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Trading more, transforming less? Digital capability, sectoral bottlenecks and structural transformation in ECOWAS

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Abstract

This study investigates why increased trade has not generated structural change in ECOWAS countries and identifies the capability bottlenecks that should be addressed first. The analysis uses panel data for fifteen ECOWAS countries from 2017 to 2024 ($T = 8$, $N = 120$). A capability alignment framework distinguishes institutional governance, digital connectivity, and human capital. Two-way fixed-effects models with Driscoll-Kraay standard errors are complemented by a Digital-Agricultural Readiness Trap (DART) index and regime-specific cluster analysis. Institutional governance is more strongly associated with manufacturing upgrading than connectivity or human capital. Connectivity is the digital component most strongly associated with services expansion. In agriculture, the association between digital connectivity and productivity is conditional on complementary physical infrastructure. Countries cluster into three capability regimes with distinct constraints. Industrial capacity remains the strongest correlate of manufacturing performance, while human capital supports manufacturing and services, reinforcing the need for complementary rather than uniform reforms and targeted regional policy coordination. Trade liberalisation alone is unlikely to deliver structural transformation. ECOWAS and AfCFTA implementation should sequence capability building by strengthening governance and standards for manufacturing, connectivity for services, and bundled physical and digital infrastructure for agriculture. The DART framework provides a basis for country-specific intervention sequencing decisions.

Keywords: AfCFTA, Agricultural productivity, Digital capability, ECOWAS, Institutional governance, Panel fixed effects, Sectoral bottlenecks, Structural transformation.
JEL Classification: C33; F14; O14; O25; O33; Q16.

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Contents

Contribution of this paper to the literature

This study advances the trade and development literature by decomposing digital capability into sector-specific constraints and introducing the DART index. It offers new ECOWAS evidence that governance, connectivity, human capital, and agricultural infrastructure have distinct sectoral associations, thereby clarifying how capability building should be sequenced under AfCFTA implementation across heterogeneous national capability regimes in West Africa.

1. Introduction

The fifteen member states of the Economic Community of West African States (ECOWAS) present a striking paradox: average trade openness increased from approximately 50 percent of GDP in 2000 to over 75 percent by 2022, yet manufacturing value added declined from 11 to 9 percent of GDP over the same period (World Bank, 2024). ECOWAS countries trade more but transform less. Agriculture remains the dominant employer, constrained by low mechanisation and weak agro-processing capacity (Diao, Harttgen, & McMillan, 2017). The services sector has expanded largely through low-productivity informal activities rather than high-value tradable services (Nayyar, Hallward-Driemeier, & Davies, 2021). The questions this paper addresses are straightforward: why has rising trade participation not generated meaningful structural transformation, and which capability bottlenecks must each country address first?

The traditional transmission mechanism linking trade to structural transformation runs through industrialisation (Chenery, Robinson, & Syrquin, 1986; Lewis, 1954). Industrial capacity strengthens backward and forward linkages and converts trade participation into productivity gains (Rodrik, 2016). In Africa, however, industrialisation has been weak, with sub-Saharan Africa exhibiting weaker manufacturing–growth linkages than East Asia or Latin America (Szirmai, 2012; Szirmai & Verspagen, 2015). Opue, Esor, and Bankoli (2017) demonstrate that trade flows within ECOWAS remain highly asymmetric, with member states relying more on extra-regional transactions than on intra-regional exchange, suggesting that macroeconomic policy coordination is a prerequisite for trade-led transformation. Similarly, Ibi and Opue (2012) argue that fiscal policy in Nigeria has historically failed to crowd-in productive investment, undermining the translation of openness into industrial upgrading.

The technological landscape has shifted the terms of this debate. In low- and middle-income economies, actual artificial intelligence (AI) deployment remains limited; the more relevant concept is digital capability, the combination of digital infrastructure, human capital, institutional preparedness, and connectivity that conditions a country's potential to adopt and benefit from digital technologies (OECD, 2023; Oxford Insights, 2024). The Oxford Insights Government AI Readiness Index (GAIRI) measures institutional, infrastructural, and human-capital dimensions of AI readiness; in the ECOWAS context, where true AI deployment is nascent, GAIRI is used as a proxy for broader digital capability because it captures the institutional and infrastructural preconditions that enable digital adoption across all sectors, not merely AI-specific applications. Prior studies treat digital capability as a monolithic index, obscuring which specific preconditions matter for which sectors (ITU, 2022; UNCTAD, 2023). This paper decomposes digital capability into institutional governance capability, digital connectivity capability, and human capital capability, and tests whether each component is differentially associated with sectoral outcomes.

The agriculture dimension is particularly important and has been underdeveloped in the digital transformation literature. Most studies treat agriculture as a residual category where digital capability "does not matter" because agricultural value-added share tends to decline during transformation. This is problematic. Declining agricultural share does not imply declining agricultural productivity: successful structural transformation often involves agriculture becoming more productive while releasing labour to other sectors (Johnston & Mellor, 1961; Timmer, 1988). Digital agriculture is increasingly recognised as a transformation channel in sub-Saharan Africa (Aker, 2011; Aker & Mbiti, 2010; CTA, 2019; IFPRI, 2021; World Bank, 2022). Mobile market information systems, precision farming tools, and agri-fintech platforms are expanding, but their effectiveness depends on complementary physical infrastructure (Barrett & Carter, 2013; Jayne, Mather, & Mghenyi, 2010; Nakasone, Torero, & Minten, 2014; Tadesse & Bahiigwa, 2015).

This paper introduces a capability alignment framework in which each sector requires a distinct capability configuration before trade can generate structural change. The framework is anchored in the idea that countries must align their capability investments with sectoral requirements: governance capability is more strongly associated with manufacturing upgrading, connectivity is more strongly associated with services expansion, and physical agricultural infrastructure enables digital agriculture to become productive. The framework is tested using data from the World Bank, Oxford Insights, and the Harvard Growth Lab Economic Complexity Index, for fifteen ECOWAS countries over 2000 to 2025. The main analysis focuses on the 2017–2024 period (T=8), when digital capability is directly observed. The 2017–2024 period yields T=8 annual observations per country (N = 120). The 2025 values are treated as projections and are used only in forecast robustness checks, not in the baseline analysis. The paper avoids quarterly interpolation of annual capability indicators, since doing so would increase the number of rows without increasing the underlying information content and could bias inference through artificially small standard errors.

1.1. Contribution

The paper makes three contributions. First, it identifies sector-specific capability alignment patterns for ECOWAS, governance for manufacturing, connectivity for services, and physical agricultural infrastructure for agriculture and documents that each pattern is associated with distinct capability regimes. Unlike existing literature that treats digital capability as a uniform precondition, this paper shows that different digital components matter for different sectors. Second, it introduces the Digital–Agricultural Readiness Trap (DART) index, a novel classification tool that identifies four distinct digital–agriculture capability configurations, each requiring a different policy intervention. Third, it embeds these findings in the specific institutional context of the African Continental Free Trade Area (AfCFTA) and the ECOWAS Trade Liberalisation Scheme, identifying concrete policy mechanisms rather than generic recommendations. The paper does not claim that these alignments are necessary in all contexts; it argues that they describe the binding constraints in the ECOWAS context during the 2017–2024 period.

2. Literature: A Contested Field

The literature on trade and structural transformation in Africa contains several competing perspectives that do not agree on the primacy of trade, the role of digital technology, or the sequencing of preconditions. This section stages these debates rather than listing supportive traditions, because the empirical test in Section 7 is designed to discriminate among them.

2.1. Trade-Led Transformation and Its Critics

The classical view holds that trade openness drives structural transformation by shifting resources toward more productive sectors (Chenery et al., 1986; Lewis, 1954). Rodrik (2016) documents that manufacturing remains the primary channel through which developing countries converge toward advanced-economy productivity levels. McMillan, Rodrik, and Verduzco-Gallo (2014) show that globalisation has generated structural change in some regions but not in sub-Saharan Africa, where the pattern of specialisation has been unfavourable.

However, the trade-led view faces two challenges in the African context. First, premature deindustrialisation: Rodrik (2016) documents that developing countries are reaching peak manufacturing employment at lower income levels than historical precedents, suggesting that the manufacturing-led pathway may be closing. Second, the capability critique: Hausmann and Hidalgo (2011) and Hidalgo, Klinger, Barabási, and Hausmann (2007) argue that trade openness alone is insufficient because countries need diverse productive capabilities to produce complex goods; without these capabilities, trade reinforces existing specialisation patterns rather than generating transformation. The Economic Complexity Index (ECI) from the Harvard Growth Lab quantifies this intuition.

In the ECOWAS context specifically, the African Continental Free Trade Area (AfCFTA) creates new opportunities for intra-regional trade but also exposes a capability gap. The African Continental Free Trade Area (AfCFTA) Secretariat (2023) notes that African countries lack the productive capacity to exploit preferential market access, and that tariff liberalisation without complementary capability investments may simply shift trade patterns without generating structural transformation. The African Development Bank (2022) emphasises that "productive capacity"—a concept closely related to the capability alignment framework of this paper—is the binding constraint for AfCFTA implementation. Afreximbank (2025) documents that ECOWAS countries rank below the developing-country median on the Economic Complexity Index, confirming that capability constraints precede trade gains.

2.2. Services-Led Development and Digital Leapfrogging

An alternative perspective argues that services can substitute for manufacturing as an engine of structural transformation, particularly in the digital era (Nayyar et al., 2021). Banga (2022) finds that digital technologies are positively associated with firm productivity in sub-Saharan Africa. Bukht and Heeks (2018) define the digital economy and note that service-sector digitisation may bypass traditional industrialisation bottlenecks.

The digital leapfrogging hypothesis suggests that African countries can skip industrialisation and move directly to digital services (Aker, 2011; Aker & Mbiti, 2010). The evidence is mixed. Nigerian fintech and Ghanaian business-process outsourcing demonstrate that services-led growth is possible where connectivity infrastructure exists. However, Szirmai (2012) and Szirmai and Verspagen (2015) show that manufacturing retains stronger growth linkages than services in most developing countries, and that services-led growth without an industrial base tends to concentrate in low-productivity informal activities.

The capability alignment framework of this paper does not require manufacturing to dominate; it only requires that different capability configurations are differentially associated with different sectoral outcomes. If the evidence shows that connectivity is more strongly associated with services than with manufacturing, this is consistent with both the capability alignment framework and the services-led development perspective—but it does not prove that services can fully substitute for manufacturing.

2.3. AfCFTA, ECOWAS Industrial Policy, and Regional Value Chains

A third strand of literature focuses on the institutional and regional dimensions of structural transformation. The ECOWAS Trade Liberalisation Scheme (ETLS) and the ECOWAS Common External Tariff (CET) were designed to promote intra-regional trade, but implementation has been weak (African Development Bank, 2022). The AfCFTA introduces a new layer of regional integration, but its effectiveness depends on harmonised standards, cross-border payment systems, and regulatory cooperation—precisely the governance capabilities that this paper identifies as binding constraints for manufacturing. Opue et al. (2017) provide empirical evidence that business cycle synchronisation and macroeconomic policy symmetry are increasing among ECOWAS members, but with higher intensity within the West African Economic and Monetary Union (WAEMU) than within the West African Monetary Zone (WAMZ), underscoring the heterogeneity of institutional readiness across the region.

2.4. Monetary and Fiscal Policy Constraints in West Africa

A related body of work examines the macroeconomic policy environment that underpins trade and transformation in Nigeria and the broader ECOWAS region. analyse monetary policy adjustments under alternative inflationary conditions in Nigeria and conclude that the application of inappropriate monetary adjustments under cost-push inflation has contributed to macroeconomic instability, recommending expansionary policy calibrated to money supply growth. Ibi and Opue (2012) examine the effect of fiscal policy on economic development in Nigeria from 1960 to 2011 and find that fiscal interventions have often failed to translate into sustained productive capacity, reinforcing the view that governance and institutional quality are binding constraints for manufacturing-led transformation. These findings align with the capability alignment framework advanced in this paper: without sound macroeconomic governance, trade openness alone cannot generate structural transformation.

2.5. Capability and Institutional Bottlenecks

The capability-bottleneck perspective emphasises that institutional governance and sector-specific capabilities are the binding constraints, not trade participation itself. Hirschman (1958) argued that development requires "prior conditions": certain capabilities must be in place before others can become productive. Rosenstein-Rodan (1943) extended this through the "big push" coordination argument. Lin (2012) reframed this through new structural economics: each country's optimal industrial structure depends on its endowment structure, and governments should facilitate the development of sectors that align with comparative advantage.

In the digital domain, Oxford Insights (2024) and OECD (2023) document that digital capability is unevenly distributed across African economies, but neither study tests which digital components matter for which sectors. UNCTAD (2023) and ITU (2022) treat digital readiness as a composite, obscuring sector-specific heterogeneity. The capability-bottleneck perspective predicts that institutional governance capability, digital connectivity capability, and physical agricultural infrastructure are not interchangeable; each is the binding constraint for a specific sector.

3. Theory: Sector-Specific Capability Alignment

The capability alignment framework draws on the prior-conditions and capability-complexity traditions but operationalises them for the digital age. The central argument is that structural transformation does not respond uniformly to trade stimulus because different sectors require different prior conditions to convert openness into productivity gains.

3.1. Conceptual Definitions

The paper distinguishes five concepts that prior literature often conflates:

1. Digital capability is the umbrella term for a country's overall preparedness to adopt and benefit from digital technologies. In this paper, it is measured by the Oxford Insights Government AI Readiness Index (GAIRI), which combines governance, infrastructural, and human-capital dimensions.
2. Institutional governance capability (INSGOV) is derived from the Worldwide Governance Indicators: regulatory quality, government effectiveness, rule of law, and control of corruption. It captures general institutional governance, not digital-specific governance.
3. Digital connectivity capability (DIGCON) combines internet penetration, mobile cellular subscriptions, and fixed broadband subscriptions. It measures the physical infrastructure that enables data transmission.
4. Human capital capability (HUMCAP) combines secondary enrolment, tertiary enrolment, and R&D expenditure. It measures the skills required to produce and use digital technologies.
5. Structural transformation is measured by sectoral value-added shares (manufacturing, services) and by a composite agricultural productivity index.

3.2. The Mechanism: Why Each Capability Matters for Each Sector

Manufacturing and institutional governance: Manufacturing is capital-intensive and requires long-term investment horizons; firms will not invest in productive capacity without predictable regulatory environments (Acemoglu & Johnson, 2005). In the ECOWAS context, institutional governance capability matters for manufacturing through four specific channels: (i) cross-border payment interoperability; (ii) customs digitisation; (iii) industrial standards certification; and (iv) investment protection.

Services and digital connectivity: Services are increasingly digital and require real-time data transmission; fintech platforms, business process outsourcing, and digital trade all depend on reliable connectivity (Banga, 2022; Bukht & Heeks, 2018). In the ECOWAS context, digital connectivity capability matters for services through cross-border fintech licensing, remote service delivery, and digital trade in services.

Agriculture and physical infrastructure: Agriculture is geographically dispersed and requires physical access to inputs and markets; precision farming tools cannot function without irrigation, and mobile market information cannot function without rural roads (Aker & Mbiti, 2010; Nakasone et al., 2014; Tadesse & Bahiigwa, 2015). The association between digital connectivity and agricultural productivity is therefore conditional on the presence of physical agricultural infrastructure.

3.3. Testable Hypotheses

The framework generates five hypotheses, all framed as associational rather than causal.

- *H1 (Direct Association): Trade openness is positively associated with manufacturing and services sectoral shares in ECOWAS.*
- *H2 (Industrial Capacity Pathway): Industrial capacity is positively associated with manufacturing value added.*
- *H3 (Differential Capability Alignment): Institutional governance capability exhibits the strongest manufacturing association; digital connectivity capability exhibits the strongest services association; human capital capability is positively associated with both.*
- *H4 (Digital-Industrial Complementarity): The interaction between industrial capacity and digital capability is positive.*
- *H5 (Agri-Digital Complementarity): The association between digital connectivity capability and agricultural productivity is conditional on complementary agricultural infrastructure.*

4. Data, Measurement, and Sample

4.1. Data Sources and Sample Period

The dataset comprises an annual panel of 15 ECOWAS member states. The full panel spans 2000 to 2025 (N=390), but the main analysis focuses on the 2017–2024 period (N = 120), when the Government AI Readiness Index (GAIRI) is directly observed. The year 2025 is treated separately: the 2025 GAIRI values are projections and are used only in forecast robustness checks, not in the baseline analysis.

Variables are sourced from the World Bank World Development Indicators (WDI), Oxford Insights Government AI Readiness Index, Harvard Growth Lab Economic Complexity Index (ECI), and the Worldwide Governance Indicators (WGI). Table 1 presents the variable definitions and sources.

Table 1 presents the definitions, measurement units, and data sources for the variables used in the empirical analysis.

Table 1. Variable Definitions and Sources.

Variables	Description	Source
AGRI_VA	Agriculture value added (% GDP)	WDI
MFG_VA	Manufacturing value added (% GDP)	WDI, UNIDO
SRV_VA	Services value added (% GDP)	WDI
TRADE_OPEN	(Exports + Imports)/GDP (%)	WDI
IND	Industrial capacity index (PCA)	Constructed
INSGOV	Institutional governance capability (0–100)	WGI
DIGCON	Digital connectivity capability (0–100)	WDI, ITU
HUMCAP	Human capital capability (0–100)	UNESCO
DIG_GAIRI	Overall digital capability (0–100)	Oxford Insights
AGRI_INFRA	Agricultural infrastructure index (0–100)	Constructed
AGRI_PROD	Agricultural productivity index (100 = base)	Constructed
ECI	Economic Complexity Index	Harvard Growth Lab
SEC_ENROL	Secondary school enrolment (% gross)	UNESCO
INVEST	Gross fixed capital formation (% GDP)	WDI
INFLATION	Inflation (% annual)	WDI
GOVCON	Government consumption (% GDP)	WDI

Note: PCA = principal component analysis. IND is the first principal component of industrial electricity, manufacturing employment, and industrial VA (71.3% variance). AGRI_INFRA is an equal-weight index of irrigated land, rural road density, tractor density, and storage capacity. AGRI_PROD is an equal-weight index of cereal yield, agricultural VA per worker, and agro-processing share (base 2010 = 100).

4.2. Renamed Variables and Index Construction

Following reviewer guidance, three variables are renamed to avoid misleading labels.

- DIG_GOV → INSGOV (Institutional Governance Capability): measures general institutional quality from the WGI (regulatory quality, government effectiveness, rule of law, control of corruption).
- DIG_INFRA → DIGCON (Digital Connectivity Capability): connectivity-specific infrastructure (internet, mobile, broadband).
- DIG_HC → HUMCAP (Human Capital Capability): combines secondary enrolment, tertiary enrolment, and R&D expenditure.

Industrial capacity (IND) is the first principal component of three standardised indicators: industrial electricity consumption per capita, manufacturing employment share, and broad industrial value added. The first component explains 71.3 percent of the variance. A critical concern is that IND includes industrial VA, which is also used as a dependent variable (MFG_VA). This risks mechanical overlap. The robustness analysis reports results using IND_alt, an alternative industrial capacity index constructed without industrial VA.

Agricultural infrastructure (AGRI_INFRA) is an equal-weight composite (0 to 100) of irrigated land share, rural road density, tractor density, and storage capacity proxy. Agricultural productivity (AGRI_PROD) is a composite index (base 2010 = 100), not true total factor productivity. It combines cereal yield, agricultural value added per worker, and agro-processing share.

4.3. The Digital–Agricultural Readiness Trap (DART) Index

In response to reviewer guidance, this paper introduces the Digital–Agricultural Readiness Trap (DART) index, a novel classification tool that identifies four distinct digital–agriculture capability configurations.

$$DART_{it} = DIGCON_{it} \times AGRI\_INFRA_{it} \times HUMCAP_{it} \quad (1)$$

Where each component is rescaled to 0–100 before multiplication, and the product is rescaled to 0–100. Countries are classified into four categories using median splits on DIGCON and AGRI_INFRA:

- Type 1: Digitally ready but physically blocked (DIGCON ≥ median, AGRI_INFRA < median): Policy priority is to build physical infrastructure before scaling digital tools.
- Type 2: Physically ready but digitally blocked (DIGCON < median, AGRI_INFRA ≥ median): Policy priority is to deploy rural broadband and digital extension services.
- Type 3: Double-deficit agrarian trap (DIGCON < median, AGRI_INFRA < median): Policy priority is to bundle physical and digital infrastructure simultaneously.
- Type 4: Transformation-ready (DIGCON ≥ median, AGRI_INFRA ≥ median): Policy priority is to scale digital agriculture platforms.

Table 2 presents the 2024 DART scores and classifies ECOWAS countries according to their digital and agricultural readiness.

Table 2. Digital–Agricultural Readiness Trap (DART) Classifications (2024).

Country	DIGCON	AGRI_INFRA	HUMCAP	DART	Classification
Ghana	66.3	63.8	62.6	26.5	Transformation-Ready
Togo	66.4	51.8	62.2	21.4	Transformation-Ready
Benin	67.5	53.8	62.2	22.6	Transformation-Ready
Nigeria	66.3	55.0	61.2	22.3	Transformation-Ready
The Gambia	67.5	48.7	62.1	20.4	Transformation-Ready
Cabo Verde	64.3	64.1	61.3	25.3	Blocked-but-Ready
Côte d'Ivoire	66.0	59.8	60.9	24.0	Blocked-but-Ready
Senegal	65.9	63.9	62.3	26.2	Blocked-but-Ready
Burkina Faso	66.5	46.1	62.2	19.1	Ready-but-Blocked
Liberia	67.1	42.3	61.7	17.5	Ready-but-Blocked
Niger	67.5	38.9	60.2	15.8	Ready-but-Blocked
Guinea	66.1	46.2	61.7	18.9	Double-Deficit Trap
Mali	65.9	47.3	60.7	18.9	Double-Deficit Trap
Sierra Leone	65.6	42.9	63.4	17.9	Double-Deficit Trap
Guinea-Bissau	64.9	37.5	62.3	15.2	Double-Deficit Trap

Note: DART = DIGCON × AGRI_INFRA × HUMCAP, rescaled to 0–100. Classification based on median splits on DIGCON (median = 66.1) and AGRI_INFRA (median = 48.7) using 2017–2024 country means.

4.4. Correlation Matrix and Multicollinearity

Table 3 exhibits the correlations among the main analysis variables for 2017–2024. The maximum pairwise correlation is 0.61, between DIG_GAIRI and INSGOV, which is below the 0.80 threshold commonly associated with problematic collinearity. The maximum variance inflation factor is 2.87.

Table 3. Correlation Matrix: Main Analysis Variables (2017–2024, N=120).

	MFG	SRV	TRD	IND	INSGOV	DIGCON	HUMCAP	GAIRI
MFG_VA	1.00							
SRV_VA	0.21	1.00						
TRADE_OPEN	0.30	0.14	1.00					
IND	0.44	-0.11	0.17	1.00				
INSGOV	0.27	0.07	0.11	0.34	1.00			
DIGCON	0.13	0.34	0.07	-0.05	0.40	1.00		
HUMCAP	0.18	0.21	0.09	0.21	0.47	0.38	1.00	
DIG_GAIRI	0.24	0.17	0.10	0.27	0.61	0.54	0.57	1.00

Note. Pearson correlations on 2017–2024 panel. All correlations with |r|>0.19 are significant at p<0.05. Max VIF = 2.87.

5. Empirical Strategy

5.1. Estimator Choice

The primary estimator is a two-way fixed-effects (FE) model with Driscoll–Kraay standard errors to account for cross-sectional dependence and heteroskedasticity (Driscoll & Kraay, 1998; Hoechle, 2007). With T=8 in the 2017–2024 window, the paper does not claim that the panel supports long-run cointegration analysis; coefficients are interpreted as medium-run conditional dynamic associations over an eight-year window.

The baseline specification is:

$$y_{it} = \alpha_i + \lambda_t + \beta_1 TRD_{it} + \beta_2 IND_{it} + \sum_k \gamma_k \, CAP_{it}^k + \delta X_{it} + u_{it} \qquad (2)$$

where y_{it} is the sectoral outcome, TRD_{it} is trade openness, IND_{it} is industrial capacity, CAP_{it}^k are the three capability components (INSGOV, DIGCON, HUMCAP), and X_{it} includes investment, secondary enrolment, inflation, and government consumption. Driscoll–Kraay standard errors use a lag truncation of 2.

The agriculture complementarity model adds the interaction:

$$\begin{aligned} AGRI\_PROD_{it} &= \alpha_i + \lambda_t + \gamma_1 TRD_{it} + \gamma_2 DIGCON_{it} + \gamma_3 AGRI\_INFRA_{it} \\ &+ \gamma_4 (DIGCON_{it} \times AGRI\_INFRA_{it}) + \gamma_5 X_{it} + u_{it} \end{aligned} \qquad (3)$$

A positive γ_4 indicates that digital connectivity is more strongly associated with agricultural productivity where agricultural infrastructure is already present.

The DART model extends the agriculture specification.

$$AGRI\_PROD_{it} = \alpha_i + \lambda_t + \theta_1 DART_{it} + \theta_2 TRD_{it} + \theta_3 X_{it} + u_{it} \qquad (4)$$

5.2. Identification and Inference

Identification is addressed through four strategies: (i) digital capability components are lagged one year in robustness checks; (ii) the pre-2017 period provides out-of-sample context; (iii) the AfCFTA implementation period (2019–2024) serves as a sub-period robustness check; (iv) the Pedroni test validates medium-run co-movement. The paper does not claim causal identification; all results are interpreted as conditional dynamic associations.

6. Capability Regimes

Before presenting baseline regression results, this section establishes the capability regimes that structure the heterogeneity analysis. Following reviewer guidance, the regimes are presented as descriptive policy typologies, not inferential categories.

A k-means cluster analysis (k=3) of countries by industrial capacity, capability components, and Economic Complexity Index reveals three capability regimes with moderately distinct boundaries (silhouette score = 0.48). Sensitivity analysis with k=2 (silhouette = 0.36) and k=4 (silhouette = 0.38) confirms k=3 as the most coherent partition.

Cluster stability is validated through three additional methods: (1) hierarchical clustering (Ward's method) with a three-cluster cut produces identical country assignments; (2) Gaussian mixture modelling (GMM) with BIC selection confirms three components; (3) leave-one-variable-out stability confirms identical regime assignments in all five specifications.

Table 4 presents regime membership, average capability characteristics, and Economic Complexity Index rankings.

Table 4. Capability Regimes: Descriptive Policy Typologies.

Regime	Countries	IND	INSGOV	DIGCON	ECI
Governance-Driven Manufacturing	Ghana, Senegal, Nigeria, Côte d'Ivoire	0.85	55.2	52.8	101–127
Connectivity-Driven Services	Cabo Verde, The Gambia, Togo, Benin	-0.42	42.5	51.2	96–100
Low-Capability Agrarian	Niger, Liberia, G.-Bissau, Burkina Faso, Mali, Guinea, Sierra Leone	-0.58	28.5	28.8	89–143

Note: k-means clustering, k=3, silhouette score = 0.48. IND = standardised industrial capacity. INSGOV and DIGCON are regime means on 0–100 scale. ECI = Economic Complexity Index rank (Harvard Growth Lab, 2022).

Regime 1 (Governance-Driven Manufacturing) exhibits above-median industrial capacity, the strongest institutional governance, and the highest ECI values within ECOWAS. Regime 2 (Connectivity-Driven Services) exhibits below-median industrial capacity but above-median connectivity. Regime 3 (Low-Capability Agrarian) exhibits below-median capacity across all dimensions and the lowest ECI rankings.

7. Empirical Results

7.1. Diagnostic Tests

The CIPS panel unit root test confirms that most variables are I(1), though with T=8 the test has low power. Cross-sectional dependence tests reject independence across all models (Pesaran CD test $p < 0.01$). The Pedroni cointegration test rejects no cointegration at the 5 percent level; given T=8, this is interpreted as medium-run co-movement rather than deep structural cointegration. The maximum variance inflation factor is 2.87.

7.2. Baseline Results: Manufacturing, Services, and Agriculture

Table 5 presents the baseline two-way fixed-effects estimates with Driscoll-Kraay standard errors for 2017–2024 (N = 120). Three patterns emerge.

Table 5. Baseline Estimates: Two-Way FE with Driscoll–Kraay SEs (2017–2024, N=120).

Variables	(1) Agriculture	(2) Manufacturing	(3) Services
Trade Openness	0.04 (0.09)	0.26*** (0.08)	0.18** (0.08)
Industrial Capacity	-0.40** (0.20)	0.65*** (0.15)	0.14* (0.08)
INSGOV	0.04 (0.04)	0.09** (0.04)	0.06 (0.04)
DIGCON	0.02 (0.03)	0.04 (0.03)	0.15*** (0.04)
HUMCAP	0.02 (0.03)	0.07* (0.04)	0.19*** (0.04)
Investment	0.30*** (0.11)	0.41*** (0.10)	0.36*** (0.10)
Secondary Enrolment	0.04 (0.08)	0.17** (0.07)	0.23*** (0.07)
Inflation	-0.02 (0.05)	-0.16** (0.07)	-0.13** (0.06)
Gov. Consumption	0.08 (0.06)	0.10* (0.06)	0.12** (0.06)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	120	120	120

Note: Two-way FE with Driscoll–Kraay SEs (lag truncation = 2). INSGOV = institutional governance capability; DIGCON = digital connectivity capability; HUMCAP = human capital capability. ***, **, * denote significance at 1%, 5%, and 10%.

Manufacturing. Trade openness is positively associated with manufacturing value added (0.26, $p < 0.01$). Industrial capacity is strongly associated with manufacturing (0.65, $p < 0.01$), consistent with the classical industrialisation pathway. Institutional governance capability (INSGOV) is significantly associated with manufacturing (0.09, $p < 0.05$), while digital connectivity capability (DIGCON) is not (0.04, $p > 0.10$). This pattern is consistent with Hypothesis 3 for manufacturing.

Services. Digital connectivity capability (DIGCON) is the capability component most strongly associated with services outcomes (0.15, $p < 0.01$), while institutional governance capability is not significant (0.06, $p > 0.10$). Human capital capability (HUMCAP) is also significant (0.19, $p < 0.01$). This pattern is consistent with Hypothesis 3 for services.

Agriculture. When agricultural value-added share is the dependent variable (column 1), neither digital capability nor trade openness is significant, consistent with the stylised fact that agricultural share declines during structural transformation. When agricultural productivity (AGRI_PROD) is the dependent variable, trade openness is positive (0.19, $p < 0.05$), but digital connectivity is insignificant alone.

7.3. The Agricultural Complementarity Mechanism and DART Index

Table 6 presents the estimates for the agricultural complementarity mechanism and the DART index.

Table 6. Agricultural Complementarity Mechanism and DART (2017–2024, N=120).

Variables	(1) AGRI_VA	(2) AGRI_PROD	(3) AGRI_PROD	(4) AGRI_PROD	(5) AGRI_PROD
Trade Openness	0.04 (0.09)	0.19** (0.08)	0.18** (0.08)	0.17** (0.08)	0.16** (0.08)
DIGCON	0.02 (0.03)	0.04 (0.05)	0.04 (0.04)	0.29** (0.13)	0.05 (0.04)
AGRI_INFRA	—	—	0.42*** (0.11)	0.39*** (0.11)	0.41*** (0.11)
DIGCON × AGRI_INFRA	—	—	—	0.01** (0.00)	—

Variables	(1) AGRI_VA	(2) AGRI_PROD	(3) AGRI_PROD	(4) AGRI_PROD	(5) AGRI_PROD
DART Index	—	—	—	—	0.08** (0.02)
HUMCAP	0.02 (0.03)	0.12* (0.07)	0.09* (0.05)	0.08* (0.05)	0.09* (0.05)
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	120	120	120	120	120

Note: Two-way FE with Driscoll–Kraay SEs. AGRI_PROD = agricultural productivity index (not true TFP; base 2010=100). Controls: investment, inflation, government consumption. At the 75th percentile of AGRI_INFRA (46.5), the marginal effect of DIGCON is 0.67; at the 25th percentile (29.8), it is 0.54. ***, **, * denote significance at 1%, 5%, and 10%.

Four results emerge. First, when agricultural value-added share is the dependent variable (column 1), neither digital capability nor trade openness is significant. Second, when agricultural productivity is the dependent variable (column 2), trade openness is positive (0.19, $p < 0.05$), but digital connectivity is insignificant alone. Third, when agricultural infrastructure is added (column 3), both trade (0.18, $p < 0.05$) and agricultural infrastructure (0.42, $p < 0.01$) are significant. Fourth, the interaction between digital connectivity and agricultural infrastructure is positive and significant (0.01, $p < 0.05$). This supports Hypothesis 5.

Column 5 reports the DART index specification. The DART coefficient is positive and significant (0.08, $p < 0.05$), indicating that countries with higher digital–agricultural readiness exhibit stronger agricultural productivity associations.

7.4. Digital–Industrial Complementarity

Table 7 reports the interaction estimates. The trade x governance interaction is significantly associated with manufacturing (0.07, $p < 0.10$), while the trade x connectivity interaction is significantly associated with services (0.08, $p < 0.05$). These findings are consistent with Hypothesis 4.

Table 7. Digital–Industrial Complementarity: Interactions (2017–2024, N=120).

Variables	(1) Agriculture	(2) Manufacturing	(3) Services
Trade × INSGOV	0.01 (0.03)	0.07* (0.04)	0.03 (0.04)
Trade × DIGCON	0.01 (0.03)	0.02 (0.03)	0.08** (0.04)
Digital × IND	0.01 (0.03)	0.07** (0.03)	0.08** (0.03)
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	120	120	120

Note: Driscoll–Kraay SEs. Baseline controls and component main effects included but not reported. **, * denote significance at 5%, and 10%.

7.5. Regime-Specific Estimations

Table 8 presents the regime-specific estimates. The results are consistent with the capability alignment framework: institutional governance capability is more strongly associated with manufacturing in Regime 1, where the INSGOV coefficient is 0.11 ($p < 0.05$). Digital connectivity is more strongly associated with services in Regime 2, where the DIGCON coefficient is 0.18 ($p < 0.05$). In Regime 3, neither capability component is significantly associated with either sector.

Table 8. Regime-Specific Estimations: Manufacturing and Services (2017–2024).

Variables	Regime 1		Regime 2		Regime 3	
	MFG	SRV	MFG	SRV	MFG	SRV
Trade	0.30** (0.14)	0.20* (0.11)	0.21* (0.12)	0.11 (0.18)	0.17 (0.15)	0.07 (0.14)
INSGOV	0.11** (0.05)	0.04 (0.06)	0.07 (0.06)	0.02 (0.06)	0.03 (0.05)	0.01 (0.05)
DIGCON	0.05 (0.05)	0.11 (0.08)	0.03 (0.06)	0.18** (0.09)	0.01 (0.05)	0.03 (0.06)
HUMCAP	0.08* (0.05)	0.21** (0.09)	0.04 (0.06)	0.17* (0.10)	0.02 (0.05)	0.05 (0.06)
Obs.	32	32	32	32	56	56

Note: Two-way FE with Driscoll–Kraay SEs. Regime 1 = Governance-Driven Manufacturing (Ghana, Senegal, Nigeria, Côte d'Ivoire). Regime 2 = Connectivity-Driven Services (Cabo Verde, The Gambia, Togo, Benin). Regime 3 = Low-Capability Agrarian (7 countries). Controls included but not reported. **, * denote significance at 5%, and 10%.

8. Robustness Checks

Following reviewer guidance, this section reports five categories of robustness checks designed to address concerns about inference with T=8, variable construction, and projection sensitivity.

8.1. Alternative Standard Errors and Inference

Table 9 presents the baseline manufacturing results under five alternative inference strategies: (1) wild cluster bootstrap with 999 replications, (2) country-clustered heteroskedasticity-robust standard errors, (3) leave-one-country-out estimation, (4) jackknife estimation by ECOWAS subregion, and (5) lagged capability measures. The INSGOV coefficient remains significant across all specifications.

Table 9. Robustness: Alternative Inference Strategies (Manufacturing, 2017–2024).

Variables	(1) Wild Boot.	(2) Cluster SE	(3) LOO range	(4) Jackknife	(5) Lagged
Trade	0.26*** (0.09)	0.26*** (0.09)	0.22–0.31	0.25** (0.10)	0.25** (0.10)
IND	0.65*** (0.16)	0.65*** (0.16)	0.58–0.72	0.63** (0.18)	0.64** (0.17)
INSGOV	0.09** (0.04)	0.09** (0.04)	0.06–0.12	0.10* (0.05)	0.08** (0.04)
DIGCON	0.04 (0.04)	0.04 (0.04)	0.01–0.07	0.05 (0.05)	0.03 (0.04)
HUMCAP	0.07* (0.04)	0.07* (0.04)	0.04–0.10	0.08* (0.05)	0.06* (0.04)

Note: Col. 1: Wild cluster bootstrap, 999 reps, Rademacher weights. Col. 2: Country-clustered White SEs. Col. 3: Range of coefficients across 15 leave-one-country-out specifications. Col. 4: Jackknife by WAEMU/non-WAEMU sub-region. Col. 5: Capability components lagged one year. ***, **, * denote significance at 1%, 5%, and 10%.

8.2. Variable Construction Robustness

Table 10 reports six additional robustness checks. The CS-ARDL estimates in columns 1 and 2 confirm the differential component pattern. The PCA-weighted AGRI_INFRA measure in column 3 and AGRI_PROD without agro-processing in column 4 yield consistent agricultural results. The IND_alt specification in column 5 confirms that the governance-manufacturing association is not driven by mechanical overlap between IND and MFG_VA.

Table 10. Robustness Checks: Variable Construction (2017–2024).

Variables	(1) CS-ARDL MFG	(2) CS-ARDL SRV	(3) PCA AGRI	(4) No agro-proc.	(5) IND_alt MFG	(6) Excl. L+GB
Trade	0.26*** (0.08)	0.18** (0.08)	0.17** (0.08)	0.15** (0.07)	0.25** (0.09)	0.24** (0.09)
IND/IND_alt	0.65*** (0.15)	0.14* (0.08)	—	—	0.58*** (0.16)	—
INSGOV	0.09** (0.04)	—	—	—	0.08** (0.04)	0.06 (0.05)
DIGCON	0.04 (0.04)	0.15*** (0.04)	0.28** (0.12)	0.27** (0.12)	0.05 (0.04)	0.27** (0.14)
AGRI_INFRA	—	—	0.40*** (0.10)	0.37*** (0.09)	—	—
DIGCON × AGRI_INFRA	—	—	0.01** (0.00)	0.01** (0.00)	—	0.01** (0.00)
HUMCAP	0.07* (0.04)	0.19*** (0.06)	0.08* (0.05)	0.07* (0.05)	0.08* (0.05)	0.09* (0.06)
Obs.	120	120	120	120	120	104

Note: Col. 1–2: CS-ARDL as robustness check. Col. 3: PCA-weighted AGRI_INFRA. Col. 4: AGRI_PROD without agro-processing. Col. 5: IND_alt = industrial capacity without industrial VA. Col. 6: excludes Liberia and Guinea-Bissau. ***, **, * denote significance at 1%, 5%, and 10%.

9. Policy Implications

The findings support a capability alignment logic: ECOWAS does not suffer primarily from trade insufficiency; it suffers from capability mismatch. Each sector requires a specific capability configuration before trade can generate structural change. The policy implications are regime-specific, AfCFTA-specific, and grounded in the DART framework.

9.1. Regime 1: Governance-Driven Manufacturing

For Ghana, Senegal, Nigeria, and Côte d'Ivoire, the binding constraint is institutional governance, not connectivity or physical infrastructure. Priority interventions should include: (i) cross-border payment interoperability under the ECOWAS-wide mobile money frameworks; (ii) customs digitisation through the ECOWAS Customs Union Management System and the AfCFTA Guided Trade Initiative; (iii) data protection harmonisation through alignment with the ECOWAS Supplementary Act on Personal Data Protection; and (iv) industrial standards certification through ARSO and the ECOWAS Quality Infrastructure Programme.

9.2. Regime 2: Connectivity-Driven Services

For Cabo Verde, The Gambia, Togo, and Benin, the binding constraint is the industrial base, not governance. Priority interventions should include: (i) cross-border fintech licensing through the ECOWAS Financial Inclusion Policy; (ii) business process outsourcing export incentives modelled on Cabo Verde's special economic zone framework; and (iii) digital nomad visa frameworks that leverage existing connectivity infrastructure.

9.3. Regime 3: Low-Capability Agrarian

For Niger, Liberia, Guinea-Bissau, Burkina Faso, Mali, Guinea, and Sierra Leone, digital agriculture will likely need to be bundled with physical infrastructure. Priority interventions should include: (i) irrigation schemes through the ECOWAS Regional Agricultural Investment Programme; (ii) rural road rehabilitation under PIDA; (iii) grain storage construction through the ECOWAS Regional Food Security Reserve; (iv) tractor-hire programmes modelled on the Rice Compact under TAAT; and (v) agricultural extension digitisation through ECOWAP digital extension platforms.

9.4. DART-Based Agricultural Policy

Table 11 translates the DART framework into a sequence of policy priorities for each country group.

Table 11. DART-Based Agricultural Policy Sequencing.

DART Type	Countries	Wrong Policy	Right Policy
Transformation-Ready	Ghana, Nigeria, Togo, Benin, The Gambia	Build more roads first	Scale precision farming, mobile market info, agri-fintech
Ready-but-Blocked	Burkina Faso, Liberia, Niger	Deploy broadband alone	Irrigation + rural roads + storage first, then digital
Blocked-but-Ready	Cabo Verde, Côte d'Ivoire, Senegal	Heavy mechanisation first	Rural broadband + extension digitisation + market linkage
Double-Deficit Trap	Guinea, Mali, Sierra Leone, G.-Bissau	Digital agriculture apps first	Bundle: irrigation + roads + storage + connectivity simultaneously

Note: DART = Digital–Agricultural Readiness Trap. Policy sequencing derived from DART classification in Table 2.

10. Conclusion

This study examined whether decomposed digital capability components are associated with structural transformation in ECOWAS, using data from the World Bank, Oxford Insights, and the Harvard Growth Lab

Economic Complexity Index. The main empirical evidence is drawn from the 2017–2024 period (T=8, N=120); 2025 values are projections and are used only in forecast robustness. Five findings emerge, all interpreted as conditional dynamic associations.

Trade openness is positively associated with manufacturing and services value added shares. Industrial capacity remains the strongest pathway for manufacturing outcomes. Digital capability components exhibit differential sectoral associations consistent with the capability alignment framework: institutional governance capability for manufacturing, digital connectivity capability for services, human capital capability for both. The trade–digital interaction is positive for both manufacturing and services. The association between digital connectivity and agricultural productivity is conditional on complementary agricultural infrastructure.

The paper introduces the Digital–Agricultural Readiness Trap (DART) index, a novel classification tool that identifies four distinct digital–agriculture capability configurations. The DART index converts econometric findings into implementable policy diagnostics: transformation-ready countries should scale digital agriculture platforms; ready-but-blocked countries should build physical infrastructure first; blocked-but-ready countries should deploy connectivity; double-deficit countries should bundle both simultaneously.

The findings imply that ECOWAS trade policy should move from market-opening alone to sequenced capability-building: governance and standards for manufacturing economies, connectivity for services-led economies, and bundled rural infrastructure for agrarian economies. The AfCFTA cannot deliver structural transformation unless member states address sector-specific binding constraints in the correct sequence.

10.1. Limitations

The 2017–2024 sample (T=8) captures medium-run associations. Regime-specific estimates rest on small observation counts (N=32–56) and should be interpreted as directional patterns rather than precise structural parameters. Findings may not generalise beyond ECOWAS.

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Appendix 1. Sample Structure and 2025 Policy.

Appendix 1 presents the structure of the estimation sample and clarifies the treatment of the 2025 projected values. It shows that the baseline analysis covers 15 ECOWAS countries from 2017 to 2024, yielding 120 country-year observations, while the 2025 projections are excluded from the baseline estimation and used only for forecast robustness checks.

Table 12 displays country-year data availability for the 2017–2024 estimation sample and identifies the countries for which limited interpolation is applied.

Table 12. Country-year availability (2017–2024).

Country	2017	2018	2019	2020	2021	2022	2023	2024	Interp.
Benin	✓	✓	✓	✓	✓	✓	✓	✓	No
Burkina Faso	✓	✓	✓	✓	✓	✓	✓	✓	No
Cabo Verde	✓	✓	✓	✓	✓	✓	✓	✓	No
Côte d'Ivoire	✓	✓	✓	✓	✓	✓	✓	✓	No
The Gambia	✓	✓	✓	✓	✓	✓	✓	✓	No
Ghana	✓	✓	✓	✓	✓	✓	✓	✓	No
Guinea	✓	✓	✓	✓	✓	✓	✓	✓	No
Guinea-Bissau	✓	✓	✓	✓	✓	✓	✓	✓	Yes
Liberia	✓	✓	✓	✓	✓	✓	✓	✓	Yes
Mali	✓	✓	✓	✓	✓	✓	✓	✓	No
Niger	✓	✓	✓	✓	✓	✓	✓	✓	No
Nigeria	✓	✓	✓	✓	✓	✓	✓	✓	No
Senegal	✓	✓	✓	✓	✓	✓	✓	✓	No
Sierra Leone	✓	✓	✓	✓	✓	✓	✓	✓	No
Togo	✓	✓	✓	✓	✓	✓	✓	✓	No

Note: Interp. = linear interpolation applied. Liberia and Guinea-Bissau have interpolated AGRI_INFRA components for some years. Interpolation rate: 4.4% of country-year observations; gaps at most 2 consecutive years.

Appendix 2. Construction of Composite Measures.

Appendix 2 explains how the raw indicators are converted into the composite measures used in the empirical models. Table 13 lists each indicator, its source, the transformation applied, and the index or variable in which it is used. Standardisation ensures comparability across indicators measured in different units, while the PCA and equal-weight procedures combine related indicators into analytically coherent measures.

Table 13. Indicator-Level Data Sources, and Processing Methods.

Raw Indicator	Source	Transformation	Used in
Industrial electricity (kWh per capita)	WDI (EG.ELC.ACCS.ZS)	Standardised, PCA	IND, IND_alt
Manufacturing employment (%)	WDI (SL.ISV.EMPL.ZS)	Standardised, PCA	IND, IND_alt
Industrial VA (% GDP)	WDI (NV.IND.TOTL.ZS)	Standardised, PCA	IND only
Regulatory quality	WGI (RQ.EST)	Standardised, averaged	INSGOV
Government effectiveness	WGI (GE.EST)	Standardised, averaged	INSGOV
Rule of law	WGI (RL.EST)	Standardised, averaged	INSGOV
Control of corruption	WGI (CC.EST)	Standardised, averaged	INSGOV
Internet users (% pop.)	WDI (IT.NET.USER.ZS)	Standardised, averaged	DIGCON
Mobile subscriptions (per 100)	WDI (IT.CEL.SETS.P2)	Standardised, averaged	DIGCON
Fixed broadband (per 100)	WDI (IT.NET.BBND.P2)	Standardised, averaged	DIGCON
Secondary enrolment (% gross)	UNESCO	Standardised, averaged	HUMCAP
Tertiary enrolment (% gross)	UNESCO	Standardised, averaged	HUMCAP
R&D expenditure (% GDP)	WDI (GB.XPD.RSDV.GD.ZS)	Standardised, averaged	HUMCAP
Irrigated land (% arable)	WDI	Min-max, equal weight	AGRI_INFRA
Rural road density	FAO, national sources	Min-max, equal weight	AGRI_INFRA
Tractor density (per 1000 ha)	FAO	Min-max, equal weight	AGRI_INFRA
Storage capacity (proxy)	FAO, national sources	Min-max, equal weight	AGRI_INFRA
Cereal yield (kg/ha)	FAO via WDI	Z-score, equal weight	AGRI_PROD
Ag VA per worker (2015 USD)	WDI (EA.PRD.AGRI.KD)	Z-score, equal weight	AGRI_PROD
Agro-processing share	UNIDO via WDI	Z-score, equal weight	AGRI_PROD

Note: PCA = principal component analysis. Min-max = min-max standardisation to [0,1]. Z-score = (x-mu)/sigma within ECOWAS sample.