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DETERMINANTS OF GDP IN SAUDI ARABIA: AN ARDL–ECM ANALYSIS OF HUMAN CAPITAL AND CAPITAL CONTRIBUTIONS, 1976–2024

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ABSTRACT

This paper investigates the determinants of Saudi Arabia's nominal GDP from 1976 to 2024 using an Autoregressive Distributed Lag and Error Correction Model framework, based on 49 annual observations. By decomposing the contributions of ICT capital, non-ICT capital, labor quality, and labor quantity, the study captures both short-run dynamics and long-run equilibrium relationships in a resource-rich economy undergoing structural transformation. The findings reveal that while non-ICT capital and labor inputs are significant long-run drivers of output, ICT capital has yet to exhibit robust effects—highlighting a lag between digital investments and measurable productivity gains. This lag reflects institutional readiness, digital ecosystem maturity, and sector-specific rigidity, contrasting with the UAE's success in translating ICT investments into economic complexity. Moreover, the estimated error-correction term indicates a slow but statistically significant convergence speed of approximately 2.6% per year, implying that deviations from long-run equilibrium are corrected gradually. This result underscores the need for persistent and sustained reform under Vision 2030. The study also emphasizes sectoral heterogeneity, showing that productivity gains are unevenly distributed across industries, with strategic sectors like logistics, tourism, and finance responding more rapidly to reforms than manufacturing and retail. By situating Saudi Arabia's experience within broader comparisons with Norway and the UAE, the paper advances academic debates on growth in resource-dependent economies while offering policy-relevant insights for diversification, human capital development, and digital transformation.

KEYWORDS: Total Factor Productivity, Saudi Arabia, Vision 2030, Panel ARDL, Sectoral Decomposition, Resource Dependence, Economic Diversification.

JEL Codes : O47, Q32, C33, O53

1. INTRODUCTION

Productivity growth remains the foundation of sustainable economic development, raising living standards, strengthening fiscal resilience, and enabling adaptation to global structural shifts (Solow, 1957; Hulten, 2001). For resource-rich economies, however, sustaining growth through productivity rather than resource rents is a persistent challenge (Sachs & Warner, 1995; Auty, 2001). Saudi Arabia exemplifies this dilemma: hydrocarbon dependence has long shaped fiscal stability, structural transformation, and vulnerability to oil price cycles (Elshafei, Bawazir, & Hasan, 2025; Sweidan & Elbargathi, 2023). Total Factor Productivity (TFP), as a measure of input efficiency, is thus central to the Kingdom's diversification agenda under Vision 2030 (Mehlum, Moene, & Torvik, 2006; Van der Ploeg, 2011).

Despite its importance, empirical studies on Saudi productivity remain limited. Much of the existing research employs static growth accounting or broad TFP indices, offering only partial insights into the roles of capital and labor inputs while neglecting structural breaks from reforms and oil shocks (Albassam, 2015; Alghamdi & Liu, 2020; Aljarallah, 2020; Alharthi, 2022). To fill this gap, this paper examines the determinants of Saudi Arabia's nominal GDP from 1976 to 2024 using an Autoregressive Distributed Lag (ARDL) and Error-Correction Model (ECM) framework (Pesaran, Shin, & Smith, 1999, 2001). This methodology captures both short-run adjustments and long-run equilibrium relationships while accommodating mixed integration orders and structural volatility.

The findings reveal that labor quality and quantity serve as the most robust long-run anchors of growth, non-ICT capital contributes mainly in the short run, and ICT capital—despite substantial investment—has yet to generate significant long-run effects. These results suggest lags in digital ecosystem maturity and the absorptive capacity of human capital, echoing experiences in other late-transforming economies (Hasanov & Razek, 2023; IMF, 2022). Comparatively, Norway illustrates how strong institutions can convert resource rents into productivity gains (Mehlum et al., 2006), while the UAE demonstrates the catalytic role of ICT and human capital in accelerating diversification (Alabdulwahab, 2021; Hasanov & Razek, 2023).

Thus, this study contributes by applying a dynamic ARDL–ECM framework to the Saudi context, empirically disaggregating the roles of capital and labor inputs, and providing policy-relevant insights for sustaining productivity-led growth under Vision 2030.

2. LITERATURE REVIEW

Total Factor Productivity (TFP) remains central in growth theory and applied economics as it captures the efficiency with which capital and labor inputs are transformed into output, reflecting not only technological progress but also institutional quality, learning-by-doing, and structural reallocation (Solow, 1957; Hulten, 2001). In resource-rich economies, where output growth has often been driven by commodity exports and capital accumulation, TFP provides a critical lens to distinguish sustainable productivity-led growth from transient rent extraction (Syverson, 2011). The early "resource curse" hypothesis argued that natural resource abundance induces Dutch disease, rent-seeking, and institutional weakening, resulting in long-run stagnation (Sachs & Warner, 1995; Auty, 2001; Corden & Neary, 1982). More nuanced perspectives later emphasized conditional outcomes: where rents are governed by strong institutions and reinvested in technology, education, and infrastructure, resource wealth can underpin long-run productivity improvements (Mehlum et al., 2006; Robinson et al., 2006; van der Ploeg, 2011). Empirical work has further highlighted the dual role of structural transformation: productivity depends not only on within-sector efficiency but also on the reallocation of labor and capital from low-productivity to high-productivity sectors, a process that has been positive in East Asia but growth-reducing in many commodity-dependent economies (McMillan & Rodrik, 2011; Dabla-Norris et al., 2013). This debate continues to shape policy concerns for resource exporters such as Saudi Arabia, which face the challenge of transforming hydrocarbon rents into sustainable TFP growth under the pressures of global energy transition.

Comparative evidence from other resource-dependent economies highlights both successful and limited trajectories. Norway is often cited as a benchmark case, having mitigated Dutch disease through transparent governance of its sovereign wealth fund and fiscal rules that smoothed commodity cycles, thereby creating space for private investment and innovation (Holden, 2019). Chile's copper-driven economy illustrates how diversification and institutional reforms can support productivity growth, though bottlenecks in intermediate linkages persist (De la Cruz et al., 2020). In the Gulf region, the United Arab Emirates demonstrates how strategic investment in digital infrastructure, artificial intelligence, and innovation ecosystems has accelerated productivity and economic complexity (IMF, 2023), whereas Qatar's experience reveals the limits of public investment-led growth absent deep labor market and human capital reforms (Cherif & Hasanov, 2016). Beyond the Gulf, South Korea's transition from resource scarcity to a knowledge-driven economy illustrates the potential of education and technology policies to sustain TFP growth, underscoring the importance of complementarity between human capital and digital transformation (Lee, 2022). These comparative experiences reveal that institutional quality, digital readiness, and labor market flexibility are critical mediators of TFP in resource-dependent economies, providing useful benchmarks for Saudi Arabia's Vision 2030 reforms.

Methodologically, approaches to measuring and analyzing productivity have evolved from traditional growth accounting and Solow residuals to more flexible econometric frameworks that address heterogeneity, non-stationarity, and structural breaks (Coelli et al., 2005; Syverson, 2011). The Autoregressive Distributed Lag (ARDL) model developed by Pesaran, Shin, and Smith (1999, 2001) has become particularly influential in applied macroeconomics, as it accommodates mixed integration orders, cointegration, and dynamic short-run adjustments. Its extended versions, including ARDL with error correction mechanisms (ECM) and panel ARDL, have been used to study the growth impacts of education spending, ICT adoption, and institutional reforms across both OECD and emerging economies (Aghion et al., 2019; Farzanegan & Markwardt, 2009). Recent applications have leveraged ARDL frameworks to assess the asymmetric effects of oil prices on productivity in Iran (Farzanegan & Markwardt, 2009), broadband expansion on sectoral efficiency in Europe (Koutroumpis, 2019), and human capital investments on long-run growth in MENA countries (Elshafei et al., 2025). These methodological advances are well suited to the Saudi context, where reforms intersect with global shocks such as oil price volatility, digital adoption, and decarbonization.

The empirical literature on Saudi Arabia itself reflects both historical constraints and emerging opportunities. Earlier studies emphasized the dominance of capital accumulation over TFP in driving growth, with productivity contributions volatile and often negative due to labor market segmentation and energy subsidies (Albassam, 2015; Alghamdi & Liu, 2020). More recent analyses point to modest gains from reforms under Vision 2030, particularly in logistics, ICT, and finance, while also stressing that labor quality and private sector productivity remain below potential (IMF, 2022; KAPSARC, 2023). Aljarallah (2020) highlights the role of ICT capital services in enhancing nominal GDP, while Alharthi (2022) and Alam et al. (2025) stress the importance of education spending and human capital development for sustaining diversification. Hasanov and Razek (2023) provide evidence that productivity gains in the Gulf require both digital investment and institutional deepening, while Sweidan and Elbargathi (2023) underscore the risks of asymmetric oil dependence and global transition pressures. Collectively, this literature suggests that Saudi Arabia is at a pivotal juncture: while structural rigidities such as reliance on expatriate labor and public sector dominance constrain TFP, reforms in digital infrastructure, education, and institutional capacity could replicate the successes of comparator economies if implemented effectively.

Despite these contributions, significant research gaps remain. Much of the existing Saudi literature has relied on growth accounting or static regressions, with limited use of dynamic econometric models capable of capturing long-run elasticities, structural breaks, and sectoral heterogeneity. Few studies systematically examine the differential adjustment speeds across ICT and non-ICT capital, or the interactions between labor quality, labor quantity, and aggregate output. Moreover, the literature has not sufficiently addressed how global megatrends—decarbonization, demographic shifts, and rapid digital adoption—interact with domestic reforms to shape productivity dynamics. By employing an ARDL–ECM framework with long-run and short-run decomposition, this paper seeks to fill these gaps, providing robust empirical evidence on the contributions of ICT capital, non-ICT capital, labor quality, and labor quantity to Saudi Arabia's nominal GDP between 1976 and 2024, while situating the findings within the broader comparative experience of resource-rich economies.

3. METHODOLOGY

The empirical strategy in this paper is grounded in the autoregressive distributed lag (ARDL) framework (Pesaran & Shin, 1998; Pesaran, Shin, & Smith, 2001). Unlike Johansen cointegration, which requires all variables to be I(1), the ARDL model can handle a mix of I (0) and I (1) variables and performs robustly in small samples, while permitting valid inference on long-run relationships through the Bounds testing approach. Given that Saudi Arabia's economy is characterized by oil-driven cycles and structural breaks, ARDL is particularly suitable (Narayan, 2005).

The dataset comprises annual data for 1976–2024 (49 usable observations). The dependent variable is the logarithm of nominal GDP (log (NGDP)), reflecting total economic activity in current prices. Nominal GDP is used instead of real GDP to maintain consistency with capital investment, which is measured in nominal terms, thereby ensuring coherence between the dependent variable and the key explanatory variables in the model. The regressors are derived from the Conference Board's growth-accounting contribution series for ICT capital services (CC_ICTGDPY_Y), non-ICT capital services (CCNON_ICTGDPY_Y), labor quality (CLABQLGDPY_Y), and labor quantity CLABQNGDPY_Y). The Zivot–Andrew's test identified a structural break in labor quality in 1982; therefore, a dummy variable D_1982 is included. Variables identified as I(0) are modeled in levels, while I(1) regressors are entered in differences.

Unit-root testing proceeds in two steps. First, Augmented Dickey–Fuller (ADF) tests with a constant are run using Schwarz-selected lags (maximum 10) and MacKinnon one-sided p-values. Second, to guard against spurious unit-root findings in the presence of structural change, a Zivot–Andrews (ZA) endogenous-break test (innovational-outlier, intercept break) is applied when the ADF suggests non-stationarity.

The AIC-selected specification is ARDL (3, 0, 4, 2, 1, 4) for log (NGDPCP) on {CC_ICTGDPY_Y, ΔCCNON_ICTGDPY_Y, CLABQLGDPY_Y, CLABQNGDPY_Y, D_1982}. This respects the integration map: the non-ICT contribution (I (1)) appears only through differences, while ICT, labor quality (treated as I(0) with break), and labor quantity (I (0)) enter in levels. Long-run form, short-run dynamics, and the ECM are reported from the ARDL long-run and ECM views.

3.1. Model Specification

In unrestricted error-correction (UECM) form:

$$\boldsymbol{\Delta ln\,NGDPCP_t = \alpha_0 + \phi_1 \Delta ln\,NGDPCP_{t-1} + \phi_2 \Delta ln\,NGDPCP_{t-2}}$$
$$\boldsymbol{+\gamma_0 \Delta CCNON_t + \gamma_1 \Delta CCNON_{t-1} + \gamma_2 \Delta CCNON_{t-2} + \gamma_3 \Delta CCNON_{t-3}}$$
$$\boldsymbol{+\delta_1 CCICT_t + \kappa_0 \Delta CLABQL_t + \kappa_1 \Delta CLABQL_{t-1}}$$
$$\boldsymbol{+\mu_0 \Delta CLABQN_t + \omega_0 \Delta D_{1982,t}}$$
$$\boldsymbol{+\psi(ln\,NGDPCP_{t-1} - \lambda_1 CCNON_{t-1} - \lambda_2 CCICT_{t-1}}$$
$$\boldsymbol{-\lambda_3 CLABQL_{t-1} - \lambda_4 CLABQN_{t-1} - \lambda_5 D_{1982,t-1}) + \varepsilon_t}$$

Here ψ (< 0) measures the speed at which deviations from the long-run equilibrium are corrected. The λ's are the implied long-run parameters. Non-ICT contributions enter only via differences (I (1)); the other contributions enter in levels (I (0) or I (0) with a break).

3.2. Unit-Root Tests and Break Adjustment

ADF tests indicate a mix of orders. CC_ICTGDPY_Y is I (0) (ADF t = −3.640, p = 0.008). CCNON_ICTGDPY_Y fails to reject a unit root in levels (t = −2.567, p = 0.106) but is stationary after first differencing (ADF on Δ: t = −5.603, p ≈ 1.7×10^{-5}), hence I (1). CLABQNGDPY_Y is I (0) (t = −3.443, p ≈ 0.014). For CLABQLGDPY_Y, standard ADF fails to reject at level (t = −1.960, p = 0.303) and at first difference (t = −0.972, p = 0.754), yet a Zivot–Andrews intercept-break test detects a break in 1982 with a highly negative test statistic (≈ −7.98), implying stationarity once the break is included; we therefore treat CLABQLGDPY_Y as I(0) with D_1982.

For the dependent, ADF on Δ log (NGDPCP$) rejects strongly (t = −4.528, p ≈ 0.0006), implying log (NGDPCP) is I (1); this justifies the ARDL/Bounds approach. These findings support a specification with CC_ICTGDPY_Y, CLABQLGDPY_Y (plus D_1982), and CLABQNGDPY_Y in levels, and CCNON_ICTGDPY_Y in differences only.

Table 1: Unit-Root and Break Tests (Variables Used in the ARDL).

Variable	ADF level (t, p)	ADF Δ (t, p)	ZA break (spec; date; t)	Integration decision
CC_ICTGDPY_Y	−3.640; 0.008	–	–	I (0)[1]
CCNON_ICTGDPY_Y	−2.567; 0.106	−5.603; 1.7×10^{-5}	–	I (1)[1]
CLABQLGDPY_Y	−1.960; 0.303	−0.972; 0.754	Intercept break; 1982; ≈−7.98	I (0) with break[1]
CLABQNGDPY_Y	−3.443; ≈0.014	–	–	I (0)[1]
ln (NGDPCP)	–	−4.528; 0.0006	–	I (1)[1]

Note: [1] Decisions based on 1% significance level. Critical values: MacKinnon (ADF), Zivot & Andrews (ZA). Data: GASTAT

3.3. ARDL Results: Short-Run, Long-Run, And ECM

The AIC-selected model is ARDL (3, 0, 4, 2, 1, 4) for log (NGDPCP). Residual diagnostics are clean (SER ≈ 0.027; DW ≈ 2.21; AIC ≈ −4.06). Short-run dynamics show sizable and persistent effects from changes in non-ICT capital contributions: current ΔCCNON_ICTGDPY_Y is positive (≈ 0.014, $p < 0.001$), followed by significant corrections at lags 1–3 (≈ −0.020 to −0.027, all $p < 0.001$), indicating impulse–response patterns that propagate and partially reverse. Labor quantity exerts a clear contemporaneous positive effect (ΔCLABQNGDPY_Y ≈ 0.017, p ≈ 0.00013). Labor quality exhibits a near-term positive effect with subsequent mean reversion (ΔCLABQLGDPY_Y ≈ 0.029, p ≈ 0.002; ΔCLABQLGDPY_Y (−1) ≈ −0.031, p ≈ 0.00026). The first difference of the break dummy signals a discrete negative shift around 1982 (ΔD_1982 ≈ −0.159, $p \approx 1.3\times10^{-5}$).

In the long-run block (conditional on cointegration), labor quality and labor quantity are positively associated with nominal GDP: CLABQLGDPY_Y (−1) ≈ 0.099 (p ≈ 0.005) and CLABQNGDPY_Y (−1) ≈ 0.026 (p ≈ 0.001). The coefficient on CC_ICTGDPY_Y is not statistically significant once these controls and the break are included. The level effect of D_1982 is weak in the long run, indicating that most of the break effect is absorbed through the short-run channel.

The ECM confirms cointegration and convergence. The error-correction term indicates an implied speed of adjustment of about −0.0255 per year (reported in the ECM view as COINTEQ = 0.0255 with a highly significant t-statistic), meaning roughly 2.6% of any deviation from the long-run path is corrected annually. Convergence is statistically strong but economically slow; long-run multipliers should therefore be interpreted with caution and accompanied by stability (CUSUM/CUSUMSQ) and residual diagnostics.

Table 2: ARDL (3,0,4,2,1,4) Highlights (ECM View; Dependent: Δ Log (NGDPCP$)).

Component	Estimate (SE)	Sig.	Interpretation
ECM Speed (ECT_{t-1})	−0.0255 (0.00304)	***	Significant cointegration; ≈2.6% annual reversion
Long-run: CLABQLGDPY_Y	0.099 (0.035)	**	Positive long-run association with income
Long-run: CLABQNGDPY_Y	0.026 (0.008)	***	Positive long-run association with income
Long-run: CC_ICTGDPY_Y	n.s.	–	No robust long-run effect in this specification
Short-run: ΔCCNON_ICTGDPY_Y	+0.014 (0.003) lags −0.020 to −0.027 (each p<0.001)	***	Impulse correction dynamic; positive initial impact with reversal over 1–3 years
Short-run: ΔCLABQNGDPY_Y	+0.017 (0.005)	***	Boost to near-term income growth
Short-run: ΔCLABQLGDPY_Y	+0.029 (0.009)); lag −0.031 (0.008)	***	Positive short-run impact followed by mean reversion
Break (ΔD_1982)	−0.159 (0.034)	***	Significant negative structural shift around 1982
Fit / Diagnostics	SER ≈ 0.027; DW ≈ 2.21; AIC ≈ −4.06	–	Good in-sample fit with well-behaved residuals

Notes: Standard errors in parentheses). *, **, * denote 1%, 5%, 10% significance Sources: GSTAT, and The Conference Board (via Macrobond)**

3.4. Bounds Testing for Cointegration

To empirically investigate the presence of a long-run equilibrium relationship among the variables, we employ the bounds testing procedure advanced by Pesaran, Shin, and Smith (2001) under a restricted-constant specification (Case 2). The null hypothesis of no levels relationship is tested against the alternative. The optimal lag structure, selected by the Akaike Information Criterion (AIC), results in a model with five dynamic cointegrating variables and an effective sample size of 49 annual observations

Table 3.: Ardl Bounds Test Summary.

Item	Value
Null hypothesis	No levels relationship
Deterministics	Restricted constant (Case 2)
Number of dynamic cointegrating variables	5
Sample size	49
F-statistic	8.319902215518075

Table 4: Bounds Critical Values (Case 2; Finite-Sample and Asymptotic).

Sample size	Bound	10%	5%	1%
45	I(0)	2.276	2.694	3.674
45	I(1)	3.297	3.829	5.019
50	I(0)	2.259	2.670	3.593
50	I(1)	3.264	3.781	4.981
Asymptotic	I(0)	2.080	2.390	3.060
Asymptotic	I(1)	3.000	3.380	4.150

The computed F-statistic (8.320) exceeds the 1% upper bound for I (1) at all relevant benchmarks (e.g., 4.981 for N=50; 5.019 for N=45; 4.150 asymptotically). This dominance over the I (1) upper bounds implies rejection of the null hypothesis of no levels relationship at the 1% level, thereby substantiating the presence of cointegration in the ARDL (3,0,4,2,1,4) specification for log (NGDPCP). In practical terms, the cointegrating relationship justifies reporting the long-run coefficients and the error-correction representation: the ECM's speed-of-adjustment parameter indicates gradual but statistically significant reversion (about 2.6% of disequilibrium corrected per year).

Because the conclusion is insensitive to which finite-sample benchmark is used (N=45 or N=50) and remains valid against asymptotic bounds, the evidence for cointegration is robust. This robustness, combined with clean residual diagnostics in the ARDL, increases confidence in the interpretation of both the long-run associations (labor quality and quantity) and the short-run dynamics (the impulse correction pattern following non-ICT capital shocks).

3.5. Stability Diagnostics (Cusum)

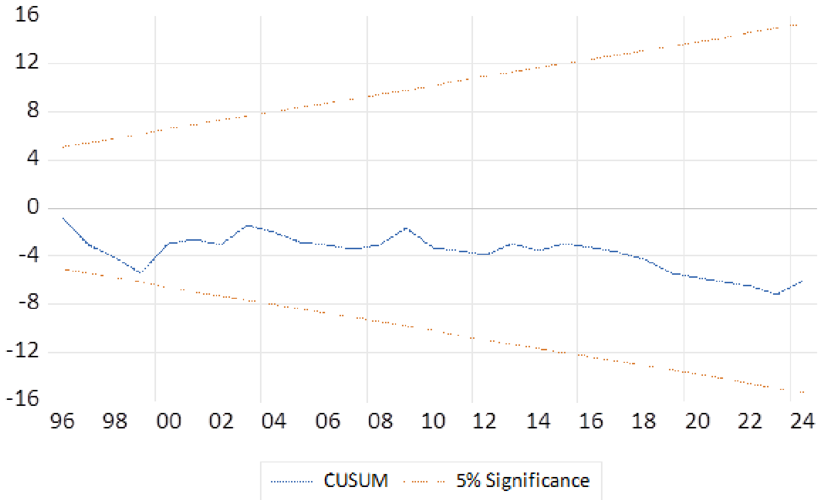

Figure 2. CUSUM Of Recursive Residuals With 5% Significance Bands (ARDL (3,0,4,2,1,4); Sample 1996–2024).

The CUSUM of recursive residuals remains entirely within the 5% significance bands over the recursive estimation window (approximately 1996–2024). Hence, the null of parameter constancy cannot be rejected, and there is no evidence of systematic structural instability in the ARDL coefficients over the evaluation period. The gradual downward drift after 2016 is well contained within the bands and is followed by a modest correction near the end of the sample, suggesting local variation but not a parameter break. Taken together with the Bounds test and ECM significance, the CUSUM result supports the internal consistency of the model: the long-run relation is statistically present (cointegration) and the short-run dynamics appear stable.

3.6. Variance Stability (Cusumsq)

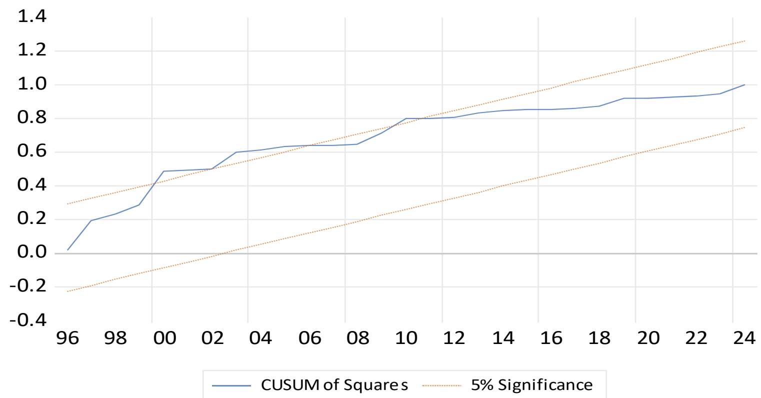

Figure 3. CUSUMSQ Of Recursive Residuals With 5% Significance Bands — Placeholder Figure

For completeness, the CUSUM of Squares (CUSUMSQ) statistic, displayed in Figure 3, tracks the cumulative squared recursive residuals against 5% significance bands to test the stability of parameter variance. The plotted line remains well within the upper and lower significance bounds across the entire sample period (1996–2024), indicating the absence of variance instability or structural breaks in the error variance of the ARDL (3,0,4,2,1,4) specification. This result complements the standard CUSUM test by confirming not only coefficient constancy but also the homoscedasticity of residuals over time. In other words, the estimated model is robust to heteroskedastic shocks and does not exhibit episodic volatility that would undermine inference. Taken together, the stability of both the CUSUM and CUSUMSQ tests strengthens confidence in the validity of the long-run relationships and the reliability of short-run dynamics derived from the ARDL–ECM framework.

3.7. Summary And Conclusions

This paper employs an ARDL framework to analyze the determinants of Saudi Arabia's nominal GDP using annual data from 1976 to 2024. Unit-root and structural-break testing reveals a mixed order of integration: ICT capital services, labor quality (when accounting for the 1982 break), and labor quantity are I (0), whereas non-ICT capital services are I(1). Accordingly, the model includes stationary regressors in levels, differences in the non-ICT capital variable, and incorporates a 1982 intercept-shift dummy to capture structural discontinuities. The Pesaran–Shin–Smith Bounds test decisively rejects the null of no long-run relationship at the 1% level (F = 8.32, exceeding all I(1) critical bounds), confirming the existence of cointegration and validating the estimation of both long-run coefficients and the ECM representation. Short-run dynamics indicate that non-ICT capital shocks exert meaningful but transitory effects: a positive contemporaneous contribution followed by statistically significant corrections over the subsequent three years, consistent with cyclical impulse–correction behavior. Labor quantity provides a clear near-term boost to GDP growth, while labor quality exerts a positive immediate effect that subsequently mean-reverts. The first difference of the break dummy confirms a discrete negative shift in 1982, reflecting a structural slowdown in labor quality contributions.

In the long-run equilibrium, however, both labor quality and labor quantity display robust positive associations with GDP, underscoring their foundational role in sustaining growth. By contrast, ICT capital does not emerge as statistically significant once other channels and the structural break are controlled for, suggesting that digital investments have yet to translate into durable productivity gains. The error-correction coefficient (≈ −0.026) implies slow but statistically significant convergence, with about 2.6% of disequilibrium corrected annually. Stability diagnostics confirm the internal consistency of the model: recursive residuals remain within the 5% CUSUM significance bands, while CUSUMSQ results corroborate the absence of variance instability. Taken together, these results point to a coherent long-run relationship where labor quality and labor quantity anchor nominal GDP, while non-ICT capital operates primarily through short-run transmission channels.

4. DISCUSSION AND POLICY RECOMMENDATIONS

The empirical findings of this study offer nuanced implications for Saudi Arabia's economic policy at a pivotal stage of its Vision 2030 transformation. The strong role of labor quality in driving nominal GDP underscores the urgency of sustained investment in education, vocational training, and human capital development. This finding reinforces Vision 2030's emphasis on educational reform, talent development, and labor market modernization, showing that improvements in the quality—not merely the quantity—of education yield the highest returns. It lends empirical support to flagship initiatives such as the **Human Capability Development Program (HCDP)**, which seeks to equip Saudi citizens with globally competitive skills through education modernization, reskilling, and digital literacy. Complementary programs, including expanded scholarship schemes and *Future Skills*, already align with this insight, though their success will depend on matching graduates' skills with labor market demand and incentivizing private-sector absorption of highly skilled workers (IMF, 2023; Hasanov & Razek, 2023). By aligning productivity-driven growth with labor market readiness, these initiatives address the study's central finding that human capital quality—not workforce expansion alone—is critical to sustaining long-term growth.

The significance of labor quantity in the short run highlights the importance of job creation policies and labor force expansion for immediate growth. Ongoing reforms to increase female labor force participation, reduce unemployment, and shift employment from the public to the private sector can therefore provide a short-term stimulus. However, the smaller long-run coefficient for labor quantity suggests that workforce expansion alone is insufficient to sustain growth. Simply enlarging the labor pool without commensurate gains in productivity risks diminishing returns. This finding reinforces the need to combine labor quantity growth with quality improvements, ensuring that the new entrants into the labor force possess the skills and competencies to contribute to higher productivity rather than merely inflating employment statistics (Alharthi, 2022; Elshafei et al., 2025).

The transient role of non-ICT capital further illustrates that heavy reliance on traditional physical capital investment provides only short-lived growth effects. This evidence suggests that Saudi Arabia's historical strategy of driving growth through large-scale infrastructure and public investment projects, while beneficial in the short run, cannot anchor long-term productivity. Policy makers should therefore prioritize the efficiency and productivity of capital rather than its volume, avoiding "white-elephant" projects and instead channeling investments into areas with higher multiplier effects. Strengthening project evaluation, deepening institutional reforms, and encouraging private sector participation are critical to ensuring that non-ICT capital contributes sustainably to output growth (Sweidan & Elbargathi, 2023).

The current lack of significant payoff from ICT capital investment is a delicate but important finding. Rather than indicating the futility of ICT investment, it points to the lagged nature of technology's productivity benefits. ICT capital often requires complementary investments in human capital, digital literacy, and organizational restructuring to unlock its potential. International experience demonstrates that network effects and absorptive capacity are crucial: in economies such as the UAE, investments in ICT capital yielded stronger productivity gains once paired with workforce training and innovation ecosystem development (IMF, 2023). For Saudi Arabia, this means that digital transformation goals under Vision 2030 remain valid, but policymakers must temper expectations regarding short-term returns and focus instead on fostering conditions—such as digital literacy programs, public-private innovation partnerships, and regulatory frameworks—that enable ICT investments to translate into productivity gains over time (Hasanov & Razek, 2023).

Comparative evidence strengthens these implications. The results resonate with Norway's strategy of channeling oil rents into long-term productivity-enhancing assets, contrasting with countries where capital-heavy strategies produced diminishing returns (Holden, 2019). Similarly, the UAE's successful alignment of ICT investment with education reforms illustrates how Saudi Arabia could amplify ICT capital productivity through complementary policies. At the same time, the findings diverge from Chile's experience with copper, where institutional reforms improved investment productivity, signaling that Saudi Arabia must continue reforming its governance frameworks to maximize capital efficiency. These comparisons reinforce that Vision 2030's dual emphasis on human capital and digital transformation is both empirically supported and globally validated, though patience and consistent implementation will be required.

Finally, the discussion must acknowledge persistent structural impediments. Labor quality improvements will require not only educational reform but also deeper labor market integration, ensuring that skilled workers are not confined to the public sector but fully utilized in private industry. Similarly, the modest role of capital reflects the inefficiencies of past public-sector-led investment; improving returns will necessitate stricter project appraisal and greater reliance on private-sector investment. Moreover, while ICT capital effects remain muted in the current period, the transition toward a knowledge-based economy implies that productivity improvements may increasingly emerge from TFP gains rather than input accumulation. Recognizing these limitations, policymakers should view the results as a call to complement input-driven growth strategies with innovation policies, institutional reforms, and targeted support for entrepreneurship. In sum, while the ARDL–ECM framework captures the historical contribution of key growth drivers, it also highlights the conditional pathways through which Saudi Arabia can convert its resource wealth into sustainable productivity-led growth in line with Vision 2030.

5. CONCLUSION

This study set out to examine the long- and short-run drivers of economic growth in Saudi Arabia, with a particular focus on the differential roles of labor quality and quantity, ICT and non-ICT capital, and their interaction with total factor productivity under the framework of Vision 2030. The empirical analysis, based on an ARDL–ECM approach with structural break considerations, provides robust evidence of a stable long-run cointegration relationship among these variables. The findings indicate that labor quality emerges as the cornerstone of Saudi Arabia's sustainable growth, while labor quantity has a more transient role, boosting output in the short run but contributing less in the long term. Similarly, non-ICT capital appears to deliver temporary gains that taper over time, whereas ICT capital has yet to exhibit measurable productivity effects at the aggregate level, likely due to absorptive capacity constraints and the time needed for digital investments to mature. Taken together, the results highlight that the path toward sustainable, post-oil growth lies less in the accumulation of physical capital and more in enhancing productivity through human capital development, institutional efficiency, and innovation capacity.

The study contributes to the literature in three distinct ways. Methodologically, it is among the first to apply an ARDL–ECM framework with structural breaks to the Saudi growth experience, ensuring robustness in the presence of mixed integration orders and historical shocks. Empirically, it sheds light on the differentiated roles of ICT versus non-ICT capital, and labor quality versus quantity, in shaping growth in a resource-rich economy. Theoretically, it enriches the comparative debate on the resource curse by demonstrating that long-term growth in oil economies depends critically on the effective conversion of resource rents into human capital and productivity-enhancing assets, rather than on sheer input accumulation.

The policy implications of these findings are clear. The evidence reinforces the strategic emphasis of Vision 2030 on human capital, digital readiness, and institutional reforms. However, it also cautions that returns from ICT investments may take time to materialize, underscoring the importance of patience, complementary reforms, and the development of absorptive capacity. Structural reforms aimed at improving the allocative efficiency of capital, strengthening the private sector's role, and integrating skilled workers more effectively into the labor market will be vital to translating investments into long-run productivity gains. These insights align with international experience, from Norway's successful conversion of resource rents into long-term wealth to the UAE's synergistic pairing of ICT and human capital, suggesting that Saudi Arabia is on the right path but must continue to prioritize quality over quantity in its growth strategies.

At the same time, the study recognizes its limitations. The analysis treats the Saudi economy in aggregate, potentially masking sector-specific dynamics that could reveal more immediate payoffs from ICT capital or labor reforms in industries such as services, finance, or manufacturing. Moreover, while the dataset extends to 2024, the structural transformation of Saudi Arabia is still ongoing; future research should revisit these questions as new data become available to assess whether the productivity effects of digital transformation and innovation policies begin to materialize more clearly. Further work could also extend the analysis to regional comparisons across Gulf economies or employ micro-level firm data to uncover mechanisms through which ICT and human capital interact to drive productivity at the organizational level.

In conclusion, the evidence presented in this paper suggests that Saudi Arabia's long-run growth trajectory depends on its ability to transition from input-driven expansion to productivity-led development. Human capital investments, institutional reforms, and the gradual maturation of ICT capital and innovation ecosystems will be decisive in ensuring that Vision 2030 achieves its goal of a diversified, knowledge-based economy. The results affirm that while capital accumulation and labor force expansion can deliver short-term gains, it is the sustained enhancement of productivity—rooted in education, skills, and efficient institutions—that holds the key to unlocking Saudi Arabia's long-term prosperity in the post-oil era.

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