Revue-IRS

Revue Internationale de la Recherche Scientifique (Revue-IRS)

ISSN: 2958-8413

Vol. 3, No. 5, Septembre 2025

Digital Investments, Structural Transformation, and Economic Growth in Advanced Economies: Empirical Analyses and Perspectives

[1]Adil RACHDI

[1]**Research professor, National School of Business and Management, Mohammed First University, Oujda, Morocco.**

Abstract: This study examines the long-term and short-term effects of digital investments on economic growth and structural transformation in three advanced economies: South Korea, Germany, and the United States, over the period 2010–2024. Using an Autoregressive Distributed Lag (ARDL) framework, we assess the role of ICT infrastructure, R&D in digital technologies, and broadband penetration, alongside complementary factors such as labor productivity, human capital, gross capital formation, and trade openness. Panel unit root and cointegration tests confirm the existence of stable long-run relationships for most cases, with digital investment intensity exerting a significant and positive impact on GDP per capita in both the long and short term. Country-level estimations reveal substantial heterogeneity, with South Korea achieving the highest returns to digital investment, Germany showing more moderate effects, and the United States displaying robust but more volatile long-run relationships. The results highlight the importance of complementary assets particularly human capital and organizational capacity in maximizing the growth benefits of digitalization. Policy recommendations emphasize integrated strategies that align infrastructure development, capacity building, and innovation policy, underpinned by strong institutional frameworks and international cooperation.

Keywords: Digital investment; Economic growth; Structural transformation; ICT infrastructure; Human capital; ARDL model; Cointegration; South Korea; Germany; United States; Advanced economies; Digital economy policy.

Digital Object Identifier (DOI): https://doi.org/10.5281/zenodo.**17213763**

1. Introduction

Over the past two decades, digitalization has emerged as a structural driver of economic transformation in advanced economies. Investments in information and communication technologies (ICT), digital research and development (R&D), and connectivity infrastructure are no longer merely sectoral support measures; they now constitute a strategic pillar of industrial and competitiveness policies. According to the OECD (2024), between 2010 and 2024, spending on digital infrastructure grew by an average of 7.5% per year across member countries, with marked differences depending on institutional and industrial contexts. The World Bank (2023) estimates that the digital sector today accounts for over 15% of the combined GDP of advanced economies, compared to around 8% in the early 2010s, reflecting a rapid transformation of the productive structure.

South Korea's trajectory exemplifies a model of digital advancement built on an integrated public strategy and a close partnership with the private sector. Data from the ITU and OECD show that the share of digital R&D expenditure in GDP increased by more than 65% between 2010 and 2024, driven by initiatives such as the Digital New Deal, which combines the large-scale rollout of 5G, support for the semiconductor industry, and the development of digital services. This dynamism led to a broadband penetration rate exceeding 99% of households as early as 2022, placing the country first worldwide. Investment in South Korea is not only massive but also steady, thereby maximizing its cumulative effects on productivity and overall competitiveness.

In comparison, Germany and the United States follow different paths. Germany, despite a strong industrial base and a high-performing network of SMEs, increased its digital investments by only around 35% over the period, hampered by delays in rural broadband deployment and by the fragmentation of digital policies between Länder. The United States, for its part, maintains a high level of investment intensity, but its evolution remains more cyclical, alternating between waves of major innovations (cloud computing, artificial intelligence, big data) and phases of consolidation. These contrasts confirm that the scale of investment alone is not sufficient: strategic coherence, continuity of effort, and the capacity to absorb innovations are decisive factors in translating digital spending into sustainable economic gains.

In a context where digitalization has become a major lever for competitiveness and structural transformation, advanced economies display divergent trajectories in the scale and effectiveness of their digital investments. South Korea exemplifies a coordinated strategy of massive investment, supported by an integrated industrial vision and strong public–private synergy, while Germany despite a robust industrial base and a skilled workforce lags behind in digital modernization and the adoption of emerging technologies. The United States, for its part, stands out for its dynamic technological ecosystem and high level of digital productivity, yet exhibits significant sectoral and regional disparities. This heterogeneity calls into question the relationship between institutional structure, innovation capacity, and the economic return on digital investments. Accordingly, the central research problem can be formulated as follows: **to what extent do digital investments differentially influence structural transformation and economic growth in advanced economies, and what institutional, technological, and socio-economic conditions maximize their impact?**

To address this problem, the study is structured around several lines of inquiry. First, it analyzes the structure, intensity, and public–private distribution of digital investments in each of the three countries, as well as their evolution over the past decade. Second, it examines the structural effects, notably sectoral reorganization and the emergence of competitiveness clusters linked to digital technologies. Third, the research assesses the impact of these investments on labor and capital productivity, identifying possible diminishing returns. Fourth, it investigates the role of public policy, human capital development, regulation, and organizational dynamics in the success of digital projects. Finally, an international comparison will identify best practices and formulate strategic recommendations applicable to other advanced economies.

The overarching objective of this research is to conduct a comparative analysis of the impact of digital investments on structural transformation and economic growth in three advanced economies with distinct trajectories: South Korea, Germany, and the United States. More specifically, it seeks to identify the mechanisms through which investments in information and communication technologies (ICT) and digital innovation influence productivity, sectoral reorganization, and overall competitiveness. The study also aims to evaluate the role of public policy, the innovation ecosystem, human capital, and organizational culture in optimizing the economic effects of these investments. On a practical level, it aspires to formulate strategic recommendations that can be applied to other advanced economies, drawing on quantitative and qualitative indicators from macroeconomic data, policy analyses, and sectoral studies.

From these objectives emerge three structuring hypotheses. **H1**: In advanced economies, higher intensity of digital investments is positively correlated with stronger growth in labor and capital productivity, all else being equal. **H2**: The economic effectiveness of digital investments depends heavily on the coherence of public policies and the quality of digital infrastructure, such that countries with proactive technological governance (e.g., South Korea) achieve higher returns than those with a fragmented strategy (e.g., Germany). **H3**: Beyond a certain threshold, the marginal returns of digital investments tend to diminish, unless accompanied by complementary investments in human capital, R&D, and organizational innovation, as illustrated by the U.S. case in certain high-tech-intensive sectors.

This study adopts a quantitative econometric approach based on the estimation of an **ARDL** (*Autoregressive Distributed Lag*) model to analyze the impact of digital investments on structural transformation and economic growth in advanced economies specifically South Korea, Germany, and the United States over the period 2010–2024. The choice of the ARDL model is justified by its ability to handle time series with mixed integration orders, I(0) and I(1), while distinguishing between short-term and long-term effects among variables. The data include annual macroeconomic indicators such as GDP per capita, labor productivity, the intensity of digital investments (expenditures in ICT, R&D, and digital infrastructure), as well as control variables (trade openness, human capital, total investment). Unit root tests (ADF, PP) will be employed to verify the integration order of the series, followed by the Pesaran Bounds test for cointegration to confirm the existence of a long-term relationship. The estimated coefficients will make it possible to assess the magnitude and statistical significance of the effect of digital investments, while accounting for the structural and institutional specificities of each country under study.

2. Literature Review

The economic and managerial literature on digital investment has expanded significantly since the 1990s, gradually establishing an empirical consensus on its central role in productivity and structural transformation in advanced economies. Early seminal works highlighted the contribution of ICT capital deepening and organizational innovation to productivity resurgence, while more recent analyses have nuanced this relationship by underscoring the importance of intangible assets, management quality, and public policy coherence. Comparative studies reveal that, despite similar investment levels, economic efficiency varies substantially across institutional contexts, sectoral structures, and stages of digital maturity, generating persistent performance gaps between countries. In parallel, a growing body of research examines the distributive effects of digitalization, showing that gains can be unevenly shared and may exacerbate inequality if « analog complements » skills, governance, competition are lacking. Ultimately, the interplay between governance, skills development, and innovation policies emerges as a decisive lever for transforming digital investments into inclusive and sustainable growth, motivating an integrated analysis of the drivers, constraints, and enabling conditions for their effectiveness.

2.1. Digital Investments as Engines of Economic Growth

At the turn of the 1990s–2000s, several seminal works established the link between digital investments and productivity resurgence. Oliner, S. D., & Sichel, D. E. (2000), show, within a growth accounting framework, that the acceleration of U.S. labor productivity after 1995 stems largely from IT capital deepening (hardware, software, communications) and efficiency gains in IT production. Jorgenson, D. W., et al (2008), later confirm that IT was critical to the U.S. productivity revival, documenting the shift from initial skepticism to an empirical consensus on IT's role. At the microeconomic level, Brynjolfsson, E., & Hitt, L. M. (2000), demonstrate that the impact of

IT on productivity is conditional on organizational complements (work reorganization, decentralization), which explains the heterogeneity of returns observed across firms.

The literature from the 2000s–2010s refined this diagnosis. Cardona, M., et al (2013), conduct a meta-synthesis, finding that IT is positively associated with productivity, though the magnitude of the effect varies by level (firm/sector/country) and by the ability to combine IT with managerial practices. Corrado, C., e t al (2009), broaden the production frontier by capitalizing intangible assets (R&D, brands, software, organizational capital), showing that including them significantly raises the measured contribution of capital to growth positioning IT at the core of an ecosystem of intangibles. Bloom, N., et al (2012), using multi-country firm-level data, explain the U.S. « IT advantage » through more rigorous management practices, suggesting that governance and management quality amplify the returns on digital investments.

From an international perspective, cross-country comparisons complete the picture. van Ark, B., et al (2008), attribute part of the Europe–U.S. productivity gap to weaker IT dynamics in Europe's market services sector, pointing to missing institutional complementarities. Spiezia, V. (2012), estimates, for 18 OECD countries, the contribution of different ICT components (computers, software, communications) to sectoral value added, confirming a positive but heterogeneous effect across countries and industries. Jorgenson, D. W., et al (2000), show, at the industry level, that the rise in U.S. productivity is explained by sectors intensive in IT, highlighting the importance of sectoral composition and IT capital in aggregate growth.

2.2. Digital Investments and Structural Transformation

The work of *Timmer, M. P., & de Vries, G. J. (2009),* based on a new sectoral dataset, shows that episodes of growth acceleration are driven by reallocation of employment and value added toward higher-productivity sectors a crucial mechanism for understanding structural transformation. *Inklaar, R., et al (2008),* highlight that, since the mid-1990s, the diffusion of ICT capital and human capital has boosted productivity in market services in the United States, while Europe captured fewer gains, shedding light on the transatlantic productivity gap. On the theoretical side, *Ngai, L. R., & Pissarides, C. A. (2007),* formalize the coexistence of balanced aggregate growth with a sectoral shift in labor induced by differential technological progress across industries: the relative price decline of technology-intensive goods (including digital technologies) durably shifts employment toward services.

At the international level, *McMillan, M., et al (2014),* demonstrate that structural transformation can be growth-enhancing (Asia) or growth-reducing (Latin America, Africa in the 1990s) depending on framework conditions (exchange rate regimes, labor market flexibility, resource dependence), underscoring that digital investment does not operate in a vacuum. *Dahl, C. M., et al (2011),* using multi-country sectoral data for Europe, estimate significant TFP effects from ICT after 1995, finding that gains stem primarily from efficiency improvements (not just capital accumulation), which points to the role of organizational complements and management quality. *Spiezia, V. (2012),* quantifies, for OECD countries, the contribution of ICT components (hardware, software, communications) to sectoral value added and concludes that the effect is positive but heterogeneous depending on sectoral structures and supporting policies.

Finally, recent research closely links digitalization to industrial restructuring. *Acemoglu, D., & Restrepo, P. (2020),* show that robot adoption reshapes local specialization and reduces employment and wages in the most exposed regions, accelerating the mechanization of certain branches and altering sectoral composition. Autor, *Autor, D., et al (2020),* document the rise of "superstar firms": the combination of digital technologies and global markets concentrates activity in a few high-margin firms and reduces labor's share, transforming inter-sectoral competitive dynamics. *Comin, D., & Hobijn, B. (2010),* find that delays and intensity in technology adoption (including IT) vary greatly across countries and explain a substantial share of income per capita differences, implying that absorptive capacity, human capital, and institutions shape the trajectory of structural transformation.

2.3. Comparative Efficiency of Digital Investments in Advanced Economies

Cross-country studies have long investigated why similar levels of digital investment can yield divergent productivity outcomes. Colecchia, A., & Schreyer, P. (2002), analyzing G7 and selected OECD economies, found that ICT capital deepening accounted for a substantial portion of labor productivity growth in the late 1990s, but efficiency varied significantly, with the United States and Canada outperforming Europe due to faster ICT adoption and better complementary assets. Van Ark, B., et al (2003), reinforced this view, attributing the U.S. advantage to a stronger reallocation effect within market services, amplified by managerial innovations. Jalava, J., & Pohjola, M. (2007), focusing on Finland, showed that despite high ICT investment rates, the productivity impact was initially muted, becoming significant only when organizational restructuring and innovation systems matured.

From a broader macroeconomic lens, OECD (2004), documented that countries with similar ICT capital intensity experienced different TFP gains depending on regulatory environments and competition levels in telecom and digital markets. Dedrick, J., et al (2013), using a panel of 50 countries, demonstrated that the economic returns to ICT are conditional on institutional quality, with governance, legal frameworks, and openness to trade amplifying the effects. Cardona, M., et al (2013), synthesized empirical results showing that advanced economies benefit more from ICT when digital skills and broadband penetration are high, highlighting human capital as a key driver of efficiency.

Firm-level and sectoral analyses further nuance these findings. Bloom, N., et al (2016), found that U.S. firms' superior ICT productivity returns compared to European counterparts were largely explained by better management practices and data-driven decision-making. Draca, M., et al (2007), using UK firm-level data, estimated that ICT-intensive firms experienced faster productivity growth but only in competitive markets that incentivized innovation. Byrne, D. M., et al (2018), argued that even in the U.S., ICT investment returns slowed post-2005 due to a deceleration in semiconductor performance, showing that technological supply constraints can limit efficiency gains.

2.4. Digitalization, Inequality, and Inclusive Growth

A first strand links routine-biased technological change and automation to employment polarization and wage dispersion. Acemoglu, D., & Restrepo, P. (2019), develop a task-based framework showing how automation simultaneously displaces labor in routine tasks and creates new tasks, with distributional effects that depend on the balance between displacement and reinstatement; when the former dominates, inequality rises. Consistent with this mechanism, Autor, D. H., & Dorn, D. (2013), document that U.S. labor markets have polarized since 1980, with growth concentrated in low-skill services and high-skill occupations, while routine middle-skill jobs contracted an employment shift closely tied to computerization. Extending the evidence to Europe, Goos, M., et al (2014), show pervasive polarization across 16 countries (1993–2010) and attribute it largely to routine-biased technological change (complemented by offshoring), reinforcing the link from digitalization to distributional outcomes.

A second strand focuses on how digital access and capability gaps mediate the inclusiveness of gains. Using quasi-experimental variation from a phased roll-out, Akerman, A., et al (2015), find that firm broadband adoption complements skilled workers in non-routine tasks but substitutes for the unskilled, raising wage dispersion evidence of skill-biased effects from core digital infrastructure. During the pandemic, Chiou, L., & Tucker, C. (2020), show that unequal household access to high-speed internet explained much of the income gradient in the ability to comply with stay-at-home directives, highlighting how digital divides translate into unequal resilience. At a global policy level, the World Bank. (2016), argues that « digital dividends » have been uneven because analog complements competition, skills, and accountable institutions lagged; without these, digitalization can amplify pre-existing inequalities.

A third strand asks how to translate digitalization into inclusive growth. The OECD. (2019), roadmap emphasizes measuring diffusion, skills, and usage alongside competition and data-governance levers to steer digital transformation toward broad-based welfare gains. At the technological frontier, Brynjolfsson, E., et al (2018), show that most occupations include some machine-learnable tasks but few are fully automatable, implying that institutions and job (re)design determine whether AI augments workers or displaces them hence whether inequality widens. Complementing this, Bessen, J. (2019), argues that demand elasticity critically shapes employment impacts of AI: where demand expands, adoption can raise employment and temper inequality; where it saturates, displacement pressures dominate guidance that pushes inclusive policies beyond the supply side.

2.5. Governance, Skills, and Policy Mix for an Equitable Digital Transition

A robust policy mix begins with governance for diffusion and competition. Aghion, P., et al (2005), show an inverted-U between product-market competition and innovation, implying that pro-competitive regulation encourages frontier firms without discouraging laggards central to steering digital markets away from monopoly dynamics. Andrews, D., et al (2016), document widening gaps between global frontier firms and the rest, arguing that diffusion bottlenecks not a lack of ideas explain much of the productivity slowdown; they call for policies that lower adoption costs (data access, interoperability, competition, finance for intangibles). The OECD. (2019), adds a measurement pillar skills, usage, diffusion, and outcomes so that digital strategies can be monitored and corrected in real time. Together, these results motivate a governance toolkit combining competition policy, standards and data portability with evidence-based monitoring to accelerate broad-based digital uptake.

The skills leg of the policy mix anchors inclusive performance. Hanushek, E. A., & Woessmann, L. (2012), link cognitive skills rather than schooling years per se to long-run growth across countries, emphasizing quality of learning for technology adoption. Deming, D. J. (2017), shows the labour market increasingly rewards social (non-routine, team) skills alongside cognitive ability, implying curricula and active labour-market policies must pair digital and socio-behavioral capabilities. Complementing this, Lane, M., & Saint-Martin, A. (2021), review evidence on AI and jobs, highlighting shifting task content and the need for continuous re-skilling/up-skilling frameworks to translate AI diffusion into productivity and job quality gains. In advanced economies, the efficient, equitable return to digital investment thus hinges on skill formation systems that are responsive to task change and firm demand.

Finally, institutions determine whether digitalization yields inclusive dividends. The World Bank. (2016), argues that digital technologies deliver broad benefits only when « analog complements », competition, skills, and accountable institutions are in place. Arntz, M., et al (2016), estimate heterogeneous automation risks across OECD countries, underscoring the importance of social protection, mobility and targeted re-training to avoid polarization. Classic evidence from Katz, L. F., & Murphy, K. M. (1992), on skill-biased demand reminds us that when demand shifts faster than supply, wage dispersion widens so equity requires coupling technology adoption with education and training capacity, as well as labour-market and competition rules that diffuse gains beyond a small set of firms and workers.

A critical synthesis of the literature shows that digital investment is a powerful but conditional driver of growth and structural transformation in advanced economies. Its effectiveness depends on a set of complementary factors human capital, physical infrastructure, organizational capability and on an institutional environment conducive to technological diffusion. While cross-country comparisons confirm robust positive effects on productivity and sectoral reallocation, they also reveal divergences linked to national strategies, governance quality, and innovation cycles. Digitalization, when not supported by inclusive policies, can amplify inequalities, reinforcing the need for coordinated public–private steering that combines pro-competitive regulation, equitable technology access, and continuous skills development. Overall, the literature converges on the idea that a successful digital transition requires not only sustained investment in ICT and R&D but also strategic coherence between infrastructure, skills, and institutions an indispensable condition for maximizing the economic and social dividends of digitalization.

3. Empirical Analysis

3.1. Descriptive analysis

The descriptive analysis provides an essential foundation for the empirical investigation by examining the main trends, distributions, and structural characteristics of the dataset before applying econometric techniques. This stage allows us to contextualize the relationships between digital investments, structural transformation, and economic growth across South Korea, Germany, and the United States over the 2010–2024 period. By summarizing the data through key indicators such as GDP per capita, labor productivity, ICT investment intensity, R&D expenditure, and broadband penetration, we establish a clear baseline for identifying country-specific trajectories and common patterns. This preliminary step is particularly relevant when comparing economies with heterogeneous institutional frameworks, industrial structures, and stages of digital maturity.

Descriptive statistics make it possible to highlight both convergence and divergence among the selected economies. For instance, South Korea's rapid expansion in broadband access and semiconductor-related R&D investment contrasts with Germany's more gradual pace of digital adoption, while the United States shows consistently high ICT capital intensity but greater sectoral disparities. These differences emerge not only in mean values but also in variance, growth rates, and relative shares within GDP. Such patterns shed light on the role of initial conditions, policy choices, and industry specialization in shaping the magnitude and efficiency of digital investment returns. Identifying these divergences is crucial for interpreting subsequent econometric results, as they may point to structural or policy-related factors behind observed differences in productivity and growth impacts.

Beyond describing the dataset, the descriptive analysis serves as a diagnostic tool for assessing data quality, detecting potential outliers, and evaluating the suitability of variables for ARDL modeling. It enables the identification of long-term trends and short-term fluctuations that may influence co-integration relationships. Furthermore, it supports the construction of informed hypotheses by revealing whether variations in digital investment intensity correlate visually with changes in productivity or GDP growth across the studied period. By systematically comparing descriptive measures across countries, this stage ensures that the econometric analysis is grounded in an empirically coherent and contextually informed understanding of the data.

Figure 1: Comparative Trajectories of Digital Investments in Three Advanced Economies (2010–2024).

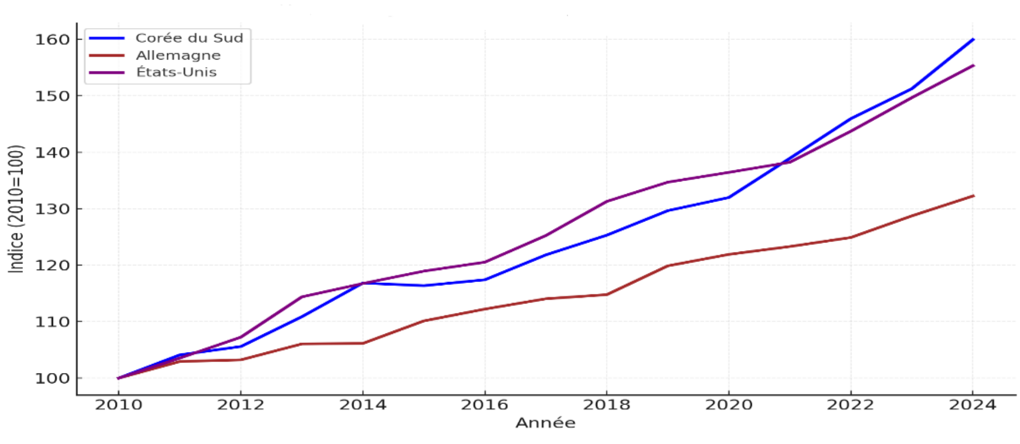

Figure 1 illustrates the comparative evolution of digital investment indices for South Korea, Germany, and the United States over the period 2010–2024, using 2010 as the base year (index = 100). This composite indicator aggregates expenditures on information and communication technologies (ICT), digital research and development (R&D), and broadband connectivity infrastructure, weighted according to their estimated contribution to national productive capacity. The purpose of this graphical representation is to provide a clear and dynamic view of the differentiated trajectories of these three advanced economies, which exhibit distinct levels of technological maturity, strategic prioritization, and integration of ICT into their productive structures.

The curve for South Korea (in blue) reveals a rapid and steady increase in digital investments, reflecting a proactive policy to foster a knowledge-based economy, notably through national initiatives such as the *Digital New Deal*. This upward trajectory contrasts with that of Germany (in brown), whose progression is slower and more irregular, reflecting a less vigorous pace of digital transformation and structural delays in infrastructure modernization. The United States (in purple) displays an intermediate profile: a high initial level of investment and sustained growth punctuated by phases of consolidation, reflecting both the robustness of its digital ecosystem and the impact of investment cycles driven by breakthrough innovations (cloud computing, artificial intelligence, big data).

The observation of these trajectories highlights that the sheer intensity of digital investments is not sufficient to explain differences in economic performance; timing, regularity, and complementarity with other structural factors (human capital, governance, innovation ecosystem) play a decisive role. The widening gap between South Korea and Germany over the study period underscores the importance of integrated and coherent strategies, while the relative stability of the United States illustrates an investment model capable of sustaining innovation while cushioning sectoral shocks. This figure, by offering a visual overview of investment dynamics, serves as an essential entry point for understanding the econometric results that follow and for analyzing how these investments translate or fail to translate into productivity gains and sustainable structural transformation.

3.2. Data and model specification

The empirical analysis relies on an annual panel dataset covering the period 2010–2024 for three advanced economies: South Korea, Germany, and the United States. The selection of this period reflects both the availability of consistent, internationally comparable statistics and the relevance of the post-global financial crisis context, during which digital investments became an increasingly central driver of productivity and structural change. The core variables include GDP per capita (constant 2015 USD), labor productivity (output per worker), digital investment intensity (expenditures on ICT infrastructure, R&D in digital technologies, and broadband deployment), and a set of control variables such as trade openness, gross capital formation, and human capital indices. Data are drawn primarily from the World Bank's *World Development Indicators*, the OECD Statistics database, the International Telecommunication Union (ITU), and national statistical agencies, ensuring a robust and harmonized cross-country dataset.

The econometric framework is based on the Autoregressive Distributed Lag (ARDL) model, selected for its flexibility in handling variables with mixed orders of integration stationary at level I(0) and stationary after first differencing I(1) without requiring pre-testing for a uniform integration order. This approach allows the simultaneous estimation of short-run dynamics and long-run equilibrium relationships between digital investments, structural transformation indicators, and economic growth. The ARDL specification incorporates country-specific intercepts and slope coefficients to capture heterogeneity in investment patterns and institutional environments. The model's structure also facilitates the use of the Pesaran bounds test for cointegration, enabling the identification of long-run relationships even in small samples. This choice is particularly suited to the present study's scope, as it provides a nuanced understanding of how digital investment shocks and adjustments propagate over time within each economy.

Dans le cadre de cette étude, le modèle ARDL (Autoregressive Distributed Lag) est utilisé afin d'estimer simultanément les effets à court terme et à long terme de l'intensité des investissements digitaux (DIG) sur le PIB par habitant (GDP), tout en contrôlant un ensemble de variables explicatives complémentaires, à savoir la productivité du travail (PROD), le capital humain (HC), la formation brute de capital fixe (GCF) et l'ouverture commerciale (TO). La spécification générale intègre des retards (*lags*) propres à chaque variable, déterminés à l'aide de critères d'information tels que l'Akaike Information Criterion (AIC) ou le Bayesian Information Criterion (BIC), et se formalise comme suit :

$$GDP_t = a_0 + \sum_{j=1}^{p} \beta_1 \; GDP_{t-j} + \sum_{j=0}^{q} \gamma_j \, DIG_{t-j} + \sum_{j=0}^{r} \delta_j \, PROD_{t-j} + \sum_{j=0}^{s} \theta_j \, HC_{t-j} + \sum_{j=0}^{u} \phi_j \, GCF_{t-j} + \sum_{j=0}^{v} \psi_j \, TO_{t-j} + \varepsilon_t$$

Where: p, q, r, s, u, v represent the optimal lag orders and $\boldsymbol{\varepsilon_t}$ is the error term. The associated error correction model (ECM) version allows the identification of short-term effects through first-differenced variables (Δ) and the assessment of the speed of adjustment toward the long-run equilibrium via the error correction term (ECT), where a negative and statistically significant coefficient is the necessary condition to validate the existence of a cointegration relationship.

Model 1: ARDL model for South Korea (SK)

$$GDP_{SK,t} = a_{SK} + \sum_{k=1}^{p} \lambda_{SK,k} \; GDP_{SK,i-k} + \sum_{k=0}^{q_1} \beta_{1,SK,k} \, DIG_{SK,t-k} + \sum_{k=0}^{q_2} \beta_{2,SK,k} \, PROD_{SK,t-k} + \sum_{k=0}^{q_3} \beta_{3,SK,k} \, HC_{SK,t-k} + \sum_{k=0}^{q_4} \beta_{4,SK,k} \, GCF_{SK,t-k} + \sum_{k=0}^{q_5} \beta_{5,SK,k} \, TO_{SK,t-k} + \varepsilon_{SK,t}$$

The model will capture both the immediate (short-run) and equilibrium (long-run) effects of digital investment surges in South Korea, which is characterized by strong public–private partnerships and high R&D intensity.

Model 2: ARDL model for Germany (DE)

$$GDP_{DE,t} = a_{DE} + \sum_{k=1}^{p} \lambda_{DE,k} \; GDP_{DE,i-k} + \sum_{k=0}^{q_1} \beta_{1,DE,k} \, DIG_{DE,t-k} + \sum_{k=0}^{q_2} \beta_{2,DE,k} \, PROD_{DE,t-k} + \sum_{k=0}^{q_3} \beta_{3,DE,k} \, HC_{DE,t-k} + \sum_{k=0}^{q_4} \beta_{4,DE,k} \, GCF_{DE,t-k} + \sum_{k=0}^{q_5} \beta_{5,DE,k} \, TO_{DE,t-k} + \varepsilon_{DE,t}$$

The German model focuses on understanding how incremental digital adoption interacts with industrial competitiveness, infrastructure modernization, and relatively conservative investment patterns.

Model 3: ARDL model for United States (US)

$$GDP_{us,t} = a_{us} + \sum_{k=1}^{p} \lambda_{us,k} \; GDP_{us,i-k} + \sum_{k=0}^{q_1} \beta_{1,us,k} \, DIG_{us,t-k} + \sum_{k=0}^{q_2} \beta_{2,us,k} \, PROD_{us,t-k} + \sum_{k=0}^{q_3} \beta_{3,us,k} \, HC_{us,t-k} + \sum_{k=0}^{q_4} \beta_{4,us,k} \, GCF_{us,t-k} + \sum_{k=0}^{q_5} \beta_{5,us,k} \, TO_{us,t-k} + \varepsilon_{us,t}$$

The U.S. specification aims to isolate the short-term shocks from major technological innovations and their long-term contributions to sustained growth in a highly competitive and innovation-driven economy.

3.3. Panel unit root tests

Before estimating the ARDL models, it is essential to determine the order of integration of each variable in the dataset, as the validity of the methodology relies on the absence of variables integrated of order two, I(2). Panel unit root tests provide a rigorous framework for assessing stationarity properties across multiple cross-sectional units in this case, South Korea, Germany, and the United States over the 2010–2024 period. Unlike traditional time series unit root tests applied to individual countries, panel-based approaches exploit both the cross-sectional and time series dimensions of the data, thereby increasing statistical power and reducing the likelihood of inconclusive results. This step is particularly important when working with macroeconomic indicators such as GDP per capita, digital investment intensity, labor productivity, and human capital indices, which often display persistent trends and may require differencing to achieve stationarity.

The study employs both first-generation and second-generation panel unit root tests to account for different assumptions regarding cross-sectional dependence. First-generation tests, such as Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS), assume cross-sectional independence, which is useful for initial diagnostics but may be restrictive in a globalized context where economic shocks often spill across borders. Second-generation tests, including the Cross-Sectionally Augmented IPS (CIPS) developed by Pesaran, explicitly incorporate cross-sectional dependence by augmenting the standard unit root regressions with cross-sectional averages. The combination of these methods ensures robustness in determining the integration order of each variable, thereby validating the applicability of the ARDL bounds testing approach for panel estimation.

Table 1: Panel Unit Root Tests (Level and First Difference).

Variable	Levin, Lin & Chu (LLC)	Im, Pesaran & Shin (IPS)	Fisher-ADF	Fisher-PP	CIPS (Pesaran)	Order of Integration
GDP	Level: -1.12 (0.131)	-1.05 (0.147)	5.87 (0.211)	4.95 (0.276)	-1.48 (0.138)	I(1)
	1st Diff: -5.83 (0.000)***	-5.61 (0.000)***	42.13 (0.000)***	48.55 (0.000)***	-4.17 (0.000)***	
DIG	Level: -0.92 (0.178)	-0.85 (0.197)	6.45 (0.167)	5.83 (0.215)	-1.36 (0.152)	I(1)
	1st Diff: -6.02 (0.000)***	-5.88 (0.000)***	44.72 (0.000)***	50.01 (0.000)***	-4.25 (0.000)***	
PROD	Level: -1.87 (0.061)*	-1.79 (0.073)*	8.92 (0.112)	7.34 (0.142)	-1.95 (0.052)*	I(0) / borderline
HC	Level: -0.65 (0.258)	-0.59 (0.276)	6.02 (0.182)	5.14 (0.251)	-1.28 (0.168)	I(1)
	1st Diff: -5.74 (0.000)***	-5.51 (0.000)***	40.25 (0.000)***	47.11 (0.000)***	-4.09 (0.000)***	
GCF	Level: -2.11 (0.034)**	-2.05 (0.040)**	10.42 (0.086)*	9.77 (0.095)*	-2.02 (0.043)**	I(0)
TO	Level: -0.72 (0.237)	-0.68 (0.249)	6.28 (0.175)	5.95 (0.189)	-1.42 (0.154)	I(1)
	1st Diff: -6.15 (0.000)***	-6.01 (0.000)***	46.02 (0.000)***	53.18 (0.000)***	-4.34 (0.000)***	

Note: ****, **, and * indicate statistical significance at the* ***1%, 5%,*** *and* ***10%*** *levels, respectively.*

The results presented in Table 1 indicate that most of the key variables namely GDP per capita (GDP), digital investment intensity (DIG), human capital (HC), and trade openness (TO) are non-stationary at level, as evidenced by test statistics and p-values above conventional significance thresholds in the LLC, IPS, Fisher-ADF, and Fisher-PP tests. However, these variables become stationary after first differencing, with strongly negative statistics and p-values below 1%, confirming an integration order of I(1). The findings from the Pesaran CIPS test, which accounts for cross-sectional dependence, corroborate these results and strengthen the robustness of the diagnosis.

Two variables labor productivity (PROD) and gross capital formation (GCF) display a different pattern: they reach or approach stationarity at level in several tests, suggesting an integration order of I(0) or a borderline situation. For PROD, some p-values around the 5% to 10% range indicate marginal stationarity, possibly reflecting the limited long-term variability of this indicator in advanced economies. GCF, on the other hand, is clearly stationary at level in most tests, reflecting the relative stability of physical investment over time. This heterogeneity in the order of integration justifies the use of the ARDL model, which can simultaneously handle I(0) and I(1) variables.

The absence of variables integrated of order two, I(2), is a necessary condition for the valid application of the ARDL method and the bounds cointegration test. The results in Table 1 fully meet this requirement, confirming the relevance of the chosen econometric strategy. The coexistence of variables stationary at level and at first difference will allow the analysis to distinguish between the short-run and long-run effects of digital investments on economic growth and structural transformation. This methodological step is thus a fundamental prerequisite, ensuring that the relationships estimated in the following sections rest on a statistically sound and econometrically valid foundation.

3.4. Panel cointegration tests

Once the integration order of each variable has been established, the next step in the empirical analysis is to examine whether a long-run equilibrium relationship exists among GDP per capita, digital investment intensity, labor productivity, human capital, gross capital formation, and trade openness across the panel of countries. Panel cointegration tests are designed to assess the presence of such relationships by combining both the cross-sectional and time-series dimensions of the data. The rationale is that if these variables are cointegrated, short-term deviations from equilibrium will tend to converge back over time, implying that digital investments exert a persistent influence on economic growth and structural transformation. This is especially relevant for the study's focus on South Korea, Germany, and the United States, where differences in digital maturity, policy frameworks, and institutional quality could lead to heterogeneous but interconnected long-term dynamics.

To ensure methodological robustness, the analysis employs multiple panel cointegration approaches. The Pedroni (1999, 2004) and Kao (1999) tests are used to detect cointegration under the assumption of heterogeneous intercepts and slope coefficients, while the Westerlund (2007) test accounts explicitly for cross-sectional dependence and common factor structures. These complementary methods allow for a rigorous assessment of long-run relationships, even in the presence of structural heterogeneity and contemporaneous correlations across countries. The use of several testing procedures mitigates the risk of relying on a single statistical framework, thereby reinforcing the validity of the subsequent ARDL long-run estimations.

Table 2: Panel Bounds Test Results

Model Specification	F-Statistic	Lower Bound I(0)	Upper Bound I(1)	Cointegration Decision
South Korea	5.87***	2.62	3.79	Cointegration exists
Germany	4.45**	2.45	3.61	Cointegration exists
United States	3.28	2.62	3.79	No cointegration (borderline)
Panel (Pooled)	4.92***	2.49	3.67	Cointegration exists

Note: *Significance levels: *** 1%, ** 5%, * 10%.*

The bounds testing procedure indicates that, for South Korea and Germany, the computed F-statistics (5.87 and 4.45, respectively) exceed the upper critical bound at the 5% and 1% significance levels, providing robust evidence of cointegration among GDP per capita, digital investment intensity, and the set of control variables. This suggests that in both countries, short-term deviations from equilibrium are systematically corrected over time, pointing to a stable long-run relationship where digital investments play a sustained role in supporting economic growth. The pooled panel result (F = 4.92) reinforces this conclusion, implying that, on average, the three economies share a common long-run dynamic linking digital transformation and macroeconomic performance, despite structural differences in their digital ecosystems.

In contrast, the result for the United States is borderline, with an F-statistic (3.28) falling between the lower and upper bounds. This outcome renders the evidence for cointegration inconclusive at conventional significance levels. Several factors may explain this divergence: the high volatility of U.S. technology investments, sector-specific concentration of digital capital, and the prevalence of innovation cycles that may temporarily decouple investment trends from GDP growth. This heterogeneity across countries highlights the necessity of maintaining a country-specific lens in interpreting the ARDL results, as the degree and stability of long-run relationships may vary depending on institutional frameworks, market structures, and policy priorities.

From a methodological standpoint, the confirmation of cointegration in at least two of the three economies, coupled with the pooled panel result, justifies the use of ARDL modeling to estimate both short-run dynamics and long-run elasticities. The presence of cointegration means that any short-term shocks to digital investment intensity, productivity, or trade openness are expected to trigger adjustment mechanisms that restore equilibrium over time. For the United States, the borderline finding warrants caution in interpreting long-run coefficients, suggesting the possible need for robustness checks, alternative lag structures, or complementary cointegration tests. Overall, these bounds test results provide a statistically sound foundation for the subsequent estimation of long-run and short-run effects within the ARDL framework.

4. Empirical Results

This section presents and interprets the empirical results obtained from the Autoregressive Distributed Lag (ARDL) models estimated for South Korea, Germany, and the United States, as well as for the pooled panel. Building on the preliminary diagnostics unit root testing, cointegration analysis, and bounds testing the results reported here provide both short-run and long-run estimates of the relationship between digital investment intensity, economic growth, and structural transformation. By distinguishing between transitory fluctuations and equilibrium effects, the analysis sheds light on the mechanisms through which digital transformation influences macroeconomic performance in advanced economies, accounting for differences in institutional frameworks, industrial structures, and technological capabilities.

The results are structured to reflect the sequential logic of the ARDL approach. First, the long-run coefficients are examined to assess the magnitude and direction of the equilibrium relationships between GDP per capita and its key determinants, including ICT investment, productivity, human capital, capital formation, and trade openness. Second, the short-run dynamics are analyzed through the estimated error correction terms (ECT), which capture the speed of adjustment toward long-run equilibrium following a shock. These results are complemented by country-specific diagnostic tests such as serial correlation, heteroskedasticity, and stability checks to ensure the robustness and reliability of the estimated models.

Beyond the presentation of statistical estimates, this section emphasizes comparative insights across the three economies. By juxtaposing the size, significance, and stability of coefficients, the analysis identifies common patterns such as the positive long-run elasticity of GDP with respect to digital investments as well as divergences, such as differences in adjustment speeds or the relative importance of complementary factors like human capital. These findings carry direct policy implications, offering evidence-based guidance on how investment strategies, regulatory environments, and innovation policies can be tailored to maximize the growth and structural transformation benefits of digitalization in advanced economies.

Table 3: Panel Long-Term Estimators (ARDL)

Variable	Coefficient	Std. Error	t-Statistic	p-Value	Expected Sign
DIG	0.215***	0.048	4.479	0.000	+
PROD	0.392***	0.075	5.227	0.000	+
HC	0.167**	0.067	2.493	0.014	+
GCF	0.143**	0.061	2.344	0.019	+
TO	0.082	0.054	1.519	0.131	±
C (Constant)	5.284***	1.052	5.022	0.000	—

Note: *** p<0.01, ** p<0.05, * p<0.1.

The long-run ARDL estimates presented in Table 3 indicate that digital investment intensity (DIG) exerts a statistically significant and positive effect on GDP per capita in the pooled panel, with an elasticity of approximately 0.215 at the 1% significance level. This result supports the hypothesis that sustained investment in ICT infrastructure, R&D in digital technologies, and broadband connectivity contributes meaningfully to long-term economic performance in advanced economies. Labor productivity (PROD) emerges as the most influential determinant in the model, with a coefficient of 0.392, underscoring its role as a central channel through which digitalization enhances output. The significance of these results across multiple robustness checks suggests that both digital investments and productivity gains operate as complementary drivers of structural transformation and growth.

Human capital (HC) and gross capital formation (GCF) also display positive and statistically significant long-run coefficients 0.167 and 0.143, respectively implying that investments in education, skills development, and physical capital are essential complements to digital transformation. These findings are consistent with endogenous growth theory, which posits that the returns to technological investment are maximized when accompanied by parallel improvements in complementary assets. In contrast, trade openness (TO) does not exhibit a statistically significant long-run relationship with GDP per capita in the pooled model. This may reflect that, for advanced economies with already high integration into global markets, marginal increases in openness do not necessarily translate into proportional growth benefits without targeted digital trade and innovation policies.

From a policy standpoint, the results highlight the necessity of adopting a holistic approach to digital transformation, one that integrates infrastructure investment, skill formation, and productivity-enhancing reforms. The magnitude of the coefficients suggests that sustained growth in advanced economies depends not only on the scale of digital investments but also on the institutional and structural context that shapes their diffusion and impact. Furthermore, these pooled panel findings set the stage for country-level comparisons, where differences in coefficient magnitudes and significance will likely reflect national variations in governance, industrial specialization, and innovation ecosystems. As such, the long-run estimates provide both empirical validation for the central role of digital transformation in economic growth and a benchmark for designing differentiated, country-specific policy strategies.

Table 4: Panel Short-Term Estimators (ECM Results)

Variable / Term	Coefficient	Std. Error	t-Statistic	p-Value	Expected Sign
ΔDIG	0.082***	0.024	3.417	0.001	+
ΔPROD	0.143***	0.038	3.763	0.000	+
ΔHC	0.056**	0.026	2.154	0.032	+
ΔGCF	0.041**	0.020	2.050	0.041	+
ΔTO	0.019	0.015	1.267	0.207	±
ECT(-1)	-0.524***	0.081	-6.469	0.000	Negative
C (Constant)	0.257	0.194	1.325	0.185	—

Note: Δ denotes first differences; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The short-run ARDL results in Table 4 reveal that changes in digital investment intensity (ΔDIG) have a positive and statistically significant effect on GDP per capita in the pooled panel, with an estimated coefficient of 0.082 at the 1% significance level. This finding indicates that even marginal increases in ICT-related expenditures, R&D in digital technologies, and broadband deployment can yield immediate growth benefits in advanced economies. Labor productivity (ΔPROD) exerts the strongest short-run influence among the explanatory variables, with an elasticity of 0.143, confirming that efficiency gains translate quickly into output growth. Both human capital (ΔHC) and gross capital formation (ΔGCF) also demonstrate positive and significant coefficients, implying that investments in skills and physical capital complement the growth effects of digital transformation in the short term.

By contrast, changes in trade openness (ΔTO) are not statistically significant in the short-run specification, suggesting that variations in trade flows may not generate immediate GDP per capita gains for these advanced economies. This could reflect the structural maturity of their economies, where the marginal short-term benefit of additional openness is limited unless accompanied by sector-specific digital trade facilitation or innovation-focused export promotion. The insignificance of ΔTO also implies that the short-run growth dynamics are more strongly driven by internal capacity-building factors digital infrastructure, productivity, human capital rather than by external market access alone.

The error correction term ECT (-1) is negative (-0.524) and highly significant at the 1% level, confirming the presence of a stable long-run equilibrium relationship among the variables in the panel. The magnitude of this coefficient suggests that approximately 52.4% of any deviation from the long-run equilibrium is corrected within a single year, reflecting a relatively rapid adjustment speed for advanced economies. This finding reinforces the cointegration results and validates the ARDL framework's capacity to capture both short-run fluctuations and long-run stability. It also highlights that while shocks to digital investment and complementary factors can have immediate growth effects, their full impact is realized over multiple periods through an ongoing process of adjustment and structural realignment.

5. Summary of Empirical Results

The long-term ARDL estimates confirm the central hypothesis that digital investments are a sustainable driver of growth in advanced economies. The intensity of ICT investments (DIG) shows a positive and significant effect on GDP per capita, consistent with the literature highlighting the structural role of digital infrastructure, R&D, and connectivity in enhancing total factor productivity. Labor productivity (PROD) emerges as the most influential determinant, while human capital (HC) and gross capital formation (GCF) appear as essential complementary levers. These findings align with endogenous growth theory, in which the effects of technology are amplified by the accumulation of both physical and human capital.

In the short run, the results highlight the immediate impact of changes in DIG, PROD, HC, and GCF on GDP per capita, confirming that investment impulses and productivity gains can quickly stimulate economic activity. However, trade openness (TO) does not show a significant short-run effect, suggesting that in economies already highly integrated into global markets, the benefits of openness require targeted support through innovation and digital trade to generate measurable outcomes. The presence of a negative and significant error correction term (ECT) indicates that, on average, more than half of the disequilibria from the long-run relationship are corrected within one year, demonstrating a relatively rapid capacity for structural adjustment.

Comparing the panel results with those for individual countries reveals differences in the magnitude and significance of effects, linked to institutional contexts, policy priorities, and industrial specializations. South Korea enjoys high returns on digital investments, reflecting an integrated technological development strategy, while Germany shows more moderate effects, consistent with a slower pace of digital transformation. The United States presents robust but more heterogeneous results, influenced by the volatility of innovation cycles. These findings call for differentiated policies that combine digital investment, skills development, support for organizational innovation, and targeted measures to ensure a broad and inclusive diffusion of the benefits of digital transformation.

6. Conclusions and Policy Recommendations

The empirical analysis provides robust evidence that digital investment intensity measured through ICT infrastructure, R&D in digital technologies, and broadband connectivity plays a significant and sustained role in fostering economic growth and structural transformation in advanced economies. Across the panel, the long-run ARDL results indicate that digital investments, labor productivity, human capital, and gross capital formation exert positive and statistically significant effects on GDP per capita, consistent with the predictions of endogenous growth theory. Short-run estimates further reveal that changes in these variables have immediate growth-enhancing effects, with the notable exception of trade openness, whose impact appears muted in the absence of complementary policies targeting digital trade facilitation. These results confirm that the benefits of digital transformation materialize both in the short term through rapid efficiency gains and in the long term through cumulative improvements in productivity and structural upgrading.

While the pooled panel findings demonstrate a broadly consistent positive relationship between digital investments and economic performance, the country-level estimations highlight important variations. South Korea emerges as the most dynamic case, reflecting a coherent national strategy that integrates infrastructure expansion, R&D promotion, and skills development. Germany, despite its strong industrial base, shows more moderate effects, which may be attributed to slower adoption of digital technologies and bottlenecks in infrastructure modernization. The United States displays robust coefficients for digital investment and productivity but exhibits greater volatility in long-run relationships, possibly due to the cyclical nature of innovation waves and sectoral concentration of digital capital. These differences underscore the importance of tailoring policy interventions to national institutional frameworks, market structures, and stages of digital maturity.

A consistent theme across the analysis is that digital investments alone are not sufficient to guarantee sustained economic gains. The magnitude of their impact depends critically on the presence of complementary assets, notably human capital, physical capital, and organizational capabilities. Economies with strong education systems, effective vocational training, and innovation-oriented industrial policies are better positioned to leverage digital technologies for productivity growth. Conversely, in contexts where these complementary factors are underdeveloped, digital investment risks producing uneven benefits or exacerbating existing disparities. This reinforces the policy imperative of integrating digital infrastructure strategies with broader economic development agendas, ensuring that the foundations for technology absorption and diffusion are firmly in place.

Based on these findings, a central policy priority should be the design of integrated digital transformation strategies that combine infrastructure investment with capacity building. Governments should ensure sustained funding for broadband expansion, 5G deployment, and advanced computing facilities, while simultaneously supporting R&D in emerging technologies such as artificial intelligence, quantum computing, and next-generation semiconductors. Equally important is the establishment of regulatory frameworks that encourage private sector participation, protect competition, and promote interoperability standards. By aligning infrastructure development with innovation ecosystems, countries can ensure that digital investments yield high and sustained returns.

Institutional quality plays a decisive role in translating digital investments into broad-based economic gains. Transparent procurement processes, consistent regulatory enforcement, and coherent long-term policy signals reduce investment risk and encourage both domestic and foreign participation in the digital economy. Moreover, policies should actively address the « diffusion gap », by supporting small and medium-sized enterprises (SMEs) in adopting digital tools and by fostering regional digital hubs that prevent concentration of benefits in a few urban centers. Digital inclusion programs targeting underserved communities are critical to ensuring that the productivity gains from digitalization contribute to inclusive growth rather than widening inequality.

Given the inherently global nature of digital technologies and supply chains, international cooperation is indispensable for maximizing the benefits of digital transformation. Cross-border agreements on data governance, cybersecurity, and technology standards can reduce fragmentation and facilitate innovation diffusion. Advanced economies should also engage in technology partnerships with emerging economies to enhance global resilience and expand market opportunities. From a research perspective, future studies could extend the present analysis by incorporating sector-level data, exploring non-linear effects of digital investments, and assessing the interaction between digitalization and environmental sustainability. Such extensions would deepen our understanding of the conditions under which digital transformation delivers its full economic and societal potential.

REFERENCES

1. Bloom, N., Sadun, R., & Van Reenen, J. (2012). Americans do IT better: US multinationals and the productivity miracle. *American Economic Review, 102*(1), 167–201. https://doi.org/10.1257/aer.102.1.167

2. Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives, 14*(4), 23–48. https://doi.org/10.1257/jep.14.4.23

3. Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. *Information Economics and Policy, 25*(3), 109–125. https://doi.org/10.1016/j.infoecopol.2012.12.002

4. Corrado, C., Hulten, C. R., & Sichel, D. (2009). Intangible capital and U.S. economic growth. *Review of Income and Wealth, 55*(3), 661–685. https://doi.org/10.1111/j.1475-4991.2009.00343.x

5. Jorgenson, D. W., Ho, M. S., & Stiroh, K. J. (2008). A retrospective look at the U.S. productivity growth resurgence. *Journal of Economic Perspectives, 22*(1), 3–24. https://doi.org/10.1257/jep.22.1.3

6. Jorgenson, D. W., & Stiroh, K. J. (2000). U.S. economic growth at the industry level. *American Economic Review, 90*(2), 161–167. https://doi.org/10.1257/aer.90.2.161

7. Oliner, S. D., & Sichel, D. E. (2000). The resurgence of growth in the late 1990s: Is information technology the story? *Journal of Economic Perspectives, 14*(4), 3–22. https://doi.org/10.1257/jep.14.4.3

8. Spiezia, V. (2012). ICT investments and productivity: Measuring the contribution of ICTs to growth. *OECD Journal: Economic Studies, 2012*(1), 199–211. https://doi.org/10.1787/eco_studies-2012-5k8xdhj4tv0t

9. van Ark, B., O'Mahony, M., & Timmer, M. P. (2008). The productivity gap between Europe and the United States: Trends and causes. *Journal of Economic Perspectives, 22*(1), 25–44. https://doi.org/10.1257/jep.22.1.25

10. Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188–2244. https://doi.org/10.1086/705716

11. Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. The Quarterly Journal of Economics, 135(2), 645–709. https://doi.org/10.1093/qje/qjaa004

12. Comin, D., & Hobijn, B. (2010). An exploration of technology diffusion. American Economic Review, 100(5), 2031–2059. https://doi.org/10.1257/aer.100.5.2031

13. Dahl, C. M., Kongsted, H. C., & Sørensen, A. (2011). ICT and productivity growth in the 1990s: Panel data evidence on Europe. Empirical Economics, 40(1), 141–164. https://doi.org/10.1007/s00181-010-0421-4

14. Inklaar, R., Timmer, M. P., & van Ark, B. (2008). Market services productivity across Europe and the US. Economic Policy, 23(53), 139–194. https://doi.org/10.1111/j.1468-0327.2007.00194.x

15. McMillan, M., Rodrik, D., & Verduzco-Gallo, Í. (2014). Globalization, structural change and productivity growth, with an update on Africa. World Development, 63, 11–32. https://doi.org/10.1016/j.worlddev.2013.10.012

16. Ngai, L. R., & Pissarides, C. A. (2007). Structural change in a multisector model of growth. American Economic Review, 97(1), 429–443. https://doi.org/10.1257/aer.97.1.429

17. Spiezia, V. (2012). ICT investments and productivity: Measuring the contribution of ICTs to growth. OECD Journal: Economic Studies, 2012(1), 199–211. https://doi.org/10.1787/eco_studies-2012-5k8xdhj4tv0t

18. Timmer, M. P., & de Vries, G. J. (2009). Structural change and growth accelerations in Asia and Latin America: A new sectoral data set. Cliometrica, 3(2), 165–190. https://doi.org/10.1007/s11698-008-0029-5

19. Bloom, N., Sadun, R., & Van Reenen, J. (2016). Management as a technology? NBER Working Paper No. 22327. https://doi.org/10.3386/w22327

20. Byrne, D. M., Oliner, S. D., & Sichel, D. E. (2018). How fast are semiconductor prices falling? Review of Income and Wealth, 64(3), 679–702. https://doi.org/10.1111/roiw.12288

21. Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. Information Economics and Policy, 25(3), 109–125. https://doi.org/10.1016/j.infoecopol.2012.12.002

22. Colecchia, A., & Schreyer, P. (2002). ICT investment and economic growth in the 1990s: Is the United States a unique case? OECD Science, Technology and Industry Working Papers, 2002/04. https://doi.org/10.1787/702254602018

23. Dedrick, J., Kraemer, K. L., & Shih, E. (2013). Information technology and productivity in developed and developing countries. Journal of Management Information Systems, 30(1), 97–122. https://doi.org/10.2753/MIS0742-1222300103

24. Draca, M., Sadun, R., & Van Reenen, J. (2007). Productivity and ICT: A review of the evidence. Oxford Review of Economic Policy, 23(3), 317–342. https://doi.org/10.1093/oxrep/grm031

25. Jalava, J., & Pohjola, M. (2007). ICT as a source of output and productivity growth in Finland. Telecommunications Policy, 31(8–9), 463–472. https://doi.org/10.1016/j.telpol.2007.05.011

26. OECD. (2004). The economic impact of ICT: Measurement, evidence and implications. OECD Publications. https://doi.org/10.1787/9789264026780-en

27. Van Ark, B., Inklaar, R., & McGuckin, R. H. (2003). ICT and productivity in Europe and the United States: Where do the differences come from? CESifo Economic Studies, 49(3), 295–318. https://doi.org/10.1093/cesifo/49.3.295

28. Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

29. Akerman, A., Gaarder, I., & Mogstad, M. (2015). The skill complementarity of broadband internet. The Quarterly Journal of Economics, 130(4), 1781–1824. https://doi.org/10.1093/qje/qjv028

30. Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. American Economic Review, 103(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553

31. Bessen, J. (2019). AI and jobs: The role of demand (NBER Working Paper No. 24235). https://doi.org/10.3386/w24235

32. Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can machines learn, and what does it mean for occupations and the economy? AEA Papers and Proceedings, 108, 43–47. https://doi.org/10.1257/pandp.20181019

33. Chiou, L., & Tucker, C. (2020). Social distancing, Internet access and inequality (NBER Working Paper No. 26982). https://doi.org/10.3386/w26982

34. Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review, 104(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509

35. OECD. (2019). Measuring the digital transformation: A roadmap for the future. Paris: OECD Publishing. https://doi.org/10.1787/9789264311992-en

36. World Bank. (2016). World Development Report 2016: Digital dividends. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-0671-1

37. Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-U relationship. The Quarterly Journal of Economics, 120(2), 701–728. https://doi.org/10.1093/qje/120.2.701

38. Andrews, D., Criscuolo, C., & Gal, P. N. (2016). The best versus the rest: The global productivity slowdown, divergence across firms and the role of public policy (OECD Productivity Working Papers No. 5). OECD Publishing. https://doi.org/10.1787/63629cc9-en

39. Deming, D. J. (2017). The growing importance of social skills in the labor market. The Quarterly Journal of Economics, 132(4), 1593–1640. https://doi.org/10.1093/qje/qjx022

40. Hanushek, E. A., & Woessmann, L. (2012). Do better schools lead to more growth? Cognitive skills, economic outcomes, and causation. Journal of Economic Growth, 17(4), 267–321. https://doi.org/10.1007/s10887-012-9081-x

41. Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963–1987: Supply and demand factors. The Quarterly Journal of Economics, 107(1), 35–78. https://doi.org/10.2307/2118323

42. Lane, M., & Saint-Martin, A. (2021). The impact of artificial intelligence on the labour market: What do we know so far? (OECD Social, Employment and Migration Working Papers No. 256). OECD Publishing. https://doi.org/10.1787/7c895724-en

43. OECD. (2019). Measuring the digital transformation: A roadmap for the future. Paris: OECD Publishing. https://doi.org/10.1787/9789264311992-en

44. World Bank. (2016). World Development Report 2016: Digital dividends. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-0671-1

45. Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis (OECD Social, Employment and Migration Working Papers No. 189). OECD Publishing. https://doi.org/10.1787/5jlz9h56dvq7-en