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Technological Innovation and Agricultural Productivity in Nigeria Amidst Oil Transition: ARDL Analysis

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Abstract: In contemporary discourse, Nigeria's reliance on its oil sector is proving insufficient for sustained economic growth. The volatility of oil prices, geopolitical tensions, technological advancements, and environmental sustainability concerns have exposed the vulnerabilities of an oil-dependent economy, emphasizing the need for diversification and a renewed focus on agriculture. This study investigates the relationship between technological innovation and agricultural productivity in Nigeria, contrasting it with the oil sector. Using the ARDL estimation technique, our findings reveal a significant negative influence of immediate lagged agricultural productivity (AGTFP(−1)), indicating technological constraints. Technological innovation, proxied by TFP, shows a substantial impact on agricultural productivity, with a negative long-term effect (−90.71) but a positive, though insignificant, impact on agricultural output (0.0034). The comparative analysis underscores that the agricultural sector tends to benefit more from technological innovation than the oil sector. This highlights the critical need to prioritize technological advancements in agriculture to drive sustainable growth and economic resilience in Nigeria.

Keywords: technological innovation; agricultural productivity; oil; ARDL; Nigeria

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1. Introduction

In contemporary discourse, it is evident that Nigeria's once-thriving oil sector is insufficient for ensuring sustained economic growth (Ben Salem et al. 2022; Tabe-Ojong et al. 2023). The previous belief that oil was the key to national prosperity has given way to a harsh reality: relying heavily on oil revenues cannot guarantee long-term stability and development. This shift is driven by several challenges, among which are price volatility, geopolitical tensions, technological advancements, and the call for environmental sustainability (Chatziantoniou et al. 2021; Lawal et al. 2015; Ben Salem et al. 2022; Jacal et al. 2022). As highlighted by Yilanci et al. (2021), the susceptibility of oil-dependent economies like Nigeria to global market fluctuations emphasizes the necessity for diversification, emphasizing the revival of the nation's original economic backbone—agriculture—as an increasingly imperative course of action.

The ascent of non-fossil-fuel technologies further looms as an ominous specter over Nigeria, an economy intricately tethered to its oil sector. Precise projections and compelling statistics accentuate the gravity of this impending dilemma. The International Energy Agency (IEA)'s World Energy Outlook predicts an exponential growth trajectory for electric vehicles (EVs), estimating that by 2030, global EV sales could reach a staggering 250 million. This seismic shift threatens to eviscerate the demand for traditional hydrocarbon fuels, and for Nigeria, a prominent oil exporter, the ramifications are dire. The Nigerian National Petroleum Corporation (NNPC) underscores this concern, projecting a conspicuous decline in crude oil demand as nations galvanize their commitment to cleaner energy alternatives. The traditional modus operandi of oil extraction and exploration, reliant on outdated technologies, is proving to be steadily costly and environmentally detrimental (Jacal et al. 2022). The emergence of advanced drilling techniques, the rise of electric vehicles, and the global push for decarbonization have collectively led to a decreased global appetite for oil, rendering Nigeria's oil-centric economy progressively precarious (Kayode et al. 2022; Djoumessi 2022). Adding to the fray is the plummeting cost of renewable energy technologies; solar energy costs, for instance, have diminished by over 80% since 2010, setting the stage for a pivotal transition away from fossil fuels. Reflecting this transformative trajectory, the International Renewable Energy Agency (IRENA) estimates that renewable capacity could surge by 50% globally by 2030. In this shifting landscape, Nigeria's entrenched dependency on oil could precipitate an economic abyss, necessitating a paradigm shift towards diversification, innovation, and a resurgent focus on sectors like agriculture.

Interestingly, while technological evolution casts a shadow of uncertainty over Nigeria's oil sector, it also ushers in a promising era of prosperity for Nigeria's agriculture industry. This transformative shift can be a beacon not only for Nigeria but for the entirety of Africa (Tabe-Ojong et al. 2023). The convergence of cutting-edge technologies, from precision agriculture to data-driven decision-making, holds the potential to encourage large-scale farming and unlock the latent possibilities of agriculture (Adeagbo et al. 2023). For Nigeria, where a significant portion of the population is engaged in farming, innovative tools such as smart sensors, drone-assisted crop monitoring, and digital platforms for market access can catalyze a modern agricultural revolution. These advancements not only enhance productivity but also mitigate the challenges of climate change, enabling more efficient water usage and soil management (Mandal et al. 2022; Balana and Oyeyemi 2022; Ejem et al. 2023). Technology-driven agriculture has the potential to uplift smallholder farmers, a cornerstone of Nigeria's agrarian landscape, by elevating their access to vital resources and markets, ultimately fostering sustainable rural development (Etuk and Ayuk 2021; Akinola et al. 2023).

Before the oil boom of the 1970s, Nigeria's economy was predominantly driven by its agricultural sector. In the 1960s, agriculture accounted for nearly 50% of government revenue, 65% of GDP, and over 80% of export earnings. However, over time, the significance of agriculture to Nigeria's economic growth has diminished, with agriculture contributing approximately 26.84% to the GDP in 2021. This decline in agricultural contributions has negatively impacted the welfare of low-income earners. Additionally, the recent decline in global oil prices has raised concerns about the sustainability of the country's economy (Ojo and Baiyegunhi 2023).

Uji (2020) highlights corruption as a major issue affecting development in many developing nations, including Nigeria. The agricultural sector, a key component of national development, is significantly hindered by corruption, despite government efforts to enhance agricultural production through projects and research institutes (Sarimiento 2000). This challenge has led to diminished agricultural output, limiting Nigeria's potential despite its rich resources (Ani and Nuhu 2010). Although measures like the Economic and Financial Crimes Commission (EFCC), the Independent Corrupt Practices Commission (ICPC), and Nigerian Transparency International have been established to combat corruption, the issue persists, partly due to the involvement of those meant to fight it (Uji 2020; Abah et al. 2024). This entrenched corruption continues to undermine efforts to revitalize the agricultural sector and, by extension, the overall development of the country.

Over the years, Nigeria's agricultural sector has undergone several reform efforts, starting with initiatives like Operation Feed the Nation, the Structural Adjustment Program for agriculture, and the Green Revolution. The most recent initiative, the Agricultural Transformation Agenda (ATA), was introduced by the government around 2015 to modernize the sector through the promotion of digital technologies (Federal Ministry of Agriculture and Rural Development (FMARD) 2015). As part of this agenda, grassroots farmers were provided with free mobile phones to facilitate their participation in e-agriculture. Although the concept of e-agriculture was initially unfamiliar to many farmers, its growing acceptance was driven by the convenience it offered, such as the delivery of fertilizers and farming tools through digital means.

To further support this transition, the National Information Technology Development Agency (NITDA) established an e-portal to help farmers leverage digital tools for better productivity (National Information Technology Development Agency (NITDA) 2015). However, despite these advancements, many farmers remained unaware of the portal and its potential benefits, resulting in underutilization of the available resources. Adoption of e-agriculture before the year 2000 was notably slow, as the technology and its applications were poorly understood by the farming community (Mwangi and Kariuki 2015; Eweoya et al. 2021). Thus, while there have been efforts to modernize farming practices, there is still much work to be done to ensure widespread awareness and adoption of digital solutions for agricultural development in Nigeria.

In tandem with these challenges, the COVID-19 pandemic has also exacerbated vulnerabilities in Nigeria's oil sector, notably in the oil industry itself (Chiaramonti and Maniatis 2020; Valadkhani et al. 2021). Ongoing geopolitical tensions between Russia and Ukraine have further heightened the situation, causing an unprecedented surge in crude oil prices. The apprehensions of major oil-importing nations that conflict could disrupt global oil markets led to pre-emptive actions, propelling oil prices to a 14-year peak of USD 140 per barrel on 7 March 2022. Russia, contributing about 14% of global production, grapples with these ramifications. For Nigeria, heavily reliant on oil exports, escalating oil prices due to geopolitical turmoil offer temporary relief but do not resolve deeper sectoral issues. The global oil market's volatility, coupled with shifts to renewable energy sources, underscores Nigeria's fragile oil revenue dependency (Ben Salem et al. 2022).

Rapid population growth exacerbates food insecurity in Nigeria, with predictions indicating a population of 400 million by 2050, emphasizing the urgent need to address this issue for improved food security (Otekunrin et al. 2019; Amzat et al. 2020). This aligns with the African Union's Malabo Declaration, underscoring the vital role of agriculture in achieving inclusive growth and food security across the continent by 2025. The exponential growth of mobile technology penetration in Africa, as indicated by the International Telecommunication Union (ITU), paves the way for digital platforms to reach even the most remote farming communities, providing them with critical information on weather patterns, market prices, and best agricultural practices. The success stories from countries like Kenya, where mobile payment systems have revolutionized small-scale farming, inspire optimism for Africa's agricultural future (Parlasca et al. 2022; Andati et al. 2023). Thus, as suggested in the research of Rongjian et al. (2019) and Djoumessi (2022), technological innovations have the potential to leapfrog traditional barriers, amplifying agricultural productivity and forging a sustainable development trajectory for both Nigeria and the broader African continent.

Nigeria stands at a pivotal juncture as it grapples with the challenges posed by its heavy dependence on the volatile oil sector. The vulnerabilities inherent in relying on oil revenues for economic stability have become increasingly evident, necessitating a crucial shift back to the agricultural sector, historically the nation's economic backbone (Eleke et al. 2019; Yilanci et al. 2021). While existing literature has extensively examined the effects of technological practices on various aspects of agriculture, such as output, crop yields, food security, and economic development in certain regions of Nigeria, Africa, and around the world (Olayide et al. 2016; Balana and Oyeyemi 2022; Djoumessi 2022; Edafe et al.

2023; Ejem et al. 2023; Wang and Qian 2024), there has been limited focus on agricultural productivity, particularly within Nigeria. Furthermore, few studies have delved into the potential trade-offs between the oil and agricultural sectors based on technological progress. As such, there is a noticeable gap in the literature, highlighting the imperative for an investigation into the aggregate impact of technological innovation on agricultural productivity in the country.

Given the precarious state of the Nigerian economy and the significant role the agricultural sector plays in sustaining growth, it is crucial to meticulously examine and measure the intricate relationship between technological innovation and agricultural productivity. Therefore, this study seeks to understand the nature of the relationship between technological innovation and agricultural productivity in Nigeria, assess the impact of agricultural innovation on agricultural output, and compare the effects of technological innovation on the oil and agricultural sectors within Nigeria's context. To address these objectives, the study will be guided by the following research questions: What is the relationship between technological innovation and agricultural productivity in Nigeria? How does agricultural innovation affect agricultural output in Nigeria? How do the effects of technological innovation differ between the oil and agricultural sectors in Nigeria? This implies conducting a national analysis, a sectoral analysis, and a comparative analysis between the two sectors. Anchored on the Solow–Swan Growth model, the study will utilize the Autoregressive Distributed Lag (ARDL) model for estimation. This thorough exploration is essential for providing valuable insights and guiding strategic decisions aimed at strengthening agricultural technology. By doing so, we can enhance growth and food security not only in Nigeria but also extend the positive impact across Africa.

2. Empirical Review

An in-depth examination of the extant literature underscores the enduring importance of the nexus between technological innovation and agricultural growth, especially in the Nigerian economy. In the ever-evolving landscape of agriculture, technology has emerged as a transformative force, capable of shaping the trajectory of productivity, food security, and economic progress in Nigeria.

This literature review is organized into four distinct strands. The first strand explored the dynamic intersections between energy considerations and agriculture. From mechanization to the adoption of renewable energy, this section uncovered the varied ways in which technological innovations affect efficiency, yield, and the overall agricultural landscape. Transitioning to the second strand, we delved into the connection between climate change and technological agricultural practices, as it brings to light how innovative solutions contribute to adaptive and resilient farming techniques.

Furthermore, the third strand addressed the foundational elements of agriculture: land and soil-related issues. Here, we dissected the effects of technological interventions on soil selection and sustainable land management with the aim of underpinning their crucial role in influencing overall productivity. Lastly, the fourth strand placed governmental and non-governmental agriculture programs into focus. Through an examination of their design, implementation, and outcomes, the review sought to unravel the collective impact of technological innovation on large-scale agricultural initiatives.

2.1. Energy Diversification and Agricultural Development

Nigeria's economy faces challenges stemming from its heavy dependence on the oil sector, a vulnerability that has been underscored by external crises. Recognizing the need for diversification, there is a growing emphasis on revitalizing the agricultural industry, which historically served as the country's backbone (Eleke et al. 2019). Aye and Odhiambo (2021) conducted a threshold analysis to identify critical tipping points where fluctuations in oil prices negatively impact agricultural growth. Their findings underscored the importance of reducing reliance on fossil fuels in the agricultural sector to enhance energy and food security, especially in contexts like that of South Africa, where oil reserves are not as abundant, rendering the economy vulnerable to external shocks.

While the threshold analysis provides valuable insights, one of its weaknesses lies in its reliance on predetermined thresholds, which can be arbitrary and subjective. In a related study, Olujobi et al. (2023) delved into the availability of low-carbon energy sources in Nigeria to ensure a reliable electricity supply and foster industrial sustainability. Their research included a comparative analysis of legal frameworks for low-carbon energy adoption in China, Spain, Germany, and Nigeria. The study highlighted the importance of establishing robust legal structures that leverage Nigeria's abundant renewable energy resources to maximize low-carbon energy adoption, drawing insights from the legal frameworks of other countries.

Furthermore, Aworunse et al. (2023) conducted exploratory research on the prospects of building a sustainable bioeconomy in Nigeria. They identified biomass energy as a promising avenue for fostering resilience in the bioeconomy, driven by environmental concerns, climate change, municipal solid waste management, and the imperative of energy diversification (Okafor et al. 2022). These studies collectively underscore the importance of transitioning towards sustainable energy sources, such as low-carbon and biomass energy, to mitigate environmental impacts, enhance energy security, and promote economic resilience in Nigeria's agricultural sector.

2.2. Climate Change, Technology, and Food Security

Rongjian et al. (2019) conducted a comprehensive review across three distinct economic contexts—China, Pakistan, and Nigeria—revealing contrasting scenarios in agricultural technological advancements. While China has made strides in introducing technological innovations to enhance agriculture, Pakistan, despite being agriculturally self-sufficient, has harnessed such advances effectively. In stark contrast, Nigeria, despite its vast farmland endowment, lags due to backwardness in agricultural technology. Weak institutional support, a deficient educational system, brain drain, underfunded educational systems, and inadequate infrastructure were identified as significant barriers hindering technological advancements in Nigeria (Balana and Oyeyemi 2022; Edafe et al. 2023). Notably, communication emerged as a major obstacle to agricultural innovations among rural farmers in Nigeria, prompting Ejem et al. (2023) to advocate for a more effective two-way communication approach within Nigeria's extension system to disseminate global agricultural practices.

In Sub-Saharan Africa, Djoumessi (2022) employed the stochastic frontier analysis (SFA) to unveil positive and statistically significant production elasticity regarding land, capital, and machinery, while labor appeared insignificantly positive. This finding seemingly contradicts the region's labor-intensive agricultural practices, potentially influenced by the SFA estimation approach's functional-form choices, which could impact the analysis's robustness and interpretation. Conversely, Amare and Balana (2023) underscored climate change's adverse impact on agricultural productivity and farmers' revenue distribution. However, Olayide et al. (2016) and Tabe-Ojong et al. (2023) showcased climate-smart agriculture (CSA)'s effectiveness in mitigating climate change's adverse effects, thereby enhancing crop yields and promoting food security. Awolala et al. (2023) delved into weather and climate-information consumption, estimating a significant market value in Nigeria. They identified institutional and socioeconomic conditions as pivotal determinants of climate change-adaptation technologies. Moreover, factors such as performance expectancy, effort expectancy, and social effort were found to influence the usage intention of adopting e-agriculture (Adeagbo et al. 2023; Eweoya et al. 2021; Babatunde et al. 2021).

Isukuru et al. (2023) explored bamboo's ecological benefits, highlighting its renewable nature and versatility across various sectors, including construction and paper production. Bamboo's ability to grow in diverse climatic conditions and soil types positions it as an effective tool for erosion control and soil conservation, contributing significantly to climate-change mitigation. Conservation efforts in agriculture were also emphasized by Kolapo and Kolapo (2023), who employed multinomial endogenous switching regression (MESR) models to underscore the importance of conservation practices in mitigating climate change and enhancing crop productivity. They identified gender, age, farm size and experience, formal education, access to extension services, and association membership as significant factors influencing the adoption of conservation agricultural practices and crop yields among farmers.

Studies focusing on smallholder farmers highlighted the pivotal role of improved practices and ICT in enhancing income distributions and value-chain processes, reducing gender disparities, ensuring food security, influencing consumption patterns, and driving economic growth (Ayanwale et al. 2023; Matthew et al. 2023; Ndaghu et al. 2023; Melesse et al. 2023; Eke et al. 2019). Melesse et al. (2023) employed endogenous switching regression models to assess the relationship between improved groundnut varieties and household food security, demonstrating that adoption increases groundnut consumption and reduces vulnerability to food insecurity. Similarly, Ayanwale et al. (2023) utilized instrumental variable quantile treatment effects (IV-QTEs) to examine the distributional effects of improved practices adoption on the income of smallholder maize farmers, revealing significant influences on revenue distributions, particularly among impoverished households. Matthew et al. (2023) identified farmgate collectors as pivotal actors in the agricultural value chain, with ICT deployment significantly impacting their roles. Ogunsolu (2021) explored the potential impact of digitizing the Nigerian agricultural industry, offering insights into its ability to remedy economic recessions, albeit with sustainability concerns. Moreover, technological adoption exhibited varied effects in Africa, with factors such as data availability, region, model specification, and sample size identified as being responsible for such variations (Habtewold and Heshmati 2023).

2.3. Sustainable Land Management and Agricultural Productivity

The study conducted by Kayode et al. (2022) investigated the relationship between soil parameters and agricultural productivity, focusing on a commercial farm in Omu-Aran, Nigeria. Utilizing vertical electrical sounding (VES) and 2D resistivity inversion models, the research revealed the prevalence of gravelly and sandy soils within the area. The findings suggest potential challenges related to soil quality that could impact agricultural productivity. In response to identified nutrient deficiencies, the authors recommended regular fertilization practices as a means to enhance soil fertility and ultimately improve agricultural productivity (Kianguebene-Koussingounina et al. 2023). These recommendations align with the broader consensus within agricultural research regarding the importance of soil management practices, such as fertilization, in optimizing crop yields and ensuring sustainable agricultural development.

Maertens et al. (2023) further support the significance of site-specific nutrient management (SSNM), particularly in soil fertilization, for fostering gradual and sustainable agricultural development in Nigeria. Their research emphasizes the importance of tailored approaches to soil fertility management, considering the specific needs and characteristics of individual agricultural sites. By implementing SSNM practices, farmers can optimize nutrient use efficiency, minimize environmental impacts, and achieve more sustainable increases in agricultural productivity over the long term. These findings contribute to a growing body of literature highlighting the potential for a more gradual and sustainable intensification of smallholder agriculture in Sub-Saharan Africa (SSA), in contrast to the rapid intensification observed during the Asian Green Revolution. The emphasis on increased fertilizer use accompanied by improved fertilizer management underscores the importance of precision agriculture techniques in optimizing resource utilization and promoting sustainable agricultural growth in the region.

Mandal et al. (2022) conducted a study employing 300 paired soil and rice plants, which identified Bisalayi as the most suitable rice type for cultivation on polluted farmlands in Nigeria. This finding sheds light on potential solutions for addressing agricultural challenges in areas affected by land pollution, offering insights into crop-resilience and -adaptation strategies. Furthermore, Adenle et al. (2022) revealed that human activities, migration, and land tenure issues significantly contribute to land degradation in the country. Understanding these underlying factors is crucial for implementing effective land management policies and practices to mitigate degradation and ensure sustainable agricultural development.

On a positive note, the maize sector in Nigeria has experienced notable improvements in productivity over recent decades. Wossen et al. (2023) attributed this growth to tailored policies and institutional arrangements that promote access to modern inputs and expand markets for maize grain. Additionally, the surge in productivity is further explained by the adoption of improved maize varieties (IMVs), crop diversification (CD), and sustainable land management practices (SLMPs), as demonstrated by studies conducted by Baiyegunhi et al. (2022) and Kolapo et al. (2022). These findings underscore the importance of policy support and agricultural innovations in driving productivity gains in staple crops like maize, contributing to food security and economic development in the country.

However, challenges persist in ensuring widespread adoption of sustainable agricultural practices (SAPs) across communities. Oyetunde-Usman et al. (2021) found that household head characteristics, including size, wealth status, education, gender, and access to extension services, collectively influence the adoption of multiple SAPs. This highlights the need for targeted interventions and capacity-building efforts to promote sustainable farming methods among diverse farming households. In contrast, Edafe et al. (2023) demonstrated that communities with land investments have a lower probability of achieving food security compared to those without land investments, pointing to potential trade-offs between land ownership and food security outcomes that warrant further investigation and policy consideration.

2.4. Agricultural Programs and Gender-Based Disparities

Etuk and Ayuk (2021) conducted a comprehensive analysis using various poverty measures to evaluate the impact of the Commercial Agricultural Development Project (CADP) in Nigeria. Employing the Average Treatment effect on the Treated (ATT), Foster–Greer–Thorbecke (FGT) poverty measures, and the Poverty Equivalent Growth Rate (PEGR) pro-poor measure, their study revealed that CADP effectively mitigates poverty and substantially enhances commercialization, particularly benefiting its beneficiaries. The research highlighted that almost 43% of the sample data consisted of non-beneficiaries who experienced lesser improvements. As a result, the authors emphasized the importance of ensuring that development intervention programs effectively target the poor, stressing the need for focused efforts to address poverty alleviation.

Akinola et al. (2023) delved into the factors influencing tomato yields in rural Nigeria, uncovering the significant impact of membership in agricultural cooperatives under equal circumstances. Their findings underscored the pivotal role of cooperative membership in enhancing agricultural productivity, particularly in the tomato sector. However, Balana and Oyeyemi (2022) shed light on a major obstacle faced by smallholder farmers: insufficient collateral hindering their access to necessary credit facilities for adopting agricultural technologies and improving yields. This highlights the need for supportive policies and financial mechanisms tailored to the specific needs of smallholder farmers to facilitate their adoption of modern agricultural practices.

In a related context, Ikuemonisan et al. (2022) explored the determinants influencing individuals' decisions to pursue a career in agribusiness. Their study identified teaching quality, learning environment, and course difficulty as significant factors shaping individuals' career choices in the agricultural sector. Conversely, Bello et al. (2021) found gender disparities among rice farmers, with men outperforming women by 11%. Furthermore, Ojo and Baiyegunhi (2023) identified key drivers of gender inequality in agricultural productivity, including marital status, farm size, education, and market access. These studies collectively underscore the multifaceted nature of challenges and opportunities within the agricultural sector, highlighting the importance of addressing systemic barriers and promoting inclusive policies to foster sustainable agricultural development.

2.5. Theoretical Review of Literature

This study examines a few relevant theories, offering an analysis of those deemed most pertinent. However, the primary theory underpinning this research is the Solow–Swan growth model due to its emphasis on technological progress, capital accumulation, and long-run equilibrium analysis, all of which align closely with the research objectives. This model provides a robust framework for understanding how technological advancements contribute to sustained growth in the agricultural sector.

2.5.1. Solow–Swan Growth Model

The Solow–Swan Growth (SSG) model, formulated by Robert Solow and Trevor Swan during the 1950s and 1960s, stands as a fundamental concept in economic theory. It extends the Harrod–Domar model by incorporating labor as a factor of production and allowing for variable capital-output ratios. The model aims to elucidate the factors driving long-term economic growth, emphasizing the contributions of capital accumulation and technological progress (Solow 1956).

At its core, the SSG model posits that economic growth is a function of increases in capital (both physical and human) and technological advancements. Mathematically, this can be expressed as follows:

$$Y = f(K, H, A, L)$$

where Y represents output or GDP, K denotes the stock of physical capital, H represents the stock of human capital, A signifies technological progress or total factor productivity (TFP), and L denotes the labor force.

In the absence of technological breakthroughs, the model predicts that economies will eventually reach a steady state where further accumulation of capital ceases to significantly impact growth. Mathematically, this steady state can be represented by the following condition:

$$\mathrm{sY} = (\mathrm{n} + \delta)\mathrm{K}$$

where s denotes the savings rate, n represents the rate of population growth, and δ signifies the depreciation rate of capital.

Technological progress, considered an external force, becomes imperative for breaking out of this equilibrium and achieving sustained economic growth (Frey 2017). Endogenous growth theory further extends the Solow model by emphasizing the role of knowledge and human capital (Romer 1990). It posits that technological advancements are endogenously determined by factors such as research and development (R&D) investments, and human capital is considered a critical driver of growth.

Critics argue that endogenous growth theory lacks empirical evidence and may not fully explain observed growth patterns. Additionally, convergence theory suggests that poorer countries tend to catch up with richer ones over time. Empirical studies, however, have found mixed evidence regarding convergence, with some countries converging while others diverging. Critics argue that convergence may not occur uniformly due to differences in institutions, policies, and technological adoption.

The Solow model's assumptions about exogenous technological growth have also been challenged by economists like Robert Gordon, who argue that the pace of technological progress has slowed significantly. Gordon's thesis suggests that recent technological advancements may not be as impactful as transformative innovations of the past (Gordon

2012). Critics highlight the importance of institutions and policy frameworks in shaping economic growth, factors which the Solow model abstracts from.

The relevance of this model to the study of technological innovation's impact on agricultural productivity in Nigeria lies in its recognition of the transformative potential of technological progress. While initial investments in capital, such as modern machinery and infrastructure, may yield short-term gains in agricultural productivity, the model suggests that the sustained impact comes from exogenous technological innovation (Olayide et al. 2016; Tabe-Ojong et al. 2023). This implies that for long-term and sustained growth in the agricultural sector in Nigeria, the adoption of cutting-edge technologies like precision farming, genetic modifications, and data-driven decision-making is paramount.

In summary, the SSG model offers a solid theoretical foundation for understanding the interplay between technological progress, capital accumulation, and economic growth. Applied to agriculture, it highlights the crucial role of technological innovation in enhancing productivity and achieving sustainable agricultural practices, making it a pertinent guide for examining the impact of technological innovation on agricultural productivity in Nigeria.

2.5.2. Endogenous Growth Theory

The endogenous growth theory (EGT) represents a significant advancement in economic thought, addressing limitations observed in traditional models such as the neoclassical growth theory. Unlike conventional viewpoints that attribute growth solely to external factors, EGT redirects attention towards internal elements within an economy, particularly emphasizing the significance of human capital, innovation, and knowledge in propelling long-term growth (Romer 1990). In contrast to the perspective that regards technological advancements as externally driven forces, EGT asserts that purposeful activities within an economy, such as research and development, serve as primary drivers of technological innovation, thereby fueling economic growth (Romer 1987; Latzer et al. 2019). It places crucial emphasis on human capital—the skills, knowledge, and expertise possessed by individuals—arguing that investments in education and training play a pivotal role in fostering economic growth by enhancing productivity and stimulating innovation.

Human capital augmented endogenous growth theory further emphasizes the role of human capital accumulation in driving long-term economic growth. Developed by Lucas (1988), Romer (1990), and others, this theory posits that investments in education, training, and skills development can enhance labor productivity, technological innovation, and overall economic performance. The mathematical representation of this theory can be depicted by the following production function:

$$Y = A(K, H)F(L, E)$$

where Y represents output or GDP, A denotes total factor productivity (TFP), which captures technological progress and efficiency, K denotes physical capital, H represents human capital, L denotes labor input, E represents the level of technology, and F is the production function indicating the relationship between inputs and output.

The inclusion of human capital (H) as a determinant of output reflects the key tenet of human capital augmented endogenous growth theory, emphasizing the importance of education and knowledge accumulation in fostering economic growth.

Another supporting theory of endogenous growth is based on the idea of innovation and technological spillovers. Pioneered by Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992), this theory argues that technological progress can be driven by knowledge spillovers and externalities arising from innovation activities. The mathematical formulation of this theory often involves incorporating a knowledge production function, where technological progress is endogenously determined by investments in research and development (R&D), knowledge creation, and diffusion processes. One such representation is given by the following:

$$A^{\cdot} = \gamma \cdot A(K, H) \cdot R$$

where $A^{\cdot}$ represents the rate of technological progress, γ denotes the effectiveness of R&D investments, $A(K, H)$ represents the level of TFP, and R denotes R&D expenditure.

This formulation highlights the self-sustaining nature of technological progress, where investments in R&D lead to the creation of new knowledge and innovations, which, in turn, drive further economic growth.

Critics of EGT often target its reliance on the assumption of increasing returns to scale, commonly utilized in models like that of Romer (1990) and Lucas (1988) to generate sustained endogenous growth. They argue that this assumption may lack empirical support in many industries and could lead to unrealistic predictions about the long-term behavior of the economy. Additionally, the presence of increasing returns to scale might exacerbate income inequality and market distortions, undermining market efficiency and potentially impeding economic growth. Consequently, proponents of alternative theories, such as neoclassical growth theory, highlight the importance of diminishing returns to scale in driving convergence to steady-state levels of output per capita.

While EGT extends its relevance to various sectors, including agriculture, where intentional technological advancements enhance practices, its application serves as a secondary focus in this research. EGT provides a comprehensive framework for understanding economic growth dynamics, particularly within agriculture, emphasizing the role of innovation and human capital. By employing EGT as a guide, this study aims to delve into the impact of technological innovation on agricultural productivity in Nigeria, offering insights into strategies for fostering sustainable economic growth in the agricultural sector.

2.5.3. Innovation Diffusion Theory

Everett Rogers introduced the Innovation Diffusion Theory (IDT) in 1962 as a framework for comprehending how technological innovations are embraced within a social framework over time. Within the agricultural sector, innovations encompass new technologies and methodologies aimed at enhancing productivity. These innovations are disseminated through various channels, including agricultural extension services, research entities, and mass media. Over time, farmers progress through stages of awareness, interest, evaluation, trial, and adoption regarding these innovations. Adoption rates are influenced by social factors such as resource accessibility, cultural norms, and governmental policies (Ejem et al. 2023). Farmers are often categorized into groups based on their inclination to adopt new technologies. The characteristics of innovations, including their advantages and compatibility with existing practices, significantly influence their adoption trajectory. Utilizing this theory, researchers can discern factors driving or hindering adoption and devise strategies to facilitate widespread adoption of agricultural innovations, thereby bolstering agricultural productivity and sustainability.

The contemporary literature further supports the validity of the IDT in the agricultural context. Recent studies have highlighted its efficacy in explaining the adoption patterns of various agricultural innovations, ranging from precision farming technologies to sustainable agricultural practices. For instance, research by Teklu et al. (2023) demonstrated how the principles of the IDT can be applied to understand the adoption of climate-smart agricultural practices among smallholder farmers in developing countries. The authors also found that social networks play a crucial role in facilitating the diffusion of agricultural innovations among farmers, corroborating the central tenets of the theory.

However, while the IDT remains a widely accepted framework, some scholars have raised concerns regarding its applicability in contemporary agricultural contexts. Critics argue that the theory may oversimplify the complex socio-economic dynamics influencing technology adoption in agriculture (Mardiana and Kembauw 2021). They suggest that factors such as institutional barriers, market structures, and power dynamics among stakeholders may not be adequately addressed within the framework of the Innovation Diffusion Theory. Additionally, the rapid pace of technological change and globalization in the agricultural sector may necessitate a more dynamic and nuanced approach to understanding innovation adoption processes.

Despite these critiques, the IDT continues to provide valuable insights into the adoption and diffusion of agricultural innovations. By integrating contemporary perspectives and addressing emerging challenges, researchers can further enhance the applicability and robustness of this theoretical framework in driving agricultural development and sustainability agendas.

3. Data and Estimation Techniques

3.1. Data

The study draws data from five reputable sources: The World Development Indicators (WDIs), the United States Department of Agriculture (USDA), the Penn World Table (PWT), the World Intellectual Property Organization (WIPO), and the Central Bank of Nigeria (CBN) statistical bulletin. Total factor productivity (TFP), gross fixed capital formation (GFCF), agricultural credit guarantee scheme fund (ACGSF), trade (TRADE), and exchange rate (EXR) serve as independent variables.

TFP, the core independent variable, acts as the primary proxy for technological innovation, indicating advancements in technology and innovation that lead to higher output levels without a corresponding increase in input usage. GFCF serves as a proxy for investment in agricultural infrastructure and equipment, which can influence the adoption and effectiveness of technological innovations in farming practices. ACGSF reflects a government lending scheme to encourage large-scale farming. TRADE facilitates access to new technologies and markets for agricultural products, thereby influencing productivity and innovation. This is particularly significant for Nigeria, as the country heavily relies on imports for technology. EXR affects agricultural exports and imports, influencing technology adoption and competitiveness.

Dependent variables include agricultural total factor productivity (AGTFP), agricultural output (AGO), agricultural value added (AGVA), and oil rents (OLRs). The use of AGTFP and AGO as dependent variables for assessing the impact of technological innovation on the Nigerian agricultural sector is justified because AGTFP captures efficiency improvements resulting from innovation within the sector, while AGO represents the quantitative increase in agricultural production facilitated by technological advancements. These variables offer a comprehensive view of the sector's performance and the effectiveness of innovation strategies in enhancing productivity and output levels.

The basis for using AGVA and OLR in comparing the effects of technological advancements on both sectors lies in how they capture more precisely the sector-specific economic contributions. AGVA represents the net value created within the agricultural sector, reflecting its economic significance and productivity. Conversely, OLR represents the income generated specifically from the oil sector, indicating its importance to the overall economy. By analyzing both AGVA and OLR, we can assess how technological advancements impact the economic performance and productivity of each sector independently, providing valuable insights for policymakers and stakeholders seeking to promote balanced economic development and innovation strategies across both agriculture and oil industries.

Patent applications (PATs), scientific and technical published articles (SCIs), credit to the private sector (CPS), foreign direct investment (FDI), and interest rate (INR) are included as additional control variables in the analysis to account for their potential impacts on the relationship between technological innovation and agricultural productivity. PAT represents the level of innovation and technological advancement, which can directly influence agricultural productivity through new methods and tools. SCI measures the dissemination of knowledge and research, which can enhance agricultural practices and productivity. CPS indicates the availability of domestic financial resources for investment in agricultural technologies and infrastructure. FDI reflects the inflow of capital and expertise from abroad, potentially introducing advanced technologies and practices into the agricultural sector. INR affects the cost of borrowing and investment decisions, influencing the ability of farmers and agribusinesses to invest in new technologies. By including these control variables, this analysis aims to mitigate potential confounding factors and ensure a more robust assessment of the relationship between technological innovation and agricultural productivity.

The study focuses on the period from 1981 to 2021 due to strategic considerations and data availability. This timeframe encompasses significant events relevant to the study's objectives. Firstly, it includes the initial oil boom in Nigeria, extending into the early 1980s, a pivotal period for economic development. Additionally, it covers the establishment of the Federal Ministry of Science and Technology on 1 January 1980, indicating a shift towards prioritizing technological innovation. The study also spans the era when mobile technological devices, such as Global Systems for Mobile Communications (GSMs), and various forms of Information and Communication Technology (ICT) gained prominence in Nigeria in the early 2000s. Moreover, this timeframe captures the integration of smart agriculture in the country and the COVID-19 period.

3.2. Estimation Technique

This study employs the Autoregressive Distributed Lag (ARDL) model, contingent upon the time-series data meeting essential criteria following preliminary tests such as correlation, stationarity, causality, and cointegration, conducted using the EViews Statistical Software Package. These tests ensure the suitability of the data for ARDL modelling, which is effective when the variables are stationary and exhibit cointegrated relationships, thus producing reliable estimates. The appropriateness of employing ARDL is supported by its ability to incorporate variables with differing timeframes, capture both short-term dynamics and long-term equilibrium relationships, and provide insights into temporal interdependencies between variables (Lawal et al. 2016; Apraku et al. 2021; Aragie et al. 2023; Jiaduo et al. 2023). The ARDL bounds test requires that the order of integration of all variables does not exceed I (1), given that the presence of I (2) among the considered variables may likely result in spurious results. In the presence of I(2) variables, the computed F-statistic provided by the ARDL bound test becomes invalid, for the ARDL bound test is based on the assumption that the variables are either I(0), I(1) or a mixture of both (Lawal et al. 2018; Lawal et al. 2016). Augmented Dickey–Fuller and Philip–Perron (PP) were employed to validate the order of integration of the employed variables.

To measure the adequacy of the model specification, the study conducted some diagnostic and stability tests. While we employed the Cumulative Sum test (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) to test for model stability, we employed a diagnostic test to address problems associated with non-normality, functional form, serial correlation, and heteroscedasticity (Tabash et al. 2024).

Moreover, ARDL accommodates both stationary and non-stationary variables and has seen limited application in examining the nexus between technological innovation and agricultural productivity in Nigeria.

The ARDL model equations are specified as follows in the unrestricted form to achieve our objectives:

$$\Delta AGTFP_t = \alpha_{01} + \sum_{i=1}^{p} \alpha_{1i}\Delta AGTFP_{t-i} + \sum_{i=1}^{q} \alpha_{2i}\Delta TFP_{t-i} + \sum_{i=1}^{q} \alpha_{3i}\Delta GFCF_{t-i} + \sum_{i=1}^{q} \alpha_{4i}\Delta ACGSF_{t-i} + \sum_{i=1}^{q} \alpha_{5i}\Delta TRADE_{t-i} + \sum_{i=1}^{q} \alpha_{6i}\Delta EXR_{t-i} + \lambda \mathrm{ECT}_{t-1} + \mu_t \quad (1)$$

$$\Delta AGO_t = \beta_{01} + \sum_{i=1}^{p} \beta_{1i}\Delta AGO_{t-i} + \sum_{i=1}^{q} \beta_{2i}\Delta TFP_{t-i} + \sum_{i=1}^{q} \beta_{3i}\Delta GFCF_{t-i} + \sum_{i=1}^{q} \beta_{4i}\Delta ACGSF_{t-i} + \lambda ECT_{t-1} + \eta_t \quad (2)$$

$$\Delta OLR_t = \gamma_{01} + \sum_{i=1}^{p} \gamma_{1i}\Delta OLR_{t-i} + \sum_{i=1}^{q} \gamma_{2i}\Delta TFP_{t-i} + \sum_{i=1}^{q} \gamma_{3i}\Delta GFCF_{t-i} + \sum_{i=1}^{q} \gamma_{4i}\Delta TRADE_{t-i} + \sum_{i=1}^{q} \gamma_{5i}\Delta EXR_{t-i} + \varepsilon_{1t} \quad (3)$$

$$\Delta AGVA_t = \delta_{01} + \sum_{i=1}^{p} \delta_{1i}\Delta AGVA_{t-i} + \sum_{i=1}^{q} \delta_{2i}\Delta TFP_{t-i} + \sum_{i=1}^{q} \delta_{3i}\Delta GFCF_{t-i} + \sum_{i=1}^{q} \beta_{4i}\delta TRADE_{t-i} + \sum_{i=1}^{q} \delta_{5i}\Delta EXR_{t-i} + \varepsilon_{2t}$$

where Δ is the difference operator, indicating changes in the variables from one period to the next; t is time period; $\sum$ is the summation symbol, indicating the sum over specified lags; α_{01}, β_{01}, γ_{01}, and δ_{01} are the constant terms for their respective models; α_{1i}, β_{1i}, γ_{1i}, and δ_{1i} are the coefficients for the respective lagged differences of variables; p and q are the lag orders of the dependent and independent variables, respectively; λ is the coefficient of the error correction term (ECT); ECT_{t-1} is the error-correction term at lag $t-1$; and μ_t, η_t, ϵ_{1t}, and ϵ_{2t} are the error terms.

The study employs the Akaike Information Criterion (AIC) for selecting the appropriate lag order in its time series analysis. The AIC is a widely used statistical measure that helps identify the model that best fits the data while balancing model complexity and goodness of fit. By minimizing the AIC value, the study ensures that the chosen lag length captures the underlying data patterns without overfitting, thereby enhancing the reliability and validity of the results. This criterion is particularly useful in a time-series analysis, as it aids in determining the optimal number of lagged observations to include, which is crucial for accurate model specification and subsequent interpretation of the relationships among the variables.

4. Results

4.1. Descriptive Statistics

The descriptive statistics in Table 1 reveal key insights into the characteristics and distribution of the variables examined in our study. The means and medians of variables related to agricultural productivity, such as agricultural total factor productivity (AGTFP), logarithm of agricultural output (LOG(AGO)), and agricultural value added (AGVA), indicate relatively stable central tendencies. This stability suggests consistency in agricultural performance over the study period. However, the standard deviations for AGTFP (11.27) and AGVA (4.59) highlight notable fluctuations, indicating some degree of variability in agricultural productivity and value added. These fluctuations may be influenced by factors such as technological advancements, policy interventions, and external market dynamics.

Turning to the variables associated with economic indicators and innovation, such as oil rents (OLRs), total factor productivity (TFP), gross fixed capital formation (GFCF), logarithm of agricultural credit guaranteed scheme fund (LOG(ACGSF)), trade volume (TRADE), exchange rate (EXR), logarithm of patents (LOG(PAT)), logarithm of scientific publications (LOG(SCI)), credit to the private sector (CPS), foreign direct investment (FDI), and interest rates (INRs), we observe a wider range of values, indicating greater variability. For instance, the standard deviations of OLR, GFCF, and EXR suggest considerable dispersion around their respective means, highlighting heterogeneity in oil sector revenue and investment patterns over time. The presence of skewness and kurtosis in some variables further underscores deviations from normal distribution, indicating potential asymmetry and peakiness in their distributions.

The Jarque–Bera test results provide additional insights into the distributional properties of the variables. While some variables exhibit p-values that fail to reject the null hypothesis of normality, indicating relatively normal distributions, others such as AGVA, GFCF, EXR, CPS, FDI, and INR display significant departures from normality, with p-values below the conventional significance level of 0.05. This deviation from normality suggests that certain variables may be influenced by non-normal factors or exhibit non-linear relationships, warranting further investigation into their underlying dynamics.

Table 1. Descriptive statistics.

	AGTFP	LOG(AGO)	AGVA	OLR	TFP	GFCF	LOG(ACGSF)	TRADE	EXR	LOG(PAT)	LOG(SCI)	CPS	FDI	INR
Units of Measurement	**Index, 2015 = 100**	**Naira**	**% of GDP**	**% of GDP**		**% of GDP**	**Naira**	**% of GDP**	**Local Currency per USD**	**Count of Patent Applications**	**Count of Scientific Publications**	**% of GDP**	**% of GDP**	**%**
Mean	96.38836	7.300383	22.88138	11.51401	0.363506	35.63058	13.46867	31.67436	108.0868	6.200730	7.136119	9.387385	1.476171	0.453578
Median	99.78920	7.608584	22.23471	11.14464	0.372391	33.10736	13.49881	33.71975	111.2313	6.143809	6.954143	8.234514	1.087951	4.310292
Maximum	111.0581	10.62440	36.96508	28.70544	0.695784	89.38613	16.38023	53.27796	401.1520	7.022868	8.974612	19.62560	5.790847	18.18000
Minimum	75.15485	2.836278	12.24041	1.573876	0.115230	14.16873	10.11273	9.135846	0.617708	5.459586	5.290134	4.957522	0.183822	−65.85715
Std. Dev.	11.26548	2.535542	4.589772	6.173340	0.181204	18.96943	2.115533	12.42937	109.9700	0.408439	0.947922	3.559186	1.235819	14.25917
Skewness	−0.759089	−0.403899	0.440302	0.477526	0.215744	1.087484	−0.046453	−0.260245	0.978891	0.138853	0.045019	1.039979	1.766764	−2.717477
Kurtosis	2.335507	1.735150	4.732787	2.875631	1.677406	3.924531	1.413048	2.128483	3.189257	2.012887	2.104805	3.625500	6.193077	12.91104
Jarque–Bera	4.691796	3.847817	6.454107	1.584635	3.145085	9.541464	4.317038	1.760356	6.609079	1.752519	1.349135	8.059020	38.74765	218.2694
Probability	0.095761	0.146035	0.039674	0.452794	0.207517	0.008474	0.115496	0.414709	0.036716	0.416337	0.509377	0.017783	0.000000	0.000000
Sum	3951.923	299.3157	938.1364	472.0742	14.17674	1460.854	552.2154	1298.649	4431.558	248.0292	285.4448	384.8828	60.52301	18.59670
Sum Sq. Dev.	5076.444	257.1590	842.6402	1524.405	1.247721	14,393.57	179.0193	6179.566	483736.1	6.506085	35.04373	506.7123	61.08993	8132.960
Observations	41	41	41	41	39	41	41	41	41	40	40	41	41	41

4.2. Correlation Matrix

The correlation coefficients presented in Table 2 above are suggestive of the direction and strength of relationships among the selected variables, shedding light on the impact of technological innovation on agricultural productivity in Nigeria. A notable finding is the weak negative correlation between agricultural total factor productivity (AGTFP) and total factor productivity (TFP) (−0.3957). This suggests that advancements in technological innovation across sectors may not necessarily translate into immediate improvements in agricultural productivity, indicating potential challenges in aligning agricultural practices with broader technological trends in the country. TFP, as a measure of technological innovation, exhibits moderate negative correlations with agricultural value added (AGVA) (−0.630) and oil rents (OLRs) (−0.638), suggesting that increased technological innovation may coincide with reduced agricultural value added and oil revenues. However, TFP shows weak positive correlations with agricultural credit (LOG(ACGSF)) (0.268) and exchange rate (EXR) (0.381), implying potential links between technological progress and agricultural credit availability, as well as exchange rate dynamics.

Table 2. Correlation matrix.

	AGTFP	LOG(AGO)	AGVA	OLR	TFP	GFCF	LOG(ACGSF)	TRADE	EXR	LOG(PAT)	LOG(SCI)	CPS	FDI	INR
AGTFP	1													
LOG(AGO)	0.760	1												
AGVA	0.727	0.468	1											
OLR	0.383	−0.000	0.362	1										
TFP	−0.395	0.095	−0.630	−0.638	1									
GFCF	−0.718	−0.929	−0.520	−0.114	0.036	1								
LOG(ACGSF)	0.605	0.952	0.322	−0.100	0.267	−0.900	1							
TRADE	0.759	0.567	0.623	0.556	−0.499	−0.538	0.452	1						
EXR	0.476	0.875	0.176	−0.252	0.380	−0.764	0.853	0.267	1					
LOG(PAT)	0.418	0.659	0.307	−0.033	0.189	−0.580	0.666	0.435	0.541	1				
LOG(SCI)	0.623	0.967	0.328	−0.042	0.181	−0.922	0.944	0.463	0.913	0.624	1			
CPS	0.413	0.741	0.170	−0.209	0.284	−0.696	0.808	0.237	0.675	0.512	0.749	1		
FDI	0.304	0.0741	0.357	0.685	−0.419	−0.140	0.037	0.293	−0.119	−0.011	0.046	0.087	1	
INR	0.296	0.462	0.342	−0.035	−0.077	−0.559	0.459	0.227	0.379	0.331	0.490	0.421	−0.049	1

Moving to gross fixed capital formation (GFCF), a key indicator of investment, its strong negative correlations with agricultural output (LOG(AGO)) (−0.930) and agricultural credit (LOG(ACGSF)) (−0.900) highlight the inverse relationship between capital formation and agricultural credit or output. Additionally, GFCF demonstrates moderate-to-strong negative correlations with trade volumes (TRADE) (−0.538) and exchange rates (EXR) (−0.765), indicating potential impacts of investment activities on trade volumes and exchange rate fluctuations. The matrix also reveals that patent counts (LOG(PAT)) and scientific publications (LOG(SCI)) (0.659 and 0.967, respectively) are positively associated with agricultural output, suggesting a strong connection between scientific and technological advancements and agricultural output, albeit not as directly with productivity.

Considering agricultural credit (ACGSF), the correlation matrix indicates very strong positive associations with agricultural output (LOG(AGO)) (0.952) and scientific publications (LOG(SCI)) (0.945), emphasizing the intertwined nature of agricultural credit with agricultural output and scientific advancements. Moreover, ACGSF displays strong positive correlations with exchange rates (EXRs) (0.853) and credit to the private sector (CPS) (0.808), suggesting connections between credit availability, exchange rates, and financial sector performance.

There is a moderate negative correlation between technological advancement (TFP) and oil rents (OLRs) (−0.638), indicating a potential trade-off between technological progress and revenues from the oil sector. Additionally, weak correlations between oil rents (OLRs) and exchange rates (EXRs) (−0.252) and the moderate positive relationship between OLRs and trade volume (TRADE) (0.557) suggest the influence of global market dynamics on the oil sector in Nigeria. Moreover, the weak negative relationship between investment in fixed assets (GFCF) and the oil sector (−0.114) implies limited impact of capital investment on oil sector performance. EXR displays notable positive correlations with agricultural output (LOG(AGO)) (0.876) and scientific publications (LOG(SCI)) (0.913), suggesting interdependencies between exchange rates and agricultural organizations or scientific innovations.

Finally, positive correlations between real interest rates (INRs) and agricultural productivity and output (0.297 and 0.463) indicate potential benefits of higher real interest rates on agricultural performance, highlighting the importance of monetary policy in shaping agricultural productivity dynamics. Foreign direct investment (FDI), however, depicts weak positive correlations with agricultural performance indicators, suggesting a nuanced and possibly indirect relationship between foreign investment and agricultural productivity.

The unit root test results offer crucial information about the stationarity properties of the variables examined in this study. Employing both the Augmented Dickey–Fuller (ADF) and Philips–Perron (PP) tests, we assessed whether the variables possess a unit root and thereby determine their stationarity status.

The results of the unit root tests is presented in Table 3, the table is divided into two distinct categories based on the null hypothesis: 'level' and 'first difference'. Our analysis reveals that most of the variables (AGTFP, AGO, AGVA, OLR, TFP, ACGSF, TRADE, EXR, PAT, SCI, and CPS) demonstrate signs of non-stationarity in their level form, with *p*-values exceeding the conventional threshold of 0.05 for both the ADF and PP tests.

Table 3. Unit root tests.

Variables	ADF		PP	
	Level	**First Difference**	**Level**	**First Difference**
AGTFP	0.2375	0.0362	0.3344	0.0000
LOG(AGO)	0.2182	0.0035	0.2182	0.0030
AGVA	0.1096	0.0000	0.0726	0.0000
OLR	0.3749	0.0000	0.0640	0.0000
TFP	0.3495	0.0000	0.3328	0.0000
GFCF	0.0064	0.0012	0.0086	0.0017
LOG(ACGSF)	0.6497	0.0029	0.7382	0.0029
TRADE	0.1541	0.0000	0.1821	0.0000
EXR	1.0000	0.0032	1.0000	0.0043
LOG(PAT)	0.7455	0.0090	0.5506	0.0000
LOG(SCI)	0.9208	0.0061	0.9083	0.0071
CPS	0.2186	0.0000	0.5362	0.0000
FDI	0.0049	0.0000	0.0059	0.0000
INR	0.0000	0.0000	0.0000	0.0001

However, exceptions exist, notably GFCF, FDI, and INR, which exhibit stationarity at the level for both tests. For instance, AGTFP yields *p*-values of 0.2375 and 0.3344 in its level form for the ADF and PP tests, respectively, indicating non-stationarity.

Yet, upon differencing, the *p*-values reduce significantly to 0.0362 and 0.000, signifying the attainment of stationarity. Similar patterns are observed across other variables, underscoring the effectiveness of differencing in rendering the variables stationary for subsequent analysis.

Evidence from this test indicates that the regression model used to examine the impact of technological innovation on agricultural productivity in Nigeria is appropriate and consistent with the ARDL estimation technique. This is because the variables under consideration exhibit a mixed stationarity form, comprising both levels and first differences. This supports the validity and reliability of the conclusions regarding the impact of technological innovation on agricultural productivity amidst oil transition in Nigeria.

The Granger causality test in Table 4 assesses the directional relationship between two key variables: AGTFP and TFP, with the latter representing technological innovation. The results show a statistically significant unidirectional causality from TFP to AGTFP, with a *p*-value of 0.0009, indicating that technological innovation has a strong predictive influence on agricultural productivity at the 1% significance level. However, AGTFP does not Granger Cause TFP, as reflected by the non-significant *p*-value of 0.1280. This suggests that while technological innovation drives changes in agricultural productivity, the reverse is not true, indicating no evidence of feedback effects or endogeneity concerns between the variables. These findings underscore the role of technological progress in shaping agricultural outcomes in Nigeria.

Table 4. Causality test.

Null Hypothesis	Obs	F-Statistic	Prob.
AGTFP does not Granger Cause TFP	37	2.19377	0.1280
TFP does not Granger Cause AGTFP		8.79471	0.0009

4.2.1. Objectives 1: Impact of Technological Innovation on Agricultural Productivity

The results of the ARDL bounds test is presented in Table 5, it assesses the presence of a long-run equilibrium relationship among the variables of interest. With an F-statistic value of 6.28, exceeding the critical values of the lower and upper bounds at a 5% significance level, we find evidence supporting the existence of long-run relationships among the variables under consideration. Therefore, there is sufficient evidence to reject the null hypothesis and conclude that a long-run equilibrium relationship exists between agricultural productivity (AGTFP) and technological innovation (TFP, GFCF, LNACGSF, TRADE, and EXR) in Nigeria.

Table 5. Results of bounds test.

	F-Statistic	I0 Bound	I1 Bound
Values	6.277068	2.62	3.79

The ARDL regression analysis offers valuable insights into the short and long-run relationships between AGTFP and its determinants, focusing on technological innovation (TFP), GFCF, ACGSF, TRADE, and EXR from 1981 to 2021.

In Table 6, we present the results of the short run, lagged values of agricultural productivity (AGTFP) show a mixed impact: a one-period lag exhibits a statistically significant negative effect of −0.4856 on its current value, while a two-period lag shows a positive but weaker impact of 0.3132. This is suggestive of a complex relationship between AGTFP and its lagged values, likely associated with technological constraints within the sector and market dynamics, particularly input prices, considering the high inflationary pressures in the country over time (Rongjian et al. 2019; Djoumessi 2022).

TFP and its lags exhibit statistically significant positive coefficients and consistent with a priori expectations, indicating that increased technological innovation leads to higher agricultural productivity. For instance, a 1% rise in technological innovation (TFP) induces approximately a 13% increase in agricultural productivity in the short term. However, significance diminishes with lagged values, with TFP(−1) not being significant and TFP(−2) being marginally significant. These lagged values are likely to capture the adjustments and adaptations in agricultural practices preceding the gradual unfolding of technological adoption effects (Ndaghu et al. 2023).

Table 6. Results of regression analysis.

Dep. Variable: AGTFP	Short-Run ARDL	Long-Run ARDL
AGTFP(−1)	−0.485642 *** (0.162660)	
AGTFP(−2)	0.313153 * (0.153593)	
TFP	12.996919 ** (6.129376)	−90.705103 *** (29.133142)
TFP(−1)	1.704428 (6.549078)	
TFP(−2)	10.250378 * (5.824857)	
GFCF	0.132536 (0.124183)	−0.741846 (0.723579)
GFCF(−1)	−0.415371 *** (0.127285)	
GFCF(−2)	0.305549 *** (0.085259)	
LOG(ACGSF)	−0.243834 (1.071571)	−1.158985 (5.282161)
TRADE	−0.177887 *** (0.049887)	−1.171365 * (0.596564)
EXR	−0.009330 (0.010459)	−0.044347 (0.062212)
CointEq(−1)	−0.210386 ** (0.085558)	
Constant		219.468117 * (109.461685)

Note: Standard errors are reported in parenthesis; *, **, and *** represent 10%, 5%, and 1%, respectively.

GFCF and its lags show mixed effects on AGTFP, with both positive and negative impacts, indicating a nuanced relationship. The coefficients of ACGSF, TRADE, and EXR (−0.2438, −0.1779, and −0.0093, respectively) do show negative impacts on AGTFP in the short run, with only TRADE being significant. This implies that the ACGSF might not be effectively directed toward fostering technological innovation (Balana and Oyeyemi 2022).

The presence of a significant error correction term (CointEq(−1)) with a negative coefficient (−0.2104) at the 5% level indicates the presence of a stable long-run equilibrium relationship between the variables, with adjustments occurring at a rate of approximately 21% per period when the system experiences disequilibrium.

Transitioning to the long run, TFP exhibits a significant negative coefficient, suggesting that increased technological innovation leads to decreased agricultural productivity over time. That is, a 1% increase in nation-wide total factor productivity will induce a 90.71% decrease in agricultural total factor productivity. This is suggestive of the fact that the initial positive effects may diminish or reverse over time. Conversely, the coefficient for GFCF in the long run is negative (−0.7419), although not statistically significant, suggesting a potential but uncertain impact on AGTFP over time.

ACGSF, TRADE, and EXR do not exhibit significant impacts on AGTFP in the long run, with coefficients close to zero and statistically insignificant. The constant term (C) suggests an expected AGTFP of approximately 219.47 units when all other variables are zero, albeit marginally significant.

Comparing the long-run coefficients with the short-run ones from the ARDL model, differences in significance and magnitude are apparent. In the short term, lagged AGTFP,

TFP, and GFCF exhibit significant impacts on AGTFP, while others may lack statistical significance or show mixed effects. However, in the long run, the influence of TFP becomes more pronounced and significant, indicating its dominant role in shaping agricultural productivity over time. Thus, we reject the null hypothesis and affirm a significant relationship between technological innovation and agricultural productivity in Nigeria. Conversely, the effects of variables such as GFCF, ACGSF, TRADE, and EXR are less prominent in the long run, suggesting their impacts may be more transient or influenced by unaccounted factors.

4.2.2. Objectives 2: Impact of Agricultural Innovation on Agricultural Output

The ARDL bounds test aimed to ascertain the existence of long-run relationships among the analyzed variables (AGO, AGTFP, GFCF, and ACGSF), (see Tables 7 and 8). In this instance, the calculated F-statistic (1.2291) falls below the critical value bounds provided for the conventional 5% threshold, leading us to fail to reject the null hypothesis. This indicates insufficient evidence to assert the presence of long-run relationships among the variables in the model at standard levels of significance. In essence, it suggests a lack of a long-term relationship between output and technological innovation within the agricultural sector.

Table 7. Results of bounds test.

	F-Statistic	I0 Bound	I1 Bound
Values	1.229078	3.23	4.35

Source: Author's computation (2024).

Table 8. Results of regression analysis.

Dep. Variable: LOG(AGO)	Short-Run ARDL
LOG(AGO(−1))	1.438718 *** (0.185242)
LOG(AGO(−2))	−0.757006 ** (0.287187)
LOG(AGO(−3))	0.257262 (0.169151)
AGTFP	0.003439 (0.004408)
GFCF	−0.013607 * (0.006737)
GFCF(−1)	0.018206 ** (0.008529)
GFCF(−2)	−0.012603 ** (0.005767)
LOG(ACGSF)	0.083087 (0.113581)
LOG(ACGSF(−1))	0.034489 (0.154148)
LOG(ACGSF(−2))	−0.344734 ** (0.152554)
LOG(ACGSF(−3))	0.209129 * (0.110472)
Constant	0.775767 (1.290656)

Note: Standard errors are reported in parentheses; *, **, and *** represent 10%, 5%, and 1%, respectively. Source: Author's computation (2024).

The short-run coefficients provide valuable insights into the immediate impacts of the dynamic regressors on LOG(AGO). Firstly, lagged values of AGO exhibit significant effects, with AGO(−1) showing a strong positive coefficient (1.4387) and AGO(−2) displaying a negative coefficient (−0.757). This suggests a persistent positive influence from the previous period's agricultural output, with a negative impact from two periods ago, indicating a short-term correction effect. The coefficient for AGO(−3) is positive (0.2573), albeit not statistically significant, implying a weaker but still present influence from three periods ago.

Moving to the dynamic regressors, AGTFP's coefficient (0.0034) is positive but not statistically significant, indicating a minor immediate effect on AGO. However, GFCF's coefficients show more pronounced impacts, with GFCF and its lagged values exhibiting significant effects. Specifically, GFCF has a negative coefficient (−0.0136), indicating that an increase in gross fixed capital formation leads to a decrease in agricultural output in the short run. As observed with AGTFP, the lagged values of GFCF display both positive and negative coefficients, suggesting varied short-term impacts from previous periods' investment levels.

The coefficients associated with ACGSF offer interesting observations. Although the coefficient for ACGSF in the current period is positive (0.083), it fails to reach statistical significance, implying a minor immediate impact on AGO. However, the lagged values of ACGSF demonstrate more pronounced impacts, with ACGSF(−2) and ACGSF(−3) exhibiting statistically significant negative and positive coefficients, respectively, suggesting that agricultural credit guarantee scheme fund levels from two and three periods ago have a significant short-term influence on agricultural output.

In conclusion, the short-run coefficients highlight a dynamic and intricate relationship between agricultural output and innovation in Nigeria. Lagged output values notably influence current output levels, indicating persistence over time. However, the immediate effects of innovation, investment, and credit guarantee scheme funds vary both in significance and direction, with agricultural innovation showing insignificance. Consequently, based on this outcome, we uphold the null hypothesis, suggesting that agricultural innovation has no significant influence on agricultural output in Nigeria.

4.2.3. Objective 3: Comparison of the Impact of Technological Innovation on Oil and Agriculture

In Table 9, we present the results of the ARDL bounds test for the impact of technological innovation on oil and agriculture. The ARDL bounds test examines whether a long-run equilibrium relationship exists among the variables of interest. With F-statistic values of 2.98 and 2.82, below the critical values of their respective lower and upper bounds at a 5% significance level, there is no substantiating evidence for the presence of long-run relationships among the variables being studied. Consequently, there is insufficient evidence to reject the null hypothesis, indicating no long-run equilibrium relationship between technological innovation and oil rents, as well as technological innovation and agricultural value added.

Table 9. Results of bounds test.

	F-Statistic	I0 Bound	I1 Bound
Model 1	2.974503	2.86	4.01
Model 2	2.816324	2.86	4.01

Source: Author's computation (2024).

The ARDL analysis as presented in Table 10 provides insights into the relationships between technological innovation, represented by TFP, GFCF, TRADE, and EXR, and the oil sector (OLR) and agricultural sector (AGVA) in Nigeria.

Table 10. (Results of Regression Analysis).

Explanatory Variables	Dep. Variable: OLR	Dep. Variable: AGVA
OLR(−1)/AGVA(−1)	0.411624 ** (0.170837)	0.483405 *** (0.136338)
TFP	−5.549463 (6.229909)	−9.723358 ** (3.945871)
GFCF	−0.006840 (0.081175)	−0.026433 (0.048159)
TRADE	0.249432 ** (0.101562)	−0.070126 (0.060587)
TRADE(−1)	−0.137314 (0.098422)	0.085395 (0.054002)
EXR	−0.011688 (0.016411)	0.004699 (0.008887)
Constant	6.742564 (6.670831)	15.50906 *** (5.116708)

Note: standard errors are reported in parentheses; **, and *** represent 5%, and 1%, respectively. Source: Author's computation (2024).

Starting with the oil sector, the coefficient for lagged OLR (−1) is positive and statistically significant (0.4116), indicating that past levels of oil sector revenues positively influence current revenues. Conversely, the coefficients for all the explanatory variables are not statistically significant in explaining variations in OLR, except for TRADE in its current levels. This suggests that changes in technological innovation, investment, trade volume, and exchange rates have limited short-term impacts on oil sector revenues.

In contrast, for the agricultural sector (AGVA), the coefficients present a different picture. Lagged AGVA (−1) has a positive and significant coefficient (0.4834), indicating that past levels of agricultural value added positively affect current levels. Interestingly, TFP exhibits a negative but statistically significant coefficient (−9.7234), implying that increases in technological innovation induce decreases in agricultural value added. This suggests that the relationship between technological innovation and agricultural productivity may be more nuanced than initially anticipated. However, the coefficients for GFCF, TRADE, and EXR are not statistically significant in explaining variations in AGVA.

The effects of technological innovation differ between Nigeria's oil and agricultural sectors. While past revenues significantly influence current revenues in the oil sector, technological innovation and other factors show no immediate significant effects. In contrast, in agriculture, past agricultural value added significantly impacts current levels, and technological innovation (TFP) shows a significant negative impact on agricultural productivity. This leads us to reject the null hypothesis and emphasize the need for sector-specific policies and interventions (Aye and Odhiambo 2021).

To explore the robustness of our model for the core objective, we conducted two additional regression analyses. The results are presented in Table 11. The first analysis measured technological innovation using PAT and SCI instead of TFP. The second analysis measured investments in fixed assets, using the product of CPS and FDI instead of GFCF. Both analyses incorporated other explanatory variables and maintained ARDL as the estimation technique.

In comparing the first regression with the original model, TFP remains significant in both the short and long run, while PAT*STCI is only significant in the long run (−23.79). The consistent significance of TFP supports the robustness of the initial estimates. The long-run significance of PAT*STCI, despite its short-run insignificance, suggests that while TFP has an immediate impact, the effect of patents and scientific innovation is more complex and may require further exploration.

Table 11. Robustness checks.

Dep. Variable: AGTFP	Short-Run ARDL	Long-Run ARDL
LOG(PAT*SCI)	0.615223 (2.146106)	−23.789149 ** (9.786836)
LOG(PAT*SCI(−1))	1.815923 (3.157214)	
LOG(PAT*SCI(−2))	3.649458 (3.235388)	
CPS*FDI	−0.011452 (0.035115)	−0.310681 (0.182384)

Note: Standard errors are reported in parentheses; ** represent 5%.

In examining GFCF and CPS*FDI, the first model shows a long-run coefficient of −0.7418 for GFCF, indicating an insignificant effect. The second model, replacing GFCF with CPS*FDI, yields a long-run coefficient of -0.3107, which is also insignificant. This consistent insignificance suggests that financial capital investments (GFCF or CPS*FDI) may not have a robust impact on agricultural productivity. However, the consistent significance of TFP across both models reaffirms its crucial role in determining agricultural productivity in Nigeria.

The two models for the robustness checks exhibit a long-run equilibrium relationship among the variables, with significant error-correction terms. The consistent significance of TFP in both models further supports its robustness as a critical factor. Thus, our model is consistent, appropriate, and reliable for policy implications.

The CUSUM (Cumulative Sum) test in Figure 1 assesses the stability of the relationship between technological innovation and agricultural productivity in Nigeria over time. The CUSUM line shows the cumulative sum of the residuals from the regression model, with horizontal lines representing the 5% significance level bounds. Since the CUSUM line remains within these critical bounds, the test confirms the regression model's stability, indicating that the relationship between technological innovation and agricultural productivity was consistent from 1981 to 2021.

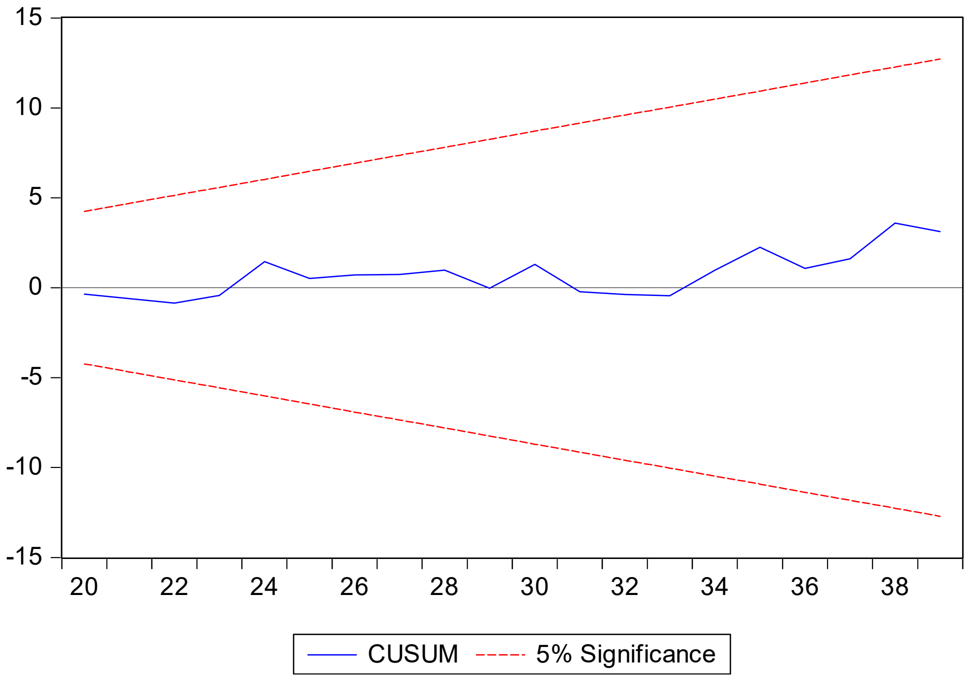

Figure 1. CUSUM test assessing the nature of the relationship between technological innovation and agricultural productivity in Nigeria.

Figure 2 illustrates the CUSUM of Squares test, a diagnostic tool for detecting systematic changes in the regression model's variance over time. This test plots the cumulative sum of squared residuals against the 5% significance bounds. Since the CUSUM of Squares line stays within the critical limits, it confirms that the variance in the relationship between technological innovation and agricultural productivity is stable throughout the study period, ensuring the reliability of the regression model's predictions and conclusions.

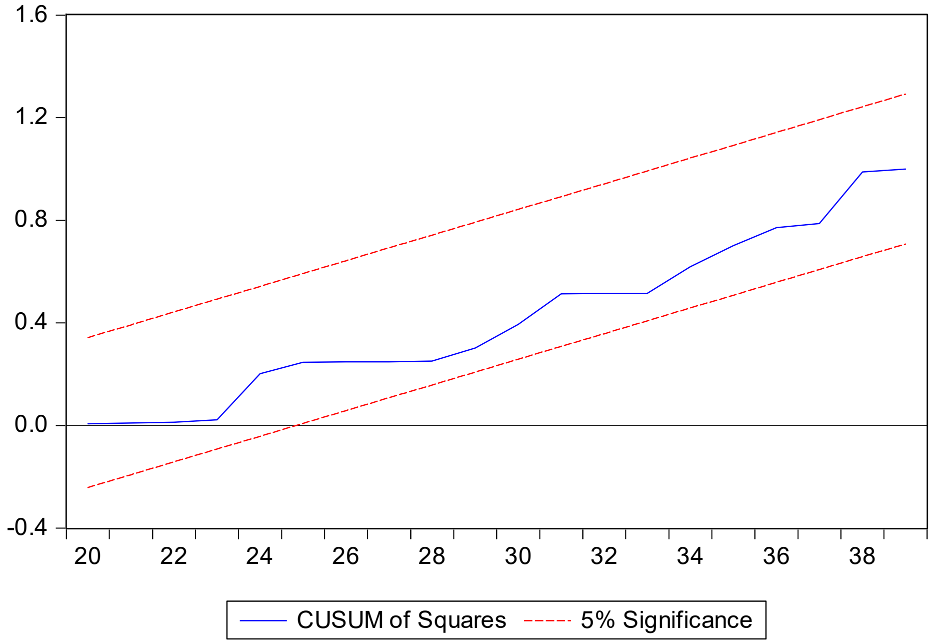

Figure 2. CUSUM of Squares test assessing the nature of the relationship between technological innovation and agricultural productivity in Nigeria.

4.3. Discussion of Results

The regression analyses provide crucial insights into the intricate relationship between technological innovation and agricultural productivity amidst Nigeria's transition away from oil dependence. Notably, the findings underscore a significant and negative influence of immediate lagged agricultural productivity (AGTFP(−1)), indicative of prevailing technological constraints within the sector. Moreover, the study reveals the substantial impact of technological innovation, proxied by total factor productivity (TFP), on agricultural productivity both in the short and long term. The lagged values of technological innovation suggest a gradual realization of its positive effect on agricultural productivity over time (Ndaghu et al. 2023). However, the long-run coefficient depicting a more pronounced, yet negative impact raises concerns. This negative correlation could be attributed to several factors, such as diminishing returns on technological investments, elevated costs of technology due to currency weakness, and a lack of skilled manpower to effectively implement technological practices, thereby limiting their productivity-enhancing potential (Akinola et al. 2023; Ejem et al. 2023).

To address these challenges, a multi-faceted policy approach is needed. First, the government should invest in capacity-building programs to equip farmers with the skills needed to effectively use new technologies, while promoting agricultural education to develop a skilled workforce. Subsidies and tax incentives for technology adoption can help reduce costs, especially in the context of currency depreciation, which local farmers may find difficult to manage. Encouraging public–private partnerships will also facilitate the development of affordable, locally suited technologies for Nigeria's agricultural sector. Also, improving infrastructure and expanding access to finance for smallholder farmers will support wider and more sustainable technology adoption, ensuring long-term productivity gains. Notably, the consistent coefficient estimates of TFP highlight its crucial role in determining agricultural productivity, as demonstrated by its impact on both AGTFP and AGVA.

The mixed findings regarding investment in fixed assets (GFCF) vis-à-vis agricultural productivity (AGTFP) and output (AGO) underscore the complexities inherent in the relationship and underscore the inadequacy of investment in agricultural-related infrastructure. Furthermore, our results indicate that agricultural innovation yields a positive albeit insignificant impact on agricultural output. This suggests that agricultural output in Nigeria is predominantly labor-induced rather than capital-induced (Ojo and Baiyegunhi 2023). The extant literature affirms this notion, with over 90% of non-mechanized production systems relying on human labor, and mechanized systems still requiring 50–60% of tasks to be performed manually (Edohen and Ikelegbe 2018; Ogunsolu 2021). It is worth noting, however, that Djoumessi's (2022) position, where the estimated elasticity of production to labor is positive but not significant, may differ due to a larger study area and distinct model specifications (Habtewold and Heshmati 2023).

Furthermore, the agricultural credit guarantee scheme funds (ACGSFs) exhibit a negative relationship with agricultural productivity in both short-run and long-run analyses. However, while their current and lagged values mostly display insignificant positive relationships with agricultural output in the short run, this may signal potential misappropriation of funds (Rongjian et al. 2019).

Given the stark disparities observed between the oil and agricultural sectors through our comparative analysis, it becomes increasingly clear that the agricultural sector stands to gain more from technological innovation compared to the oil sector. This deduction is drawn from the significant negative coefficient of TFP on AGVA, implying that technological advancements lead to decreased agricultural productivity. This underscores the potential for improvement in the agricultural sector through the adoption of advanced technologies such as precision agriculture, improved irrigation techniques, mechanization, and digital farming practices (Rongjian et al. 2019; Balana and Oyeyemi 2022; Ndaghu et al. 2023). Conversely, the oil sector, characterized by an insignificant negative coefficient estimate, may not experience significant short-term benefits from technological innovation. Therefore, given the transformative potential of technological innovation to positively impact productivity and output in the agricultural sector, prioritizing advancements in agriculture emerges as a strategic imperative to propel growth, sustainability, and resilience in Nigeria's economy.

4.4. Recommendations

The study's findings lead to the following recommendations:

1. Invest in agricultural technology infrastructure: The government and relevant stakeholders should prioritize substantial investment in agricultural infrastructure. This includes funding for advanced irrigation systems, precision agriculture tools, and mechanized farming equipment. These investments can help mitigate the diminishing returns and high technology costs currently limiting agricultural productivity.
2. Enhance agricultural education and training: To address the lack of the skilled manpower necessary for effective implementation of technological practices, educational programs and vocational training in agricultural technology should be expanded. Universities and technical institutions should collaborate with agricultural technology companies to ensure that farmers and agricultural professionals are well-trained in the latest innovations.
3. Strengthen agricultural credit schemes: Revise the Agricultural Credit Guarantee Scheme Fund (ACGSF) to ensure the proper allocation and utilization of funds. Implement robust monitoring and evaluation frameworks to prevent misappropriation of funds and ensure that financial support is effectively enhancing technological adoption and productivity in the agricultural sector.
4. Promote research and development in agriculture: Increase funding and support for research and development (R&D) in agriculture to foster innovation. Partnerships

between government agencies, research institutions, and private sector entities should be encouraged to develop and disseminate new agricultural technologies tailored to Nigeria's specific climatic and soil conditions.

5. Implement favorable trade policies: Reform trade policies to support the agricultural sector. Reducing trade barriers and providing incentives for agricultural exports can enhance market access for farmers, allowing them to benefit from economies of scale and better integrate into global value chains, which can incentivize the adoption of technological innovations.
6. Encourage private sector participation: Foster a conducive environment for private sector investments in agricultural technology. This includes creating favorable tax policies, providing subsidies for technology adoption, and establishing public-private partnerships to facilitate the development and distribution of agricultural technologies. Enhanced collaboration with technology firms can drive innovation and efficiency in the agricultural sector.

5. Conclusions

Based on our objectives and study findings, we conclude that there is a meaningful relationship between technological innovation and agricultural productivity in Nigeria. Technological innovation is a significant factor in enhancing agricultural productivity, highlighting the critical role of modern technologies in the sector. Conversely, agricultural innovation, in terms of new methods and practices, appears to have an insignificant impact on overall output, indicating that Nigeria's agricultural sector relies more heavily on labor than on capital investments. This reliance underscores the predominance of manual labor over mechanized or technologically driven agricultural processes.

Additionally, our comparative analysis reveals that the agricultural sector benefits more from technological innovation than the oil sector. While technological advancements in agriculture have the potential to significantly boost productivity and efficiency, the same level of impact is not observed in the oil sector. This disparity suggests that targeted technological interventions can yield substantial gains in agriculture.

Furthermore, variables such as gross fixed capital formation (GFCF) and trade have proven significant in determining agricultural productivity. Investments in fixed assets and the expansion of trade activities play crucial roles in supporting agricultural development. These findings underscore the importance of creating policies that enhance technological adoption, promote investment in agricultural infrastructure, and facilitate trade to drive growth in Nigeria's agricultural sector.

Limitations of the Study

This study acknowledges significant limitations due to data availability and accuracy issues. Missing and inconsistent data may have influenced the analysis and interpretation of results, potentially introducing biases and errors. These limitations could impact variable selection, model specification, and result interpretation, ultimately affecting the reliability and applicability of the findings. Future research should focus on addressing data-quality issues through improved collection methods and validation procedures to enhance the credibility of empirical analyses.

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