800	0.007669	-0.104335	0.9338
REALINTR_ (-2)	0.000125	0.004418	0.028310	0.9820
INFLA	0.000744	0.003381	0.219915	0.8622
INFLA (-1)	-0.000610	0.006048	-0.100864	0.9360
INFLA (-2)	0.001617	0.003106	0.520572	0.6944
PERMANENT_CROPLAND	0.148309	0.199900	0.741916	0.5936
PERMANENT_CROPLAND (-1)	-0.047304	0.314913	-0.150212	0.9051
PERMANENT_CROPLAND (-2)	-0.179817	0.274724	-0.654538	0.6310
AGRVADPERWORKER	1.90E-05	0.000200	0.095012	0.9397
AGRVADPERWORKER (-1)	-0.000101	0.000479	-0.209686	0.8684
AGRVADPERWORKER (-2)	-0.000103	0.000546	-0.189341	0.8809
C	-1.651958	1.631649	-1.012447	0.4961
RESID (-1)	-1.387816	0.750315	-1.849645	0.3155
R-squared	0.773816	Mean dependent var		3.68E-14
Adjusted R-squared	-4.654593	S.D. dependent var		0.024614
S.E. of regression	0.058529	Akaike info criterion		-4.173593
Sum squared resid	0.003426	Schwarz criterion		-2.963885
Log likelihood	79.25671	Hannan-Quinn criter.		-3.825241
F-statistic	0.142549	Durbin-Watson stat		2.965431
Prob (F-statistic)	0.985935			

Table A5.

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
F-statistic	1.708042	Prob. F (23,2)		0.4351
Obs*R-squared	24.74046	Prob. Chi-Square (23)		0.3638
Scaled explained SS	0.169691	Prob. Chi-Square (23)		1.0000
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Date: 03/26/22 Time: 13:41				
Sample: 1993 2018				
Included observations: 26				
Variable	Coefficient	Standard error	t-Statistic	Prob.
C	0.016160	0.016421	0.984104	0.4288
AGRICGDP (-1)	-2.91E-05	0.000342	-0.084981	0.9400
AGRICGDP (-2)	1.12E-05	0.000255	0.043907	0.9690
CO2_EMISSION	-2.50E-08	5.21E-08	-0.480330	0.6784
CO2_EMISSION (-1)	-6.73E-08	6.25E-08	-1.077865	0.3938
CO2_EMISSION (-2)	4.05E-08	4.49E-08	0.901159	0.4626
FERTCONSPERLAND	-5.72E-05	9.22E-05	-0.620036	0.5985
FERTCONSPERLAND (-1)	-6.64E-06	9.53E-05	-0.069688	0.9508
FERTCONSPERLAND (-2)	0.000165	0.000203	0.812348	0.5019
TLABOFORCE	1.03E-10	5.24E-10	0.196703	0.8622
TLABOFORCE (-1)	1.75E-10	1.21E-09	0.144227	0.8985
TLABOFORCE (-2)	-3.99E-10	9.75E-10	-0.409157	0.7221
REALINTR_	6.83E-05	4.03E-05	1.693582	0.2324
REALINTR_ (-1)	6.25E-05	9.21E-05	0.679166	0.5671
REALINTR_ (-2)	5.95E-05	5.31E-05	1.119472	0.3793
INFLA	-4.49E-06	4.04E-05	-0.111280	0.9216
INFLA (-1)	1.15E-05	7.26E-05	0.158826	0.8884
INFLA (-2)	7.44E-06	3.58E-05	0.207582	0.8548
PERMANENT_CROPLAND	-0.005376	0.002202	-2.441300	0.1347
PERMANENT_CROPLAND (-1)	0.001813	0.003775	0.480245	0.6785
PERMANENT_CROPLAND (-2)	0.002518	0.003090	0.814974	0.5007
AGRVADPERWORKER	-2.24E-07	2.40E-06	-0.093112	0.9343
AGRVADPERWORKER (-1)	-4.49E-07	5.73E-06	-0.078428	0.9446
AGRVADPERWORKER (-2)	1.01E-06	6.53E-06	0.155135	0.8910
R-squared	0.951556	Mean dependent var		0.000583
Adjusted R-squared	0.394453	S.D. dependent var		0.000905
S.E. of regression	0.000704	Akaike info criterion		-12.39877
Sum squared resid	9.91E-07	Schwarz criterion		-11.23745
Log likelihood	185.1840	Hannan-Quinn criter.		-12.06435
F-statistic	1.708042	Durbin-Watson stat		2.997140
Prob (F-statistic)	0.435068			

Table A6.

Ramsey RESET Test				
Equation: UNTITLED				
Specification: AGRICGDP AGRICGDP (-1) AGRICGDP (-2)				
CO2_EMISSION CO2_EMISSION (-1) CO2_EMISSION (-2)				
FERTCONSPERLAND FERTCONSPERLAND (-1)				
FERTCONSPERLAND (-2) TLABOFORCE TLABOFORCE (-1)				
TLABOFORCE (-2) REALINTR_ REALINTR_ (-1) REALINTR_ (-2) INFLA				
INFLA (-1) INFLA (-2) PERMANENT_CROPLAND PERMANENT_CROP				
LAND (-1) PERMANENT_CROPLAND (-2) AGRVADPERWORKER				
AGRVADPERWORKER (-1) AGRVADPERWORKER (-2) C				
Omitted Variables: Squares of fitted values				
	Value	df	Probability	
t-statistic	1.735900	1	0.3327	
F-statistic	3.013349	(1, 1)	0.3327	
F-test summary:				
	Sum of Sq.	df	Mean squares	
Test SSR	0.011372	1	0.011372	
Restricted SSR	0.015146	2	0.007573	
Unrestricted SSR	0.003774	1	0.003774	
Unrestricted Test Equation:				
Dependent Variable: AGRICGDP				
Method: ARDL				
Date: 03/26/22 Time: 13:41				
Sample: 1993 2018				
Included observations: 26				
Maximum dependent lags: 2 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (2 lags, automatic):				
Fixed regressors: C				
Variable	Coefficient	Standard error	t-Statistic	Prob.*
AGRICGDP (-1)	0.174148	0.041994	4.146969	0.1506
AGRICGDP (-2)	0.407537	0.090047	4.525803	0.1384
CO2_EMISSION	0.000182	4.24E-05	4.292733	0.1457
CO2_EMISSION (-1)	0.000163	4.03E-05	4.049479	0.1541
CO2_EMISSION (-2)	0.000145	3.01E-05	4.819696	0.1302
FERTCONSPERLAND	-0.226124	0.049400	-4.577422	0.1369
FERTCONSPERLAND (-1)	-0.195499	0.040389	-4.840370	0.1297
FERTCONSPERLAND (-2)	-0.647341	0.144247	-4.487713	0.1396
TLABOFORCE	4.18E-06	9.17E-07	4.564037	0.1373
TLABOFORCE (-1)	9.45E-07	2.10E-07	4.496428	0.1393
TLABOFORCE (-2)	-3.25E-06	6.89E-07	-4.718628	0.1329
REALINTR_	0.276165	0.054624	5.055722	0.1243
REALINTR_ (-1)	0.183932	0.041637	4.417543	0.1417
REALINTR_ (-2)	-0.074745	0.013311	-5.615043	0.1122
INFLA	0.297724	0.060448	4.925280	0.1275
INFLA (-1)	0.155639	0.033596	4.632724	0.1353
INFLA (-2)	-0.040236	0.006893	-5.837303	0.1080
PERMANENT_CROPLAND	-5.052648	0.909007	-5.558429	0.1133
PERMANENT_CROPLAND (-1)	-4.201465	0.988857	-4.248808	0.1472
PERMANENT_CROPLAND (-2)	0.058242	0.365762	0.159234	0.8995
AGRVADPERWORKER	0.022187	0.005108	4.343494	0.1441
AGRVADPERWORKER (-1)	-0.012538	0.002883	-4.349128	0.1439
AGRVADPERWORKER (-2)	-0.020951	0.004776	-4.387164	0.1427
C	-32.14762	10.09069	-3.185871	0.1936
FITTED^2	-0.010766	0.006202	-1.735900	0.3327
R-squared	0.999990	Mean dependent var		24.82605
Adjusted R-squared	0.999759	S.D. dependent var		3.956536
S.E. of regression	0.061431	Akaike info criterion		-4.076812
Sum squared resid	0.003774	Schwarz criterion		-2.867104
Log likelihood	77.99855	Hannan-Quinn criter.		-3.728460
F-statistic	4320.901	Durbin-Watson stat		2.961739
Prob (F-statistic)	0.012012			
*Note. p-values and any subsequent tests do not account for model selection				

Model 2

Table A7.

Dependent variable: AGRICGDP				
Method: ARDL				
Date: 03/26/22 Time: 13:42				
Sample (adjusted): 1992 2014				
Included observations: 23 after adjustments				
Maximum dependent lags: 1 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (1 lag, automatic): CO2_INTENSITY				
FERTCONSPERLAND TLABOFORCE REALINTR_ INFLA				
PERMANENT_CROPLAND AGRVADPERWORKER				
Fixed regressors: C				
Number of models evalulated: 128				
Selected Model: ARDL (1, 0, 0, 1, 1, 0, 1, 1)				
Variable	Coefficient	Standard error	t-Statistic	Prob.*
AGRICGDP (-1)	0.656411	0.065268	10.05721	0.0000
CO2_INTENSITY	-4.252292	5.121080	-0.830351	0.4257
FERTCONSPERLAND	-0.073640	0.062249	-1.182987	0.2642
TLABOFORCE	2.33E-06	3.02E-07	7.712418	0.0000
TLABOFORCE (-1)	-2.07E-06	3.20E-07	-6.478651	0.0001
REALINTR_	0.243086	0.023998	10.12947	0.0000
REALINTR_ (-1)	-0.045470	0.019836	-2.292236	0.0448
INFLA	0.159270	0.018730	8.503491	0.0000
PERMANENT_CROPLAND	-6.580449	1.361019	-4.834943	0.0007
PERMANENT_CROPLAND (-1)	4.739023	1.397314	3.391522	0.0069
AGRVADPERWORKER	0.015291	0.000945	16.17915	0.0000
AGRVADPERWORKER (-1)	-0.017822	0.001136	-15.68813	0.0000
C	12.93498	11.95883	1.081625	0.3048
R-squared	0.988754	Mean dependent var		25.31014
Adjusted R-squared	0.975259	S.D. dependent var		3.959696
S.E. of regression	0.622829	Akaike info criterion		2.188436
Sum squared resid	3.879157	Schwarz criterion		2.830237
Log likelihood	-12.16701	Hannan-Quinn criter.		2.349847
F-statistic	73.26830	Durbin-Watson stat		2.804740
Prob (F-statistic)	0.000000			
*Note. p-values and any subsequent tests do not account for model selection				

Table A8.

ARDL Long Run Form and Bounds Test				
Dependent Variable: D (AGRICGDP)				
Selected Model: ARDL (1, 0, 0, 1, 1, 0, 1, 1)				
Case 2: Restricted Constant and No Trend				
Date: 03/26/22 Time: 13:51				
Sample: 1960 2020				
Included observations: 23				
Conditional Error Correction Regression				
Variable	Coefficient	Standard error	t-Statistic	Prob.
C	12.93498	11.95883	1.081625	0.3048
AGRICGDP (-1)*	-0.343589	0.065268	-5.264301	0.0004
CO2_INTENSITY**	-4.252292	5.121080	-0.830351	0.4257
FERTCONSPERLAND**	-0.073640	0.062249	-1.182987	0.2642
TLABOFORCE (-1)	2.58E-07	2.65E-07	0.973825	0.3531
REALINTR_ (-1)	0.197617	0.032002	6.175099	0.0001
INFLA**	0.159270	0.018730	8.503491	0.0000
PERMANENT_CROPLAND (-1)	-1.841426	0.926456	-1.987602	0.0749
AGRVADPERWORKER (-1)	-0.002531	0.000767	-3.300746	0.0080
D (TLABOFORCE)	2.33E-06	3.02E-07	7.712418	0.0000
D (REALINTR_)	0.243086	0.023998	10.12947	0.0000
D (PERMANENT_CROPLAND)	-6.580449	1.361019	-4.834943	0.0007
D (AGRVADPERWORKER)	0.015291	0.000945	16.17915	0.0000
* p-value incompatible with t-Bounds distribution.				
** Variable interpreted as Z = Z (-1) + D (Z).				
Levels equation				
Case 2: Restricted Constant and No Trend				
Variable	Coefficient	Standard error	t-Statistic	Prob.
CO2_INTENSITY	-12.37611	14.05593	-0.880490	0.3993
FERTCONSPERLAND	-0.214326	0.175235	-1.223078	0.2493
TLABOFORCE	7.52E-07	8.77E-07	0.856904	0.4116
REALINTR_	0.575155	0.153830	3.738907	0.0039
INFLA	0.463549	0.111069	4.173515	0.0019
PERMANENT_CROPLAND	-5.359389	3.482386	-1.538999	0.1548
AGRVADPERWORKER	-0.007366	0.003236	-2.276033	0.0461
C	37.64668	31.33977	1.201243	0.2573
EC=AGRICGDP - (-12.3761*CO2_INTENSITY -0.2143*FERTCONSPERLAND + 0.0000*TLABOFORCE + 0.5752*REALINTR_ + 0.4635*INFLA				
-5.3594*PERMANENT_CROPLAND -0.0074*AGRVADPERWORKER+37.6467)				
F-bounds test		Null hypothesis: No levels relationship		
Test statistic	Value	Signif.	I (0)	I (1)
			Asymptotic: n=1,000	
F-statistic	56.01215	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9
Actual sample size	23		Finite sample: n=35	
		10%	2.196	3.37
		5%	2.597	3.907
		1%	3.599	5.23
			Finite sample: n=30	
		10%	2.277	3.498
		5%	2.73	4.163
		1%	3.864	5.694

Table A9.

ARDL error correction regression				
Dependent Variable: D (AGRICGDP)				
Selected Model: ARDL (1, 0, 0, 1, 1, 0, 1, 1)				
Case 2: Restricted Constant and No Trend				
Date: 03/26/22 Time: 13:51				
Sample: 1960 2020				
Included observations: 23				
ECM regression				
Case 2: Restricted constant and no trend				
Variable	Coefficient	Standard error	t-Statistic	Prob.
D (TLABOFORCE)	2.33E-06	1.69E-07	13.79129	0.0000
D (REALINTR_)	0.243086	0.010571	22.99498	0.0000
D (PERMANENT_CROPLAND)	-6.580449	0.676734	-9.723832	0.0000
D (AGRVADPERWORKER)	0.015291	0.000485	31.50648	0.0000
CointEq (-1)*	-0.343589	0.011406	-30.12303	0.0000
R-squared	0.986069	Mean dependent var		-0.038914
Adjusted R-squared	0.982973	S.D. dependent var		3.557674
S.E. of regression	0.464229	Akaike info criterion		1.492783
Sum squared resid	3.879157	Schwarz criterion		1.739630
Log likelihood	-12.16701	Hannan-Quinn criter.		1.554865
Durbin-Watson stat	2.804740			
* p-value incompatible with t-Bounds distribution.				
F-bounds test		Null hypothesis: No levels relationship		
Test statistic	Value	Signif.	I (0)	I (1)
F-statistic	56.01215	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9

Table A10.

Ramsey RESET Test				
Equation: UNTITLED				
Specification: AGRICGDP AGRICGDP (-1) CO2_INTENSITY				
FERTCONSPERLAND TLABOFORCE TLABOFORCE (-1) REALINTR_				
REALINTR_ (-1) INFLA PERMANENT_CROPLAND				
PERMANENT_CROPLAND (-1) AGRVADPERWORKER				
AGRVADPERWORKER (-1) C				
Omitted Variables: Squares of fitted values				
	Value	df	Probability	
t-statistic	1.261799	9	0.2387	
F-statistic	1.592136	(1, 9)	0.2387	
F-test summary:				
	Sum of Sq.	df	Mean Squares	
Test SSR	0.583088	1	0.583088	
Restricted SSR	3.879157	10	0.387916	
Unrestricted SSR	3.296069	9	0.366230	
Unrestricted Test Equation:				
Dependent Variable: AGRICGDP				
Method: ARDL				
Date: 03/26/22 Time: 13:52				
Sample: 1992 2014				
Included observations: 23				
Maximum dependent lags: 1 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (1 lag, automatic):				
Fixed regressors: C				
Variable	Coefficient	Standard error	t-Statistic	Prob.*
AGRICGDP (-1)	0.060573	0.476453	0.127133	0.9016
CO2_INTENSITY	-4.977089	5.008924	-0.993644	0.3464
FERTCONSPERLAND	-0.018505	0.074617	-0.247999	0.8097
TLABOFORCE	2.39E-07	1.69E-06	0.142047	0.8902
TLABOFORCE (-1)	-2.51E-07	1.48E-06	-0.169834	0.8689
REALINTR_	0.030110	0.170391	0.176709	0.8636
REALINTR_ (-1)	-0.016580	0.029928	-0.554010	0.5931
INFLA	0.026919	0.106458	0.252865	0.8061
PERMANENT_CROPLAND	-2.053098	3.823959	-0.536904	0.6044
PERMANENT_CROPLAND (-1)	1.743223	2.735015	0.637372	0.5398
AGRVADPERWORKER	-3.77E-05	0.012183	-0.003096	0.9976
AGRVADPERWORKER (-1)	-0.000290	0.013938	-0.020790	0.9839
C	20.37711	13.03095	1.563748	0.1523
FITTED^2	0.016710	0.013243	1.261799	0.2387
R-squared	0.990445	Mean dependent var		25.31014
Adjusted R-squared	0.976642	S.D. dependent var		3.959696
S.E. of regression	0.605169	Akaike info criterion		2.112505
Sum squared resid	3.296069	Schwarz criterion		2.803675
Log likelihood	-10.29381	Hannan-Quinn criter.		2.286332
F-statistic	71.75950	Durbin-Watson stat		2.904298
Prob (F-statistic)	0.000000			
*Note. p-values and any subsequent tests do not account for model selection				

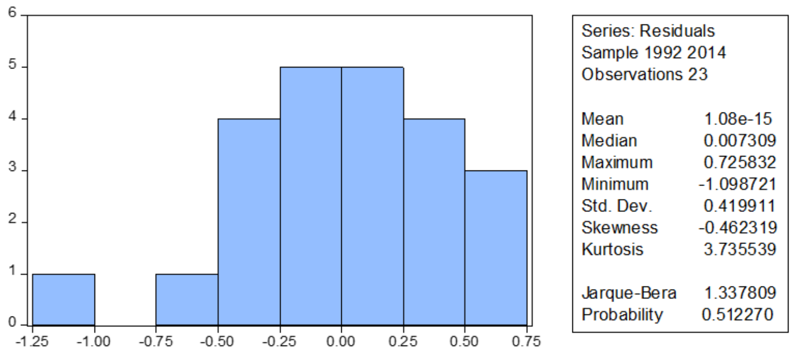

Table A11.

Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	2.270990	Prob. F (2,8)		0.1655
Obs*R-squared	8.329270	Prob. Chi-Square (2)		0.0155
Test Equation:				
Dependent Variable: RESID				
Method: ARDL				
Date: 03/26/22 Time: 13:52				
Sample: 1992 2014				
Included observations: 23				
Presample missing value lagged residuals set to zero.				
Variable	Coefficient	Standard error	t-Statistic	Prob.
AGRICGDP (-1)	-0.013148	0.058635	-0.224233	0.8282
CO2_INTENSITY	-0.834169	4.857129	-0.171741	0.8679
FERTCONSPERLAND	-0.043781	0.059730	-0.732984	0.4845
TLABOFORCE	-2.63E-08	2.71E-07	-0.096966	0.9251
TLABOFORCE (-1)	-1.02E-07	2.90E-07	-0.352931	0.7333
REALINTR_	-0.004056	0.022076	-0.183739	0.8588
REALINTR_ (-1)	-0.002506	0.018438	-0.135915	0.8952
INFLA	-0.006655	0.017285	-0.385026	0.7103
PERMANENT_CROPLAND	1.005857	1.346358	0.747095	0.4764
PERMANENT_CROPLAND (-1)	-0.718080	1.312620	-0.547058	0.5993
AGRVADPERWORKER	0.000232	0.000861	0.269586	0.7943
AGRVADPERWORKER (-1)	0.000267	0.001022	0.261098	0.8006
C	3.888828	11.39299	0.341335	0.7416
RESID (-1)	-0.840770	0.394977	-2.128655	0.0659
RESID (-2)	-0.487533	0.391741	-1.244531	0.2485
R-squared	0.362142	Mean dependent var		1.08E-15
Adjusted R-squared	-0.754109	S.D. dependent var		0.419911
S.E. of regression	0.556142	Akaike info criterion		1.912709
Sum squared resid	2.474351	Schwarz criterion		2.653248
Log likelihood	-6.996151	Hannan-Quinn criter.		2.098952
F-statistic	0.324427	Durbin-Watson stat		2.303450
Prob (F-statistic)	0.968422			

Table A12.

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
F-statistic	1.608084	Prob. F (12,10)		0.2298
Obs*R-squared	15.14937	Prob. Chi-Square (12)		0.2334
Scaled explained SS	3.916983	Prob. Chi-Square (12)		0.9849
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Date: 03/26/22 Time: 13:53				
Sample: 1992 2014				
Included observations: 23				
Variable	Coefficient	Standard error	t-Statistic	Prob.
C	2.936109	4.745734	0.618684	0.5500
AGRICGDP (-1)	0.033007	0.025901	1.274345	0.2314
CO2_INTENSITY	-1.458919	2.032246	-0.717885	0.4893
FERTCONSPERLAND	7.07E-05	0.024703	0.002863	0.9978
TLABOFORCE	-1.23E-07	1.20E-07	-1.023930	0.3300
TLABOFORCE (-1)	-2.25E-09	1.27E-07	-0.017711	0.9862
REALINTR_	-0.012915	0.009523	-1.356160	0.2049
REALINTR_ (-1)	-0.006575	0.007872	-0.835203	0.4231
INFLA	-0.003633	0.007433	-0.488786	0.6355
PERMANENT_CROPLAND	-0.065218	0.540106	-0.120750	0.9063
PERMANENT_CROPLAND (-1)	0.443243	0.554509	0.799343	0.4427
AGRVADPERWORKER	-2.24E-05	0.000375	-0.059782	0.9535
AGRVADPERWORKER (-1)	0.000402	0.000451	0.892298	0.3932
R-squared	0.658668	Mean dependent var		0.168659
Adjusted R-squared	0.249070	S.D. dependent var		0.285222
S.E. of regression	0.247163	Akaike info criterion		0.339988
Sum squared resid	0.610895	Schwarz criterion		0.981789
Log likelihood	9.090143	Hannan-Quinn criter.		0.501399
F-statistic	1.608084	Durbin-Watson stat		3.168591
Prob (F-statistic)	0.229803			

Model 3

Table A13.

Dependent Variable: FOODPI				
Method: ARDL				
Date: 03/26/22 Time: 22:54				
Sample (adjusted): 1992 2018				
Included observations: 17 after adjustments				
Maximum dependent lags: 1 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (1 lag, automatic): CO2_EMISSION				
AGRVADPERWORKER FERTILIZERCONS EMPLOYAGRIC POPLA				
INFLA ARABLE_LAND				
Fixed regressors: C				
Number of models evaluated: 128				
Selected Model: ARDL (1, 0, 1, 1, 1, 1, 1)				
Variable	Coefficient	Standard error	t-Statistic	Prob.*
FOODPI (-1)	-0.859938	0.086748	-9.913028	0.0100
CO2_EMISSION	-0.000445	4.28E-05	-10.39000	0.0091
AGRVADPERWORKER	-0.001526	0.001741	-0.876610	0.4731
AGRVADPERWORKER (-1)	-0.005587	0.001814	-3.079803	0.0912
FERTILIZERCONS	0.006298	0.000839	7.502861	0.0173
FERTILIZERCONS (-1)	0.004062	0.001505	2.700210	0.1141
EMPLOYAGRIC	7.705042	1.511080	5.099028	0.0364
EMPLOYAGRIC (-1)	-15.80827	1.138705	-13.88268	0.0051
POPLA	-4.46E-05	1.08E-05	-4.143065	0.0536
POPLA (-1)	4.61E-05	1.10E-05	4.191475	0.0525
INFLA	-0.030082	0.014949	-2.012331	0.1818
INFLA (-1)	0.042395	0.005530	7.666528	0.0166
ARABLE_LAND	0.412030	0.308299	1.336464	0.3132
ARABLE_LAND (-1)	2.077104	0.442575	4.693221	0.0425
C	431.6868	46.02363	9.379676	0.0112
R-squared	0.999986	Mean dependent var		76.63176
Adjusted R-squared	0.999888	S.D. dependent var		20.18583
S.E. of regression	0.213513	Akaike info criterion		-0.625601
Sum squared resid	0.091175	Schwarz criterion		0.109587
Log likelihood	20.31761	Hannan-Quinn criter.		-0.552522
F-statistic	10214.84	Durbin-Watson stat		2.536258
Prob (F-statistic)	0.000098			
*Note. p-values and any subsequent tests do not account for model selection				

Table A14.

ARDL Long Run Form and Bounds Test				
Dependent Variable: D (FOODPI)				
Selected Model: ARDL (1, 0, 1, 1, 1, 1, 1, 1)				
Case 2: Restricted Constant and No Trend				
Date: 03/26/22 Time: 22:57				
Sample: 1960 2020				
Included observations: 17				
Conditional Error Correction Regression				
Variable	Coefficient	Standard error	t-Statistic	Prob.
C	431.6868	46.02364	9.379676	0.0112
FOODPI (-1)*	-1.859938	0.086748	-21.44064	0.0022
CO2_EMISSION**	-0.000445	4.28E-05	-10.39000	0.0091
AGRVADPERWORKER (-1)	-0.007113	0.001716	-4.144763	0.0536
FERTILIZERCONS (-1)	0.010360	0.002172	4.770029	0.0412
EMPLOYAGRIC (-1)	-8.103224	0.721110	-11.23716	0.0078
POPLA (-1)	1.48E-06	2.43E-07	6.075666	0.0260
INFLA (-1)	0.012314	0.013778	0.893690	0.4658
ARABLE_LAND (-1)	2.489133	0.212217	11.72922	0.0072
D (AGRVADPERWORKER)	-0.001526	0.001741	-0.876609	0.4731
D (FERTILIZERCONS)	0.006298	0.000839	7.502861	0.0173
D (EMPLOYAGRIC)	7.705040	1.511081	5.099026	0.0364
D (POPLA)	-4.46E-05	1.08E-05	-4.143066	0.0536
D (INFLA)	-0.030082	0.014949	-2.012331	0.1818
D (ARABLE_LAND)	0.412030	0.308299	1.336463	0.3132
* p-value incompatible with t-Bounds distribution.				
** Variable interpreted as Z = Z (-1) + D (Z).				
Levels Equation				
Case 2: Restricted constant and no trend				
Variable	Coefficient	Standard error	t-Statistic	Prob.
CO2_EMISSION	-0.000239	1.38E-05	-17.26364	0.0033
AGRVADPERWORKER	-0.003824	0.000999	-3.826785	0.0620
FERTILIZERCONS	0.005570	0.001052	5.293812	0.0339
EMPLOYAGRIC	-4.356718	0.446499	-9.757500	0.0103
POPLA	7.95E-07	1.13E-07	7.003108	0.0198
INFLA	0.006620	0.007164	0.924137	0.4530
ARABLE_LAND	1.338289	0.079644	16.80337	0.0035
C	232.0974	28.25044	8.215711	0.0145
EC=FOODPI - (-0.0002*CO2_EMISSION -0.0038*AGRVADPERWORKER+0.0056*FERTILIZERCONS -4.3567*EMPLOYAGRIC+0.0000*POPLA +0.0066*INFLA + 1.3383*ARABLE_LAND + 232.0974)				
F-bounds test			Null hypothesis: No levels relationship	
Test statistic	Value	Signif.	I (0)	I (1)
			Asymptotic: n=1,000	
F-statistic	305.7378	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9
Actual sample size	17		Finite sample: n=35	
		10%	2.196	3.37
		5%	2.597	3.907
		1%	3.599	5.23
			Finite sample: n=30	
		10%	2.277	3.498
		5%	2.73	4.163
		1%	3.864	5.694

Table A15.

ARDL error correction regression				
Dependent Variable: D (FOODPI)				
Selected Model: ARDL (1, 0, 1, 1, 1, 1, 1, 1)				
Case 2: Restricted Constant and No Trend				
Date: 03/26/22 Time: 22:58				
Sample: 1960 2020				
Included observations: 17				
ECM Regression				
Case 2: Restricted constant and no trend				
Variable	Coefficient	Standard error	t-Statistic	Prob.
D (AGRVADPERWORKER)	-0.001526	0.000283	-5.385686	0.0328
D (FERTILIZERCONS)	0.006298	8.08E-05	77.96484	0.0002
D (EMPLOYAGRIC)	7.705042	0.126687	60.81958	0.0003
D (POPLA)	-4.46E-05	3.86E-07	-115.6062	0.0001
D (INFLA)	-0.030082	0.001622	-18.54965	0.0029
D (ARABLE_LAND)	0.412030	0.033387	12.34097	0.0065
CointEq (-1)*	-0.859938	0.015857	-54.23081	0.0001
R-squared	0.999686	Mean dependent var		2.732353
Adjusted R-squared	0.999498	S.D. dependent var		4.262773
S.E. of regression	0.095486	Akaike info criterion		-1.566778
Sum squared resid	0.091175	Schwarz criterion		-1.223690
Log likelihood	20.31761	Hannan-Quinn criter.		-1.532674
Durbin-Watson stat	2.536258			
* p-value incompatible with t-Bounds distribution.				
F-bounds test		Null hypothesis: No levels relationship		
Test statistic	Value	Signif.	I (0)	I (1)
F-statistic	305.7378	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.5%	2.43	3.51
		1%	2.73	3.9

Table A16.

Ramsey RESET Test				
Equation: UNTITLED				
Specification: FOODPI FOODPI (-1) CO2_EMISSION				
AGRVADPERWORKER AGRVADPERWORKER (-1)				
FERTILIZERCONS FERTILIZERCONS (-1) EMPLOYAGRIC				
EMPLOYAGRIC (-1) POPLA POPLA (-1) INFLA INFLA (-1)				
ARABLE_LAND ARABLE_LAND (-1) C				
Omitted Variables: Squares of fitted values				
	Value	df	Probability	
t-statistic	3.443688	1	0.1799	
F-statistic	11.85899	(1, 1)	0.1799	
F-test summary:				
	Sum of Sq.	df	Mean Squares	
Test SSR	0.084085	1	0.084085	
Restricted SSR	0.091175	2	0.045588	
Unrestricted SSR	0.007090	1	0.007090	
Unrestricted Test Equation:				
Dependent Variable: FOODPI				
Method: ARDL				
Date: 03/26/22 Time: 22:58				
Sample: 1992 2018				
Included observations: 17				
Maximum dependent lags: 1 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (1 lag, automatic):				
Fixed regressors: C				
Variable	Coefficient	Standard error	t-Statistic	Prob.*
FOODPI (-1)	-0.450256	0.123787	-3.637333	0.1708
CO2_EMISSION	-0.000263	5.53E-05	-4.767520	0.1316
AGRVADPERWORKER	-0.002798	0.000780	-3.588483	0.1730
AGRVADPERWORKER (-1)	-0.002437	0.001161	-2.098586	0.2831
FERTILIZERCONS	0.003857	0.000782	4.929017	0.1274
FERTILIZERCONS (-1)	0.003284	0.000635	5.171889	0.1216
EMPLOYAGRIC	1.788080	1.818615	0.983210	0.5054
EMPLOYAGRIC (-1)	-5.774005	2.948212	-1.958477	0.3005
POPLA	-2.34E-05	7.48E-06	-3.133316	0.1967
POPLA (-1)	2.43E-05	7.67E-06	3.168258	0.1946
INFLA	0.004777	0.011714	0.407823	0.7535
INFLA (-1)	0.021730	0.006385	3.403464	0.1819
ARABLE_LAND	-0.108715	0.194035	-0.560283	0.6749
ARABLE_LAND (-1)	1.557292	0.230758	6.748578	0.0937
C	217.0159	64.92611	3.342506	0.1851
FITTED^2	0.003343	0.000971	3.443692	0.1799
R-squared	0.999999	Mean dependent var		76.63176
Adjusted R-squared	0.999983	S.D. dependent var		20.18583
S.E. of regression	0.084205	Akaike info criterion		-3.061997
Sum squared resid	0.007090	Schwarz criterion		-2.277796
Log likelihood	42.02697	Hannan-Quinn criter.		-2.984046
F-statistic	61298.61	Durbin-Watson stat		3.333732
Prob (F-statistic)	0.003169			
*Note. p-values and any subsequent tests do not account for model selection				

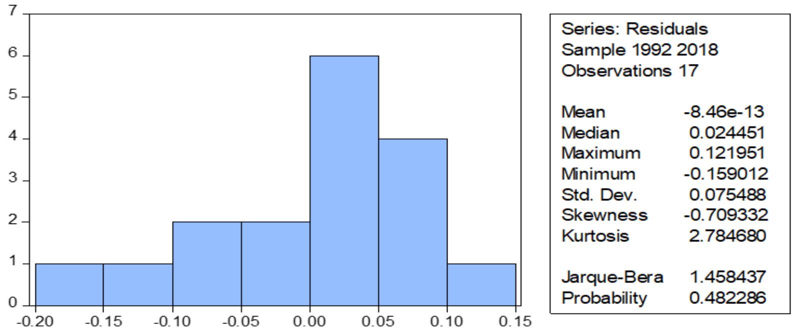

Table A17.

Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	142.0740	Prob. F (1,1)		0.0533
Obs*R-squared	16.88118	Prob. Chi-Square (1)		0.0000
Test Equation:				
Dependent Variable: RESID				
Method: ARDL				
Date: 03/26/22 Time: 22:59				
Sample: 1992 2018				
Included observations: 17				
Presample and interior missing value lagged residuals set to zero.				
Variable	Coefficient	Standard error	t-Statistic	Prob.
FOODPI (-1)	-0.021406	0.010412	-2.055778	0.2882
CO2_EMISSION	9.36E-06	5.12E-06	1.828577	0.3186
AGRVADPERWORKER	0.002861	0.000316	9.047365	0.0701
AGRVADPERWORKER (-1)	-0.000990	0.000230	-4.303330	0.1454
FERTILIZERCONS	-0.000377	0.000104	-3.619218	0.1716
FERTILIZERCONS (-1)	0.000483	0.000182	2.648450	0.2298
EMPLOYAGRIC	2.164209	0.254727	8.496177	0.0746
EMPLOYAGRIC (-1)	-0.404220	0.138837	-2.911481	0.2106
POPLA	8.05E-06	1.44E-06	5.587831	0.1127
POPLA (-1)	-8.07E-06	1.47E-06	-5.503117	0.1144
INFLA	-0.000458	0.001768	-0.259179	0.8386
INFLA (-1)	-0.000415	0.000655	-0.634403	0.6401
ARABLE_LAND	-0.535403	0.057847	-9.255455	0.0685
ARABLE_LAND (-1)	0.410219	0.062630	6.549881	0.0965
C	-105.9770	10.42405	-10.16659	0.0624
RESID (-1)	-3.701526	0.310544	-11.91948	0.0533
R-squared	0.993011	Mean dependent var		-8.46E-13
Adjusted R-squared	0.888170	S.D. dependent var		0.075488
S.E. of regression	0.025244	Akaike info criterion		-5.471316
Sum squared resid	0.000637	Schwarz criterion		-4.687115
Log likelihood	62.50619	Hannan-Quinn criter.		-5.393365
F-statistic	9.471601	Durbin-Watson stat		3.411536
Prob (F-statistic)	0.250277			

Table A18.

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
F-statistic	0.304308	Prob. F (14,2)		0.9324
Obs*R-squared	11.56896	Prob. Chi-Square (14)		0.6409
Scaled explained SS	0.142885	Prob. Chi-Square (14)		1.0000
Test equation:				
Dependent variable: RESID^2				
Method: Least squares				
Date: 03/26/22 Time: 23:00				
Sample: 1992 2018				
Included observations: 17				
Variable	Coefficient	Standard error	t-Statistic	Prob.
C	3.548709	2.545027	1.394370	0.2979
FOODPI (-1)	0.001408	0.004797	0.293502	0.7968
CO2_EMISSION	-2.34E-07	2.37E-06	-0.098730	0.9304
AGRVADPERWORKER	-4.30E-05	9.63E-05	-0.446478	0.6989
AGRVADPERWORKER (-1)	-6.68E-06	0.000100	-0.066599	0.9530
FERTILIZERCONS	7.70E-06	4.64E-05	0.165863	0.8835
FERTILIZERCONS (-1)	-1.75E-05	8.32E-05	-0.209969	0.8531
EMPLOYAGRIC	-0.047424	0.083560	-0.567547	0.6276
EMPLOYAGRIC (-1)	-0.006717	0.062968	-0.106680	0.9248
POPLA	-2.19E-07	5.96E-07	-0.367219	0.7487
POPLA (-1)	2.17E-07	6.08E-07	0.357516	0.7549
INFLA	-0.000741	0.000827	-0.896806	0.4645
INFLA (-1)	0.000369	0.000306	1.208134	0.3505
ARABLE_LAND	0.014768	0.017048	0.866216	0.4777
ARABLE_LAND (-1)	-0.017362	0.024474	-0.709417	0.5516
R-squared	0.680527	Mean dependent var		0.005363
Adjusted R-squared	-1.555783	S.D. dependent var		0.007385
S.E. of regression	0.011807	Akaike info criterion		-6.415629
Sum squared resid	0.000279	Schwarz criterion		-5.680440
Log likelihood	69.53284	Hannan-Quinn criter.		-6.342550
F-statistic	0.304308	Durbin-Watson stat		2.625020
Prob (F-statistic)	0.932404			

Model 4

Table A19.

Dependent Variable: CROPPI				
Method: ARDL				
Date: 03/26/22 Time: 23:05				
Sample (adjusted): 1992 2018				
Included observations: 17 after adjustments				
Maximum dependent lags: 1 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (1 lag, automatic): AGRVADPERWORKER				
FERTILIZERCONS EMPLOYAGRIC INFLA ARABLE_LAND				
CO2_EMISSION				
Fixed regressors: C				
Number of models evalulated: 64				
Selected Model: ARDL (1, 0, 1, 1, 1, 0, 0)				
Variable	Coefficient	Standard error	t-Statistic	Prob.*
CROPPI (-1)	-0.512220	0.081712	-6.268604	0.0008
AGRVADPERWORKER	-0.004652	0.004801	-0.968892	0.3700
FERTILIZERCONS	0.001077	0.001606	0.670700	0.5274
FERTILIZERCONS (-1)	-0.005343	0.001408	-3.795928	0.0090
EMPLOYAGRIC	12.64157	1.422447	8.887197	0.0001
EMPLOYAGRIC (-1)	-19.95782	1.667142	-11.97128	0.0000
INFLA	-0.123854	0.023381	-5.297244	0.0018
INFLA (-1)	0.052228	0.018956	2.755174	0.0331
ARABLE_LAND	2.199790	0.312959	7.029014	0.0004
CO2_EMISSION	-0.000307	6.48E-05	-4.733844	0.0032
C	410.1049	107.2093	3.825273	0.0087
R-squared	0.999423	Mean dependent var		76.06059
Adjusted R-squared	0.998462	S.D. dependent var		20.35908
S.E. of regression	0.798380	Akaike info criterion		2.640198
Sum squared resid	3.824459	Schwarz criterion		3.179336
Log likelihood	-11.44169	Hannan-Quinn criter.		2.693790
F-statistic	1039.841	Durbin-Watson stat		2.884164
Prob (F-statistic)	0.000000			
*Note. p-values and any subsequent tests do not account for model selection				

Table A20.

ARDL Long Run Form and Bounds Test				
Dependent Variable: D (CROPPI)				
Selected Model: ARDL (1, 0, 1, 1, 1, 0, 0)				
Case 2: Restricted Constant and No Trend				
Date: 03/26/22 Time: 23:06				
Sample: 1960 2020				
Included observations: 17				
Conditional Error Correction Regression				
Variable	Coefficient	Standard error	t-Statistic	Prob.
C	410.1049	107.2093	3.825273	0.0087
CROPPI (-1)*	-1.512220	0.081712	-18.50671	0.0000
AGRVADPERWORKER**	-0.004652	0.004801	-0.968892	0.3700
FERTILIZERCONS (-1)	-0.004266	0.002534	-1.683669	0.1432
EMPLOYAGRIC (-1)	-7.316252	1.750048	-4.180600	0.0058
INFLA (-1)	-0.071626	0.018011	-3.976717	0.0073
ARABLE_LAND**	2.199790	0.312959	7.029014	0.0004
CO2_EMISSION**	-0.000307	6.48E-05	-4.733844	0.0032
D (FERTILIZERCONS)	0.001077	0.001606	0.670700	0.5274
D (EMPLOYAGRIC)	12.64157	1.422447	8.887197	0.0001
D (INFLA)	-0.123854	0.023381	-5.297244	0.0018
*p-value incompatible with t-Bounds distribution				
**Variable interpreted as Z = Z (-1) + D (Z)				
Levels equation				
Case 2: Restricted constant and no trend				
Variable	Coefficient	Standard error	t-Statistic	Prob.
AGRVADPERWORKER	-0.003076	0.003143	-0.978577	0.3656
FERTILIZERCONS	-0.002821	0.001640	-1.720127	0.1362
EMPLOYAGRIC	-4.838087	1.083396	-4.465668	0.0043
INFLA	-0.047365	0.011782	-4.020217	0.0070
ARABLE_LAND	1.454676	0.212091	6.858726	0.0005
CO2_EMISSION	-0.000203	3.96E-05	-5.120416	0.0022
C	271.1939	66.68240	4.066949	0.0066
EC = CROPPI - (-0.0031*AGRVADPERWORKER -0.0028*FERTILIZERCONS-4.8381*EMPLOYAGRIC -0.0474*INFLA + 1.4547*ARABLE_LAND - 0.0002*CO2_EMISSION + 271.1939)				
F-bounds test		Null hypothesis: No levels relationship		
Test statistic	Value	Signif.	I (0)	I (1)
			Asymptotic: n=1,000	
F-statistic	53.11286	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99
Actual sample size	17		Finite sample: n=35	
		10%	2.254	3.388
		5%	2.685	3.96
		1%	3.713	5.326
			Finite sample: n=30	
		10%	2.334	3.515
		5%	2.794	4.148
		1%	3.976	5.691

Table A21.

ARDL Error Correction Regression				
Dependent Variable: D (CROPPI)				
Selected Model: ARDL (1, 0, 1, 1, 1, 0, 0)				
Case 2: Restricted Constant and No Trend				
Date: 03/26/22 Time: 23:06				
Sample: 1960 2020				
Included observations: 17				
ECM Regression				
Case 2: Restricted constant and no trend				
Variable	Coefficient	Standard error	t-Statistic	Prob.
D (FERTILIZERCONS)	0.001077	0.000516	2.088200	0.0818
D (EMPLOYAGRIC)	12.64157	0.604762	20.90340	0.0000
D (INFLA)	-0.123854	0.010408	-11.90031	0.0000
CointEq (-1)*	-0.512220	0.049840	-10.27728	0.0000
R-squared	0.989741	Mean dependent var		2.858235
Adjusted R-squared	0.987374	S.D. dependent var		4.827058
S.E. of regression	0.542392	Akaike info criterion		1.816669
Sum squared resid	3.824459	Schwarz criterion		2.012719
Log likelihood	-11.44169	Hannan-Quinn criter.		1.836157
Durbin-Watson stat	2.884164			
* p-value incompatible with t-bounds distribution				
F-bounds test		Null hypothesis: No levels relationship		
Test statistic	Value	Signif.	I (0)	I (1)
F-statistic	53.11286	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

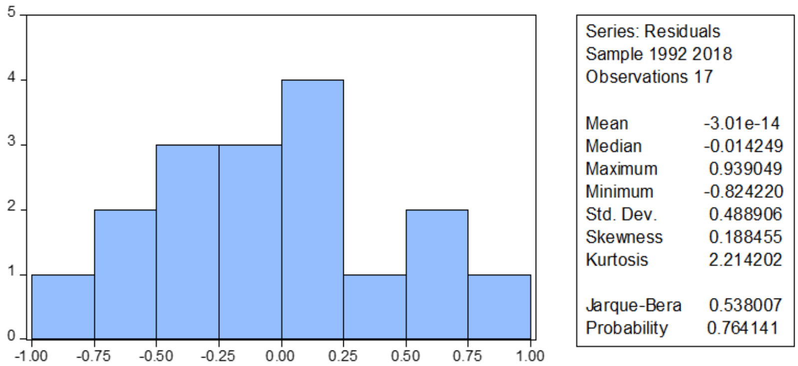

Table A22.

Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	5.168618	Prob. F (2,4)		0.0778
Obs*R-squared	12.25711	Prob. Chi-Square (2)		0.0022
Test Equation:				
Dependent Variable: RESID				
Method: ARDL				
Date: 03/26/22 Time: 23:07				
Sample: 1992 2018				
Included observations: 17				
Presample and interior missing value lagged residuals set to zero.				
Variable	Coefficient	Standard error	t-Statistic	Prob.
CROPPI (-1)	0.053588	0.055480	0.965899	0.3888
AGRVADPERWORKER	-0.002778	0.003650	-0.760970	0.4891
FERTILIZERCONS	0.001264	0.001294	0.976779	0.3840
FERTILIZERCONS (-1)	-0.000932	0.001019	-0.914369	0.4123
EMPLOYAGRIC	-0.957986	0.975669	-0.981876	0.3818
EMPLOYAGRIC (-1)	0.510761	1.128613	0.452556	0.6743
INFLA	0.044960	0.032301	1.391933	0.2363
INFLA (-1)	-0.035825	0.023979	-1.494009	0.2095
ARABLE_LAND	0.480742	0.364412	1.319227	0.2575
CO2_EMISSION	6.37E-05	6.34E-05	1.004881	0.3718
C	1.017287	70.15220	0.014501	0.9891
RESID (-1)	-1.596264	0.505662	-3.156779	0.0343
RESID (-2)	-2.192884	1.283436	-1.708605	0.1627
R-squared	0.721006	Mean dependent var		-3.01E-14
Adjusted R-squared	-0.115975	S.D. dependent var		0.488906
S.E. of regression	0.516479	Akaike info criterion		1.598927
Sum squared resid	1.067000	Schwarz criterion		2.236090
Log likelihood	-0.590878	Hannan-Quinn criter.		1.662262
F-statistic	0.861436	Durbin-Watson stat		2.154450
Prob (F-statistic)	0.624345			

Table A23.

Heteroskedasticity Test: Breusch-Pagan-Godfrey				
F-statistic	1.656630	Prob. F (10,6)		0.2772
Obs*R-squared	12.47999	Prob. Chi-Square (10)		0.2542
Scaled explained SS	0.943800	Prob. Chi-Square (10)		0.9999
Test equation:				
Dependent variable: RESID^2				
Method: Least squares				
Date: 03/26/22 Time: 23:08				
Sample: 1992 2018				
Included observations: 17				
Variable	Coefficient	Standard error	t-Statistic	Prob.
C	15.81723	28.89242	0.547453	0.6038
CROPPI (-1)	-0.001982	0.022021	-0.090020	0.9312
AGRVADPERWORKER	-0.000630	0.001294	-0.487089	0.6435
FERTILIZERCONS	-0.000447	0.000433	-1.032310	0.3417
FERTILIZERCONS (-1)	-0.000331	0.000379	-0.871331	0.4171
EMPLOYAGRIC	0.304299	0.383343	0.793803	0.4575
EMPLOYAGRIC (-1)	-0.539616	0.449287	-1.201048	0.2750
INFLA	-0.002157	0.006301	-0.342289	0.7438
INFLA (-1)	-0.007705	0.005109	-1.508166	0.1822
ARABLE_LAND	-0.022542	0.084341	-0.267271	0.7982
CO2_EMISSION	-1.56E-05	1.75E-05	-0.894167	0.4057
R-squared	0.734117	Mean dependent var		0.224968
Adjusted R-squared	0.290978	S.D. dependent var		0.255524
S.E. of regression	0.215160	Akaike info criterion		0.017791
Sum squared resid	0.277762	Schwarz criterion		0.556929
Log likelihood	10.84878	Hannan-Quinn criter.		0.071382
F-statistic	1.656630	Durbin-Watson stat		3.210551
Prob (F-statistic)	0.277225			

Table A24.

Ramsey RESET Test				
Equation: UNTITLED				
Specification: CROPPI CROPPI (-1) CO2_EMISSION				
AGRVADPERWORKER INFLA INFLA (-1) EMPLOYAGRIC				
EMPLOYAGRIC (-1) FERTILIZERCONS FERTILIZERCONS (-1)				
ARABLE_LAND C				
Omitted Variables: Squares of fitted values				
	Value	df	Probability	
t-statistic	0.153417	5	0.8841	
F-statistic	0.023537	(1, 5)	0.8841	
F-test summary:				
	Sum of Sq.	df	Mean squares	
Test SSR	0.017919	1	0.017919	
Restricted SSR	3.824459	6	0.637410	
Unrestricted SSR	3.806540	5	0.761308	
Unrestricted test equation:				
Dependent variable: CROPPI				
Method: ARDL				
Date: 03/31/22 Time: 09:27				
Sample: 1992 2018				
Included observations: 17				
Maximum dependent lags: 1 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (1 lag, automatic):				
Fixed regressors: C				
Variable	Coefficient	Standard error	t-Statistic	Prob.*
CROPPI (-1)	-0.626746	0.751820	-0.833638	0.4425
CO2_EMISSION	-0.000362	0.000368	-0.983700	0.3704
AGRVADPERWORKER	-0.005024	0.005782	-0.868914	0.4246
INFLA	-0.147554	0.156581	-0.942351	0.3893
INFLA (-1)	0.061599	0.064500	0.955034	0.3834
EMPLOYAGRIC	15.81158	20.72106	0.763068	0.4799
EMPLOYAGRIC (-1)	-24.43029	29.20918	-0.836391	0.4411
FERTILIZERCONS	0.000890	0.002135	0.416978	0.6940
FERTILIZERCONS (-1)	-0.006464	0.007467	-0.865687	0.4262
ARABLE_LAND	2.552559	2.324703	1.098015	0.3222
C	479.2606	465.7470	1.029015	0.3507
FITTED^2	-0.001206	0.007860	-0.153417	0.8841
R-squared	0.999426	Mean dependent var		76.06059
Adjusted R-squared	0.998163	S.D. dependent var		20.35908
S.E. of regression	0.872530	Akaike info criterion		2.753149
Sum squared resid	3.806540	Schwarz criterion		3.341300
Log likelihood	-11.40177	Hannan-Quinn criter.		2.811612
F-statistic	791.4686	Durbin-Watson stat		2.855614
Prob (F-statistic)	0.000000			
*Note. p-values and any subsequent tests do not account for model selection				