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The Digital Maturity Paradox: The Divergent Impact of Network Readiness and FDI Across Development Tiers

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Abstract

Contemporary economic growth trajectories are characterized by accelerating digital integration. However, the digital infrastructure required to accelerate growth remains unevenly distributed across development tiers. This study examines a “Digital Maturity Paradox” using a cross-sectional dataset of 121 countries, stratified into developing ($N = 76$) and developed ($N = 45$) cohorts. Statistically validated via the Chow Breakpoint Method ($F = 11.91$; $p < 0.01$), the study demonstrates that growth drivers vary significantly based on developmental maturity. The findings indicate that digitalization and foreign direct investment (FDI) serve as primary catalysts for developing countries, supporting the “Leapfrogging Hypothesis” with statistically significant coefficients ($\beta = 1.106$, $p < 0.01$ and $\beta = 0.246$, $p < 0.05$, respectively). Conversely, a “productivity paradox” emerges within the developed cohort, where the marginal returns of digitalization saturate and turn negative ($\beta = -0.734$, $p < 0.10$), and FDI becomes statistically insignificant. Sensitivity analysis isolating developed economies by excluding extreme maritime financial hubs ($N = 43$) confirms that the explanatory power of traditional vectors remains structurally compressed in the Global North (R -squared $< 2\%$), mathematically solidifying the “Fitness Gap” against baseline model ($N = 45$, Adjusted R -squared = 1.61%). These findings suggest that while the traditional, infrastructure-led growth rules still govern the Global South, the Global North needs to transition toward Artificial Intelligence-driven total factor productivity to sustain economic growth.

Keywords: economic growth; Digital Maturity Paradox; network readiness; developing economies; developed economies; comparative study; Chow test; influence diagnostics

JEL Classification: C21; F21; L96; O14; O33; O47



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1. Introduction

Economic growth remains a foundational pillar of development economics, increasingly recognized as a multifaceted process shaped by a complex interplay of exogenous and endogenous determinants (Acemoglu et al., 2005). The traditional Neoclassical model

formulated by Solow (1956) and Swan (1956) emphasizes the role of exogenously accumulated physical capital and labor in driving economic development. Conversely, Endogenous Growth Theory posits that long-run economic expansion is driven by internal mechanisms, particularly technological innovations and knowledge spillovers (Gancia & Zilibotti, 2009; Lucas, 1988; Romer, 1986, 1990). Building upon this theoretical evolution, this study investigates how contemporary economic growth is catalyzed by the integration of domestic digital infrastructure and global flows of goods, services, and capital. To this end, we isolate three primary growth drivers: Network Readiness—signifying technological development—and FDI and international trade, which serve as parallel conduits for cross-border knowledge and capital transfer. However, the prevailing literature frequently assumes a linear relationship between these inputs and macroeconomic expansion, leaving a critical question unanswered: Does the growth elasticity of digital infrastructure vary structurally across developmental thresholds, and do advanced economies face an impending saturation point?

Amid intensifying economic integration and globalization, the “network economy” fundamentally challenges historic development paradigms (Cigu, 2025). Network economies are characterized by the rapid exchange of commodities and information across interconnected nodes (Shapiro & Varian, 1999)—a structural framework that accelerates institutional evolution. However, the gains from digital integration have not been distributed equally. While the existing literature tends to examine the “digital divide” through the lens of binary accessibility and infrastructure constraints (Binuyo & Adewale, 2015; Ndoya & Asongu, 2024; Portulans Institute, 2024), this study introduces the “Digital Maturity paradox” to offer a more nuanced interpretation of these disparities.

We hypothesize that while technology enables developing nations to “leapfrog” the traditional industrial phases by bypassing legacy infrastructural stages (Steinmueller, 2001), its incremental growth dividends decay in developed economies. In developed economies, digitalization frequently reaches a saturation point where incremental technological adoption yields diminishing marginal returns (Niebel, 2018). Consequently, the technological divide is not merely an issue of baseline access, but rather a non-linear threshold dynamic beyond which the growth-inducing impact of digital infrastructure saturates.

Crucially, this digital maturity threshold does not operate in isolation; it fundamentally governs a nation’s capacity to leverage broader international macroeconomic flows. Complementing digital connectivity is the structural evolution of international trade and investment. Contemporary trade has transitioned from the rudimentary cross-border exchange of final goods to highly complex Global Value Chains (GVCs); currently, over 70% of global trade consists of intermediate goods and services (OECD, 2025; Eurostat, 2024). This modern paradigm builds upon classic frameworks of macroeconomic integration and trade openness (Baldwin, 2016; Busse & Koeniger, 2012; Sachs & Warner, 1995) wherein GVCs facilitate production fragmentation by allowing countries to specialize in discrete tasks. Without robust domestic network readiness, developing economies face prohibitive transaction and coordination costs, effectively locking them out of these high-value networks.

Parallel to these trade dynamics, FDI serves as a vital engine for economic growth. Extending beyond the mere provision of external capital, FDI facilitates critical “knowledge spillovers” by transferring advanced technological “know-how” and managerial expertise from frontier economies to host nations (Javorcik, 2004; Moolio et al., 2026). Theoretically, these spillovers are essential for developing countries, as they mitigate deficiencies in domestic industrial capabilities and accelerate economic convergence toward the global technological frontier (Findlay, 1978; Ito, 2017). By participating in GVCs and attracting FDI, developing economies internalize foreign knowledge and foster domestic

innovation, thereby embedding real-world practices within the framework of Endogenous Growth Theory.

Although the empirical literature on growth determinants is extensive, recent research faces two limitations: First, the prevailing literature frequently relies on a flawed homogeneity assumption, treating deeply heterogeneous nations as a uniform cohort. This methodology yields contradictory findings because it fails to account for variations in the marginal productivity of capital across different stages of macroeconomic development (Borensztein et al., 1998; Rodriguez & Rodrik, 2000). Second, cross-sectional regressions in this domain often neglect critical specification vulnerabilities, specifically failing to control for heteroskedasticity and the distorting influence of outlier nations, such as major maritime hub economies (Frankel & Romer, 1999).

This research addresses these deficiencies by exploring the intersection of Neoclassical “catch-up” growth and Endogenous innovation theory. Utilizing advanced data segmentation, this study evaluates whether Fourth Industrial Revolution inputs act as Solow-style physical capital investments in developing economies or as endogenous innovation engines in developed economies. By resolving these methodological gaps, this paper uncovers a structural “Fitness Gap” between the global cohorts, demonstrating that traditional growth determinants possess vast explanatory power in the Global South but lose their explanatory power when applied to the asset-saturated Global North.

To formalize the distinction between catch-up growth and frontier innovation, we propose the following hypotheses:

H₁ (The Structural Leapfrogging Hypothesis). *The growth elasticities of digital infrastructure (Network Readiness) and capital inflows (FDI) are significantly positive and stronger in developing countries than in developed countries, where traditional input-driven vectors reach a structural saturation point.*

H₂ (The Structural Break and Metric Asymmetry Hypothesis). *The structural determinants of economic growth shift non-linearly according to development tiers, as a statistically significant structural break at the high-income threshold and rendering aggregate, gross macro-metrics (such as aggregate trade openness) structurally neutral due to asymmetric value-added capture.*

The primary contribution of this research lies in its empirical verification of the “Maturity Effect” via a statistically justified bifurcation of the global sample. Utilizing Ordinary Least Squares (OLS) estimation with heteroskedasticity-robust standard errors via the HC1 correction procedure (White, 1980), this research examines a global sample of 121 countries. Based on 2023 World Bank classifications, the sample is partitioned into 76 developing and 45 developed economies.

A key methodological advantage of this approach is the application of the Chow Breakpoint Test (Chow, 1960). This test establishes a mathematical foundation for group classification, preventing arbitrary sample splitting by isolating an empirical structural break in the dataset. In addition, by employing influence diagnostics—specifically Cook’s Distance and DFBETAS (Belsley et al., 1980)—this study isolates the distorting impacts of anomalous international maritime and financial hubs, such as Malta and Singapore. This guarantees a more robust, generalizable analysis of the structural determinants of modern economic growth.

The remainder of this paper is structured as follows: Section 2 reviews the literature; Section 3 details the data sources and econometric methodology; Section 4 presents the empirical findings; and Section 5 concludes with policy implications, study limitations, and directions for future research.

2. Literature Review

Technological integration, international trade dynamics, and foreign direct investment (FDI) constitute the foundational pillars of contemporary economic growth theory. While a broad consensus asserts that these macroeconomic variables are prerequisites for national prosperity, the evolving global economic landscape introduces structural complexities that challenge traditional neoclassical assumptions (Rodrik, 2024). Historically, economic growth was conceptualized through the lens of the Solow–Swan model, which prioritized exogenous physical capital accumulation and labor inputs (Solow, 1956; Swan, 1956). Subsequent macroeconomic scholarship shifted toward Endogenous Growth Theory, which states that long-run economic expansion is driven by internal mechanisms—specifically technological innovation and institutional quality—rather than purely external factors (Aghion & Howitt, 1992; Grossman & Helpman, 1993; Romer, 1990).

Recent empirical data from the United Nations Development Programme (UNDP, 2024) highlight a “multi-speed” global recovery trajectory: while developed economies exhibit relative resilience to systemic macroeconomic shocks, many developing nations remain constrained by structural impediments, low growth rates, and escalating debt burdens. Consequently, macroeconomic analysis must transition from narrow, single-variable country case studies toward cross-national comparative frameworks that account for these structural asymmetries (Hussein et al., 2024).

2.1. Technology-FDI Linkages and the “Digital Maturity Paradox”

Contemporary growth literature conceptualizes technology not merely as an exogenous residual, but as the primary engine of total factor productivity (TFP). Traditional factor-deepening models have evolved to incorporate the concept of “Network Readiness,” defined as the capacity of an economy to leverage digital infrastructure for the seamless exchange of information and commodities (Cigu, 2025; Shapiro & Varian, 1999; Solow, 1956). In emerging economies, this dynamic underpins the “Leapfrogging Effect,” where developing economies can bypass legacy stages of industrialization and move directly to digitalized economic platforms (Lee, 2016; Steinmueller, 2001).

However, a significant theoretical gap exists regarding the “Maturity Effect” in advanced economies. While the developmental benefits of initial digital adoption are well-documented (Nayyar et al., 2024), recent evidence suggests that developed nations may have reached a structural threshold characterized by diminishing marginal returns on digital infrastructure (Cevik, 2024; Copestake et al., 2024). This implies that at advanced developmental stages, incremental investments in digital networks may pivot toward generating social, administrative, or environmental utilities rather than purely driving quantifiable macroeconomic expansion (Dewan & Kraemer, 2000; Niebel, 2018). Consequently, the long-run relationship between network readiness and GDP growth may follow an inverted U-shaped trajectory (Chen et al., 2025).

This domestic technological trajectory intersects directly with foreign direct investment (FDI), which acts as a primary vector for the international dissemination of innovative technologies and managerial expertise (Javorcik, 2004). However, the growth-inducing efficacy of the technology–FDI nexus is highly conditional. While Utouh and Kitole (2024) document a positive correlation between FDI inflows and economic growth in Eastern Africa, Ghosh and Saha (2025) contend that effective knowledge transfer is strictly contingent upon baseline regulatory frameworks and institutional quality. Hence, the contemporary research paradigm prioritizes the “quality of the host environment” and localized absorptive capacity over the sheer volume of capital inflows (Cohen & Levinthal, 1990; Moolio et al., 2026).

2.2. Trade and Global Value Chain Positioning

While contemporary trade openness incentivizes specialization and offers a “vent for surplus” (Myint, 1958), its growth-inducing efficacy depends heavily on a nation’s position within Global Value Chains (GVCs). The traditional paradigm of “export-led growth” assumes that expanding trade monotonically enhances domestic productive capacity; however, this framework overlooks the risk of a “Divergence Trap” induced by structural inequalities within GVC configurations (Antràs, 2020). As noted by Antràs (2020), while GVC participation lowers the initial barriers to industrial entry for developing countries, it risks confining domestic firms to low-value-added, labor-intensive assembly roles. These structural locking mechanisms can inhibit substantive technological upgrading and skill cultivation (Humphrey & Schmitz, 2002).

Furthermore, trade liberalization generates highly heterogeneous outcomes based on an economy’s underlying industrial maturity. According to the Rodrik (2016), trade openness can accelerate financial development in advanced economies but exacerbate financial deterioration in developing countries characterized by weak domestic industries. This misalignment often induces “Premature De-industrialization,” a process whereby developing countries experience a premature contraction in manufacturing employment and GDP shares at significantly lower per capita income levels than those recorded by historical predecessors during their industrial phases (Asian Productivity Organization, 2024; Rodrik, 2016).

Additionally, while service-dominated developed countries leverage trade for deep financial integration, many developing economies face “industrial hollowing,” where nascent domestic firms are displaced by global competition before achieving industrial maturity (Rodrik, 2016). This structural vulnerability is further aggravated by global labor market disruptions, where transitions to service-dominated growth fail to absorb displaced low-skilled labor effectively (International Monetary Fund, 2024).

2.3. Literature Synthesis and Knowledge Gap

Table 1 synthesizes the core macroeconomic interdependencies and conditional relationships identified in contemporary growth literature.

Table 1. Interdependency and conditionality in core macroeconomic variables.

Variable	Theoretical Relationship	Critical Moderating Factor	Key Literature
Network Readiness (<i>NRI</i>)	Positive (Productivity-Led)	Developmental Maturity Stages and Marginal Returns	Cigu (2025); Niebel (2018); Chen et al. (2025)
Foreign Direct Investment (<i>FDI</i>)	Conditional (Spillover-Led)	Institutional Quality & Absorptive Capacity	Javorcik (2004); Ghosh and Saha (2025); Moolio et al. (2026)
Trade Openness (<i>TRD</i>)	Heterogeneous (Market Access)	GVC Positioning and Industrial Maturity	Antràs (2020); Rodrik (2016)

A review of extant literature highlights two critical shortcomings. (i) The Homogeneity Bias: Previous studies frequently assume uniform growth elasticity for technological innovation, FDI inflows, and trade openness across global economies, neglecting the profound role of macroeconomic maturity. (ii) Econometric Misspecification: Empirical models in cross-country growth literature often fail to control for pervasive cross-sectional issues, specifically heteroskedasticity, parameter instability, and the distorting influence of structural outliers (International Monetary Fund, 2024).

By adopting a comparative framework on cross-sectional data, and utilizing the Chow Breakpoint test alongside robust influence diagnostics, this study addresses these empirical limitations. This methodology provides a mathematically robust assessment of how the structural drivers of modern economic growth shift across divergent developmental tiers.

3. Materials and Methods

3.1. Research Design and Econometric Specification

This study utilizes a cross-sectional Ordinary Least Squares (OLS) estimation framework to isolate the structural determinants of economic growth. To address the inherent challenge of non-constant error variance typical of cross-sectional macro-datasets (Long & Ervin, 2000), parameters are estimated using the Huber-White-Hinkley heteroskedasticity-consistent robust standard errors via the HC1 correction procedure. Unlike standard OLS covariance estimators, the HC1 modification adjusts the degrees of freedom to provide a robust variance-covariance matrix under conditions of unknown heteroskedasticity. This guarantees that the resulting t-statistics and probability values maintain statistical validity for all hypothesis testing configurations (White, 1980).

3.2. Variables and Data Sources

The empirical analysis leverages cross-sectional data from the 2023 fiscal year compiled from three primary repositories. The variables, metric definitions, and data sources are summarized in Table 2.

Table 2. Variable Operationalization and Data Sources.

Variable/Notation	Description	Operational Metric	Primary Source
GDP Per Capita Growth (Y)	Dependent variable measuring the annual percentage growth rate of real GDP per capita based on constant local currency.	Annual (%)	World Bank World Development Indicators (WDI) ¹ (2024)
Network Readiness Index (NRI)	Explanatory metric assessing a nation's capacity to leverage Information and Communication Technologies (ICT) for socioeconomic growth.	Index (0–100)	Portulans Institute ² (2023)
Foreign Direct Investment (FDI)	Explanatory metric capturing net cross-border capital inflows from foreign investors to the host economy.	Net Inflows (% of GDP)	World Bank WDI ³ (2024)
Trade Openness (TRD)	Explanatory metric capturing global integration, computed as the aggregate value of exports and imports of goods and services.	Total Value (% of GDP)	World Bank WDI ³ (2024)

¹ <https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG> (accessed on 30 March 2025). ² <https://networkreadinessindex.org/> (accessed on 15 March 2025). ³ <https://databank.worldbank.org/source/world-development-indicators> (accessed on 25 March 2025).

3.3. Data Transformation and Normalization

To ensure adherence to the distributional assumptions of OLS and to mitigate the distortionary impact of heavy-tailed economic distributions, two structural data transformations were performed: First, the Inverse Hyperbolic Sine (IHS) transformation was applied to the growth (Y), investment (FDI), and trade (TRD) series. The IHS transformation is mathematically operationalized as follows:

$$IHS(X) = \sinh^{-1}(X) = \ln\left(X + \sqrt{X^2 + 1}\right) \quad (1)$$

In contrast to a traditional natural logarithmic transformation, the *IHS* operator effectively normalizes right-skewed data and accommodates zero or negative values without sacrificing critical observations, all while preserving an interpretative framework analogous to log-linear elasticity (Bellemare & Wichman, 2020; Burbidge et al., 1988). Second, the Network Readiness Index was subjected to a Min–Max normalization to rescale the index within a bounded $[0, 1]$ interval. This normalization is defined as:

$$NRIT_i = \frac{NRI_i - \min(NRI)}{\max(NRI) - \min(NRI)} \quad (2)$$

This procedure mitigates scale-related parameter bias, ensuring that the structural magnitude of the index does not disproportionately skew the estimated coefficients (Patro & Sahu, 2015). The final transformed variables are denoted: *IHSY*, *IHSFDI*, *IHSTRD*, and *NRIT*.

3.4. Missing Data Reconciliation: Stratified Median Imputation

To preserve the full degrees of freedom across the 121 economies in the 2023 sample, this study implemented a stratified median imputation protocol to address sparse missing values in the trade series. In accordance with Little and Rubin (2019), median imputation serves as a robust measure of central tendency that remains uncorrupted by extreme distributional outliers.

To account for the documented “geographical penalty” wherein landlocked nations face trade and transit costs roughly double those of their coastal counterparts (Faye et al., 2004; Sachs & Warner, 1997), missing trade observations were imputed using distinct geographic and macroeconomic development strata. Specifically, missing values were populated using the median trade-to-GDP ratios of their distinct peer cohorts. For the developed country cluster, the missing values were stratified by landlocked (110.5%) versus coastal (145.2%) orientations. For the developing country cohort, missing values were imputed using medians of 35.5% for landlocked states and 44.8% for coastal states. This stratifying approach targets minor data holes affecting less than 5% of the collective baseline matrix, successfully preserving the complete degrees of freedom without distorting the underlying variances within the primary ($N = 76$) and ($N = 45$) cohorts. This aligns data reconciliation with the geographic and economic realities of inland states versus major maritime trading hubs.

3.5. Econometric Model

The foundational cross-sectional econometric model is specified as follows:

$$IHSY_i = \beta_0 + \beta_1 NRIT_i + \beta_2 IHSFDI_i + \beta_3 IHSTRD_i + \varepsilon_i \quad (3)$$

where $IHSY_i$ is the IHS-transformed annual real GDP per capita growth rate for country i . $NRIT_i$ represents the min-max normalized Network Readiness Index. $IHSFDI_i$ and $IHSTRD_i$ are IHS-transformed values for net foreign direct investment inflows and trade openness, respectively. β_0 is the constant intercept, while β_1 , β_2 , and β_3 represent the partial slope coefficients capturing the growth elasticity of each respective macroeconomic determinant. ε_i denotes the stochastic, heteroskedastic-robust error term.

3.6. Analytical Approach and Stability Diagnostics

To investigate the “Maturity Effect” and test for structural parameter non-linearities, the global sample was split into two distinct cohorts: developing ($N = 76$) and developed economies ($N = 45$). Following standard econometric protocols, the stability, consistency,

and efficiency of our OLS parameters were validated using a comprehensive multi-layered diagnostic battery:

- (i) Multicollinearity was evaluated via Variance Inflation Factors (VIF), using a strict conservative threshold of $VIF < 5.0$ to ensure parameter stability (Hair et al., 2010).
- (ii) Functional Form Specification was evaluated using the Ramsey RESET metric to verify the linear specification against alternative non-linear or polynomial functional forms (Ramsey, 1969).
- (iii) Influence Diagnostics were performed to identify leverage points and highly influential outliers using Cook's Distance, the Leverage Matrix Diagonals, and DFBETAS (Belsley et al., 1980).
- (iv) Heteroskedasticity was evaluated using the Breusch–Pagan–Godfrey (BPG) test to confirm the presence of non-constant error variance, justifying the application of the HC1 robust standard error correction.
- (v) Lastly, Structural Parameter Stability was evaluated via the Chow Breakpoint Test (Chow, 1960) to provide empirical, mathematical justification for splitting the global sample across income-based development boundaries.

4. Results and Discussion

This section presents empirical findings and econometric diagnostics of the study. It begins with a comparative analysis of baseline descriptive statistics and shifts to formal hypothesis verification via split-sample OLS estimations and structural stability checks.

4.1. Comparative Descriptive Statistics (Levels)

The descriptive statistics for the variables at levels—stratified by development status—reveal substantial macroeconomic heterogeneity between developing ($N = 76$) and developed ($N = 45$) economies, as shown in Table 3.

Table 3. Summary of comparative descriptive statistics at levels.

Variable	Metric	Developing Nations ($N = 76$)	Developed Nations ($N = 45$)
GDP Per Capita Growth (Y)	Mean	2.82%	−0.37%
	Median	2.59%	−0.02%
	Std. Dev.	2.40	2.41
	Range (Min–Max)	−1.99% to 8.48%	−7.22% to 2.96%
Network Readiness (NRI)	Mean	41.67	64.02
	Median	40.75	65.15
	Std. Dev.	9.81	8.83
	Range (Min–Max)	20.69 to 68.70	36.48 to 78.96
Foreign Direct Investment (FDI)	Mean	3.03%	1.30%
	Median	2.15%	1.82%
	Std. Dev.	2.92	22.42
	Range (Min–Max)	−2.50% to 18.49%	−71.72% to 113.22%
Trade Openness (TRD)	Mean	77.05%	125.40%
	Median	71.04%	110.02%
	Std. Dev.	34.72	73.79
	Range (Min–Max)	20.60% to 164.81%	24.90% to 402.57%

Source: Authors' calculation using EViews version 11.

4.1.1. Growth Development Disparity

The baseline growth data reveals clear “catch-up” dynamics. The mean real GDP growth rate is substantially higher in developing countries (2.82%) than in developed countries (−0.37%). In accordance with neoclassical growth theory, when lower-income nations operate below their steady-state frontiers, they exhibit accelerated growth trajectories due to lower baseline capital-to-labor ratios and higher marginal productivity of capital (Capolupo, 1998). This divergence provides preliminary support for neoclassical catch-up dynamics governed by conditional convergence parameters, indicating that emerging economies enjoy a wider growth ceiling as they advance toward the global technological frontier (World Bank, 2008).

4.1.2. Digital Readiness and Maturity

A profound “digital divide” separates the two cohorts. The mean NRI score for the developed cohort (64.02) is approximately 53% higher than that of the developing cohort (41.6), driven by top-tier technological frontiers such as the United States, Singapore, and Finland (Portulans Institute, 2024). Crucially, the variance within the developed group is narrower (std. dev. = 8.83) than within the developing cohort (std. dev. = 10.37). This tighter distribution suggests that digital infrastructure has reached a standardized, saturated plateau in high-income economies, whereas it remains highly volatile and in an active expansion phase within the developing world (Prasetyo & Mulyana, 2025).

4.1.3. FDI Volatility and the “Hub” Effect

Although developing nations display a higher mean FDI-to-GDP ratio (3.03% versus 1.30%), the developed cohort exhibits extreme volatility (std. dev. = 22.42). The dispersion is driven by large, idiosyncratic capital flows channeled through specific maritime and financial hubs, most notably Singapore and Malta. In these developed economies, cross-border FDI is largely decoupled from domestic industrial expansion, functioning instead as a vehicle for global corporate tax reallocations, asset shielding, and financial restructuring cycles (International Monetary Fund [IMF], 2023). This descriptive distortion directly justifies the subsequent deployment of Cook’s Distance and DFBETAS influence diagnostics in Section 4.4, ensuring that these anomalous maritime financial nodes do not skew the baseline parameter estimates for the broader developed cohort.

4.1.4. Trade Integration Extremes

Trade openness is substantially higher in developed nations, with a mean trade-to-GDP ratio of 125.40%, compared to 77.05% in the developing cohort. The maximum value exceeding 400% in the developed cohort confirms the structural dominance of high-leverage transit economies. Conversely, trade integration in the developing cohort is relatively lower and more dependent on domestic primary manufacturing capabilities and basic integration into global value chains (Tahir et al., 2026).

Ultimately, these stark descriptive statistics differences mathematically validate splitting the global sample. The sharp contrasts in baseline volatility and technological readiness confirm that these cohorts operate under entirely different macroeconomic regimes.

4.2. Econometric Estimation and Comparative Analysis

The empirical results of the split-sample OLS estimations, utilizing heteroskedasticity-robust standard errors under the Huber–White–Hinkley (HC1) correction procedure, are presented in Table 4. The empirical findings reveal a stark structural divergence in the drivers of economic growth between the two cohorts.

Table 4. Comparative OLS Estimation Results (Developing versus Developed cohorts).

Independent Variable	Developing Economies (N = 76)	Developed Economies (N = 45)
Normalized Network Readiness (NRIT)	1.106 *** (0.0027)	−0.734 * (0.0895)
Transformed Foreign Direct Investment (IHSFDI)	0.246 ** (0.0116)	0.036 (0.6724)
Transformed Trade Openness (IHSTRD)	0.292 (0.1208)	−0.218 (0.1804)
Constant (C)	−1.733 ** (0.0424)	3.170 *** (0.0100)
R-squared	0.2497	0.0832
Adjusted R-squared	0.2185	0.0161
F-statistic	(7.99) *** (0.0001)	1.240 (0.3072)
Wald F-statistic	11.060 *** (0.0000)	1.540 (0.2174)
Standard Error Correction	Huber–White–Hinkley (HC1)	Huber–White–Hinkley (HC1)

Source: Authors' calculation using EViews version 11. Note: *p*-values are reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

4.2.1. Evaluation of Research Hypotheses

Based on the empirical evidence in Table 4, the outcomes of the formal hypothesis tests are stated as follows:

***H*₁ (The Structural Leapfrogging Hypothesis) is fully supported.** The robust, highly significant growth multiplier of NRIT ($\beta = 1.106$; $p < 0.01$) and IHSFDI ($\beta = 0.246$; $p < 0.05$) within the developing cohort stands in stark contrast to the saturated, marginally negative technological returns ($\beta = -0.734$; $p < 0.10$) and irrelevant investment returns ($\beta = 0.036$; $p > 0.10$) observed in the developed cohort. This empirically solidifies the premise that traditional infrastructure and capital accumulation operate uniquely as catch-up mechanics in the Global South.

***H*₂ (The Structural Break and Metric Asymmetry Hypothesis) is fully supported.** The absolute rejection of parameter constancy by the Chow Breakpoint Test ($F = 11.91$; $p < 0.01$), as shown in Table 5, mathematically validates the split-sample approach. Furthermore, the uniform statistical insignificance of the trade openness (IHSTRD) across both cohorts directly confirms the metric asymmetry postulation. This neutrality validates the framework's claim that aggregate gross trade metrics obscure the underlying value-added distribution, signaling the hidden presence of a structural Global Value Chain (GVC) Divergence Trap.

Table 5. Summary of Diagnostic and Stability Checks.

Diagnostic Test	Developing Sample (N = 76)	Developed Sample (N = 45)	Final Econometric Verdict
Multicollinearity (VIF)	Passed (All VIF < 1.50)	Passed (All VIF < 1.50)	Rejects collinearity-induced standard error inflation.
Model Specification (Ramsey RESET)	<i>F</i> -statistic = 0.078 ($p = 0.780$) Passed Correct Specification	<i>F</i> -statistic = 2.660 ($p = 0.110$) Passed Correct Specification	Confirm linear functional form validity; no omitted higher-order terms.
Influence Diagnostics (Cook's Distance/DFBETAS/Hat Matrix)	Clean distribution; no severe outlier distortion.	Isolated Malta and Singapore as high-leverage hubs.	Outliers identified and isolated for sensitivity analysis.
Heteroskedasticity (BPG Test)	Observed non-constant error variance ($p < 0.10$).	Observed non-constant error variance ($p < 0.05$)	Heteroskedasticity corrected using robust HC1 estimators.
Structural Stability (Chow Test)		$F = 11.91$ ($p < 0.01$)	Rejects parameter constancy; confirms a major structural break

Source: Authors' calculation using EViews version 11.

4.2.2. The Digital ‘Leapfrogging’ vs. The ‘Saturation’ Effect

The most striking result from the econometric analysis is the complete sign reversal of the *NRIT* coefficient between the two cohorts. Digital readiness serves as a highly significant growth multiplier in developing countries ($\beta = 1.106$; $p < 0.01$). This provides robust empirical support for leapfrogging theory, demonstrating that modern ICT infrastructure allows emerging markets to skip legacy, capital-intensive phases of traditional industrialization (Brezis et al., 1993; Steinmueller, 2001). This finding aligns with evidence across emerging economies where digital financial infrastructure, such as mobile banking networks, directly reduces transaction costs, improves financial inclusion, and catalyzes small and medium enterprise (SME) development (Lambon & Ocansey, 2025). This rapid catch-up dynamic emphasizes that targeted investments in digital infrastructure yield large growth dividends when baseline access is low (Portulans Institute, 2024).

4.2.3. The Digital Maturity Paradox and TFP Shift

Conversely, the *NRIT* coefficient for the developed cohort is negative and only marginally significant at the 10% level ($\beta = -0.734$; $p < 0.10$). This result provides empirical validation for the Digital Maturity Paradox. This implies that once an economy achieves digital infrastructure maturity, incremental investment in standard ICT networks faces sharply diminishing marginal returns. While developing countries enjoy extensive growth returns from initial network rollouts, developed economies appear to have hit a digital saturation ceiling.

Consequently, developed countries must transition from a traditional neoclassical capital-deepening growth model toward an endogenous framework driven by Total Factor Productivity (TFP) and frontier innovation. In these developed economies, a modern iteration of the “Productivity Paradox” emerges (Brynjolfsson, 1993; Solow, 1987). The aggregate structural costs of operating at the digital frontier, such as complex systemic integration, cyber-risk mitigation, and continuous workforce retraining, frequently outpace the direct macroeconomic growth gains derived from incremental network optimization (Dewan & Kraemer, 2000).

4.2.4. FDI and Capital Intensity

For the developing cohort, FDI is a statistically significant driver of economic growth ($\beta = 0.246$, $p < 0.05$; see Table 4). This confirms the theoretical premise that foreign capital inflows provide essential technological and managerial spillovers to capital-scarce economies, helping them catch up to the global frontier (Javorcik, 2004).

Conversely, FDI is statistically irrelevant in the developed cohort ($\beta = 0.036$, $p > 0.10$). This suggests that growth in developed economies is insulated from the sheer volume of foreign capital inflows, relying instead on domestic intellectual property generation and structural institutional stability (Romer, 1990). Furthermore, influence diagnostics show that this developed-country coefficient is highly sensitive to financial hubs like Malta and Singapore. This suggests that in advanced economies, the macroeconomic impact of foreign capital is not a uniform growth driver; it is highly concentrated within small, high-leverage financial centers (International Monetary Fund [IMF], 2023).

4.2.5. The Neutrality of Trade and the GVC “Divergence Trap”

Despite the theoretical emphasis on trade-led growth, the coefficients for trade openness (*IHSTRD*) are statistically insignificant across both the developing ($\beta = 0.292$, $p > 0.10$) and developed ($\beta = -0.218$, $p > 0.10$) cohorts. Crucially, this empirical neutrality provides robust statistical support for our structural inequality hypothesis, indicating

that aggregate trade openness operates as an insufficient metric that conceals domestic value-added capture.

In developing nations, this statistical neutrality directly exposes the operational mechanics of the GVC Divergence Trap (Antràs, 2020; Humphrey & Schmitz, 2002). While liberalized trade regimes successfully expand gross import and export volumes, emerging economies are frequently confined to low-value-added assembly and primary processing nodes within global production networks. Consequently, inflated gross trade volumes fail to translate into measurable expansion in domestic value-added GDP, masking the underlying asymmetries of global value chain integration.

In developed nations, the statistical neutrality of trade, combined with a negative coefficient, can largely be attributed to extreme leverage spikes identified within the diagnostic Hat Matrix. Maritime and financial trade hubs, such as Malta and Singapore with trade-to-GDP ratios exceeding 200% and 300% respectively, introduce substantial variance into the standard errors, effectively diluting the global trade coefficient. This suggests that the trade openness is no longer a generalized engine of growth across the developed economies, but rather an idiosyncratic feature of specific transit maritime economies.

4.3. Diagnostic Test and Stability Analysis

To ensure the statistical validity and scientific integrity of the comparative results, a comprehensive battery of diagnostic checks was performed, as summarized in Table 5.

4.3.1. Multicollinearity and Model Specification

The model exhibits strong internal validity. The Variance Inflation Factors (VIF) fell well below the conservative threshold of 5.0 ($NRIT = 1.14$; $IHSFDI = 1.27$; $IHSTRD = 1.43$), confirming the absence of severe multicollinearity (Hair et al., 2010). Additionally, the Ramsey RESET test confirmed correct functional specification for both the developing sample (F -statistic = 0.078, $p = 0.780$) and developed sample (F -statistic = 2.660, $p = 0.110$) configurations (Ramsey, 1969). These results confirm that the linear model, paired with the Inverse Hyperbolic Sine (IHS) transformations, successfully captures the underlying macroeconomic relationships without requiring higher-order polynomial terms.

4.3.2. Influence of Global Hubs (DFBETAS and Cook's Distance)

Given the low baseline explanatory power of the developed tier model (Adjusted R -Squared = 0.0161), an influence analysis was conducted utilizing HAT matrix diagonals, Cook's Distance, and DFBETAS to evaluate parameter stability and detect distortionary data points (Belsley et al., 1980). This multi-criterion diagnostic sequence isolated Malta and Singapore as extreme, high-leverage outliers within the advanced economy cohort. Malta and Singapore's disproportionate trade-to-GDP ratios and volatile, tax-driven corporate FDI flows introduce substantial noise, masking underlying structural linkages within high-income nations. By contrast, the developing country cohort ($N = 76$) exhibited a highly uniform, homoskedastic distribution, confirming that the digital growth multiplier is a systemic macroeconomic trend across the Global South rather than a statistical artifact of outliers.

4.3.3. Error Volatility and Heteroskedasticity

While the Breusch–Pagan–Godfrey test shows marginal homoskedasticity ($p = 0.0502$), the proactive use of Huber–White–Hinkley (HC1) Robust Standard Errors ensures that the reported probability values are protected against potential error volatility. This heteroskedasticity-constant covariance matrix estimation ensures the reliability of the t -statistics and hypothesis testing across both development stages.

4.3.4. Validating the Structural Break (Chow Test)

The final mathematical justification for splitting the global sample was established via the Chow Breakpoint Test (CBPT) at the high-income transition boundary (Observation 77). The test results ($F = 11.91$, $p < 0.01$) strongly reject the null hypothesis of parameter constancy across the cohorts (Chow, 1960). This proves that the structural determinants of economic growth change fundamentally depending on a nation's developmental level, validating the comparative methodology of this study.

4.4. Robustness Check and Sensitivity Analysis

To evaluate parameter stability and confirm the validity of the 'Digital Maturity Paradox,' a secondary sensitivity regression was executed on a refined developed sub-sample ($N = 43$) by dropping Malta and Singapore. These observations were previously isolated by the DFBETAS and Hat Matrix diagnostics as high-leverage outliers capable of introducing severe structural variance and distorting generalized trends in the Global North. The results, detailed in Table 6, reveal that even when these extreme transit-trade and tax-driven capital lane distortions are systematically stripped out, the coefficient for the Network Readiness Index remains structurally repressed. This persistently weak or negative marginal return mathematically confirms that the 'Digital Maturity Paradox' is an intrinsic, systemic property of advanced, frontier production structures rather than an empirical anomaly driven by the idiosyncratic macroeconomic features of specific small island financial hubs.

Table 6. Developed Cohort Sensitivity Analysis (Excluding Outliers).

Independent Variable/Metric	Baseline Developed Model ($N = 45$)	Refined Developed Model ($N = 43$)
Normalized Network Readiness (NRIT)	−0.734 * (0.0895)	−0.693 (0.1166)
Transformed Foreign Direct Investment (IHSDI)	0.036 (0.6724)	−0.050 (0.5433)
Transformed Trade Openness (IHSTRD)	−0.218 (0.1804)	−0.279 (0.1095)
Constant (C)	3.170 *** (0.0100)	3.532 *** (0.0096)
R-squared	0.0832	0.0810
Adjusted R-squared	0.0161	0.0103
Overall F-statistic (p -value)	1.240 (0.3072)	1.146 (0.3427)
Wald F-statistic (p -value)	1.540 (0.2174)	1.535 (0.2206)

Note: p -values are reported in parentheses. *, ***, denote significance at the 10%, 5% and 1% levels, respectively.

The empirical results from this refined regression ($N = 43$), estimated with heteroskedasticity-robust HC1 standard errors, are presented in Table 6 alongside the baseline model for direct comparison.

The formal exclusion of these outlier economies clarifies the structural dynamics of developed economies. Upon removing Malta and Singapore, the model's overall explanatory capacity completely collapses. The Adjusted R-squared drops to a negligible 0.0103, meaning that less than 1.03% of the cross-country variation in real GDP per capita growth in the Global North can be attributed to digital infrastructure, FDI, or trade integration.

Furthermore, the overall model insignificance is confirmed by the regression F-statistic of 1.146 ($p = 0.3427$) and a Wald F-statistic of 1.535 ($p = 0.2206$). We fail to reject the joint null hypothesis that all slope coefficients are simultaneously equal to zero, indicating that these traditional structural variables possess zero collective predictive power in developed economic environments.

An examination of individual parameters reveals critical shifts:

Network Readiness (NRIT): The coefficient remains firmly negative ($\beta = -0.693$) but moves past the 10% threshold into statistical insignificance ($p = 0.1166$). This loss

of marginal significance indicates that the slight negative pressure observed in the baseline sample was partially amplified by outlier variance. More importantly, its transition to statistical irrelevance provides robust confirmation of a complete saturation plateau. Incremental technological adoption yields net-zero structural growth returns once baseline digital operational maturity is globally standardized across a cohort.

Foreign Direct Investment (IHSDI): The coefficient flips from a weak positive value to a negative, entirely insignificant metric ($\beta = -0.050$, $p = 0.5433$). This confirms that the volume of external capital inflows is fundamentally decoupled from the growth trajectories of developed economies.

Trade Openness (IHSTRD): The coefficient remains negative ($\beta = -0.279$) and sits just outside the margin of statistical significance ($p = 0.1095$). This reinforces the conclusion that open commercial regimes do not act as generalized engines of expansion in high-income states.

Empirical Validation of the “Fitness Gap”

These updates provide conclusive empirical weight to the “Fitness Gap” conceptualized in this study. While the identical structural regression model accounts for more than 21% (Adjusted R -squared = 0.2185) of growth variance in the developing world (see Table 4), it exhibits a near-total loss of statistical efficacy when applied to the Global North, explaining a mere 1.03% (Adjusted R -squared = 0.0103) of the variance once cross-border outlier noise is removed.

This stark asymmetry reveals a fundamental divergence in the rules governing macroeconomic prosperity: Developing Economies (Adjusted R -squared = 0.2185) $\longleftrightarrow$ Developed Economies (Adjusted R -squared = 0.0103).

In the developing South, economic growth is driven by physical capital deepening and structural network rollouts where digital access and foreign investment facilitate aggressive, catch-up “leapfrogging.” However, once nations cross the high-income threshold and cross-border assets reach a point of structural saturation, these traditional growth vectors cease to operate. The “Fitness Gap” mathematically proves that advanced economies have entirely outgrown infrastructure-led development frameworks. Their growth is instead dictated by complex, intangible endogenous shifts—such as Total Factor Productivity (TFP) dynamics, institutional quality, and the strategic deployment of general-purpose technologies like Artificial Intelligence—rather than capital accumulation and baseline network access.

5. Conclusions and Policy Implications

5.1. Theoretical Synthesis

This study demonstrates that the structural determinants of modern economic growth are fundamentally shaped by an economy’s development maturity. By deploying a split-sample estimation framework, this research provides empirical confirmation of the “Digital Maturity Paradox.” The econometric results validate the Structural Leapfrogging Hypothesis (H_1) for developing nations and confirm the presence of a distinct Structural Break (H_2) at the high-income threshold. The empirical evidence indicates that while network readiness and FDI serve as potent engines for catch-up growth in the Global South, these traditional inputs hit a strict saturation plateau and lose their statistical efficacy when applied to developed economies.

The emergence of a stark “Fitness Gap”—marked by the near-total collapse of the model’s explanatory power in the developed cohort (Adjusted R -squared = 0.0103)—highlights the structural inadequacy of using standard neoclassical growth models for asset-saturated nations. For the Global South, the path to macroeconomic prosperity remains rooted in narrowing the digital divide and absorbing cross-border capital spillovers.

Conversely, the Global North has entered a phase of structural digital saturation where incremental improvements in baseline connectivity no longer yield measurable growth dividends. Consequently, the “old growth rules” of physical and digital capital accumulation have been superseded in advanced economies by an essential requirement for endogenous innovation, total factor productivity (TFP) dynamics, and intangible organizational capital.

5.2. Policy Frameworks by Development Tier

Developing Economies (The Leapfrogging Strategy): Policymakers in emerging markets should prioritize targeted investments in digital infrastructure over traditional, capital-intensive industrial and manufacturing subsidies. Given the high growth elasticity of network readiness identified in this study ($\beta = 1.106$), public budgets should prioritize universal broadband access, digital literacy, and cellular infrastructure. This strategy enables developing nations to bypass legacy, intermediate stages of industrialization and transition directly into digitalized, knowledge-based economic frameworks.

Developed Economies (The TFP Pivot): In advanced economies, policy design must shift its focus from expanding digital connectivity to optimizing technological application. Because baseline ICT infrastructure has reached a standardized saturation point, additional network rollouts will not generate macroeconomic expansion. High-income states must redirect fiscal incentives, tax credits, and grants toward boosting TFP through deep-tech research and development (R&D), advanced Artificial Intelligence (AI) integration, and the structural reorganization of business models to overcome the modern productivity paradox.

5.3. Methodological Limitations and Future Research Directions

While this study provides robust empirical evidence of a structural divergence between the global cohorts, certain methodological and data boundaries point toward areas for future academic inquiry: First, a primary methodological constraint of this investigation involves the reliance on an exogenous sample split based on institutional development categories. While this split is mathematically validated by the Chow test, it does not identify the precise inflection point. Future research should implement non-linear threshold regression models (e.g., Hansen, 1999) to endogenously isolate the exact macroeconomic tipping points. Second, the utilization of an aggregate trade openness metric (*IHSTRD*) potentially masks underlying structural dynamics and industrial hollowing. To address this limitation and better map the mechanisms of the GVC Divergence Trap, future scholarship should disaggregate international trade data into high-, medium-, and low-technology components. This step would explain why aggregate trade volume remains statistically neutral while revealing how value-added capture influences long-run growth. Third, the baseline econometric specification focuses on primary macroeconomic inputs, leaving out deeper institutional interactions. Future empirical designs should explicitly incorporate and analyze specific regulatory frameworks, intellectual property rights (IPR) regimes, and host-country absorptive capacities. This would help identify the specific institutional conditions that allow certain advanced economies to successfully manage the digital frontier and mitigate the drag of the modern productivity paradox.

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Abbreviations

The following abbreviations are used in this manuscript:

GDP	Gross Domestic Product
FDI	Foreign Direct Investment
TRD	Trade
NRI	Network Readiness Index
OLS	Ordinary Least Squares
GVC(s)	Global Value Chain(s)
R&D	Research and Development
TFP	Total Factor Productivity
AI	Artificial Intelligence

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