Coastal Tourism, Fishery Production and Youth Employment in Nigeria: The Moderating Role of Digital Technology Adoption

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DOI: https://doi.org/10.47772/IJRISS.2026.101100239

Received: 06 November 2026; Accepted: 11 November 2026; Published: 24 November 2026

ABSTRACT

Nigeria's blue economy holds large untapped potential for youth employment, yet no study tests whether digital technology changes how coastal tourism and fishery production translate into jobs for young people. This study estimates the effects of coastal tourism and fishery production on youth employment in Nigeria over 1996–2024 and tests digital technology adoption as a moderator of both links. International tourism receipts proxy coastal tourism, aquaculture output measures fishery production, and the annual change in a principal-component index of internet and mobile use measures digital technology adoption; the data come from ILOSTAT, the World Bank World Development Indicators and the Central Bank of Nigeria. ARDL bounds tests with bootstrap critical values support a long-run relationship only in the moderated model, and Zivot–Andrews and Bai–Perron tests locate a structural shift in 2011–2013. Block-bootstrap, placebo and break-date checks confirm the moderated estimates. At the mean rate of digital adoption, coastal tourism raises youth employment (elasticity 0.106) and fishery production lowers it (−0.110). Digital adoption amplifies the tourism effect (interaction 0.480) and deepens the fishery effect (interaction −0.759); one standard deviation above the mean, the two elasticities reach 0.186 and −0.236. Johnson–Neyman analysis shows that the tourism effect becomes significant once the adoption index rises and the fishery effect becomes significantly negative once annual adoption growth exceeds about 0.04 index points. About 83% of any deviation from the long-run path closes within a year. Digital technology therefore amplifies the employment gains of coastal tourism and deepens the employment costs of fisheries. Policy should pair digital infrastructure with investment in coastal destinations, redesign fisheries digitalisation around labour-inclusive applications, and judge blue-economy programmes by the jobs they create for young people.

Keywords: coastal tourism; fishery production; youth employment; digital technology adoption; Nigeria **JEL Classification:** J21; L83; O13; O33; Q22

INTRODUCTION

Nigeria's blue economy remains one of the country's least exploited sources of diversification and jobs (FAO, 2022). It rests on a coastline of more than 850 kilometres across nine coastal states along the Gulf of Guinea, a fish-rich exclusive economic zone, and a network of lagoons, estuaries and mangroves. Its development matters more because Nigeria still depends on oil for revenue and exports (Daniel & Okon, 2022; Jeremiah, Okon & Daniel, 2017), a dependence linked to volatility and inequality (Ekpo, Onyemailu & Anyim, 2025) and to persistent poverty despite oil wealth (Ekpo & Udoh, 2025). The blue economy offers a pathway to sustainable development and poverty reduction, particularly for young people, who make up more than 60% of Nigeria's population (World Bank, 2023). Coastal tourism and fishery production anchor this potential. Lagos, Rivers, Bayelsa, Delta, Cross River and Akwa Ibom host beaches, wetlands and heritage sites that can draw visitors and generate foreign exchange, infrastructure and local enterprise, while artisanal operators, who supply between 68% and 74% of domestic fish output, sustain food security and over 5.8 million livelihoods in coastal

communities (UNECA, 2021; Federal Department of Fisheries [FDF], 2015). The Federal Government established the Ministry of Marine and Blue Economy in 2023 (Federal Government of Nigeria, 2023); its pioneer minister put the sector's annual potential at ₦7 trillion, a "trillion-naira ocean" still largely untapped (Oye, 2024; Federal Ministry of Marine and Blue Economy [FMMBE], 2024; CBN, 2023). The contribution of aquatic food systems to GDP rose from 0.5% in 2013 to 4.5% in 2021, and total fish output grew from 1.07 million tonnes in 2014 to 1.17 million tonnes in 2018, with 1.28 million tonnes projected for 2030 (FAO, 2020).

This potential unfolds against a youth employment crisis and a fast-digitalising economy. Youth (15–24 years) unemployment stood at 8.4% in the first quarter of 2024, alongside a youth NEET rate of 14.4% and informal employment above 92% (National Bureau of Statistics [NBS], 2024). These figures understate underemployment in an economy where subsistence and informal work remain the norm (Udo, Ekpo & Iwatt, 2023), and coastal states record some of the country's highest joblessness and restiveness rates (NBS, 2023). Digital technology—mobile payments, social-media marketing, e-booking platforms and data-driven fishing applications—cuts transaction costs, widens market access and raises productivity in tourism and fisheries (OECD, 2020; World Bank, 2022). Digital platforms let coastal tourism operators market destinations directly and give artisanal fishers access to price information, mobile banking and cold-chain logistics, while ride-hailing, delivery, content creation and online marketplaces open further channels for youth work. Yet adoption remains low among coastal small and medium enterprises (SMEs), held back by poor digital infrastructure, low digital literacy and limited finance (Nigerian Communications Commission [NCC], 2023), and by unreliable power and a weak operating environment that raise private-sector costs (Ekpo, Daniel & Udoh, 2022). Many tourism operators and fisherfolk therefore rely on traditional methods that limit their reach and their capacity to create jobs.

How coastal tourism and fishery production translate into youth employment in Nigeria remains poorly understood, and the role of digital technology in that translation has received almost no empirical attention. Blue-economy studies treat coastal tourism and fisheries mainly as drivers of GDP, trade or foreign exchange (OECD, 2020; UNECA, 2021) and give little attention to youth employment. Nigerian statistics compound the problem: the National Bureau of Statistics (2024) reports youth employment, and the Central Bank of Nigeria (2023) reports output, under conventional sectors such as agriculture and ICT, so fisheries, aquaculture and coastal tourism disappear from view. A separate literature treats digital adoption as an independent driver of employment or productivity, not as a condition that shapes the employment effects of other sectors. The two literatures run in parallel: no known Nigerian study tests digital technology adoption as a moderator of the coastal tourism–employment or fishery production–employment relationship. The omission matters for policy. If digital adoption strengthens these relationships, by helping operators reach larger markets or fishers secure better prices and logistics, digital infrastructure and skills complement blue-economy investment. If it substitutes for youth labour or favours capital-intensive operators over small-scale entrants, the two policy agendas pull against each other. Without evidence on this interaction, Nigeria risks designing blue-economy and digital-economy policies in isolation, at a cost to youth employment.

The study examines the effects of coastal tourism and fishery production on youth employment in Nigeria and the moderating role of digital technology adoption in these relationships. Specifically, it (i) examines the effect of coastal tourism on youth employment; (ii) examines the effect of fishery production on youth employment; (iii) assesses whether digital technology adoption moderates the coastal tourism–employment relationship; and (iv) assesses whether digital technology adoption moderates the fishery production–employment relationship.

Correspondingly, the study asks: (i) What effect does coastal tourism have on youth employment in Nigeria? (ii) What effect does fishery production have on youth employment in Nigeria? (iii) To what extent does digital technology adoption moderate the coastal tourism–employment relationship? (iv) To what extent does digital technology adoption moderate the fishery production–employment relationship?

The study serves several audiences. For the Federal Ministry of Marine and Blue Economy, coastal state governments, and youth-focused agencies such as the National Directorate of Employment and the National Youth Investment Fund, it provides evidence for designing blue-economy interventions around the prevailing digital environment rather than in parallel with it. For fishery cooperatives, tourism boards and coastal SMEs, it

shows whether digital adoption adds to or subtracts from their capacity to absorb young workers. For digital-economy regulators, including the National Information Technology Development Agency and the NCC, it shows how digital expansion changes the employment returns to coastal activity. For the literature, it offers one of the first tests of digital technology adoption as a moderator, rather than an independent determinant, of blue-economy employment in Nigeria, and so links two research strands that have developed separately.

In short, Nigeria designs its blue-economy and digital-economy policies without evidence on whether they interact. This study supplies that evidence. It applies ARDL bounds tests to national annual data for 1996–2024, uses bootstrap critical values to correct for the small sample, tests for structural breaks, and traces how the employment effect of each sector changes across the observed range of digital adoption with marginal-effect and Johnson–Neyman analysis. Section 2 reviews the conceptual, theoretical and empirical literature; Section 3 sets out the data and method; Section 4 presents and discusses the results; and Section 5 concludes with policy recommendations and directions for further research.

LITERATURE REVIEW

2.1 Conceptual Literature

Coastal tourism covers tourism that depends directly on proximity to the sea and shoreline: beach recreation, marine and heritage sightseeing, water sports, and eco-tourism in lagoons, estuaries and mangroves. In Nigeria it spans the Atlantic-facing states of Lagos, Ogun, Delta, Bayelsa, Rivers, Akwa Ibom and Cross River, where sites such as Lekki, Badagry, Tarkwa Bay and the Obudu-adjacent riverine corridors hold large, under-monetised potential (Aninver Development Partners, 2025).

Fishery production comprises capture fisheries and aquaculture; capture fisheries divide further into artisanal (small-scale, largely canoe-based) and industrial (trawler-based) sub-sectors. Artisanal operators supply between 68% and 74% of Nigeria's domestic fish output (UNECA, 2021). This study measures fishery production by aquaculture output, the fastest-growing segment over the sample period (Section 3.3).

Youth employment, the outcome construct, follows the International Labour Organization's 15–24 age definition. Employment differs from decent work, and both differ from underemployment and NEET status. Nigeria's post-2023 labour force methodology reports a low headline unemployment rate alongside informality above 92% and NEET incidence of about 14%, so headline figures understate the unproductive youth engagement this study addresses (NBS, 2024).

Digital technology adoption, the moderating construct, refers to the diffusion and use of information and communication technology (ICT), principally internet access and mobile telephony, within a population. Following Andrianaivo and Kpodar (2011) and Adeola and Evans (2020), the study combines internet users (% of population) and mobile subscriptions (per 100 people) into a single principal-component index. The regressor, DIGTECH, is the first difference of this index (Section 3.2), so it measures the annual change in digital adoption rather than its level. Moderation differs from mediation: a mediator carries the effect of an independent variable to the outcome, whereas a moderator changes the strength or direction of that effect. The hypotheses concern DIGTECH as a moderator; the model includes its direct term, as any interaction model must, but the interaction terms carry the hypotheses.

THEORETICAL LITERATURE

The study draws on four complementary theories, each anchoring one of its core constructs.

The Tourism-Led Growth Hypothesis (Balaguer & Cantavella-Jordá, 2002) anchors the coastal tourism–employment relationship. Extending export-led growth theory to tourism, it holds that tourism earns foreign exchange, stimulates infrastructure investment and creates forward and backward linkages with local labour markets, so employment expands beyond the tourism sector itself. In Nigeria's coastal zones, a functioning tourism sector should draw young people into direct employment (guiding, hospitality, crafts, transport) and

indirect employment (food supply chains, security, construction). Tourism also depends on access infrastructure, and Nigerian evidence links road transport output positively to economic growth (Okon, Okon & Daniel, 2016).

Common-Pool Resource Theory (Ostrom, 1990) underlies the fishery–employment relationship. Capture fisheries are a textbook common-pool resource: catches are rivalrous, yet exclusion is difficult, particularly in Nigeria's largely open-access artisanal fishing grounds. Aquaculture, the segment this study measures, is privately farmed, but it shares markets, labour and coastal space with capture fisheries, so the governance of the wider fishery shapes its employment yield. Ostrom showed that such resources need not collapse into a "tragedy of the commons" where workable local institutions govern them. In Nigeria's fishing communities, customary norms, cooperatives and government policy decide whether fishery production sustains livelihoods or drives depletion and falling employment returns.

The Lewis Dual-Sector Model (Lewis, 1954) frames youth employment as a labour-absorption problem rather than an output problem. Developing economies combine a low-productivity traditional sector holding surplus labour with a higher-productivity modern sector that absorbs this surplus as it expands. As coastal tourism and fishery production professionalise and commercialise, they can serve as an intermediate absorption channel for Nigeria's large, young and underemployed coastal labour force; this study tests that channel.

Diffusion of Innovation Theory (Rogers, 1962, 2003) motivates the moderating role of digital technology. Rogers held that an innovation spreads through a population according to its relative advantage, compatibility and observability, and in spreading reorganises how existing activities are carried out and transacted. Rising internet and mobile use should change how coastal tourism is marketed (destination discovery, direct booking, social-media visibility) and how fish is traded (price discovery, mobile money, cold-chain coordination). The same level of tourism or fishery activity can therefore yield more, or under some conditions less, youth employment as digital adoption advances.

The four theories complement one another but differ on who gains. The Tourism-Led Growth Hypothesis and the Lewis model expect employment to rise as sectors commercialise and treat technology and capital as allies of labour absorption. Common-Pool Resource Theory ties fishery employment to the quality of governing institutions and promises no jobs from output growth where governance is weak. Diffusion of Innovation Theory adds that technology can displace labour as readily as it complements it, depending on whether firms use it to widen market access or to replace workers in production and logistics. Together, the theories predict that the employment effect of digital adoption depends on the governance and labour intensity of the sector it enters; Section 4 tests this prediction.

2.3 Empirical Literature

Coastal Tourism and Employment.

Nigerian studies generally find a positive tourism–employment relationship, but small, single-site surveys dominate the evidence, and national time-series analysis is absent. Along the Lagos coastline, Ogunberu (2011), in a qualitative case study of tourist attractions, found that beach and waterfront tourism created jobs, income and infrastructure for host communities despite weak institutional coordination. Uduma-Olugu and Onukwube (2015), surveying sixty users and practitioners at four Lagos water-based sites (Tarzan Jetty, Ozumba Mbadiwe Waterfront, Bar Beach Harbour and the Marina Waterfront), documented shortages of ferries, jetties and visitor amenities that hold the sector's employment potential below its natural endowment. Giwa (2022), surveying 382 residents, locals and tourists around the Badagry beaches, found that beach tourism brings socio-economic benefits but leaves residents outside beach management and decision-making, which limits the jobs that reach host communities. Tinuoye and Paul (2025), studying Elegushi Beach in Lekki, likewise documented gains for the host community alongside government under-investment in supporting infrastructure. These Lagos studies, spanning Badagry, the waterfront and Lekki, find a positive but institutionally constrained link between coastal tourism and local employment. National-level work points the same way. Adepoju, Abdullahi and Maji (2023), applying content analysis to secondary data, identify Nigeria's coastal ecosystems, particularly in the Niger Delta, as holding large but largely unquantified potential for tourism-led job creation, while Mbee, Okeke and

Eze (2024), surveying tourism stakeholders in three coastal states, find that boat cruises, beach resorts and eco-tourism contribute significantly to youth self-employment. Beyond Nigeria, Cisneros-Montemayor, Cisneros-Mata, Harper and Pauly (2020) show, with data from fourteen developing coastal countries, that tourism and fisheries together account for over 30% of coastal household income, cross-country evidence of the livelihood dependence that the Nigerian studies document only qualitatively. Across Africa, Adeola and Evans (2020), estimating a dynamic panel gravity model for 1996–2016, find that ICT infrastructure, proxied by mobile and internet penetration, has a significant U-shaped effect on tourism arrivals: digital connectivity raises arrivals only once adoption passes a threshold.

Fishery Production and Employment.

Nigerian studies describe the fisheries sector as an important but underexploited source of jobs: artisanal operators produce between 68% and 74% of national fish output, and more than a million Nigerians earn their living from fishing, processing or fish trading (UNECA, 2021). At the community level, Mohammed, Ekundayo, Maradun, Tambari, Ejezie, Yahaya and Ukwenya (2023), surveying 110 artisanal fisherfolk in Borgu Local Government Area, Niger State, found that 73.6% took up fishing as a source of jobs and primary livelihood, and that this absorption reduced rural–urban migration and youth restiveness, micro-level evidence of the labour-absorption channel this study tests nationally. Among entrepreneurs, Ololade, Olagunju and Adejumo (2025), applying multinomial logit and multiple regression models to 320 cultured-fish marketers in Ogun, Osun and Oyo States, found that market information, gender, and the cost and quantity of fish sold determined market-outlet choice among youth and middle-aged aquapreneurs, and that sex, education, marketing cost and distance to market determined revenue; market access and human capital shape youth fish-farming enterprise as much as production volume does. At the macroeconomic level, Amadi-Robert, Agbagwa, Agbugba, Floyd and Ibigomie (2025), applying an ARDL model to fisheries output over 1981–2023, found that lending rates reduce output in the short run, the real effective exchange rate reduces it after two to three years, and inflation raises it in the short run but reduces it in the long run. Fishery production therefore responds to macroeconomic conditions, which calls for a time-series specification. Umehai, Okeke and Eze (2024), applying ARDL and Granger-causality tests to fisheries and maritime activities over 1990–2022, find a positive and significant long-run relationship between fisheries output and employment and note that artisanal fisheries employ over 70% of the sector's workers; like Amadi-Robert et al. (2025), however, they neither disaggregate employment by age nor test a role for digital technology. At the programme level, WorldFish (2025), using questionnaires and focus groups in Ondo, Ogun and Lagos States, reports that the integrated mariculture value chain could absorb many young people and women given training and finance, but the assessment covers three states and does not model national employment effects. Where fisheries meet digital technology, Akinboye (2024), surveying 166 respondents in Ogun State, finds a significant positive correlation between the use of mobile applications, USSD platforms and social media and youth participation in fish processing, marketing and logistics, micro-level evidence of the digital–fisheries link that this study tests nationally as a moderator.

Digital Technology Adoption and Employment.

A separate strand examines the employment effects of ICT without reference to any sector. In Nigeria, Rabo, Fasakin and Jimoh (2023), in a conceptual review of the fisheries sector's blue-economy potential, argue that mobile payments, weather applications and market information systems can raise efficiency in fisheries and coastal tourism, but they estimate no effect. Myovella and Wambura (2026), applying an ARDL model to Tanzanian data for 1994–2023, find a stable long-run relationship between ICT adoption (internet use, mobile and fixed-line subscriptions) and aggregate employment, with internet use tied more closely to service than to manufacturing employment and adjustment dynamics that differ by technology. Fokam, Kamga and Nchofoung (2023), using a panel of developing countries, find that ICT adoption improves employment outcomes, though the channels and magnitudes vary by country and category of worker. Matjokana and David (2024), using cointegration and variance-decomposition analysis for South Africa, find that ICT development linked to the Fourth Industrial Revolution raises employment in the short and long run. Earlier, Andrianaivo and Kpodar (2011) showed, from personal-computer and internet-user growth across African countries, that ICT diffusion raises economic growth, the broader channel through which digital adoption is expected to reach employment. Lee, Noh and Khim (2020) discuss, at a conceptual level, how the blue economy aligns with the UN Sustainable

Development Goals and the tensions between growth-oriented and conservation-oriented interests, but present no country evidence on ICT and employment. None of these studies tests employment moderation in Nigeria. Within Nigeria, Ekpo and Udobia (2025b) find that liberalising the exchange rate, foreign direct investment and trade raises employment while current-account liberalisation lowers it, and Udo, Ekpo and Iwatt (2023) find no significant effect of globalisation on unemployment; neither study examines digital adoption or the blue economy.

The three strands associate coastal tourism, fishery production and digital adoption, each on its own, with better labour-market outcomes in Nigeria and comparable African settings. In every strand, however, the evidence is geographically narrow or site-specific (Ogunberu, 2011; Uduma-Olugu & Onukwube, 2015; Giwa, 2022; Tinuoye & Paul, 2025; Mohammed et al., 2023; Ololade et al., 2025; Adepoju et al., 2023; Mbee et al., 2024; WorldFish, 2025; Akinboye, 2024), conceptual (Rabo et al., 2023), or treats digital technology as a direct determinant of tourism arrivals or aggregate employment rather than as a conditioning factor (Adeola & Evans, 2020; Myovella & Wambura, 2026). No identified study tests whether digital technology adoption strengthens or weakens the employment effects of coastal tourism or fishery production in Nigeria, a gap Section 2.4 develops.

2.3.1 Critique of the Literature

Five limitations qualify this literature. First, the Nigerian tourism–employment and fishery–employment studies are almost all cross-sectional surveys confined to a single state, city or local government area (320 cultured-fish marketers in three South-West states; 110 fisherfolk in Borgu LGA; 382 residents around the Badagry beaches; 60 users and practitioners at four Lagos waterfront sites). Such samples inform community-level analysis but cannot establish a national employment relationship, and none of these studies applies time-series or panel methods able to identify a long-run relationship or to control for the macroeconomic conditions (exchange rates, inflation, credit) that the fisheries-output ARDL literature shows to matter (Amadi-Robert et al., 2025).

Second, estimates of the fisheries sector's contribution conflict: its GDP share ranges from below 0.5% to over 4%, and the artisanal output share from 68% to 74%, depending on the year, the reporting agency, and whether aquatic food systems are defined narrowly (capture fisheries) or broadly (including aquaculture and value chains). Studies rarely reconcile these figures, which complicates any attempt to benchmark fishery production consistently over a long series, as this study must.

Third, the ICT–tourism and ICT–employment literatures use stronger methods (dynamic panel gravity models, ARDL, cointegration) but treat digital technology only as a direct determinant of tourism arrivals or aggregate employment, and draw almost entirely on evidence from outside Nigeria: Tanzania (Myovella & Wambura, 2026), South Africa (Matjokana & David, 2024) and cross-country panels (Adeola & Evans, 2020; Andrianaivo & Kpodar, 2011; Fokam et al., 2023). None estimates digital adoption as a moderator of another sector's employment effect. Adeola and Evans (2020), for instance, show that ICT affects tourism arrivals directly, a proposition adjacent to, but distinct from, the one tested here: that ICT conditions the strength of tourism's own effect on employment.

Fourth, none of the reviewed studies disaggregates employment by age. The Nigerian tourism and fisheries literature treats employment as an undifferentiated aggregate, although Nigeria's National Youth Policy identifies youth (15–35 years) as a distinct labour-market cohort facing barriers different from those of older workers. That definition is broader than the ILO's 15–24 band adopted here (Section 2.1), and the literature applies no consistent age band at all. Existing findings therefore cannot show whether coastal tourism and fishery production create jobs that young Nigerians can access.

Finally, most Nigerian tourism and fisheries studies predate 2020, and none covers the post-2023 period of the revised labour force survey, the new Ministry of Marine and Blue Economy, and the latest acceleration in mobile and internet use. The evidence base therefore needs updating with current national time-series data.

2.4 Gap in the Literature

Four gaps follow. First, a sectoral integration gap: no Nigerian study models coastal tourism and fishery production as parallel employment channels in one econometric framework, although both draw on the same coastal geography, the same blue-economy policy architecture and, plausibly, the same pool of young workers. Second, a moderation gap: the literature treats digital adoption only as an independent driver of tourism arrivals or aggregate employment, never as a condition that strengthens or weakens the tourism–employment or fishery–employment relationship, despite the grounds Diffusion of Innovation Theory gives for expecting such conditioning. Third, a youth-specificity gap: studies report employment effects in aggregate, so the youth employment implications of coastal tourism and fishery production remain untested in Nigeria. Fourth, a methodological and temporal gap: Nigerian evidence rests on small, localised surveys rather than national time series, and none of it reaches the period of accelerated digital adoption and blue-economy policy from 2023. This study addresses all four gaps. It estimates a national time-series model of youth employment as a function of coastal tourism and fishery production, tests a composite PCA-based measure of digital adoption (DIGTECH) as a moderator of both relationships, traces each sector's effect across the observed range of DIGTECH, and extends the sample to 2024.

2.5 Research Hypothesis

The review yields four hypotheses:

H1: Coastal tourism has a significant effect on youth employment in Nigeria.

H2: Fishery production has a significant effect on youth employment in Nigeria.

H3: Digital technology adoption significantly moderates the relationship between coastal tourism and youth employment in Nigeria.

H4: Digital technology adoption significantly moderates the relationship between fishery production and youth employment in Nigeria.

METHODOLOGY

3.1 Research Design

The study uses a quantitative, longitudinal time-series design. Because the researchers cannot manipulate the variables, the design is associational: it traces coastal tourism, fishery production, digital adoption and youth employment in Nigeria over time, estimates their long-run and short-run associations, and tests for structural breaks.

One caveat on identification applies. The ARDL bounds-testing framework establishes long-run and short-run association under the maintained assumption that coastal tourism, fishery production and digital adoption are at least weakly exogenous with respect to youth employment; it does not by itself resolve reverse causality or omitted-variable bias. Rising youth employment and local activity may attract tourism investment, for instance, or unobserved regional infrastructure may drive both sector output and employment. The study retains the single-equation ARDL approach, standard in this literature, for its small-sample properties (Section 3.2.2), and reads the long-run coefficients in Section 4 as conditional associations consistent with a causal channel rather than as identified causal effects. Section 5.3 returns to this limitation.

3.2 Model Specification and Technique of Data Analysis

The study builds on the baseline model of Umehai, Okeke and Eze (2024) and estimates two ARDL models: Model 1 for the direct effects of coastal tourism and fishery production, and Model 2, which adds digital technology adoption as a moderator. Youth employment, coastal tourism, fishery production and capital

formation enter in natural logarithms, so their coefficients read as elasticities; DIGTECH, the interaction terms and the D2011 dummy enter in levels.

Model 1: Baseline Model — Direct Effect

Model 1 estimates the direct effects of coastal tourism and fishery production on youth employment, without digital moderation:

$lnYEMP = f\ (lnCT, lnFSP, lnGFCF, D2011)$ **(3.1)**

Model 2: Augmented Model — Moderating Role of Digital Technology Adoption

$lnYEMP = f(lnCT, lnFSP, DIGTECH, lnCT{\times}DIGTECH, lnFSP{\times}DIGTECH, lnGFCF, D2011)$ **(3.2)**

Model 2 adds digital technology adoption and its interactions with coastal tourism and fishery production.

Equations 3.1a and 3.2a state the two models in econometric form:

$$lnYEMP_t = \beta_0 + \beta_1 lnCT_t + \beta_2 lnFSP_t + \beta_3 lnGFCF_t + \beta_4 D2011_t + \mu_{1t} \quad \textbf{(3.1a)}$$

$$lnYEMP_t = \gamma_0 + \gamma_1 lnCT_t + \gamma_2 lnFSP_t + \gamma_3 DIGTECH_t + \gamma_4 (lnCT_t \times DIGTECH_t) + \gamma_5 (lnFSP_t \times DIGTECH_t) + \gamma_6 lnGFCF_t + \gamma_7 D2011_t + \mu_{2t} \quad \textbf{(3.2a)}$$

A Priori Expectations

Theory, prior evidence and Nigeria's blue-economy context suggest the following signs. Coastal tourism and fishery production should raise youth employment because their value chains are labour-intensive: added output creates direct jobs in hospitality, transport, processing and marketing, and indirect jobs through linkages. Faster digital adoption should also raise youth employment directly, since digital platforms cut transaction costs, create platform-based work and raise productivity (Rogers, 2003). The interaction terms carry the study's core contribution. Under the complementarity hypothesis, e-marketing, mobile payments and weather information amplify the job-creating capacity of both sectors, so lnCT×DIGTECH and lnFSP×DIGTECH should carry positive coefficients ($\gamma_4 > 0$, $\gamma_5 > 0$). Gross fixed capital formation (lnGFCF), a control, should carry a positive sign, since investment in infrastructure and equipment usually expands employment. The structural dummy D2011 equals one from 2011 onward. It captures the shift associated with the 2011 National Fisheries and Aquaculture Policy and Strategy Framework and the consolidation of post-Amnesty coastal investment, and should carry a positive sign if these interventions raised youth employment.

Following Aiken and West (1991) and Dawson (2014), the study mean-centres lnCT, lnFSP and DIGTECH before forming the interaction terms. Centring reduces collinearity between each interaction term and its components, and it makes the lnCT and lnFSP coefficients in Model 2 measure each sector's effect at the mean rate of digital adoption. A positive interaction coefficient means that faster digital adoption strengthens the corresponding employment effect; a negative one means that it weakens or reverses that effect.

Construction of the Digital Technology Index

A principal-component index measures digital technology adoption, an approach Ekpo, Iwatt and Eyo (2026) also use to build composite indices of inclusive economic transformation and financial sector development for Nigeria. Following the ICT diffusion and digital readiness literature (Awad & Albaity, 2022; ITU, 2023), the index combines two indicators: mobile cellular subscriptions per 100 people and internet users per 100 people. Together they capture access and use at the macro level, and they are the indicators most consistently available for Nigeria over the study period.

Mobile penetration and internet use correlate highly, so principal component analysis reduces the two to one dimension and avoids multicollinearity in the regression. The first principal component forms the composite

index, as in earlier ICT indices for developing economies (Andrianaivo & Kpodar, 2011). DIGTECH, the regressor in all models, is the first difference of this index, consistent with its treatment as an I(0) regressor in Table 4a.Equations 3.3a and 3.3b give the long-run (bounds-testing) ARDL model and the corresponding short-run error-correction model for Model 1:

$$\Delta \ln YEMP_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta \ln YEMP_{t-i} + \sum_{i=0}^{q_1} \beta_{2i} \Delta \ln CT_{t-i} + \sum_{i=0}^{q_2} \beta_{3i} \Delta \ln FSP_{t-i} + \sum_{i=0}^{q_3} \beta_{4i} \Delta \ln GFCF_{t-i} + \beta_5 D2011_t + \lambda_1 \ln YEMP_{t-1} + \lambda_2 \ln CT_{t-1} + \lambda_3 \ln FSP_{t-1} + \lambda_4 \ln GFCF_{t-1} + \mu_{1t} \quad \textbf{(3.3a)}$$

$$\Delta \ln YEMP_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta \ln YEMP_{t-i} + \sum_{i=0}^{q_1} \beta_{2i} \Delta \ln CT_{t-i} + \sum_{i=0}^{q_2} \beta_{3i} \Delta \ln FSP_{t-i} + \sum_{i=0}^{q_3} \beta_{4i} \Delta \ln GFCF_{t-i} + \beta_5 D2011_t + \varphi ECT_{t-1} + \mu_{2t} \quad \textbf{(3.3b)}$$

Equations 3.4a and 3.4b give the corresponding forms of Model 2:

$$\Delta \ln YEMP_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln YEMP_{t-i} + \sum_{i=0}^{q_1} \alpha_{2i} \Delta \ln CT_{t-i} + \sum_{i=0}^{q_2} \alpha_{3i} \Delta \ln FSP_{t-i} + \sum_{i=0}^{q_3} \alpha_{4i} \Delta DIGTECH_{t-i} + \sum_{i=0}^{q_4} \alpha_{5i} \Delta (\ln CT \times DIGTECH)_{t-i} + \sum_{i=0}^{q_5} \alpha_{6i} \Delta (\ln FSP \times DIGTECH)_{t-i} + \sum_{i=0}^{q_6} \alpha_{7i} \Delta \ln GFCF_{t-i} + \alpha_8 D2011_t + \theta_1 \ln YEMP_{t-1} + \theta_2 \ln CT_{t-1} + \theta_3 \ln FSP_{t-1} + \theta_4 DIGTECH_{t-1} + \theta_5 (\ln CT \times DIGTECH)_{t-1} + \theta_6 (\ln FSP \times DIGTECH)_{t-1} + \theta_7 \ln GFCF_{t-1} + \varepsilon_{1t} \quad \textbf{(3.4a)}$$

$$\Delta \ln YEMP_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln YEMP_{t-i} + \sum_{i=0}^{q_1} \alpha_{2i} \Delta \ln CT_{t-i} + \sum_{i=0}^{q_2} \alpha_{3i} \Delta \ln FSP_{t-i} + \sum_{i=0}^{q_3} \alpha_{4i} \Delta DIGTECH_{t-i} + \sum_{i=0}^{q_4} \alpha_{5i} \Delta (\ln CT \times DIGTECH)_{t-i} + \sum_{i=0}^{q_5} \alpha_{6i} \Delta (\ln FSP \times DIGTECH)_{t-i} + \sum_{i=0}^{q_6} \alpha_{7i} \Delta \ln GFCF_{t-i} + \alpha_8 D2011_t + \psi ECT_{t-1} + \varepsilon_{2t} \quad \textbf{(3.4b)}$$

Here Δ is the first-difference operator; p and q_1–q_6 are lag orders selected by the Akaike Information Criterion (AIC); β, λ, α and θ are the short-run and long-run parameters of Models 1 and 2; ECT_{t-1} is the lagged error-

correction term from the residuals of equations 3.3a and 3.4a; φ and ψ are the speed-of-adjustment coefficients, expected to be negative and significant; and μ_{1t}, μ_{2t}, ε_{1t} and ε_{2t} are white-noise errors. A lag order of zero means that the regressor enters only contemporaneously.

3.2.1 Pre-Estimation Diagnostic Test

The bounds test requires that no series be integrated of order two, so the study first establishes each variable's order of integration. The Augmented Dickey–Fuller (ADF) test regresses the first difference of a series on its lagged level, deterministic terms and lagged differences:

$$\Delta y_t = \alpha y_{t-1} + x'_t\delta + \beta_1\Delta y_{t-1} + \ldots + \beta_p\Delta y_{t-p} + v_t \qquad (3.5)$$

The null hypothesis of a unit root is $\alpha = 0$, against the stationary alternative $\alpha < 0$. Structural breaks such as policy shifts or crises can bias the ADF test towards non-rejection.

The Phillips–Perron (PP) test corrects the Dickey–Fuller statistic non-parametrically for serial correlation and heteroskedasticity and so needs no lag selection. It cross-checks the ADF results; disagreement between the two signals uncertainty about the order of integration. The PP test starts from the unaugmented regression

$$\Delta y_t = \alpha y_{t-1} + x'_t\delta + \varepsilon_t \quad (3.6)$$

and modifies the t-ratio of α so that serial correlation does not affect its asymptotic distribution:

$$t^*_\alpha = (\gamma_0/f_0)^{1/2}\, t_\alpha - T(f_0 - \gamma_0) / [2f_0^{1/2}\, se(\hat{\alpha})] \quad \textbf{(3.7)}$$

where $\hat{\alpha}$ is the estimated coefficient, t_α its t-ratio and $se(\hat{\alpha})$ its standard error; γ_0 is a consistent estimate of the error variance and f_0 the residual spectral density at frequency zero.

The KPSS test reverses the null hypothesis and tests stationarity against a unit root. Combining KPSS with ADF and PP guards against misclassifying a series whose trend or level shifts distort the unit-root tests. Section 4.3.1 adds the Zivot–Andrews test, which allows for one endogenous break.

3.2.2 The Bounds Test for Cointegration

Once the orders of integration are known, the bounds test of Pesaran, Shin and Smith (2001) checks for cointegration: an F-statistic above the upper critical bound indicates a long-run relationship.

Given cointegration, equations 3.3b and 3.4b describe short-run dynamics and the adjustment towards equilibrium after a shock. The speed-of-adjustment coefficients φ and ψ on ECT_{t-1} must be negative, below one in absolute value and significant for adjustment to be stable.

3.2.3 Marginal Effects and the Johnson–Neyman Test

A significant interaction coefficient shows that the effect of a sector depends on DIGTECH, but not where in the observed range of DIGTECH that effect differs from zero (Brambor, Clark & Golder, 2006). The study therefore computes the marginal effect of each sector over the full observed range of DIGTECH. The long-run coefficients of Model 2 follow from equation 3.4a as

$$\pi_j = -\frac{\theta_j}{\theta_1},\ j = 2, \ldots, 7 \qquad \textbf{(3.8)}$$

With lnCT, lnFSP and DIGTECH mean-centred, the marginal effects of coastal tourism and fishery production at a centred value Z of DIGTECH are

$$\frac{\partial \ln YEMP}{\partial \ln CT} = \pi_2 + \pi_5 Z \quad \textbf{(3.9)}$$

$$\frac{\partial \ln YEMP}{\partial \ln FSP} = \pi_3 + \pi_6 Z \quad \textbf{(3.10)}$$

and the variance of each marginal effect, shown here for coastal tourism, is

$$\mathrm{Var}(\widehat{\pi_2} + \widehat{\pi_5} Z) = \mathrm{Var}(\widehat{\pi_2}) + Z^2 \mathrm{Var}(\widehat{\pi_5}) + 2Z\mathrm{Cov}(\widehat{\pi_2}, \widehat{\pi_5}) \quad \textbf{(3.11)}$$

where the variances and covariance of the long-run coefficients come from the covariance matrix of equation 3.4a by the delta method. A marginal effect is significant at 5% wherever its ratio to its standard error exceeds 1.96 in absolute value. The Johnson–Neyman technique (Johnson & Neyman, 1936; Bauer & Curran, 2005) solves

$$(\widehat{\pi_2} + \widehat{\pi_5} Z)^2 = z_{0.025}^2 [\mathrm{Var}(\widehat{\pi_2}) + Z^2 \mathrm{Var}(\widehat{\pi_5}) + 2Z\mathrm{Cov}(\widehat{\pi_2}, \widehat{\pi_5})] \quad \textbf{(3.12)}$$

for Z; the roots mark the values of DIGTECH at which the marginal effect enters or leaves significance. The same expressions, with π_3 and π_6, apply to fishery production. Section 4.5.1 reports the marginal effects one standard deviation below the mean, at the mean and one standard deviation above it (Aiken & West, 1991), plots them across the observed range of DIGTECH with 95% confidence bands, and reports the Johnson–Neyman bounds.

3.3 Data Description and Sources

Table 1. Explanation of variables and *a priori* expectation

S/N	Variables	Description	Sources	A Priori Expectation
1.	Youth employment (lnYEMP)	Youth employment refers to individuals aged 15–24 participating in the labour market through full-time, part-time, seasonal, or temporary work, as well as entrepreneurship and self-employment, following the age band used in United Nations labour statistics. Its converse, youth unemployment, denotes those in this age group who are actively seeking work but unable to find it.	**ILOSTAT (WDI)**	NA
2	Coastal Tourism (lnCT)	Coastal tourism denotes tourism activity generated by proximity to the sea and shoreline: beach recreation, water sports and heritage sightseeing. No consistent series isolates shoreline tourism for 1996–2024, so the study proxies it with international tourism receipts as a share of Nigeria's total exports (WDI series ST.INT.RCPT.XP.ZS). This national aggregate also records business and inland arrivals (see the note on the proxy below Table 1).	**WDI CBN statistical bulletin**	lnCT > 0
3.	Fishery Production (lnFSP)	Fishery production, measured by aquaculture output: the farmed production of fish and other aquatic species, in metric tons (FAO data via World Bank WDI series ER.FSH.AQUA.MT). Aquaculture output grew about sixteen-fold between 1996 and 2015, against roughly two-fold growth in capture output.	**WDI**	lnFSP > 0
4.	Digital Technology Adoption (DIGTECH)	Composite index of digital technology adoption, extracted via principal component analysis from two indicators: internet users (% of population) and mobile cellular subscriptions (per 100 people). The regressor used throughout the empirical models is the first difference of this index, consistent with its treatment as an I(0) variable.	**WDI, Computed (PCA)**	DIGTECH > 0

5.	Coastal Tourism × Digital Technology (lnCT×DIGTECH)	Interaction term formed from the mean-centred natural log of coastal tourism and mean-centred DIGTECH. It tests whether digital technology adoption strengthens or weakens the effect of coastal tourism on youth employment.	**Computed**	lnCT×DIGTECH > 0
6.	Fishery Production × Digital Technology (lnFSP×DIGTECH)	Interaction term formed from the mean-centred natural log of fishery production and mean-centred DIGTECH. It tests whether digital technology adoption strengthens or weakens the effect of fishery production on youth employment.	**Computed**	lnFSP×DIGTECH > 0
7.	Gross Fixed Capital Formation, % of GDP (lnGFCF)	Value of net acquisitions of fixed assets — machinery, equipment, and infrastructure — by businesses, government, and households, expressed as a share of GDP. Included as a control variable for the independent contribution of capital investment to employment.	**CBN (Computed)**	lnGFCF > 0
8.	Structural Policy Dummy (D2011)	Equals 1 from 2011 onward and 0 before. It captures the shift associated with the 2011 National Fisheries and Aquaculture Policy and Strategy Framework and the consolidation of post-Amnesty coastal investment.	**Computed**	D2011 > 0

Source: Authors' compilation from ILOSTAT, CBN, and World Bank (WDI) data

Limits of the coastal tourism proxy. The proxy needs two qualifications. First, the World Bank series records spending by all international inbound visitors, including payments to national carriers for international transport, and the World Bank notes that it does not fully capture tourism (World Bank, n.d.). lnCT therefore also records business and inland arrivals, such as corporate travel to Abuja and the Lagos commercial districts, alongside beach, lagoon and heritage visits, and so measures coastal tourism with error. Under classical assumptions such error attenuates the estimated coefficient, so the positive lnCT elasticities in Section 4 more likely understate than overstate the coastal tourism–employment link. Second, oil dominates the denominator, total exports, so the ratio rises whenever oil earnings fall. The series peaks at 5.14% of exports in 2017, against a sample mean of about 1.2%, after the 2016 recession that followed a 17.48% contraction of the oil sector (NBS, 2016); part of that peak reflects a shrinking export base rather than more visitors. To cross-validate the proxy, the authors searched for annual coastal-state tourism series (arrivals, hotel occupancy or tourism revenue for Lagos, Cross River, Akwa Ibom, Rivers, Delta and Bayelsa) but found none covering 1996–2024 consistently. The study therefore retains the national proxy, reads its coefficient as the employment association of internationally financed tourism, of which coastal destinations form one part, and lists sub-national validation among the priorities for future work (Section 5.3).

RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Table 2. Descriptive Statistics of Model Variables

Statistic	lnYEMP	lnCT	DIGTECH	CT×DIGTECH	D2011	lnFSP	FSP×DIGTECH	lnGFCF
Mean	3.250527	-0.10396	0.121341	-0.01554	0.5	11.66674	0.046864	3.053866
Median	3.31364	-0.13808	0.154004	-0.00524	0.5	12.25762	0.057067	3.164304
Maximum	3.344274	1.637594	0.376818	0.23632	1	12.6658	0.219695	3.533132
Minimum	3.057768	-2.05105	-0.4692	-0.27753	0	9.926129	-0.50648	2.292232
Std. Dev.	0.097418	0.816677	0.165781	0.092024	0.509175	1.040345	0.147633	0.345296
Skewness	-0.80443	-0.18838	-1.43695	-0.21275	0	-0.59774	-1.88183	-0.81109
Kurtosis	2.170119	3.300847	6.761393	5.361176	1	1.650573	8.064934	2.664546

Probability	0.147833	0.873195	0.000002	0.034812	0.096972	0.150184	0.000000	0.201759
Observations	28	28	28	28	28	28	28	28

Source: Authors' computation from ILOSTAT, CBN, and World Bank (WDI) data, using Python.

Note: CT×DIGTECH and FSP×DIGTECH are the coastal tourism and fishery production interaction terms with DIGTECH; Probability refers to the Jarque-Bera normality test.

Youth employment (lnYEMP) varies little (standard deviation 0.097 against a mean of 3.25) and passes the normality test ($p = 0.148$). It moves slowly rather than in booms and busts, which suggests that sector shocks reach youth employment with a lag and supports an error-correction specification. Coastal tourism (lnCT) is volatile (standard deviation 0.817, range −2.05 to 1.64) around a near-zero mean, so the sector has not settled on a stable growth path. Fishery production grew roughly sixteen-fold, from 19,491 tonnes in 1996 to a peak of 316,727 tonnes in 2015, before easing to about 258,500 tonnes in 2024; the low output of the early years pulls the mean of lnFSP (11.67) below its median (12.26).

DIGTECH, the annual change in the digital adoption index, averages 0.121 but departs sharply from normality (skewness −1.44, kurtosis 6.76) because of a few large reversals, the deepest in 2024. Both interaction terms inherit this non-normality, the fishery interaction most strongly (skewness −1.88, kurtosis 8.06). A handful of years may therefore carry disproportionate weight in the moderation estimates; the marginal-effect analysis in Section 4.5.1 and the block-bootstrap checks in Section 4.6 address this. The D2011 dummy splits the sample evenly, 14 years on each side of the break.

4.2 Correlation Analysis

Correlations with the dependent variable (lnYEMP)

Table 3a. Correlation Matrix

Pair	r	Reading
lnYEMP–lnCT	−0.130	weak negative
lnYEMP–DIGTECH	+0.073	weak positive
lnYEMP–CT×DIGTECH	−0.060	weak negative
lnYEMP–D2011	−0.785	strong negative
lnYEMP–lnFSP	−0.640	moderately strong negative
lnYEMP–FSP×DIGTECH	+0.286	weak-to-moderate positive
lnYEMP–lnGFCF	+0.011	negligible

Source: Authors' computation from ILOSTAT, CBN, and World Bank (WDI) data, using Python.

Two features stand out. First, youth employment correlates negatively with coastal tourism (−0.130) and fishery production (−0.640), the opposite of H1 and H2. The D2011 dummy explains much of this: it correlates at −0.785 with youth employment and +0.843 with fishery production, because employment fell and fish output kept rising after the break. Much of the negative fishery correlation is therefore a shared break, which the multivariate ARDL model, with the dummy included, separates from the long-run relationship. Capital formation is uncorrelated with youth employment (+0.011), so any contribution it makes can emerge only in the multivariate model.

Second, the fishery interaction correlates positively with youth employment (+0.286) while the tourism interaction correlates weakly and negatively (−0.060). Bivariate correlations cannot test moderation, so Section 4.5 takes up both interactions in the full model.

Correlations among the regressors (multicollinearity screen)

Most regressor pairs correlate weakly; coastal tourism and fishery production, for instance, correlate at 0.258, so they capture distinct variation.

D2011 and lnFSP correlate at 0.843, the highest pair in the matrix, because fish output grew through the break. This collinearity could blur the separate effects of fishery production and the break, so Table 3b reports variance inflation factors for each model.

DIGTECH and FSP×DIGTECH correlate at 0.557, partly by construction, since the interaction contains DIGTECH; mean-centring limits this overlap (Section 3.2).

Table 3b. Variance Inflation Factor

Model 1 (Baseline) — No Concern

Variable	**VIF**
lnCT	1.057
lnFSP	1.090
lnGFCF	1.036

All three Model 1 regressors sit close to the minimum of 1.0, so collinearity poses no problem. The consumer price index, dropped from the final model as insignificant, also showed no collinearity (VIF 1.05–1.11).

Model 2 (DIGTECH-Augmented) — Moderate, Flagged but Not Disqualifying

Variable	**VIF**
lnCT	1.920
lnFSP	4.453
DIGTECH	4.144
lnCT × DIGTECH	1.538
lnFSP × DIGTECH	5.341
lnGFCF	1.431

VIF computed via statsmodels.stats.outliers_influence.variance_inflation_factor (Python 3, statsmodels 0.15) on the long-run regressor sets (with an added constant term) used in the final ARDL specifications reported in the accompanying results section

Every Model 2 value lies below the conventional threshold of 10; the highest, 5.34 for lnFSP×DIGTECH, only just exceeds the stricter threshold of 5 and reflects the shared variance between an interaction term and its components. Moderate collinearity widens standard errors, which works against finding significance, so it cannot explain the significant coefficients reported in Section 4.5.

4.3 Unit Root Test

Before bounds testing, three tests establish that no series is integrated of order two, the condition under which the Pesaran–Shin–Smith procedure remains valid for any mix of I(0) and I(1) regressors: the ADF and PP tests, with a unit-root null, and the KPSS test, with a stationarity null.

Table 4a. ADF, PP and KPSS Unit Root Test Results

Variable	ADF (level)	PP (level)	KPSS (level)	ADF (Δ)	PP (Δ)	Verdict
lnYEMP	0.974	0.791	0.019**	0.000***	0.000***	I(1)
lnCT	0.096*	0.300	0.100	0.000***	0.000***	I(1)
lnFSP	0.000***	0.538	0.011**	0.174	0.000***	I(1) †
lnGFCF	0.316	0.237	0.100	0.000***	0.000***	I(1)
DIGTECH	0.203	0.340	0.100	—	—	I(0) ††
lnCT×DIGTECH	0.000***	0.000***	0.100	—	—	I(0)
lnFSP×DIGTECH	0.248	0.759	0.048**	—	—	borderline, not I(2)

p-values shown; ***/**/* = reject the test's null at 1%/5%/10%. For ADF and PP the null is 'unit root' (small p ⇒ stationary); for KPSS the null is 'stationary' (small p ⇒ non-stationary). † lnFSP's ADF(level) rejects a unit root while PP and KPSS do not — a common small-sample power conflict; the weight of evidence (PP + KPSS + first-difference PP all confirming non-stationarity at level / stationarity after differencing) supports I(1). †† DIGTECH and the interaction terms are already first-difference/product constructs by design, consistent with an I(0) classification.

All four candidate I(1) variables (lnYEMP, lnCT, lnFSP and lnGFCF) reject a unit root decisively in first differences (ADF and PP, $p<0.001$), so none is I(2). The three level tests agree fully only for youth employment. For coastal tourism and capital formation, KPSS does not reject stationarity while ADF (at 5%) and PP do not reject a unit root, and for fishery production ADF alone points to stationarity. The tourism interaction is stationary in levels under all three tests; DIGTECH is treated as I(0) mainly because it is a first difference by construction, and the fishery interaction, which all three level tests classify as non-stationary, is treated as borderline. Section 4.3.1 resolves the level conflicts with a break-robust test.

4.3.1 Zivot-Andrews Structural-Break Unit Root Test

Standard ADF and PP tests can fail to reject a unit root when a series contains a structural break (Perron, 1989), a concern here because D2011 already marks a suspected break. The Zivot–Andrews (1992) test allows one endogenously selected break in the intercept (and, optionally, the trend), so a rejection means the series is stationary around its best-fitting break.

Table 4b. Zivot-Andrews Structural-Break Unit Root Test

Variable	ZA stat (c)	p-value	Break yr	Verdict
lnYEMP	-4.834	0.047**	2012	Break-stationary at 5%; break one year after D2011
lnCT	-3.802	0.477	2003	Unit root not rejected — confirms I(1)
lnFSP	-2.249	0.993	2005	Unit root not rejected: I(1); resolves the conflict in Table 4a
lnGFCF	-3.318 / -7.630(ct)	0.786 / 0.001(ct)	2011	Sensitive to trend specification; break year matches D2011
DIGTECH	-2.787	0.957	2005	Unit root not rejected even with a break — flagged below

Variable	ZA stat (c)	p-value	Break yr	Verdict
lnCT × DIGTECH	-5.848	0.001***	2018	Break-stationary, confirms I(0)
lnFSP × DIGTECH	-2.921	0.931	2012	Unit root not rejected — flagged below

The test dates the break in youth employment to 2012, one year after the D2011 dummy starts, and the break in capital formation under the trend specification to 2011 exactly, which gives data-driven support to the dummy. Coastal tourism and fishery production do not reject a unit root even with a break, which confirms their I(1) classification. DIGTECH and the fishery interaction also keep a unit root in levels, in some tension with their I(0) treatment, but both reject it in first differences: ΔDIGTECH under the PP test ($p<0.001$) and the Zivot–Andrews test (-6.795, $p<0.001$, break in 2018), and Δ(lnFSP×DIGTECH) under ADF ($p=0.037$), PP ($p<0.001$) and Zivot–Andrews (-6.063, $p=0.001$, break in 2011). Both are therefore at most I(1), which meets the bounds-test requirement (Pesaran et al., 2001). Their persistence still shapes interpretation: the DIGTECH and interaction coefficients describe co-movement among persistent series, so the bootstrap critical values in Section 4.4, which condition on the actual regressor paths, serve as the relevant benchmark.

4.3.2 Placebo Test on the Structural Break

To test whether 2011 and its neighbours 2012 and 2013 stand out from other candidate break dates, the study runs a sup-F (Quandt–Andrews type) search on the long-run regression of each model, computing the break F-statistic for every feasible year with all long-run coefficients free to shift and 15% trimming.

Table 4c. Placebo Break-Date F-Statistic Ranking

Model	Rank 1 (peak)	Rank 2	Rank 3	Weakest candidate
Model 1	2012 (F = 14.53)	2013 (F = 13.32)	2011 (F = 10.18)	2002 (F = 1.29)
Model 2	2013 (F = 3.90)	2016 (F = 2.65)	2012 (F = 2.44)	2006 (F = 0.37)

Source: Authors' computation. F-statistics from a global sum-of-squared-residuals-minimising break search allowing every long-run coefficient to shift; ranked by magnitude across all feasible candidate years (15% trimming).

For Model 1 the profile peaks sharply at 2012 (F = 14.53), falls by more than half within two years on either side, and reaches only 1.29 at the weakest candidate, the signature of a true break. For Model 2 the peak at 2013 (F = 3.90) is less isolated, with 2016 and 2012 also elevated, as expected from a richer specification with less power. Both models nonetheless place their maximum inside the 2011–2013 window.

The Bai–Perron procedure (Bai & Perron, 1998, 2003), which selects the number and dates of breaks by the Schwarz criterion, confirms these dates: one break at 2012 lowers the BIC of Model 1 from −140.09 to −165.10, and one break at 2013 lowers that of Model 2 from −141.87 to −148.85, while a second break either adds little (Model 1) or over-fits (Model 2). Three independent procedures, the Zivot–Andrews test, the sup-F search and the Bai–Perron search, therefore place the break in the 2011–2013 window.

Because the data-driven searches point slightly later than 2011, the study re-estimates both models with the dummy starting in 2012 and in 2013, holding the lag structure and all other regressors fixed.

Table 4d. Break-Date Sensitivity of the Long-Run Coefficients

Long-run coefficient	with D2011	with D2012	with D2013
Model 1: lnCT	0.080 (p=0.020)	0.102 (p=0.005)	0.084 (p<0.001)
Model 1: lnFSP	-0.018 (p=0.690)	-0.064 (p=0.002)	-0.058 (p<0.001)
Model 1: lnGFCF	-0.039 (p=0.535)	-0.022 (p=0.739)	-0.060 (p=0.133)
Model 2: lnCT	0.106 (p<0.001)	0.089 (p<0.001)	0.103 (p<0.001)
Model 2: lnFSP	-0.110 (p=0.003)	-0.092 (p=0.003)	-0.130 (p<0.001)
Model 2: DIGTECH	0.613 (p<0.001)	0.538 (p<0.001)	0.668 (p<0.001)
Model 2: lnCT×DIGTECH	0.480 (p=0.012)	0.451 (p=0.003)	0.481 (p=0.009)
Model 2: lnFSP×DIGTECH	-0.759 (p<0.001)	-0.682 (p<0.001)	-0.815 (p<0.001)

Source: Authors' computation. Model 2 rows refer to the preferred, lag-pruned ARDL(1,1,0,0,1,0,1) specification (Section 4.4), holding its lag structure fixed across the three dummies.

Model 2 withstands the dating choice: every coefficient keeps its sign and stays significant at 5% or better under all three dummies. Model 1 does not. Fishery production is insignificant under D2011 ($p = 0.690$) but negative and significant under D2012 ($p = 0.002$) and D2013 ($p<0.001$), with three times the magnitude. Coastal tourism's positive effect holds under every dummy. The study keeps D2011, anchored on the policy date and fixed before estimation, as its main dummy, and reads the baseline fishery estimate as sensitive to the break date.

The 2011–2013 window matches a documented policy turning point. The Federal Ministry of Agriculture and Rural Development launched the National Fisheries and Aquaculture Policy and Strategy Framework in 2011 to formalise fisheries governance, attract private investment and draw young people into the fisheries value chain, and the same period saw the consolidation of the Presidential Amnesty Programme in the Niger Delta. The break, however, marks a fall in the level of youth employment: the series fell from 28.34 in 2011 to 21.52 in 2013, and the D2011 coefficient is negative in both models and significant in Model 2 (Section 4.6). The data therefore date a structural shift to the policy window but do not show that the interventions raised youth employment.

4.4 Cointegration Analysis

Because the variables mix I(0) and I(1) series (Section 4.3), the ARDL bounds test of Pesaran, Shin and Smith (2001), which the first author has applied to fiscal–monetary dynamics in Nigeria (Ekpo & Udobia, 2025a), provides the appropriate test for a long-run relationship. Its asymptotic critical values suit large samples, while this study has 27 effective annual observations. A residual bootstrap (3,000 replications), following McNown, Sam and Goh (2018) and its application to Nigerian data by Ekpo, Iwatt and Eyo (2026), therefore supplies specification-specific critical values: youth employment is simulated under the null of no cointegration from each model's restricted short-run dynamics and the actual regressor paths, and the bounds F-statistic is recomputed on every replication.

Lag selection. To conserve degrees of freedom, the study selects the lag orders of Model 2 by exhaustive search over all 64 combinations of zero or one lag on its six regressors ($p = 1$, common sample 1998–2024), ranked by the AIC and the BIC. The AIC selects ARDL(1,1,0,0,1,0,1), with 12 parameters (AIC −93.45 against −89.84 for the uniform first-order specification, which has 15); the BIC selects ARDL(1,1,0,0,1,0,0), with 11 (BIC −79.18 against −70.41). The AIC-selected specification is the preferred Model 2, and Table 8b compares all three. Model 1 is ARDL(1,1,2,1).

Treatment of the dummy. The statsmodels bounds_test routine omits fixed regressors such as D2011 from the test regression. Because the dummy belongs to the estimated model, the study computes the Model 2 F-statistic

in the regression that contains it and takes the critical values from the bootstrap, which absorbs the dummy's effect on the null distribution. For Model 1, this construction gives F = 3.949 with a bootstrap p-value of 0.21, so the conclusion of Table 5a holds under either construction.

Table 5a. Bounds Test for Cointegration — Model 1 (Baseline)

Statistic	Asymptotic (Pesaran)	Bootstrap-corrected
F-statistic	4.047	4.047
k (regressors)	3	3
I(0)/I(1) bound — 10%	2.457 / 3.516	— / 5.05
I(0)/I(1) bound — 5%	2.877 / 4.011	— / 6.27
I(0)/I(1) bound — 1%	3.780 / 5.050	— / 9.11
p-value	0.047 (upper bound)	0.19–0.20
Decision	Reject H0 at 5%	Do not reject H0

Table 5b. Bounds Test for Cointegration — Model 2 (DIGTECH-Augmented, ARDL(1,1,0,0,1,0,1))

Statistic	Asymptotic (Pesaran)	Bootstrap-corrected
F-statistic	5.510	5.510
k (regressors)	6	6
I(0)/I(1) bound — 10%	2.031 / 3.136	— / 4.31
I(0)/I(1) bound — 5%	2.328 / 3.500	— / 5.44
I(0)/I(1) bound — 1%	2.957 / 4.252	— / 7.87
p-value	<0.01 (upper bound)	0.049
Decision	Reject H0 at 1%	Reject H0 at 5%

Source: Authors' computation (Python 3, statsmodels 0.15; 3,000-replication residual bootstrap). The F-statistic comes from the conditional ECM that contains D2011. Under the same construction, the uniform first-order specification ARDL(1,1,1,1,1,1,1) gives F = 4.614 (bootstrap p = 0.071). When D2011 is omitted from the test regression, the preferred model gives F = 3.479 (bootstrap p = 0.135) and the uniform specification F = 4.058 (bootstrap p = 0.094).

Against the asymptotic critical values of Pesaran et al. (2001), both models appear to cointegrate (Model 1: F = 4.047 > 4.011 at 5%; Model 2: F = 5.510 > 4.252 at 1%). McNown, Sam and Goh (2018) show that the classical test over-rejects in samples this small, and the bootstrap bears this out: its critical values sit well above the asymptotic ones, consistent with the finite-sample bias documented by Narayan (2005). Against the bootstrap values, Model 1 no longer rejects the null of no cointegration (bootstrap p ≈ 0.19–0.20), while Model 2 rejects it at 5% (bootstrap p = 0.049). The lag-pruned specification also improves on the uniform first-order one, which rejects only at 10% (bootstrap p = 0.071).

The baseline relationship between coastal tourism, fishery production and youth employment is not reliably identified on its own; it becomes identifiable once digital technology adoption enters as a moderator. Digital adoption is central, not peripheral, to how the two sectors translate into youth employment. One caveat applies: the 5% rejection depends on computing the test in the regression that contains D2011; when the dummy is omitted, the bootstrap p-value of Model 2 rises to 0.135 (note to Table 5b).

4.5 Long Run Estimation

Table 6a reports the long-run relationship for Model 1. Because Model 1 fails the bootstrap bounds test, it describes a fitted long-run association rather than a confirmed cointegrating relationship.

Table 6a. Long-Run (Level) Relationship — Model 1

Regressor	Coefficient	Std. Error	t-stat	p-value
Constant	3.6146	0.400	9.042	0.000***
lnCT	0.0797	0.034	2.333	0.020**
lnFSP	-0.0179	0.045	-0.398	0.690
lnGFCF	-0.0393	0.063	-0.620	0.535

lnYEMP = 3.6146 + 0.0797 lnCT − 0.0179 lnFSP − 0.0393 lnGFCF. Source: Authors' computation (ARDL(1,1,2,1), D2011 fixed).

Coastal tourism is the only significant regressor in the baseline model: a 1% rise in coastal tourism is associated with a 0.080% rise in youth employment (p = 0.020). Fishery production carries a small, insignificant negative coefficient (p = 0.690), a result that Section 4.3.2 shows depends on the D2011 dating, and capital formation is negative and insignificant.

Table 6b adds digital technology adoption and its interactions with both sectors. Model 2 is the specification that passes the bootstrap bounds test (Section 4.4).

Table 6b. Long-Run (Level) Relationship — Model 2 (DIGTECH-Augmented, ARDL(1,1,0,0,1,0,1))

Regressor	Coefficient	Std. Error	t-stat	p-value
Constant	5.0402	0.462	10.913	0.000***
lnCT	0.1064	0.021	4.977	0.000***
lnFSP	-0.1102	0.038	-2.938	0.003***
DIGTECH	0.6132	0.167	3.682	0.000***
lnCT × DIGTECH	0.4796	0.191	2.513	0.012**
lnFSP × DIGTECH	-0.7586	0.209	-3.638	0.000***
lnGFCF	-0.1497	0.038	-3.946	0.000***

lnYEMP = 5.0402 + 0.1064 lnCT − 0.1102 lnFSP + 0.6132 DIGTECH + 0.4796[lnCT×DIGTECH] − 0.7586[lnFSP×DIGTECH] − 0.1497 lnGFCF. Source: Authors' computation (ARDL(1,1,0,0,1,0,1) selected by AIC, D2011 fixed); confirmed by moving-block bootstrap inference (block lengths 2–4, 1,000 replications each; all 95% intervals exclude zero) and robust to the D2011/D2012/D2013 dating choice (Section 4.3.2).

Every coefficient in Table 6b is significant. Coastal tourism's elasticity rises from 0.080 in the baseline model to 0.106 at the mean rate of digital adoption. Fishery production lowers youth employment (−0.110, p = 0.003), consistent with output growth achieved through capital intensification that reduces labour absorption per unit of output. Faster digital adoption raises youth employment directly (0.613, p<0.001). The tourism interaction is positive and significant (0.480, p = 0.012): digital adoption amplifies the tourism–employment link, as Diffusion of Innovation Theory (Rogers, 1962, 2003) predicts through digital booking, marketing and payment platforms.

The fishery interaction is negative and significant (−0.759, p<0.001), the opposite of the positive moderation expected in Section 3.2: digital adoption deepens the negative employment effect of fishery production. Capital formation turns significantly negative (−0.150, p<0.001), in line with Ekpo, Daniel and Okon (2025b), who find that domestic capital weighs on Nigerian growth in both the short and long run.

Adding digital adoption changes the results qualitatively (Tables 6a and 6b). The tourism effect strengthens, the fishery effect becomes negative and significant, and the two interactions pull in opposite directions, amplifying the tourism channel and deepening the adverse fishery channel. This asymmetry is the study's central empirical finding.

4.5.1 Marginal Effects and Johnson–Neyman Analysis of the Moderation

Table 6b shows that the interaction coefficients differ from zero, but not how large, or how precisely estimated, each sector's effect is at different rates of digital adoption. Following Section 3.2.3, Table 6c evaluates the marginal effects of coastal tourism and fishery production one standard deviation below the mean of DIGTECH, at the mean, and one standard deviation above it (Aiken & West, 1991), and Figure 1 plots them across the full observed range of DIGTECH with 95% confidence bands and the Johnson–Neyman bounds.

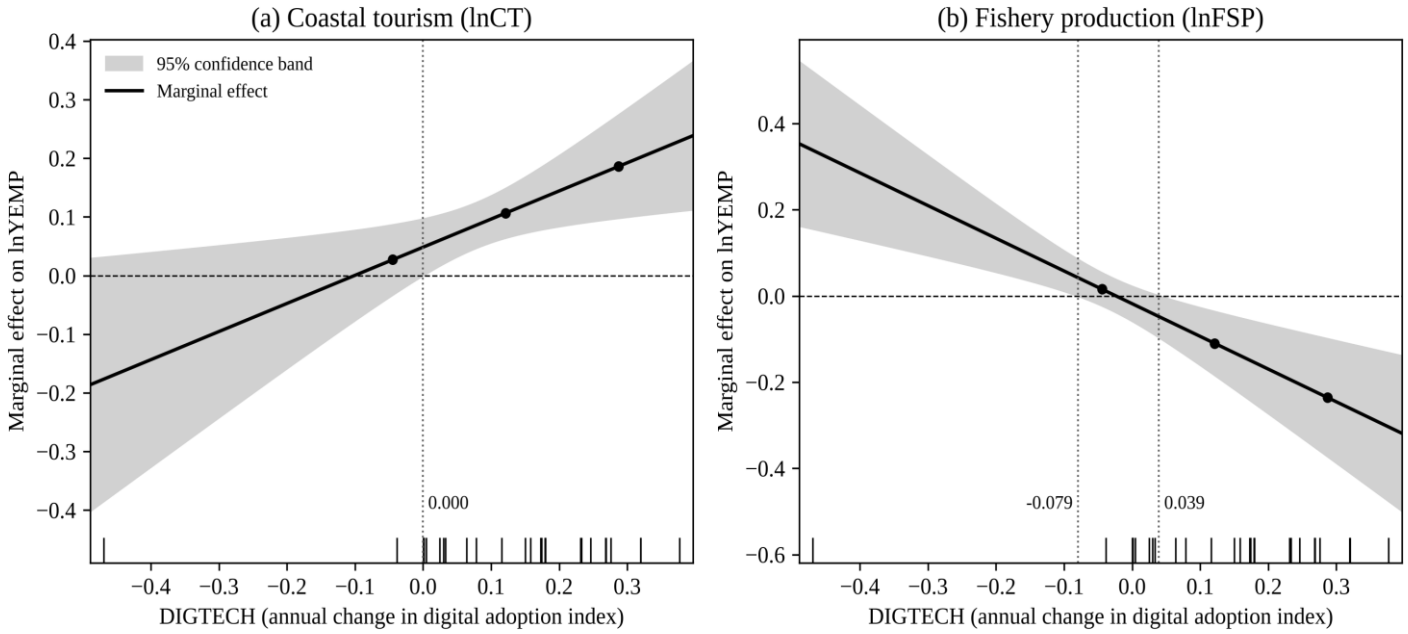
Table 6c. Marginal Effects of Coastal Tourism and Fishery Production on Youth Employment at Selected Values of DIGTECH

Value of DIGTECH	Marginal effect of lnCT	Marginal effect of lnFSP
Mean − 1 SD (−0.044)	0.027 (SE 0.030, p=0.374)	0.016 (SE 0.019, p=0.420)
Mean (0.121)	0.106*** (SE 0.021, p<0.001)	-0.110*** (SE 0.038, p=0.003)
Mean + 1 SD (0.287)	0.186*** (SE 0.045, p<0.001)	-0.236*** (SE 0.070, p=0.001)

Source: Authors' computation. Delta-method standard errors from the full UECM parameter covariance matrix; the Mean row reproduces the lnCT and lnFSP estimates in Table 6b.

One standard deviation below the mean of DIGTECH (−0.044, a year in which the adoption index fell slightly), neither sector has a detectable effect on youth employment (coastal tourism 0.027, p = 0.374; fishery production 0.016, p = 0.420). Both effects emerge as adoption accelerates. Coastal tourism's elasticity grows from 0.106 at the mean to 0.186 one standard deviation above it, about 75% higher, and the fishery effect deepens from −0.110 to −0.236.

Figure 1. Marginal Effects of Coastal Tourism and Fishery Production on Youth Employment across the Observed Range of DIGTECH



Note: Solid lines show the long-run marginal effects (equations 3.9 and 3.10); shaded areas show 95% confidence bands from delta-method standard errors (equation 3.11). Dotted vertical lines mark the Johnson–Neyman bounds (equation 3.12). Dots mark the values in Table 6c (mean − 1 SD, mean, mean + 1 SD), and tick marks along the horizontal axis show the 28 annual values of DIGTECH (1997–2024). Source: Authors' computation.

Figure 1 extends these three points to the whole observed range of DIGTECH (−0.469 to 0.377), and the Johnson–Neyman bounds mark where each effect turns significant at 5%. The coastal tourism effect is significantly positive wherever DIGTECH exceeds 0.000, that is, in every year in which the adoption index rose: 26 of the 28 sample years. It is indistinguishable from zero only in 2017 and 2024, the two years in which the index fell. The fishery effect is significantly negative wherever DIGTECH exceeds 0.039, which covers 18 years (2004–2016 and 2018–2022), and indistinguishable from zero between −0.079 and 0.039, which covers the near-zero adoption growth of 1997–2003 and the years 2017 and 2023. Below −0.079 the fishery effect turns significantly positive, reaching 0.34 at the sample minimum, but only one year, 2024, falls in this region, so the study does not read the positive segment as a finding.

The marginal-effect analysis strengthens the support for H3 and H4. Digital adoption does more than scale existing effects: the positive tourism effect and the negative fishery effect appear only when adoption advances, so the sector effects themselves, and not only the interaction coefficients, depend on the pace of digital adoption. Because every value of DIGTECH comes from one short annual series, the curves describe variation over time rather than independent replications.

4.6 Short Run Error Correction Model

The short-run error-correction model shows how the explanatory variables affect youth employment from year to year and how quickly the system returns to its long-run path after a shock.

Table 7a. Short-Run ECM — Model 1

Regressor	Coefficient	Std. Error	t-stat	p-value
Constant	2.2860	0.693	3.299	0.004***

Regressor	Coefficient	Std. Error	t-stat	p-value
ECT(-1) [speed of adjustment]	-0.6324	0.171	-3.705	0.002***
ΔlnCT	0.0162	0.018	0.911	0.375
ΔlnFSP	0.1246	0.129	0.968	0.346
ΔlnFSP(-1)	0.1238	0.122	1.013	0.325
ΔlnGFCF	-0.0784	0.059	-1.319	0.205
D2011	-0.0836	0.079	-1.053	0.307

The error-correction term is negative, below one in absolute value and significant (−0.632, p = 0.002): about 63% of any deviation from the long-run path closes within a year (half-life about 8 months). No short-run term is significant, so coastal tourism affects youth employment through the long run rather than within the year.

Table 7b. Short-Run ECM — Model 2 (ARDL(1,1,0,0,1,0,1))

Regressor	Coefficient	Std. Error	t-stat	p-value
Constant	4.1876	0.780	5.371	0.000***
ECT(-1) [speed of adjustment]	-0.8308	0.151	-5.494	0.000***
ΔlnCT	0.0282	0.016	1.749	0.101
ΔlnFSP (impact; lag order 0)	-0.0916	0.033	-2.817	0.013**
ΔDIGTECH (impact; lag order 0)	0.5094	0.151	3.374	0.004***
Δ[lnCT×DIGTECH]	0.1733	0.109	1.595	0.132
Δ[lnFSP×DIGTECH] (impact; lag order 0)	-0.6303	0.179	-3.527	0.003***
ΔlnGFCF	-0.1658	0.042	-3.947	0.001***
D2011	-0.1104	0.042	-2.624	0.019**

The preferred model's error-correction term (−0.831, p<0.001) exceeds Model 1's in absolute value: about 83% of any disequilibrium closes within a year (half-life about 5 months) once digital technology adoption enters. Because the AIC assigns lag order zero to fishery production, DIGTECH and the fishery interaction, their short-run impact equals the contemporaneous coefficient on the level term, reported in Table 7b as an impact effect; all three are significant (p ≤ 0.013) and share the signs of their long-run counterparts. Capital formation has an immediate negative effect (p=0.001), and the D2011 shift turns significant (−0.110, p=0.019) once the redundant short-run terms leave the model. Coastal tourism and its digital interaction remain insignificant contemporaneously, so the tourism–employment channel and its digital complementarity operate mainly through the long run.

Table 8. Post-Estimation Diagnostics

Test	Model 1	Model 2 (preferred)
Breusch-Godfrey LM (1 lag)	1.061 (p=0.303)	1.117 (p=0.290)
Breusch-Godfrey LM (2 lags)	3.914 (p=0.141)	12.727 (p=0.002) — flagged
ARCH-LM (1/2 lags)	0.043/0.128 (p=0.836/0.938)	1.594/1.582 (p=0.207/0.453)

Test	Model 1	Model 2 (preferred)
Breusch-Pagan heteroskedasticity	7.110 (p=0.626)	13.252 (p=0.277)
Ramsey RESET	F=0.791 (p=0.387)	F=0.755 (p=0.400)
Jarque-Bera normality	5.933 (p=0.051)	3.761 (p=0.152)
Max VIF	1.09	5.34 (interaction terms)
Adjusted R^2 / Durbin-Watson	0.771 / 1.718	0.858 / 2.306

Source: Authors' computation. Diagnostics via statsmodels.stats.diagnostic (Breusch–Godfrey, ARCH-LM, Breusch–Pagan, Ramsey RESET with squared fitted values, Jarque–Bera). Adjusted R^2 refers to the level of youth employment.

Model 1 passes every diagnostic at conventional levels. The preferred Model 2 passes the ARCH-LM, Breusch–Pagan, RESET and Jarque–Bera tests; pruning the redundant short-run terms removes the residual non-normality of the uniform first-order specification (Jarque–Bera p rises from 0.014 to 0.152). Second-order serial correlation persists ($p = 0.002$) under every alternative tried: the uniform and BIC-selected specifications (Table 8b), a second autoregressive lag ($p = 0.004$), and the D2012 and D2013 dummies ($p = 0.023$ and $p = 0.003$). Parameter saturation therefore does not cause it. The lag-two residual autocorrelation (−0.58) concentrates in the break window, where the youth employment series fell from 28.34 in 2011 to 21.52 in 2013 and recovered to 24.36 by 2015; an impulse dummy for 2013 lowers the Breusch–Godfrey statistic from 12.73 to 8.89. Heteroskedasticity- and autocorrelation-robust standard errors are biased downward in samples this small (Kiefer & Vogelsang, 2005), so inference on the long-run coefficients rests on a moving-block bootstrap that preserves the residual autocorrelation (1,000 replications for each block length of 2, 3 and 4 years). With a block length of 3, the 95% intervals are lnCT [0.072, 0.133], lnFSP [−0.172, −0.056], DIGTECH [0.364, 0.829], lnCT×DIGTECH [0.141, 0.784], lnFSP×DIGTECH [−1.050, −0.433] and lnGFCF [−0.202, −0.090]; every interval excludes zero at all three block lengths.

The recursive CUSUM paths of Model 1 and the preferred Model 2 both stay inside the 5% corridor over the whole monitoring window (2013–2024); Model 2's largest value, −4.21 in 2024, lies well within the critical bound of ±9.85. The uniform first-order specification, by contrast, breaches the corridor from 2016 onward. The post-2016 window holds three shocks that a saturated short-run structure fits poorly. First, the oil sector contracted by 17.48% and real GDP by 2.06% in the second quarter of 2016, taking the economy into recession (NBS, 2016); because lnCT divides tourism receipts by total exports, the fall in oil earnings lifted the tourism share from 0.94% in 2015 to 5.14% in 2017 without a matching rise in visitors. Second, the Central Bank of Nigeria floated the naira from 20 June 2016, after its monthly foreign-exchange earnings fell from about US$3.2 billion to below US$1 billion (Emefiele, 2016); exchange-rate volatility of this kind has had predominantly negative effects on Nigerian growth (Ekpo, Iwatt & Uduimoh, 2023a). Third, the COVID-19 pandemic produced a second recession in 2020, with real GDP contracting by 6.10% in the second quarter and 3.62% in the third (NBS, 2020). Each shock moved several regressors at once; a specification with a separate short-run coefficient on every regressor spreads such co-movement across unstable estimates, while the preferred model, with fewer short-run terms, does not.

Two further checks guard against over-fitting. A white-noise placebo regressor added to Model 2 is insignificant ($t = -0.19$, $p = 0.85$), while every substantive coefficient keeps its sign and significance. To assess out-of-sample performance, the study re-estimates each model on data through 2021 and produces dynamic forecasts for 2022–2024. The preferred Model 2 records a root mean squared error of 0.041, close to the no-change benchmark (0.036) and below both Model 1 (0.054) and the uniform first-order Model 2 (0.098). No model beats the naive benchmark, so the findings explain the historical long-run relationship rather than forecast short-horizon movements.

Table 8b. Specification Comparison for Model 2: Uniform Lags versus Information-Criterion Selection

Statistic	ARDL(1,1,1,1,1,1,1) — uniform lags	ARDL(1,1,0,0,1,0,1) — AIC, preferred	ARDL(1,1,0,0,1,0,0) — BIC
Parameters / residual df	15 / 12	12 / 15	11 / 16
AIC / BIC	-89.84 / -70.41	-93.45 / -77.90	-93.44 / -79.18
Long run: lnCT	0.108***	0.106***	0.106***
Long run: lnFSP	-0.131***	-0.110***	-0.115***
Long run: DIGTECH	0.741***	0.613***	0.635***
Long run: lnCT×DIGTECH	0.528**	0.480**	0.530***
Long run: lnFSP×DIGTECH	-0.833***	-0.759***	-0.810***
Long run: lnGFCF	-0.154***	-0.150***	-0.170***
ECT(-1)	-0.867***	-0.831***	-0.819***
Bounds F (bootstrap p)	4.614 (0.071)	5.510 (0.049)	5.363 (0.049)
Breusch-Godfrey LM (2 lags)	12.259 (p=0.002)	12.727 (p=0.002)	14.617 (p=0.001)
Jarque-Bera normality	8.475 (p=0.014)	3.761 (p=0.152)	8.643 (p=0.013)
Recursive CUSUM (5%)	Breach 2016–2024	Stable	Stable
Wald: interactions jointly = 0	F(2,12)=4.82 (p=0.029)	F(2,15)=6.72 (p=0.008)	F(2,16)=7.83 (p=0.004)
Out-of-sample RMSE, 2022–2024	0.098	0.041	0.044

Source: Authors' computation. Common sample 1998–2024 (T = 27); all specifications include a constant and D2011. Bounds F computed in the regression containing D2011, with 3,000-replication bootstrap p-values. ***/** = significant at 1%/5% (delta-method standard errors). Naive no-change benchmark RMSE = 0.036.

Pruning the uniform specification to the AIC selection changes no long-run sign or significance level, and no long-run coefficient moves by more than 0.13. It restores normal residuals, removes the CUSUM breach, lifts the bootstrap bounds test from 10% to 5% significance and more than halves the forecast error. It does not remove second-order serial correlation, which reflects the 2011–2015 episode rather than over-fitting. The BIC version, one term leaner still, leaves non-normality in place, which is why the AIC version serves as the preferred Model 2.

4.6.1 Synthesis

Table 9 tests the moderating role of digital technology jointly, since individually significant t-tests do not establish that the interactions matter as a set or that the moderated model outperforms a restricted one.

Table 9. Formal Test of the Moderating Role of Digital Technology

Test	Statistic	p-value	Conclusion
Wald test: both interaction terms jointly = 0	F(2,15) = 6.717	0.008***	Reject — moderating role confirmed jointly
Wald test: all six long-run terms jointly = 0	F(6,15) = 4.028	0.013**	Reject — corroborates the long-run relationship

Test	Statistic	p-value	Conclusion
Encompassing F-test: full model vs. tourism/fishery/capital-only model	F(4,15) = 3.544	0.032**	Reject — full model encompasses the restricted model

The two interaction terms are jointly significant (p = 0.008), and the encompassing test, which also penalises the four extra parameters that DIGTECH brings into the dynamic model, rejects the restricted tourism/fishery/capital model at 5% (p = 0.032). The evidence therefore supports H1; supports H2 with a negative sign, robust in Model 2 and sensitive to the break date in Model 1; supports H3 in the hypothesised direction; and supports H4 with a sign opposite to the one expected. Section 4.7 discusses each hypothesis.

DISCUSSION OF FINDINGS

The results tell one coherent story. Coastal tourism raises youth employment, and faster digital adoption strengthens that effect. Fishery production lowers youth employment, and faster digital adoption deepens that effect. Digital technology is therefore not a neutral control: it pulls the two blue-economy channels in opposite directions.

Evidence on H1: Coastal tourism has a significant effect on youth employment in Nigeria.

H1 is supported. Coastal tourism is positive and significant in the baseline model (0.080, p = 0.020) and in the moderated model (0.106, p<0.001), and its coefficient survives the break-date sensitivity analysis, the block bootstrap and the placebo check. The effect is conditional, however: Figure 1 shows that it is significant only in years in which digital adoption advanced. The result matches the Tourism-Led Growth Hypothesis (Balaguer & Cantavella-Jordá, 2002): coastal tourism draws young people into direct employment in hospitality, transport and crafts and into indirect employment along food supply chains. Because the national receipts proxy also records business travel (Section 3.3), measurement error more likely understates than overstates this effect.

Evidence on H2: Fishery production has a significant effect on youth employment in Nigeria.

H2 is supported, with a negative sign. Fishery production is insignificant in the baseline model under D2011 (p = 0.690), but negative and significant under D2012 and D2013 and in the moderated model under every dummy (−0.110, p = 0.003, with D2011). The fishery series measures aquaculture, whose output grew sixteen-fold between 1996 and 2015 while youth employment stagnated and then fell. This pattern suggests output growth driven by larger, more capital-intensive operations that raise production per worker rather than the number of young workers. Common-Pool Resource Theory (Ostrom, 1990) adds that where governance of the wider fishery is weak, output growth need not translate into jobs.

Evidence on H3: Digital technology adoption significantly moderates the relationship between coastal tourism and youth employment in Nigeria.

H3 is supported in the hypothesised direction. The tourism interaction is positive and significant (0.480, p = 0.012), jointly significant with the fishery interaction (p = 0.008) and robust to the break-date choice, and the Johnson–Neyman analysis shows that it decides whether the tourism effect is significant at all: the effect clears the 5% threshold once the adoption index rises. As Diffusion of Innovation Theory (Rogers, 1962, 2003) predicts, digital adoption changes how coastal tourism is marketed and transacted, through destination discovery, direct booking, social-media visibility and mobile payments, so the same level of tourism activity supports more youth employment. This complements Adeola and Evans (2020), who find that ICT raises tourism arrivals in Africa once adoption passes a threshold.

Evidence on H4: Digital technology adoption significantly moderates the relationship between fishery production and youth employment in Nigeria.

H4 is supported, but in the direction opposite to the a priori expectation ($\gamma_5 > 0$). The fishery interaction is negative and significant (−0.759, $p<0.001$) and robust to the break date and the block bootstrap, and Figure 1 shows the fishery effect turning significantly negative once annual adoption growth exceeds about 0.04 and deepening as growth accelerates. Rather than strengthening the employment payoff of fishery production, digital adoption deepens its negative relationship with youth employment. This is the study's most policy-relevant finding: the same lever that amplifies employment gains in tourism deepens employment losses in fisheries.

The national data cannot isolate which digital applications drive this result, because DIGTECH measures economy-wide internet and mobile adoption rather than technology on fish farms or in fish markets. Two documented features of Nigeria's fish economy suggest plausible channels. The first is import supply. Nigeria produces about 1.07 million tonnes of fish a year against demand of 3.36 million tonnes, a gap of about 2.5 million tonnes (Central Bank of Nigeria, n.d.), and its fish imports exceeded US$0.5 billion in 2023 (Premium Times & Pluboard, 2025). Mobile payments and digital coordination plausibly cut the cost of the importer–cold store–trader chain that fills this gap, shifting marketing and distribution work away from domestic producers and landing sites towards a smaller number of urban cold-chain operators. The second is scale. Digital tools for farm management, input ordering and market information plausibly favour larger commercial farms able to adopt them, so digitally enabled output growth raises production per worker without drawing more young people into fish farming, processing and trading. Both channels raise supply per worker while shrinking the number of young people the sector absorbs, consistent with the negative lnFSP and lnFSP×DIGTECH coefficients. A direct test requires farm-level and market-level data on technology use and employment, which future work should collect.

Implications for the blue economy and structural transformation

Youth employment serves here as the measure of the blue economy's contribution to structural transformation in the sense of Lewis (1954): transformation occurs when a commercialising sector absorbs surplus labour from low-productivity activity. Coastal tourism behaves like such a sector, absorbing more young workers as it professionalises and digitalises. Fishery production, as currently practised and digitalised, does the opposite, raising output while employing fewer young people. The evidence does not support a uniform claim that the blue economy creates youth jobs. Its employment dividend runs through coastal tourism and the digital tools that amplify it, while fisheries digitalisation, without deliberate labour-inclusive design, works against youth employment.

CONCLUSION AND POLICY RECOMMENDATIONS

5.1 Conclusion

This study asked whether coastal tourism and fishery production raise youth employment in Nigeria and whether digital technology adoption moderates either link. ARDL bounds tests on annual data for 1996–2024, with bootstrap critical values, information-criterion lag selection, structural-break tests, block-bootstrap inference, placebo and out-of-sample checks, and marginal-effect and Johnson–Neyman analysis, support four conclusions. Coastal tourism raises youth employment in every specification (H1). Fishery production, measured by aquaculture output, lowers youth employment in the moderated model (H2, with a negative sign). Digital adoption amplifies the tourism–employment link (H3). Digital adoption deepens the negative fishery–employment link (H4, opposite to the expected sign). Both sector effects depend on the pace of digital adoption: the tourism effect is significant only in years in which adoption advanced, and the negative fishery effect only once annual adoption growth exceeds about 0.04 index points.

The bootstrap bounds test identifies a long-run relationship only once digital adoption enters as a moderator, so digital adoption is central to how coastal tourism and fishery production convert activity into youth employment. Three break-detection procedures place a structural shift in 2011–2013, after the National Fisheries and Aquaculture Policy and Strategy Framework and the consolidation of post-Amnesty coastal investment, but the

shift lowered the level of youth employment. Digital adoption therefore shapes the blue economy's employment yield, but not uniformly: it raises youth employment through tourism and lowers it through fisheries.

5.2 Policy Recommendations

The findings support six policy recommendations:

1. Pair digital enablement with investment in coastal tourism. Coastal tourism yields the study's strongest and most robust employment effect, and digital adoption amplifies it. Because the effect is significant only while adoption advances (Figure 1), digital expansion in coastal areas should be sustained rather than one-off. Government and development partners should extend broadband access, digital marketing training, and online booking and payment platforms to coastal tourism enterprises and destination-management bodies, alongside the jetties, ferries and visitor facilities that tourism needs. Because infrastructure complements private investment (Ekpo, Daniel & Okon, 2025a), project-tied borrowing for high-return uses should finance this spending (Ekpo, Daniel & Okon, 2025b) within fiscal limits. Nigerian evidence finds that fiscal deficits support long-run growth (Ekpo, Anyim & Akabuokwu, 2025) only up to about 2% (Onyemailu, Ekpo & Iwatt, 2025); that open-ended deficits crowd out private investment and weaken development outcomes (Ubi-Abai, Daniel & Okon, 2025) with no significant growth payoff (Akpan et al., 2023); and that inflation above about 13% harms growth (Ekpo & Onyemailu, 2025). Government capital spending has shown no significant growth effect in Nigeria (Ekpo & Udoh, 2022), so outlays should be tied to measurable outputs, and any debt-linked financing should be structured around financial deepening (Ekpo, Iwatt & Eyo, 2026).

2. Redesign fisheries digitalisation around labour-inclusive applications. Digital adoption deepens the negative employment effect of fishery production, so current digitalisation raises output per worker without drawing young people into the sector. Fisheries programmes should fund digital tools that connect young fish farmers, processors and traders to markets, credit and cold-chain services, and should judge these tools by the jobs they create, not by output alone.

3. Strengthen fisheries governance so that output growth creates jobs. Consistent with Common-Pool Resource Theory, the negative fishery effect may reflect governance as much as technology. Licensing, cooperative structures and co-management arrangements, which the Federal Ministry of Marine and Blue Economy can support, can help future output growth expand rather than shrink youth employment. Weak regulatory institutions have long obstructed Nigeria's diversification efforts (Jeremiah, Okon & Daniel, 2017).

4. Evaluate blue-economy policies by their employment outcomes. The 2011–2013 structural break followed a major fisheries policy and coastal investment programme, yet youth employment fell. Future interventions, including those of the Ministry of Marine and Blue Economy established in 2023, should build youth-employment targets and before-and-after evaluation into their design.

5. Screen capital investment for labour displacement. Gross fixed capital formation lowers youth employment in the moderated model, consistent with the authors' earlier finding that the employment and output effects of private investment in Nigeria are conditional rather than automatic (Ekpo, Iwatt & Uduimoh, 2023b). Capital programmes in coastal tourism and fisheries should be paired with youth-employment safeguards.

6. Extend the evidence base. The short annual series (27 effective observations), the persistent second-order residual autocorrelation and the weak out-of-sample performance all limit precision. Statistical agencies and sector ministries should collect consistent annual data on coastal tourism, fishery output by sub-sector, digital adoption and youth employment, including at state level, so that these relationships can be re-estimated as more data become available.

5.3 Limitations and Directions for Future Research

Five limitations qualify the findings. First, the annual sample is short, and a single year of sharp reversal in digital adoption, 2024, drives the positive segment of the fishery marginal effect; bootstrap critical values, block-bootstrap inference, placebo and out-of-sample checks guard against small-sample artefacts but cannot substitute for more data. Second, the single-equation ARDL framework identifies conditional long-run associations rather than causal effects; reverse causality and omitted regional factors cannot be ruled out, and sub-national panels, instrumental variables or policy natural experiments would strengthen identification. Third, Model 2 retains second-order residual autocorrelation concentrated in the 2011–2015 break window, so inference rests on a moving-block bootstrap, and its cointegration result depends on modelling the break. Fourth, the fishery measure covers aquaculture only; future work should test whether the results hold for capture fisheries and total fish output. Fifth, coastal tourism is proxied by national international tourism receipts, which include business and inland travel and move with the oil-dominated export base (Section 3.3), and DIGTECH measures economy-wide adoption rather than technology use within tourism firms or fish farms; coastal-state tourism series and firm-level data would allow sharper tests. Future research should also try alternative digital measures, such as mobile-money transaction volumes or e-commerce penetration.

Declarations

Ethical Approval: This study analyses publicly available, aggregate secondary data and involves no human participants or animals; ethical approval was therefore not required.

Conflict of Interest: The authors declare no conflict of interest.

Funding: This research received no external funding.

Data Availability: The annual series are publicly available from ILOSTAT (https://ilostat.ilo.org/data/), the World Bank World Development Indicators (https://databank.worldbank.org/source/world-development-indicators) and the Central Bank of Nigeria Statistical Bulletin (https://www.cbn.gov.ng), as detailed in Section 3.3. The constructed dataset and the Python estimation code are available from the corresponding author on reasonable request.

REFERENCES

1. Adeola, O., & Evans, O. (2020). ICT, infrastructure, and tourism development in Africa. Tourism Economics, 26(1), 97–114.
2. Adepoju, A. O., Abdullahi, A., & Maji, A. (2023). An empirical assessment of the blue economy as a strategy for economic diversification in Nigeria. International Journal of Development and Economic Sustainability, 11(2), 61–79.
3. Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Sage.
4. Akinboye, O. A. (2024). Utilization of digital platforms for youth engagement in fisheries supply chains in Ogun State, Nigeria. Journal of Agricultural Extension and Rural Development, 16(1), 12–25.
5. Akpan, B. L., Udo, A. B., Eduno, E. B., & Daniel, E. (2023). Does deficit financing promote economic growth? The Nigerian experience. International Journal of Novel Research and Development, 8(12), c831–c845.
6. Amadi-Robert, C. C., Agbagwa, K. S., Agbugba, I. K., Floyd, K., & Ibigomie, C. (2025). Effect of macroeconomic indicators on fisheries output in Nigeria. Journal of Biodiversity, Agriculture and Climate Action, 1(2), 1–11.
7. Andrianaivo, M., & Kpodar, K. (2011). ICT, financial inclusion, and growth: Evidence from African countries (IMF Working Paper No. 11/73). International Monetary Fund.
8. Aninver Development Partners. (2025). Unlocking Nigeria's blue economic potential with the new Ministry of Marine and Blue Economy. https://www.aninver.com
9. Awad, A., & Albaity, M. (2022). ICT and economic growth in Sub-Saharan Africa: Transmission channels and effects. Telecommunications Policy, 46(6), Article 102341.

10. Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. Econometrica, 66(1), 47–78.
11. Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1), 1–22.
12. Balaguer, J., & Cantavella-Jordá, M. (2002). Tourism as a long-run economic growth factor: The Spanish case. Applied Economics, 34(7), 877–884.
13. Bauer, D. J., & Curran, P. J. (2005). Probing interactions in fixed and multilevel regression: Inferential and graphical techniques. Multivariate Behavioral Research, 40(3), 373–400. https://doi.org/10.1207/s15327906mbr4003_5
14. Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding interaction models: Improving empirical analyses. Political Analysis, 14(1), 63–82. https://doi.org/10.1093/pan/mpi014
15. Central Bank of Nigeria. (n.d.). Fishery. https://www.cbn.gov.ng/DFD/agriculture/CDI/fishery.html
16. Central Bank of Nigeria. (2023). Statistical bulletin. https://www.cbn.gov.ng
17. Cisneros-Montemayor, A. M., Cisneros-Mata, M. A., Harper, S., & Pauly, D. (2020). A global estimate of fisheries and tourism-based livelihoods in coastal communities. Fish and Fisheries, 21(3), 496–506.
18. Daniel, E., & Okon, I. (2022). Export diversification and growth: An empirical study of the recent performance gap between Nigeria and Ghana. AKSU Journal of Social Sciences, 2(1), 53–71. https://doi.org/10.60951/afrischolar-431
19. Dawson, J. F. (2014). Moderation in management research: What, why, when, and how. Journal of Business and Psychology, 29(1), 1–19.
20. Ekpo, G. M., Anyim, E. I., & Akabuokwu, K. C. (2025). Unpacking the relationship between fiscal deficit and economic growth in Nigeria. Global Journal of Modern Research and Emerging Trends, 1(5), 22–44. https://doi.org/10.67487/gjmret.v1i5.48
21. Ekpo, G. M., Daniel, E. J., & Udoh, U. N. (2022). Taxation and economic development in Nigeria. International Journal of Research, Innovation and Sustainable Development, 11(2).
22. Ekpo, G. M., Iwatt, E. B., & Eyo, U. E. (2026). External debt, globalisation and financial sector development in Nigeria's inclusive economic transformation: A bootstrap ARDL bounds-testing analysis. International Journal of Research and Innovation in Social Science, 10(9), 3454–3476. https://doi.org/10.47772/IJRISS.2026.100900230
23. Ekpo, G. M., Iwatt, E. B., & Uduimoh, A. A. (2023a). The impact of exchange rate volatility on economic growth in Nigeria. Social Sciences and Management International Journal, 4(1), 38–78.
24. Ekpo, G. M., Iwatt, E. B., & Uduimoh, A. A. (2023b). Private investment and economic performance in Nigeria. AKSU Journal of Social Sciences, 3(1), 55–85.
25. Ekpo, G. M., & Onyemailu, V. O. (2025). Inflation and economic growth in Nigeria: A search for the ideal balance. International Journal of Economic Policy, 5(5), 89–121. https://doi.org/10.47941/ijecop.3368
26. Ekpo, G. M., Onyemailu, V. O., & Anyim, E. I. (2025). Black gold curse: Examining the link between Nigeria's oil sector and inequality. Iconic Research and Engineering Journals, 9(4), 1029–1046. https://doi.org/10.64388/IREV9I4-1711419-3385
27. Ekpo, G. M., & Udobia, I. U. (2025a). The dynamic interaction between fiscal deficit and inflation in Nigeria: Evidence from ARDL bounds test. Transnational Journal of Arts, Humanities and Sciences, 1(2), 40–64. https://doi.org/10.5281/zenodo.16938959
28. Ekpo, G. M., & Udobia, I. U. (2025b). Economic liberalisation and employment generation in Nigeria. Transnational Journal of Finance, Management and Governance, 1(2), 34–61. https://doi.org/10.5281/zenodo.16889307
29. Ekpo, G. M., & Udoh, N. A. (2025). Harnessing oil sector gains for poverty alleviation: An investigation of the link between oil sector performance and poverty incidence in Nigeria. Iconic Research and Engineering Journals, 9(4), 57–71. https://doi.org/10.64388/IREV9I4-1711026-6389
30. Ekpo, G. M., & Udoh, U. N. (2022). Impact of fiscal policy on economic growth in Nigeria. Social Sciences and Management International Journal, 3(1), 62–90. https://doi.org/10.5281/zenodo.7186853
31. Ekpo, U. N., Daniel, E. J., & Okon, I. M. (2025a). An examination of the impact of macroeconomic policies on domestic investment in Nigeria. AKSU Annals of Sustainable Development, 2(1), 175–195.

32. Ekpo, U. N., Daniel, E. J., & Okon, I. M. (2025b). External debt and external debt servicing and Nigeria's economic growth. In C. S. Akpan et al. (Eds.), Governance and development challenges in the 21st century.
33. Emefiele, G. I. (2016, June 15). Re-introducing and operationalizing Nigeria's flexible exchange rate market [Address]. Central Bank of Nigeria. https://www.cbn.gov.ng/OUT/SPEECHES/2016/FINAL%20GOVERNOR%27S%20SPEECH%20ON%20NEW%20FX%20FRAMEWORK.PDF
34. Federal Department of Fisheries. (2015). A situational analysis of small-scale fisheries in Nigeria: From vulnerability to viability.
35. Federal Government of Nigeria. (2023). FG to collaborate with stakeholders to unlock potential in fisheries sector.
36. Federal Ministry of Marine and Blue Economy. (2024). National policy on marine and blue economy 2025–2034.
37. Fokam, T. D., Kamga, B., & Nchofoung, T. N. (2023). Information communication technologies and employment in developing countries: Effects and transmission channels. Telecommunications Policy, 47(8), Article 102597. https://doi.org/10.1016/j.telpol.2023.102597
38. Food and Agriculture Organization. (2020). The state of world fisheries and aquaculture 2020: Sustainability in action. FAO.
39. Food and Agriculture Organization. (2022). The state of world fisheries and aquaculture 2022: Towards blue transformation. FAO.
40. Giwa, F. F. (2022). Residents' attitudes to the operations of beaches in Badagry, Lagos State, Nigeria [Unpublished dissertation]. Lagos City University.
41. International Telecommunication Union. (2023). Measuring digital development: Facts and figures 2023. ITU.
42. Jeremiah, O., Okon, E. O., & Daniel, E. J. (2017). The implication of economy of developmental state for economic diversification in Nigeria. Nigerian Journal of Economic and Social Studies, 59(3).
43. Johnson, P. O., & Neyman, J. (1936). Tests of certain linear hypotheses and their application to some educational problems. Statistical Research Memoirs, 1, 57–93.
44. Kiefer, N. M., & Vogelsang, T. J. (2005). A new asymptotic theory for heteroskedasticity-autocorrelation robust tests. Econometric Theory, 21(6), 1130–1164.
45. Lee, K. H., Noh, J., & Khim, J. S. (2020). The Blue Economy and the United Nations' sustainable development goals: Challenges and opportunities. Environment International, 137, Article 105528. https://doi.org/10.1016/j.envint.2020.105528
46. Lewis, W. A. (1954). Economic development with unlimited supplies of labour. The Manchester School, 22(2), 139–191.
47. Matjokana, H. R., & David, O. O. (2024). The effects of the fourth industrial revolution on employment in South Africa: Variance decomposition analysis. Technology in Society, 77, Article 102522. https://doi.org/10.1016/j.techsoc.2024.102522
48. Mbee, N. O., Okeke, I. C., & Eze, C. O. (2024). Maritime tourism development and youth employment generation in Nigeria's coastal states. African Journal of Tourism and Hospitality, 8(1), 45–62.
49. McNown, R., Sam, C. Y., & Goh, S. K. (2018). Bootstrapping the autoregressive distributed lag test for cointegration. Applied Economics, 50(13), 1509–1521.
50. Mohammed, Y. S., Ekundayo, T., Maradun, H. F., Tambari, B. M., Ejezie, B. C., Yahaya, M. M., & Ukwenya, I. I. (2023). Assessment of artisanal fisheries activities among fisherfolks in Borgu Local Government Area, Niger State, Nigeria. Asian Journal of Fisheries and Aquatic Research, 25(6), 9–19. https://doi.org/10.9734/ajfar/2023/v25i6712
51. Myovella, G., & Wambura, M. (2026). The role of information and communication technologies in shaping employment dynamics: Insights from Tanzania. SN Business & Economics, 6, Article 103. https://doi.org/10.1007/s43546-026-01098-5
52. Narayan, P. K. (2005). The saving and investment nexus for China: Evidence from cointegration tests. Applied Economics, 37(17), 1979–1990.
53. National Bureau of Statistics. (2016). Nigerian gross domestic product report: Q2 2016. https://nigerianstat.gov.ng

54. National Bureau of Statistics. (2020). Nigerian gross domestic product report: Q3 2020. https://nigerianstat.gov.ng
55. National Bureau of Statistics. (2023). Nigeria labour force survey report: Q3 2023. https://nigerianstat.gov.ng
56. National Bureau of Statistics. (2024). Nigeria labour force survey: Q1 2024 & Q2 2024. https://nigerianstat.gov.ng
57. Nigerian Communications Commission. (2023). Industry statistics: Subscription data. https://www.ncc.gov.ng
58. Ogunberu, A. F. (2011). Socio-economic impact of tourism development in Nigeria: Case study of tourist attractions along the coastline of Lagos [Bachelor's thesis, Keski-Pohjanmaan ammattikorkeakoulu].
59. Okon, E. O., Okon, I. M., & Daniel, E. J. (2016). Sustainable economic growth of Nigeria: Is road transportation an X-factor? International Journal for Research in Business, Management and Accounting, 2(8), 82–98.
60. Ololade, R. A., Olagunju, F. I., & Adejumo, T. J. (2025). Econometric analysis of factors determining market outlets choice of cultured fish farming entrepreneurship among Nigerian youths from the blue economy. International Journal of Agricultural Science and Food Technology, 11(4), 52–60. https://doi.org/10.17352/2455-815X.000229
61. Onyemailu, V. O., Ekpo, G. M., & Iwatt, E. B. (2025). Fiscal discipline and economic growth: An empirical investigation of optimal threshold for fiscal deficit in Nigeria. Journal of Novel Research and Innovative Development, 3(10), a147–a174. https://tijer.org/JNRID/papers/JNRID2510019.pdf
62. Organisation for Economic Co-operation and Development. (2020). Sustainable ocean for all: Harnessing the benefits of sustainable ocean economies for developing countries. OECD Publishing. https://doi.org/10.1787/1c3d8e3d-en
63. Ostrom, E. (1990). Governing the commons: The evolution of institutions for collective action. Cambridge University Press.
64. Oye, D. K. (2024). Nigeria's blue economy: The trillion-naira ocean we refuse to swim in [Working paper]. Alliance for Economic Research and Ethics.
65. Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. Econometrica, 57(6), 1361–1401.
66. Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289–326.
67. Premium Times & Pluboard. (2025, October 13). Investigation: Deadly attacks at sea push Nigeria's fishers, traders to the brink. Pulitzer Center. https://pulitzercenter.org/stories/investigation-deadly-attacks-sea-push-nigerias-fishers-traders-brink
68. Rabo, E., Fasakin, E. A., & Jimoh, A. A. (2023). Harnessing the fisheries sector of the blue economy for sustainable economic growth and development in Nigeria. Fisheries and Aquaculture Journal, 14(3), 1–10.
69. Rogers, E. M. (1962). Diffusion of innovations. Free Press.
70. Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.
71. Tinuoye, O., & Paul, O. (2025). The socio-economic advantages of coastal tourism: A case of the Elegushi Beach, Lagos Nigeria. In Proceedings of the SPAS & SA 7th National Conference. Federal Polytechnic Ilaro.
72. Ubi-Abai, I., Daniel, E. J., & Okon, I. M. (2025). Fiscal deficit financing strategies and human development outcomes in Nigeria. Journal of Global Economics and Sustainable Development, 2(1), 1–9.
73. Udo, S. S., Ekpo, G. M., & Iwatt, E. B. (2023). Globalisation, unemployment and Nigerian economy. Social Sciences and Management International Journal, 4(2), 128–145.
74. Uduma-Olugu, N., & Onukwube, H. N. (2015). Exploring the coastal tourism potentials of Lagos. Department of Architecture, University of Lagos.
75. Umehai, F. E., Okeke, I. C., & Eze, C. O. (2024). Impact of fisheries and maritime activities on economic development in Nigeria: An ARDL approach. Journal of Marine and Coastal Economics, 6(2), 88–104.
76. United Nations Economic Commission for Africa. (2021). Blue economy, inclusive industrialization and economic development in Southern Africa. UNECA. https://archive.uneca.org

77. World Bank. (n.d.). International tourism, receipts (% of total exports) [Indicator metadata, ST.INT.RCPT.XP.ZS]. World Development Indicators. https://databank.worldbank.org/metadataglossary/world-development-indicators/series/ST.INT.RCPT.XP.ZS
78. World Bank. (2022). Unlocking the potential of Nigeria's blue economy (Report No. 172345-NG). World Bank.
79. World Bank. (2023). Africa's blue economy: A pathway to prosperity. World Bank. https://thedocs.worldbank.org
80. WorldFish. (2025). Employment opportunities in the integrated mariculture value chain for women and youth of the Nigerian coastal states (Program Report 2025-07). WorldFish.
81. Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. Journal of Business & Economic Statistics, 10(3), 251–270.