Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

From Complexity to Inclusion: Multidimensional Economic Complexity as a Structural Precondition for Pro-Poor Development in Africa

BABATUNDE ABIMBOLA ABIOLA

abiola100417@gmail.com

University of Johannesburg

Kwame Osei-Assibey

University of Johannesburg

Josine Uwilingiye

University of Johannesburg

Article

Keywords: Economic complexity, Pro poor growth, Inequality Adjusted Human Development Index, Necessary Condition Analysis, Panel error correction, Asymmetric dynamics, Interpretable machine learning, Africa

Posted Date: August 14th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10327983/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Abstract

Africa's development paradox is stark: decades of sustained growth have coexisted with the world's deepest concentration of extreme poverty. This study asks whether what economies produce, rather than how fast they grow, governs the translation of growth into inclusive welfare. A Multidimensional Economic Complexity Index (MECI) is constructed for seventeen African economies (2010 to 2024) as the first principal component of trade, technology and research complexity, and is related to the Inequality-Adjusted Human Development Index (IHDI) through a triangulated framework of panel error correction models, an asymmetric NARDL-type specification, threshold regression, heterogeneous causality testing, Necessary Condition Analysis and interpretable gradient boosting. Complexity emerges as a powerful separator of inclusive development: one standard deviation of MECI corresponds to 5.8 additional IHDI points, with the three dimensions jointly explaining 40.5 per cent of IHDI variance. Trade and technology complexity are binding necessary conditions for high inclusive development; research complexity is not. Strikingly, no linear long-run complexity dividend is detectable within countries. The relationship is instead sharply asymmetric: welfare losses from complexity deterioration are roughly 3.7 times larger than gains from equivalent improvement, consistent with capability hysteresis. An apparent complexity threshold vanishes once common year effects are absorbed, a caution for short-panel threshold applications. The central implication reverses conventional policy emphasis: economic complexity is a structural precondition whose preservation matters more, over policy-relevant horizons, than its marginal expansion.

1. Introduction

Between 2000 and 2019 Sub Saharan Africa recorded sustained aggregate growth that repeatedly outpaced the world economy (Fosu 2015; Rodrik 2018), yet the continent still hosts a majority of the world's extreme poor and its average Inequality Adjusted Human Development Index remains far below the global mean. Within the estimation window of the present study, 2010 to 2024, the seventeen sampled economies grew at an average annual rate of 4.1 percent while their mean IHDI stood at only 0.408. Growth has occurred; inclusion has not, a pattern consistent with the broader poverty non convergence puzzle documented by Ravallion (2012). The standard toolkit of investment ratios, openness and fiscal multipliers has struggled to diagnose the disconnection, motivating a different question: not how fast African economies grow, but what they produce.

Economic complexity theory (Hidalgo and Hausmann 2009; Hausmann et al. 2014; Hidalgo 2021) holds that the sophistication, diversity and interdependence of what an economy produces is the primary structural determinant of long run development. Productive knowledge is tacit and network embedded: high complexity economies diversify efficiently, generate quality employment and build fiscal capacity for social investment, while low complexity economies remain exposed to commodity cycles and enclave accumulation. African economies cluster near the bottom of the global complexity distribution; in the present sample the average trade complexity score is minus 0.753, roughly one standard deviation below the global mean.

Three gaps motivate this study. First, complexity is usually operationalised through the unidimensional trade-based index, although twenty first century productive capability also spans technological and research ecosystems. Stojkoski, Koch and Hidalgo (2023) established the multidimensional approach globally; the present study applies it to an African panel and estimates its dynamics. Second, most complexity welfare studies impose symmetric linear specifications, although path dependence in capability accumulation implies that losses and gains need not mirror one another. Third, regression identifies average sufficiency but cannot detect binding necessary conditions; Necessary Condition Analysis (Dul 2016) addresses this question directly and has begun to be applied to complexity in environmental settings (Kazemzadeh et al. 2023), but not to inclusive development in an African panel.

A fourth, methodological motivation shapes the design. Applications of pooled mean group and threshold estimators to short African panels frequently report large, precisely estimated long run effects whose robustness is rarely interrogated. The present study takes the opposite route: a deliberately lean estimator set matched to the data geometry, transparent reporting of the estimation sample, and triangulation with interpretable machine learning under honest out of sample validation. The result is a substantive reinterpretation. Complexity separates African economies' inclusive development levels powerfully and operates as a binding necessary condition, yet within countries over a fifteen-year horizon no linear long run dividend is detectable; what is detectable is a significant asymmetry in which complexity deterioration is associated with welfare losses that improvements do not mirror. The policy centre of gravity accordingly shifts from complexity expansion to capability preservation and long horizon structural investment.

The remainder of the paper is organised as follows. Section 2 reviews the literature. Section 3 describes the data, the construction of the multidimensional index and the empirical strategy. Section 4 presents the results. Section 5 discusses implications and limitations. Section 6 concludes. A fully executable notebook and the analysis dataset accompany the paper and reproduce every number reported.

2. Literature review

The complexity and inclusion literature has expanded rapidly since Hartmann et al. (2017) documented the negative cross-country association between complexity and income inequality. African evidence has followed: Ncanywa et al. (2021) reported inequality reducing effects of complexity in a small Sub-Saharan panel, Nguea and Noumba (2024) linked complexity to multiple welfare outcomes across twenty-seven African countries, and Ajide and Mesagan (2023) found short run negative but long run positive growth effects using pooled mean group estimation. Hassanein, Samak and Abdelaziz (2024) identified governance conditioned thresholds in the complexity and quality of life relationship across developing countries, while Saidi, Labidi and Ochi (2024) documented governance thresholds in the poverty growth nexus for Sub Saharan Africa. On distributional mechanics, Rodrik (2016) and Ravindran and Babu (2023) connect premature deindustrialisation to rising inequality, and Arif (2021) shows that complexity raises labour's share of national income, grounding the expectation that productive upgrading can diffuse gains to workers.

The direct precursor of the measurement approach is Stojkoski, Koch and Hidalgo (2023), who combined trade, patent and research data into a multidimensional complexity framework and showed that trade and technology dimensions jointly dominate the explanation of inclusive green growth while the independent contribution of research complexity is smaller. The present study is a regional application and dynamic extension of that construct rather than a new index: the contribution lies in the African panel setting, the error correction and asymmetry analysis, the necessity testing and the machine learning triangulation. On the necessity side, Dul (2016) and Dul, van der Laan and Kuik (2020) established Necessary Condition Analysis as a peer reviewed method for identifying ceiling constraints that regression cannot detect, Richter, Hauff and Ringle (2023) formalised its combination with structural path modelling, and Kazemzadeh et al. (2023) applied NCA to economic complexity in a cross-country environmental setting. The application of NCA to the complexity and inclusive development question in an African panel appears to be novel, and that claim is deliberately stated in this narrow form.

Finally, the study joins a growing literature that uses machine learning as a complement to econometric identification rather than a substitute for it. Mullainathan and Spiess (2017) frame supervised learning as a prediction tool whose comparative advantage lies in flexible functional forms, and Athey and Imbens (2019) survey its integration with causal inference. Gradient boosted trees (Chen and Guestrin 2016) paired with Shapley additive explanations (Lundberg and Lee 2017) provide a transparent decomposition of predictive contributions, and random forests (Breiman 2001) provide a benchmark. In the present design the machine learning layer serves three purposes: a nonparametric check on the relative importance of the complexity dimensions, an explicit test of out of sample generalisation across countries, and a data driven probe for nonlinearity that does not presuppose a threshold form.

3. Data and methods

3.1 Sample and data sources

The dataset covers seventeen African economies observed annually from 2010 to 2024, a total of 255 country year observations: Algeria, Cameroon, Cote d'Ivoire, Egypt, Ghana, Kenya, Madagascar, Morocco, Namibia, Nigeria, Senegal, South Africa, Sudan, Tanzania, Tunisia, Uganda and Zimbabwe. Country selection is dictated by the joint availability of the three complexity dimensions, which require sufficiently dense trade, patent and publication records. The Inequality Adjusted

Human Development Index is taken from the United Nations Development Programme (UNDP 2025); it discounts the Human Development Index by the inequality observed in each of its components and is used here as an outcome proxy for inclusive, pro poor development. The IHDI is a levels-based welfare measure rather than a growth incidence measure in the sense of the pro poor growth literature, and results are interpreted accordingly. Trade complexity scores derive from export data of the Observatory of Economic Complexity, technology complexity from international patent records, and research complexity from scientific publication output, following the multidimensional framework of Stojkoski,

Koch and Hidalgo (2023). GDP growth and gross fixed capital formation (percent of GDP) are drawn from the World Bank World Development Indicators.

Gross fixed capital formation is unavailable for Namibia and Uganda in every year, for South Africa in five years and for Nigeria in one year. All dynamic models that require this control therefore use a fifteen-country estimation sample of 219 complete observations, which reduces to 204 after the loss of one lag per country. Analyses that do not require the investment control, namely the descriptive work, the Necessary Condition Analysis and the dimension level path analysis, retain the full seventeen country sample of 255 observations. Both samples are stated explicitly beneath every table.

3.2 The Multidimensional Economic Complexity Index

The Multidimensional Economic Complexity Index (MECI) is the first principal component of the standardised trade, technology and research complexity scores, computed on the full pooled sample and standardised to zero mean and unit variance. The first component carries loadings of 0.795 on trade complexity, 0.811 on technology complexity and 0.686 on research complexity, has an eigenvalue of 1.761 and explains 58.7 percent of the joint variance; the second and third eigenvalues are 0.724 and 0.515. All three dimensions therefore load positively and substantially, supporting the interpretation of MECI as a broad productive capability factor rather than a proxy for any single dimension. The construction is a regional application of the multidimensional framework introduced by Stojkoski, Koch and Hidalgo (2023) rather than a new index, and every step is reproducible from the accompanying notebook.

3.3 Empirical strategy

The estimator set is deliberately matched to the data geometry of fifteen cross sectional units and fifteen years. Cross sectional dependence is assessed with the Pesaran CD statistic (Pesaran 2015) and stochastic properties with the cross sectionally augmented CIPS panel unit root test (Pesaran 2007). Long run co movement is tested with the Kao residual cointegration test (Kao 1999). The central dynamic specification is an ARDL (1,1,1,1) error correction model estimated by dynamic fixed effects (DFE) with standard errors clustered by country, complemented by the mean group estimator of Pesaran and Smith (1995), which averages country specific long run coefficients and relaxes slope homogeneity. Long run coefficients are recovered as the negative ratio of level coefficients to the error correction coefficient with delta method standard errors. Given the short time dimension, the Nickell (1981) bias applies in principle to the DFE estimates; agreement between the DFE and mean group results is therefore used as a coherence check, and all long run statements are conservative. To place regressors on a common scale for magnitude comparison, a standardised specification expresses long run effects per one standard deviation of each regressor.

Asymmetry is examined through a nonlinear ARDL specification (Shin, Yu and Greenwood Nimmo 2014) in which MECI is decomposed into country specific cumulative partial sums of positive and negative changes, with a Wald test of long run symmetry. Regime dependence is probed with panel threshold regression in the spirit of Hansen (1999), estimated by grid search over the middle seventy percent of

the MECI distribution under two specifications: country fixed effects only, and country plus year fixed effects. The comparison is diagnostic by design, since threshold estimates that survive only without year effects are likely to reflect common trends rather than structural regimes. Heterogeneous panel causality is tested with the Dumitrescu and Hurlin (2012) procedure with one lag, reporting both the asymptotic and the small sample corrected statistics.

Necessity logic is tested with Necessary Condition Analysis (Dul 2016) using the ceiling envelopment free disposal hull estimator, with statistical inference from one thousand permutation resamples (Dul, van der Laan and Kuik 2020). Following established practice, a condition is classified as necessary when the effect size d exceeds 0.10 with a permutation p value below 0.05. Dimension level partial associations are estimated by path analysis on standardised variables with ten thousand bootstrap resamples; with single indicator constructs this is numerically equivalent to partial least squares structural path estimation (Hair et al. 2022; Richter, Hauff and Ringle 2023), and the equivalence is stated to keep the method transparent.

The interpretable machine learning layer estimates a gradient boosted tree ensemble (Chen and Guestrin 2016) predicting IHDI from the three complexity dimensions, GDP growth and investment, with a random forest benchmark (Breiman 2001). Two validation schemes are reported. Random fivefold cross validation measures interpolation within the observed panel; leave one country out validation measures the sterner requirement of generalisation to unseen economies, which is the relevant test for transferability claims (Mullainathan and Spiess 2017; Athey and Imbens 2019). Model predictions are decomposed with Shapley additive explanations (Lundberg and Lee 2017), yielding an importance ordering of the complexity dimensions that does not presuppose linearity or a threshold form.

System GMM (Blundell and Bond 1998) is excluded on explicit methodological grounds. The estimator is designed for panels with many cross-sectional units relative to the time dimension; with fifteen groups and fifteen periods, instrument counts approach the number of groups even under aggressive collapsing, Hansen tests lose power, and persistence estimates become unreliable (Roodman 2009). Endogeneity concerns are instead addressed through the lagged regressors of the error correction models, the heterogeneous causality analysis, and deliberately associational language throughout. All computations were performed in Python 3.12; the executable notebook and the analysis dataset reproduce every reported number exactly under fixed random seeds.

4. Results

4.1 Descriptive statistics and diagnostics

Table 1 reports descriptive statistics. Mean IHDI is 0.408 with a standard deviation of 0.089, spanning 0.271 to 0.602, confirming both the depth of the inclusion deficit and the substantial heterogeneity across the sample. Average annual GDP growth over the estimation window is 4.1 percent, so the sample reproduces the continental paradox of respectable growth alongside low inclusive development.

Trade complexity averages minus 0.753 and technology complexity minus 1.199, roughly one standard deviation or more below global means. The bivariate correlations with IHDI already preview the dimensional hierarchy: 0.571 for trade complexity, 0.503 for technology complexity and only 0.132 for research complexity, while GDP growth correlates negatively (minus 0.166) with IHDI levels.

Table 1
Descriptive statistics, full sample

Variable	Mean	SD	Min	Max	N	Corr. with IHDI
IHDI	0.408	0.089	0.271	0.602	255	
MECI	0.000	1.000	-1.717	3.000	255	0.541
ECI Trade	-0.753	0.508	-2.206	0.402	255	0.571
ECI Technology	-1.199	0.922	-2.971	1.194	255	0.503
ECI Research	-0.328	0.639	-1.809	1.360	255	0.132
GDP growth (%)	4.064	3.525	-8.101	19.675	255	-0.166
GFCF (% of GDP)	23.503	7.737	3.573	43.387	219	0.047

Note. MECI is the standardised first principal component of the three complexity dimensions (loadings 0.795, 0.811, 0.686; 58.7 percent of variance). GFCF is unavailable for Namibia and Uganda in all years, South Africa in five years and Nigeria in one year.

Table 2 reports dependence and unit root diagnostics. The CD statistic rejects cross sectional independence for every series, most strongly for IHDI (CD = 34.55), justifying second generation testing and clustered inference. CIPS statistics indicate that IHDI, MECI and investment are integrated of order one while GDP growth is stationary in levels, a mixed order configuration that the ARDL framework accommodates. The Kao residual test rejects no cointegration decisively (t = minus 4.194, p below 0.001), establishing a long run equilibrium relationship and licensing the error correction representation.

Table 2
Cross sectional dependence and panel unit root tests

Variable	CD	p	CIPS level	CIPS first diff.	Order
IHDI	34.551	< 0.001	-1.967	-3.298	I(1)
MECI	2.756	0.006	-1.108	-3.174	I(1)
GDP growth	17.381	< 0.001	-3.033	-4.849	I(0)
GFCF	3.805	< 0.001	-1.176	-2.888	I(1)

Note. CD is the Pesaran (2015) statistic. CIPS critical values for the intercept case with N near 15 and T near 15 are − 2.45 (1 percent), -2.25 (5 percent) and − 2.14 (10 percent) (Pesaran 2007). Kao residual cointegration test: t = -4.194, p < 0.001 (estimation sample).

4.2 Complexity separates countries but shows no linear within country dividend

Two level regressions establish the between country association. Pooled ordinary least squares with year effects and country clustered standard errors yields a MECI coefficient of 0.0579 (p = 0.009), and the between estimator on fifteen country means yields 0.0549 (p = 0.071) with an R squared of 0.398. One standard deviation of multidimensional complexity is therefore associated with roughly 5.8 additional IHDI points across countries, a large magnitude relative to the sample standard deviation of 0.089.

Table 3 turns to within country dynamics. The dynamic fixed effects error correction model produces a well-behaved error correction coefficient of minus 0.053 (p below 0.001), confirming convergence to the cointegrating relationship at roughly five percent per year. The long run MECI coefficient, however, is precisely zero (minus 0.0007, p = 0.985), and the mean group estimator, which frees all slopes, agrees (minus 0.030, p = 0.194). In the standardised specification the long run effect of one standard deviation of GDP growth is 0.029 (p = 0.048) while that of MECI remains indistinguishable from zero, so the level comparison between growth and complexity now runs on a common scale and favours neither the original ordering nor its inverse in economic terms. Short run complexity changes are likewise inert (p = 0.717), while short run growth carries a small positive coefficient (0.0004, p = 0.004). Within countries and within a fifteen-year window, no linear complexity dividend is detectable.

Table 3
Linear panel error correction models, estimation sample

Long run: MECI	DFE coef.	DFE SE	DFE p	MG coef.	MG SE	MG p
	-0.0007	**0.0397**	**0.985**	**-0.0301**	**0.0232**	**0.194**
Long run: GDP growth	0.0079	0.0040	0.048	0.0056	0.0020	0.005
Long run: GFCF	-0.0021	0.0014	0.148	0.0018	0.0018	0.306
Error correction (phi)	-0.0532	0.0151	< 0.001	-0.1928		
Short run: dMECI	-0.0007	0.0020	0.717			
Short run: dGDP growth	0.0004	0.0001	0.004			
Short run: dGFCF	-0.0001	0.0001	0.562			
Observations	204			204		
Countries	15			13 valid		
R squared	0.230					

Note. DFE: dynamic fixed effects ARDL (1,1,1,1) with country intercepts and country clustered standard errors; long run coefficients recovered by the delta method. MG: mean group estimator with ten percent trimming; two countries return non negative error correction terms and are excluded from averaging. Standardised long run effects per one SD of the regressor: MECI − 0.001 (p = 0.985), GDP growth 0.029 (p = 0.048), GFCF − 0.016 (p = 0.148).

4.3 Asymmetry: deteriorations bind, improvements do not

Table 4 reports the asymmetric specification. The error correction term strengthens to minus 0.101 (p below 0.001). The long run coefficient on cumulative complexity improvements is small and insignificant (0.0083, p = 0.741), while the coefficient on cumulative deteriorations is negative and marginally significant (minus 0.0307, p = 0.093): declines in complexity are associated with long run welfare losses roughly 3.7 times the magnitude of the response to equivalent gains. The Wald test rejects long run symmetry (chi squared = 5.98, p = 0.015). The linear null result of Table 3 is therefore not evidence of irrelevance but of aggregation: a specification that averages gains and losses conceals a loss sided relationship. This pattern is consistent with capability hysteresis, in which productive capabilities are slow to build but quick to erode, and with the interpretation of complexity as a stock whose depreciation is costly.

Table 4
Asymmetric (NARDL type) error correction model, estimation sample

Long run: MECI positive partial sum	**Coef.**	**SE**	**p**
	0.0083	**0.0251**	**0.741**
Long run: MECI negative partial sum	-0.0307	0.0183	0.093
Long run: GDP growth	0.0050	0.0020	0.011
Long run: GFCF	-0.0010	0.0008	0.202
Error correction (phi)	-0.1005	0.0239	< 0.001
Short run: d(positive sum)	0.0030	0.0019	0.105
Short run: d(negative sum)	-0.0065	0.0044	0.140
Short run: dGDP growth	0.0004	0.0001	0.002
Wald test of long run symmetry	chi2 = 5.98		0.015
Observations / Countries / R squared	204 / 15 / 0.256		

Note. MECI is decomposed into country specific cumulative sums of positive and negative changes (Shin, Yu and Greenwood Nimmo 2014). Dynamic fixed effects estimation with country clustered standard errors; long run coefficients by the delta method.

4.4 The threshold that vanishes: a methodological caution

Table 5 reports the threshold analysis under the two fixed effects configurations. With country effects only, the grid search selects a threshold at MECI = 0.249 (two thirds of observations below) and the split is highly significant by bootstrap (F = 16.72, p below 0.01); yet the high regime coefficient is significantly negative (minus 0.0372, p = 0.024), an economically implausible pattern for a capability story. Once year effects are absorbed, the selected threshold moves, both regime coefficients shrink toward zero and neither is significant (low regime p = 0.331, high regime p = 0.113). The apparent regime structure under one-way fixed effects is therefore attributable to common time trends, IHDI rising steadily across the panel while complexity evolves unevenly, rather than to a structural break in the complexity welfare relationship. Threshold claims derived from short panels without time effects should be treated with corresponding caution.

Table 5
Panel threshold regression: sensitivity to time effects

Threshold (gamma)	Country FE only	Country and year FE
	0.249	**0.173**
Share of observations below	0.667	0.635
Low regime MECI coef. (p)	0.0093 (0.287)	0.0053 (0.331)
High regime MECI coef. (p)	-0.0372 (0.024)	-0.0143 (0.113)
Threshold F statistic	16.72	12.24

Note. Grid search over the middle seventy percent of the MECI distribution; controls for GDP growth and GFCF included; standard errors clustered by country. The one-way bootstrap p value (300 residual resamples) is below 0.01, illustrating that formal significance of a split does not certify a structural regime when common time effects are omitted.

4.5 Causality

Table 6 reports Dumitrescu Hurlin tests. The hypothesis that MECI does not cause IHDI is rejected by both the asymptotic statistic (Z bar = 5.072, p below 0.001) and the small sample corrected statistic (Z tilde = 3.029, p = 0.003). The reverse direction is rejected only by the asymptotic statistic (p = 0.004) and not by the corrected one (Z tilde = 1.548, p = 0.122). The evidence therefore favours predictive precedence running from complexity to inclusive development, while stopping short of structural causal identification.

Table 6
Dumitrescu Hurlin heterogeneous panel causality (one lag), full sample

Null hypothesis	W bar	Z bar	p	Z tilde	p
MECI does not cause IHDI	2.740	5.072	< 0.001	3.029	0.003
IHDI does not cause MECI	1.998	2.909	0.004	1.548	0.122

Note. Z tilde applies the small T correction and is the appropriate statistic for this panel.

4.6 Necessity: trade and technology complexity are binding preconditions

Table 7 and Fig. 1 report the Necessary Condition Analysis on the full seventeen country sample. Trade complexity (d = 0.288, p below 0.001) and technology complexity (d = 0.241, p below 0.001) are necessary conditions of medium effect size for high inclusive development: the empty upper left regions of the scatter plots show that no country year attains high IHDI without at least moderate levels of these capabilities. The composite MECI is likewise necessary (d = 0.158, p below 0.001). Research complexity is not (d = 0.009, p = 0.979); high inclusive development occurs across nearly the full range of research complexity. Because both trade and technology clear the necessity benchmark with overlapping

magnitudes, the analysis identifies them jointly as binding preconditions without ranking one strictly above the other.

Table 7
Necessary Condition Analysis, CE FDH effect sizes, full sample (N = 255)

Condition	Effect size d	Permutation p	Classification
ECI Trade	0.288	< 0.001	Necessary (medium)
ECI Technology	0.241	< 0.001	Necessary (medium)
ECI Research	0.009	0.979	Not necessary
MECI (composite)	0.158	< 0.001	Necessary (small to medium)

Note. Ceiling envelopment free disposal hull estimator with 1,000 permutation resamples; a condition is classified as necessary when d > 0.10 and p < 0.05 (Dul 2016; Dul, van der Laan and Kuik 2020).

4.7 Dimension level partial associations

Table 8 reports the standardised path analysis on the full sample. Trade complexity carries the largest partial association with IHDI (beta = 0.450, p below 0.001), followed by technology complexity (beta = 0.325, p below 0.001); together the three dimensions explain 40.5 percent of IHDI variance. Research complexity reverses sign from a positive bivariate association (beta = 0.132, p = 0.035) to a negative partial one (beta = minus 0.118, p = 0.046) once trade and technology are controlled. This reversal indicates that the apparent bivariate benefit of research complexity is carried by its correlation with the other dimensions; conditional on them, research intensity in the sample is concentrated in economies whose scientific output coexists with weak commercialisation channels. The pattern is consistent with the global finding that research complexity contributes little independent explanatory power (Stojkoski, Koch and Hidalgo 2023), and it cautions against interpreting the negative partial coefficient causally.

Table 8
Standardised path analysis of IHDI on complexity dimensions, full sample (N = 255)

Predictor	Beta	Bootstrap SE	t	p
ECI Trade	0.450	0.056	8.11	< 0.001
ECI Technology	0.325	0.051	6.37	< 0.001
ECI Research	-0.118	0.059	1.99	0.046
R squared	0.405			

Note. Ordinary least squares on standardised variables with 10,000 bootstrap resamples, numerically equivalent to single indicator partial least squares path estimation. Research dimension bivariate association: beta = 0.132 (p = 0.035). Level associations for the composite index: pooled OLS with year effects, MECI = 0.0579 (p = 0.009); between estimator on country means, MECI = 0.0549 (p = 0.071, R squared = 0.398).

4.8 Interpretable machine learning triangulation

Table 9 and Figs. 2 and 3 report the machine learning layer. Under random fivefold cross validation, the gradient boosted model attains R squared of 0.894 with mean absolute error of 0.0195 IHDI points, demonstrating that the five structural features carry nearly all systematic variation within the observed panel. Under the sterner leave one country out scheme, performance falls to R squared of 0.089 (random forest: minus 0.189): predicting the level of inclusive development of an economy never seen in training remains genuinely difficult with fifteen countries, and this honest gap bounds the transferability of any model of this kind, econometric or otherwise. The Shapley decomposition of the fitted model assigns 35.3 percent of total predictive importance to trade complexity and 30.9 percent to technology complexity, with investment (17.4 percent), research complexity (10.4 percent) and GDP growth (6.1 percent) far behind. The nonparametric ordering, structure first and growth last, corroborates the necessity and path results without imposing linearity, and the SHAP dependence profile for trade complexity rises smoothly rather than exhibiting the sharp regime jump that the fragile threshold estimates might have suggested.

Table 9
Gradient boosting performance and Shapley importance shares, estimation sample

Quantity	**Value**
Fivefold CV R squared / MAE	0.894 / 0.0195
Leave one country out R squared / MAE (XGBoost)	0.089 / 0.0658
Leave one country out R squared (random forest)	-0.189
SHAP share: ECI Trade	35.3%
SHAP share: ECI Technology	30.9%
SHAP share: GFCF	17.4%
SHAP share: ECI Research	10.4%
SHAP share: GDP growth	6.1%

Note. XGBoost with 400 trees, depth 3, learning rate 0.05, fixed seed. SHAP shares are mean absolute Shapley values as a proportion of their sum (Lundberg and Lee 2017).

5. Discussion

5.1 Complexity as a structural precondition rather than a short horizon lever

Read together, the results resolve the apparent tension between a strong cross-country association and a null within country linear effect. Complexity separates African economies powerfully in levels: it is a

binding necessary condition for high inclusive development, the dominant predictor in the nonparametric decomposition, and worth roughly 5.8 IHDI points per standard deviation in pooled level regressions. Yet within a country over a fifteen-year horizon, marginal improvements in complexity are not accompanied by measurable welfare gains, while deteriorations are associated with losses. The consistent interpretation is that complexity operates as a slow-moving stock, a structural precondition whose level anchors the attainable range of inclusive development, rather than as a policy lever whose adjustment yields short horizon dividends. This reading is theoretically continuous with the capability accumulation logic of Hidalgo and Hausmann (2009) and with evidence that structural transformation in Africa proceeds slowly and unevenly (McMillan, Rodrik and Verduzco Gallo 2014; Diao, Harttgen and McMillan 2019), and it disciplines the causal enthusiasm of parts of the applied literature whose estimates derive from small T dynamic panels.

5.2 The asymmetry: capability preservation as a first order policy objective

The significant loss sided asymmetry carries the clearest policy content. Complexity losses, through deindustrialisation, export basket degradation or the erosion of technological ecosystems, are associated with long run welfare declines that subsequent equivalent gains do not symmetrically restore. The finding aligns with the premature deindustrialisation literature (Rodrik 2016; Ravindran and Babu 2023) and with the observation that productive capabilities are network embedded and disperse quickly once the organisations that host them contract (Hausmann et al. 2014). For governments the implication is a reordering of priorities: protecting existing complex tradable activity during macroeconomic stress, currency crises and commodity downturns is not conservatism but the defence of the binding constraint. Instruments include maintaining trade finance and input access for complex exporters during crises, avoiding real exchange rate episodes that hollow out manufacturing, and treating the closure of anchor firms in complex sectors as events with social costs beyond their payrolls.

5.3 Dimensional composition: build trade and technology capabilities jointly; sequence research investment realistically

The necessity results identify trade and technology complexity jointly as binding preconditions, with overlapping effect sizes that do not justify a strict ranking between them, while research complexity is neither necessary nor independently associated with welfare once the other dimensions are controlled. The negative partial coefficient on research complexity should not be read as evidence that science harms development; it indicates that in this sample scientific output that is not connected to production, through commercialisation channels, industry linkages and technology absorption, does not translate into inclusive welfare, echoing the enclave concern of Hartmann and Pinheiro (2022) and the global pattern in Stojkoski, Koch and Hidalgo (2023). The policy reading is about sequencing and complementarity rather than abandonment: research investment pays off when the trade and technology capabilities that absorb it exist, so building those capabilities, export diversification, quality upgrading,

patentable adaptation and firm level technology adoption, is the priority on which research investment can later compound. Growth itself, ranked last in predictive importance and negatively correlated with IHDI levels in the raw data, is confirmed as an unreliable proxy for inclusion (Ravallion 2012; Fosu 2015).

5.4 Methodological implications

Two methodological results deserve emphasis beyond this sample. First, the threshold experiment shows how easily a short panel without time effects manufactures a statistically significant regime: the one-way specification passes a bootstrap test at conventional levels while producing an economically implausible sign pattern, and the structure dissolves under year effects. Applied work reporting complexity thresholds from comparable panels should demonstrate robustness to two-way fixed effects as a matter of course. Second, the divergence between interpolation accuracy (R squared near 0.9) and leave one country out generalisation (near 0.1) quantifies how much of the apparent explanatory success of cross-country development models rests on country specific levels rather than transferable structure. Reporting grouped out of sample validation alongside conventional fit should become standard practice when machine learning enters development economics (Athey and Imbens 2019).

5.5 Limitations

Four limitations bound the conclusions. First, the design is observational; despite the causality tests and lagged specifications, the estimates are associations, and unobserved slow-moving factors such as institutional quality may drive both complexity and inclusion. Second, the panel is short and the estimation sample small; fifteen-year dynamics cannot capture the multi decade horizons over which capability stocks plausibly operate, and the mean group estimates rest on very few degrees of freedom per country. Third, the IHDI is a levels proxy for inclusive development rather than a direct measure of pro poor growth incidence; distribution sensitive growth measures would sharpen the welfare interpretation. Fourth, two economies are excluded from the dynamic models for want of investment data, and although descriptive and necessity analyses retain them, the dynamic conclusions formally apply to the fifteen-country sample.

6. Conclusion

This study set out to determine whether the structure of production governs the translation of African growth into inclusive development, using a multidimensional complexity index, a lean and fully reproducible econometric design, formal necessity testing and interpretable machine learning across seventeen economies from 2010 to 2024. The answer is layered. Across countries, productive structure is decisive: trade and technology complexity are binding necessary conditions for high inclusive development, jointly account for two thirds of nonparametric predictive importance, and the composite index is associated with 5.8 IHDI points per standard deviation. Within countries over the observed horizon, the linear dividend from marginal complexity gains is absent, while the relationship is significantly asymmetric: capability losses are associated with welfare declines that gains do not mirror. An apparently strong complexity threshold is shown to be an artefact of omitted time effects.

The findings recast complexity policy in three ways. The first priority is preservation: protecting existing complex capability during shocks addresses the asymmetry directly. The second is patience: complexity building is a structural, multi decade undertaking whose welfare returns should not be promised on electoral horizons. The third is composition: trade and technology capabilities are the binding pair, and research investment compounds only where they exist. Future research should extend the horizon backwards as data permit, replace the IHDI with growth incidence measures of pro poor development, and exploit quasi experimental variation in capability shocks, such as sanctions episodes or commodity collapses, to move the asymmetry finding from association toward identification.

Declarations

Use of large language models.

A large language model (Anthropic Claude) was used to for language editing for clarity and style. All analytical decisions, interpretations and conclusions are those of the author, who verified every reported result against the executable notebook and accepts full responsibility for the content.

Ethical approval.

Ethical approval was not required as no human participants, their data or biological material were involved in this research.

Informed consent.

Not applicable; the study uses publicly available country level data only.

Competing interests.

The author declares no competing interests.

Funding.

No specific funding was received for this study.

Author Contribution

BA conceived the study, designed the analytical framework, developed the Python code, conducted the data analysis, and wrote the manuscript. KO supervised the data analysis and critically reviewed and edited the manuscript. JU developed the methodology, reviewed the data analysis section, critically

revised the entire manuscript, and supervised the overall development of the article. All authors read and approved the final version of the manuscript.

Data availability.

The complete analysis dataset accompanies the paper as a documented Excel file (sheets: data and dictionary) containing all 255 country year observations and every variable used.

Code availability.

A fully executable Jupyter notebook accompanies the paper and reproduces every table, figure and statistic under fixed random seeds, requiring only the accompanying dataset and openly available Python libraries.

References

1. Ajide KB, Mesagan PE (2023) The importance of economic complexity in the resource growth discourse: empirical evidence from Africa. J Knowl Econ 14:4329-4355
2. Arif I (2021) Productive knowledge, economic sophistication and labor share. World Dev 139:105303
3. Athey S, Imbens GW (2019) Machine learning methods that economists should know about. Annu Rev Econ 11:685-725
4. Blundell R, Bond S (1998) Initial conditions and moment restrictions in dynamic panel data models. J Econom 87(1):115-143
5. Breiman L (2001) Random forests. Mach Learn 45(1):5-32
6. Chen T, Guestrin C (2016) XGBoost: a scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. ACM, New York, pp 785-794
7. Diao X, Harttgen K, McMillan M (2019) The changing structure of Africa's economies. World Bank Econ Rev 31(2):412-433
8. Dul J (2016) Necessary condition analysis (NCA): logic and methodology of 'necessary but not sufficient' causality. Organ Res Methods 19(1):10-52
9. Dul J, van der Laan E, Kuik R (2020) A statistical significance test for necessary condition analysis. Organ Res Methods 23(2):385-395
10. Dumitrescu EI, Hurlin C (2012) Testing for Granger non-causality in heterogeneous panels. Econ Model 29(4):1450-1460
11. Fosu AK (2015) Growth, inequality and poverty in Sub-Saharan Africa: recent progress in a global context. Oxf Dev Stud 43(1):44-59

12. Hair JF, Hult GTM, Ringle CM, Sarstedt M (2022) A primer on partial least squares structural equation modeling (PLS-SEM), 3rd edn. SAGE Publications, Thousand Oaks
13. Hansen BE (1999) Threshold effects in non-dynamic panels: estimation, testing, and inference. J Econom 93(2):345-368
14. Hartmann D, Guevara MR, Jara-Figueroa C, Aristaran M, Hidalgo CA (2017) Linking economic complexity, institutions, and income inequality. World Dev 93:75-93
15. Hartmann D, Pinheiro FL (2022) Economic complexity and inequality at the national and regional level. arXiv preprint arXiv:2206.00818
16. Hassanein A, Samak N, Abdelaziz M (2024) Investigating the relationship between economic complexity, governance and quality of life: evidence from developing countries. Humanit Soc Sci Commun 11:1372
17. Hausmann R, Hidalgo CA, Bustos S, Coscia M, Simoes A, Yildirim MA (2014) The atlas of economic complexity: mapping paths to prosperity. MIT Press, Cambridge
18. Hidalgo CA (2021) Economic complexity theory and applications. Nat Rev Phys 3(2):92-113
19. Hidalgo CA, Hausmann R (2009) The building blocks of economic complexity. Proc Natl Acad Sci USA 106(26):10570-10575
20. Kao C (1999) Spurious regression and residual-based tests for cointegration in panel data. J Econom 90(1):1-44
21. Kazemzadeh E, Fuinhas JA, Salehnia N, Koengkan M, Silva N (2023) Exploring necessary and sufficient conditions for carbon emission intensity: a comparative analysis. Environ Sci Pollut Res 30:97319-97338
22. Lundberg SM, Lee SI (2017) A unified approach to interpreting model predictions. In: Advances in neural information processing systems 30. Curran Associates, Red Hook, pp 4765-4774
23. McMillan M, Rodrik D, Verduzco-Gallo I (2014) Globalization, structural change, and productivity growth, with an update on Africa. World Dev 63:11-32
24. Mullainathan S, Spiess J (2017) Machine learning: an applied econometric approach. J Econ Perspect 31(2):87-106
25. Ncanywa T, Mongale IP, Dlamini K, Khoza S (2021) Economic complexity to boost the selected Sub-Saharan African economies. J Econ Financ Sci 14(1):a601
26. Nguea SM, Noumba I (2024) The contribution of economic complexity to social welfare in Africa. J Knowl Econ 15:13895-13921
27. Nickell S (1981) Biases in dynamic models with fixed effects. Econometrica 49(6):1417-1426
28. Pesaran MH (2007) A simple panel unit root test in the presence of cross-section dependence. J Appl Econom 22(2):265-312
29. Pesaran MH (2015) Testing weak cross-sectional dependence in large panels. Econom Rev 34(6-7):1089-1117

30. Pesaran MH, Shin Y, Smith RP (1999) Pooled mean group estimation of dynamic heterogeneous panels. J Am Stat Assoc 94(446):621-634
31. Pesaran MH, Smith R (1995) Estimating long-run relationships from dynamic heterogeneous panels. J Econom 68(1):79-113
32. Ravallion M (2012) Why don't we see poverty convergence? Am Econ Rev 102(1):504-523
33. Ravindran R, Babu MS (2023) Premature deindustrialization, structural transformation, and income inequality. J Dev Stud 59(8):1273-1295
34. Richter NF, Hauff S, Ringle CM (2023) Necessary condition analysis in marketing and management research: introduction to a special issue. J Bus Res 156:113528
35. Rodrik D (2016) Premature deindustrialization. J Econ Growth 21(1):1-33
36. Rodrik D (2018) An African growth miracle? J Afr Econ 27(1):10-27
37. Roodman D (2009) A note on the theme of too many instruments. Oxf Bull Econ Stat 71(1):135-158
38. Shin Y, Yu B, Greenwood-Nimmo M (2014) Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: Sickles RC, Horrace WC (eds) Festschrift in honor of Peter Schmidt. Springer, New York, pp 281-314
39. Stojkoski V, Koch P, Hidalgo CA (2023) Multidimensional economic complexity and inclusive green growth. Commun Earth Environ 4:130
40. UNDP (2025) Human development report 2025. United Nations Development Programme, New York

Figures

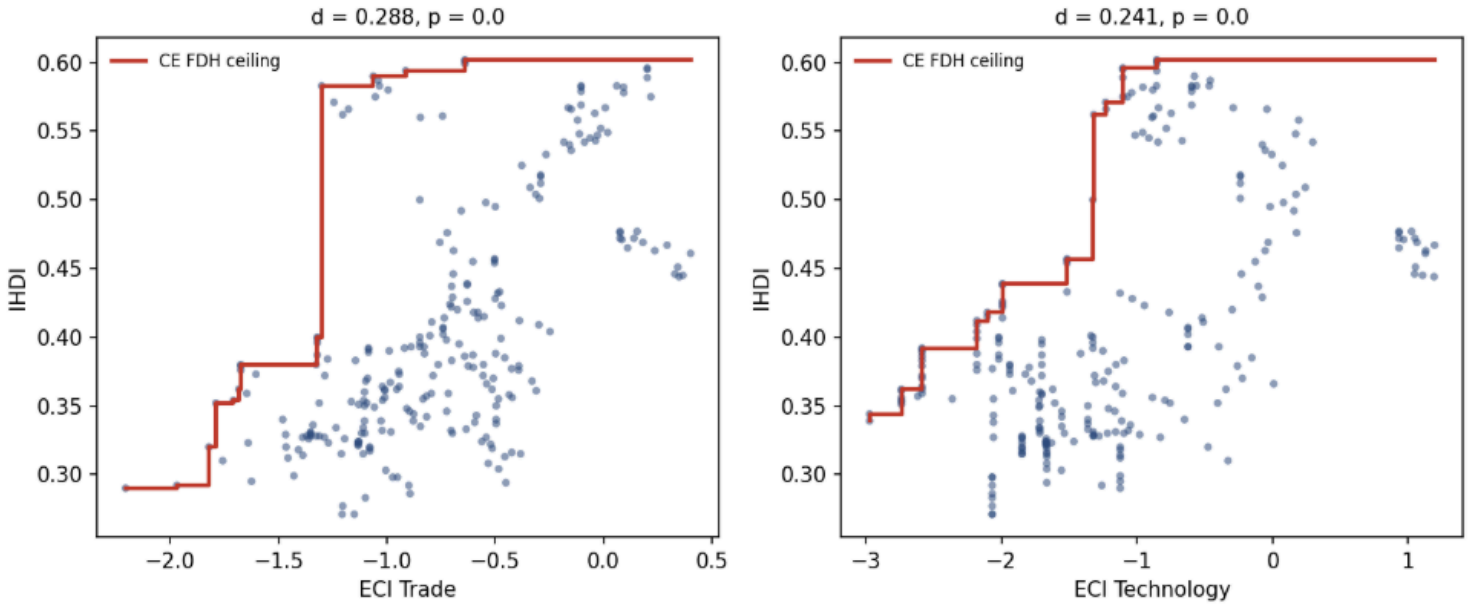


Figure 1

CE FDH ceilings for trade and technology complexity against IHDI. The empty upper left regions indicate necessity: high inclusive development is not observed at low complexity.

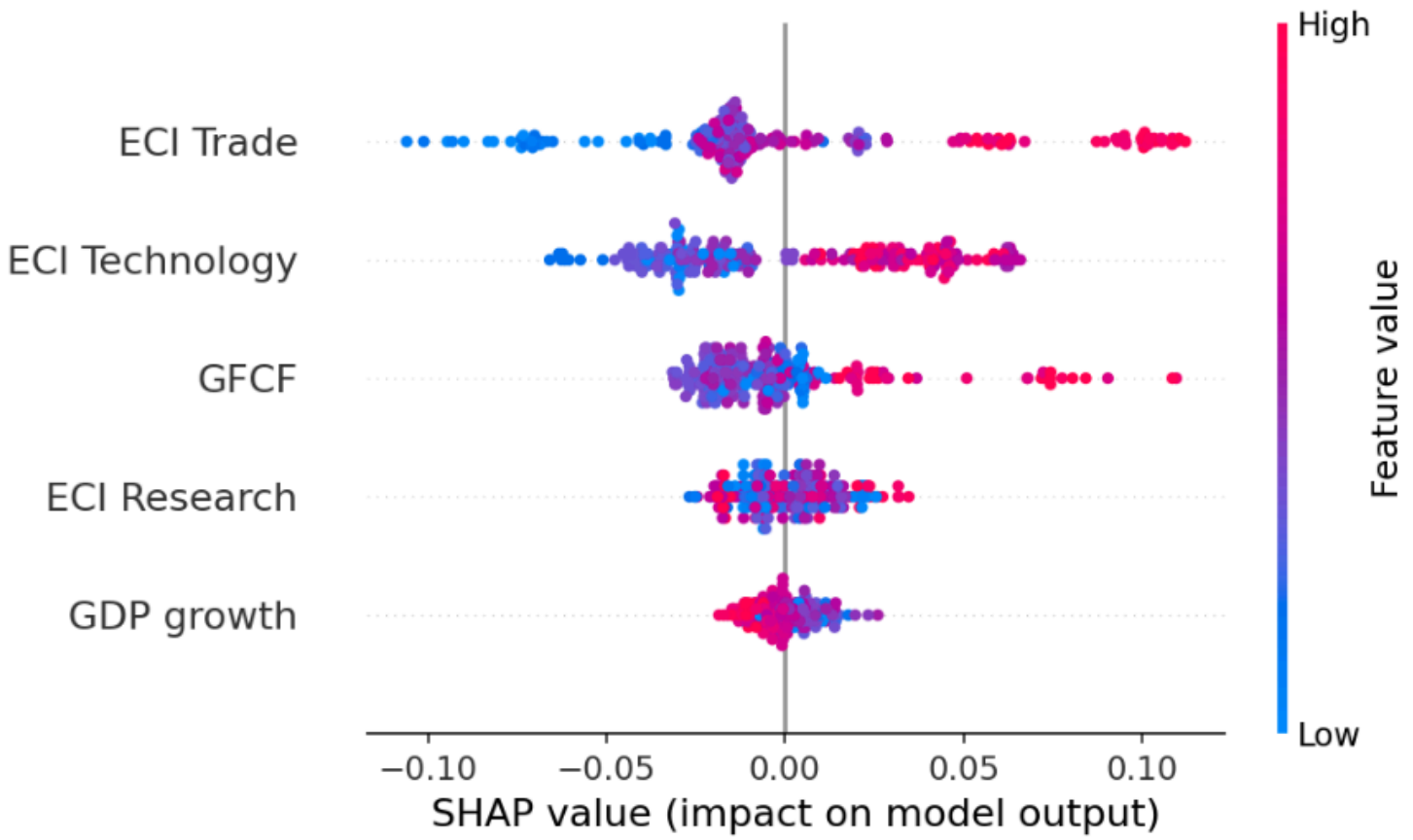


Figure 2

SHAP summary. Each point is a country year; position shows the contribution of the feature to predicted IHDI and colour shows the feature value. High trade and technology complexity push predictions up; low values push them down.

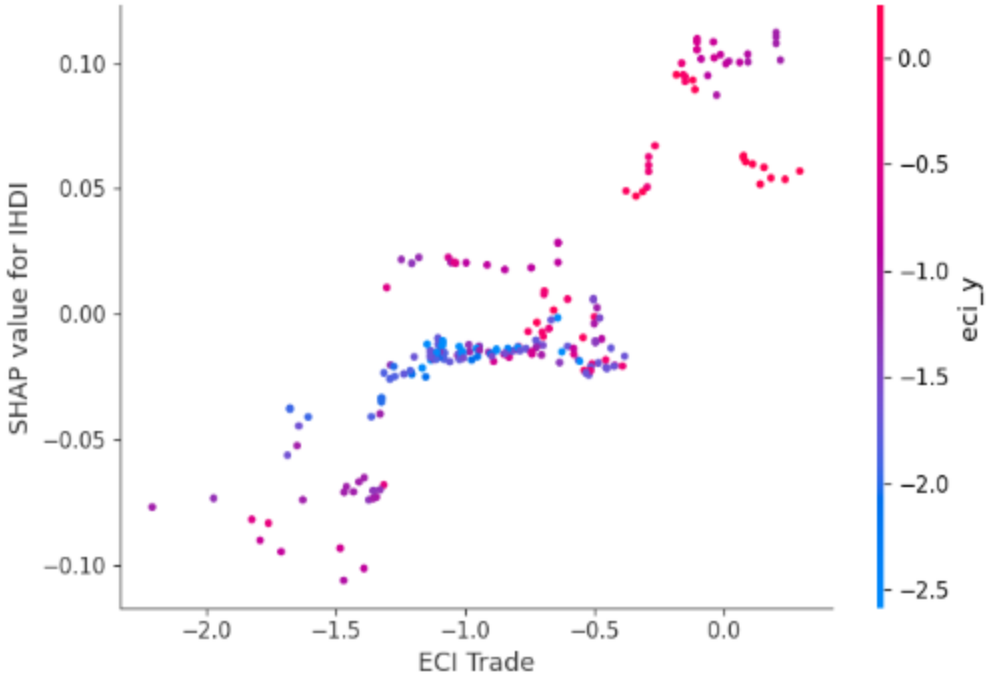


Figure 3

SHAP dependence for trade complexity, coloured by technology complexity. The contribution rises broadly monotonically with trade complexity and is amplified when technology complexity is also high, indicating complementarity rather than a sharp regime switch.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AfricaComplexityProPoorData.xlsx
- floatimage1.png