economies

MDPI

Article

Digital Economy and Growth in 58 Economies: The Moderating Role of Financial Development and Human-Capital Investment

Bogdan Mârza, Renate Bratu * and Răzvan Șerbu

Faculty of Economic Sciences, Lucian Blaga University of Sibiu, 550024 Sibiu, Romania; bogdan.marza@ulbsibiu.ro (B.M.); razvan.serbu@ulbsibiu.ro (R.Ș.)
* Correspondence: renate.bratu@ulbsibiu.ro

Abstract

The growth payoff of the digital economy may depend on complementary national capacities. This study quantifies the growth effect of deepening the digital economy. It tests how financial development and human-capital investment moderate it in 58 OECD, accession-candidate, key-partner, and EU candidate economies. A composite Digital Economy Index (DEI) aggregates digital-trade participation, infrastructure, and using the Z-score method. The index was computed through 2023, while the estimation covers 2014–2022 owing to the human-capital moderator's reporting lag. The dependent variable is the natural logarithm of real GDP per capita (constant 2015 US$). Financial development is measured by domestic credit to the private sector (% of GDP) and human-capital investment by government education expenditure (% of GDP). In two-way fixed-effects models, the DEI coefficient is positive but imprecise and is significantly positive at below-average levels of credit and education spending. Within-country digital deepening is robustly positive under country fixed effects. The dividend is smaller where private credit is abundant ("too much finance"). We find no significant interaction with a tertiary-enrolment stock proxy, indicating that moderation operates at the fiscal input margin rather than through the measured skill-stock proxy. The results are robust to instrumentation, aggregation, fixed-effects structure, and sample windows. They are not robust to country-specific linear trends, because these trends absorb most within-country variation in the index during this panel period, rather than necessarily overturning the underlying finding.

Keywords: digital economy; financial development; human-capital investment; economic growth; digital economy index; SDG8; SDG9

Check for updates

Academic Editor: Tetiana Kornieieva

Received: 25 August 2026
Revised: 1 October 2026
Accepted: 6 October 2026
Published: 5 November 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

The digital economy has moved to the center of economic policy. The objectives presented in the "Digital Decade 2030" report released by the European Union, along with those included in the "Going Digital" report published by the OECD, among others, as well as the digital elements included in the Sustainable Development Goals (SDG 8 for decent work and economic growth and SDG 9 for industry, innovation and infrastructure) adopted by all member states of the United Nations in 2015, highlight digitalization as a driver of productivity and long-term growth. A large body of empirical literature supports this framing, linking information and communication technology (ICT) intensity, high-technology trade, and digital-finance penetration to higher output across countries and regions (Endres & Steula, 2024; Lv et al., 2024; Öztürk & Ullah, 2022; Sarsar & Echaoui, 2026), and a parallel literature review maps how digital transformation contributes to the

Sustainable Development Goals across sectors and governance settings (Ghazal Masri & El-Fadel, 2026; Guandalini, 2022; Kumar & Shah, 2025; Varriale et al., 2024). Studies in related fields show how circular-economy business models are enabled and governed in the digital transition (Agrawal et al., 2024; Fatimah et al., 2023; Pietrulla, 2022; Vitolla et al., 2023). However, this agreement raises a fundamental political question: is the growth payoff to the digital economy unconditional, or is it gated by the complementary assets a country brings to digital diffusion?

The distinction matters because policy depends on which of these alternatives is true. If digitalization raises growth unconditionally, the optimal policy is to produce more of it, to ensure broader connectivity, and to develop larger ICT sectors and deeper technology trade. If instead its returns are conditional on financial depth and human capital, then digital investment must be sequenced with, and sometimes subordinated to, complementary reforms. The theoretical basis for conditionality is well established. In endogenous growth theory, technology raises output through its interaction with human capital and institutional capacity, not in isolation, and the absorptive-capacity tradition holds that converting external technology into domestic productivity requires a workforce and financial system able to adopt and fund it. These frameworks predict that the same digital input will yield different output gains across countries. But explicit moderation designs that test this on broad country panels remain rare; for instance, the few available examples moderate the energy transition–growth link by digital transformation (Sarsar & Echaoui, 2026), detect conditional digital–growth effects through threshold rather than interaction designs (Hwang, 2023), or test moderation at the firm level on eco-innovation outcomes (Mansour et al., 2026).

Three gaps in the literature motivate this study. First, the digitalization–growth link is typically estimated as a stand-alone effect rather than as a conditional relationship whose magnitude depends on financial development and human-capital investment. Second, the "digital economy" is usually proxied by a single indicator (broadband penetration or ICT exports) or a digital-finance index, or by trade-side composites alone, leaving multidimensional constructs that combine participation, infrastructure, and usage under-exploited (Magazzino et al., 2025; X. Wang et al., 2023). Third, OECD members, accession candidates, key partners, and EU candidate economies are rarely analyzed within a single comparative framework, even though the convergence question of whether digitally lagging economies capture a larger marginal benefit from digitalization is directly relevant to EU enlargement and OECD accession decisions being made now. The European Commission already tracks relevant candidate digital performance through the DESI framework (European Commission, 2022), and the emerging evidence on digital economy development in the Balkan economies underscores how uneven that performance remains (Radulović & Jovović, 2025).

This paper addresses all three gaps together. To what extent does the digital economy promote sustainable economic growth across OECD, partner, and EU candidate economies, and how do financial development and human-capital investment moderate this relationship? We adapt a composite Digital Economy Index (DEI) model covering three dimensions: (1) digital-trade participation (ICT goods imports and ICT service exports), (2) digital infrastructure (fixed broadband, mobile subscriptions, and secure Internet servers), and (3) digital usage (Internet users), aggregated by the Z-score method, and estimate two-way fixed-effects panel models of GDP per capita augmented with interaction terms for financial development and human-capital investment, together with a group interaction distinguishing mature from catching-up economies. The sample brackets the COVID-19 digital acceleration, which the two-way structure absorbs through year effects so that identification rests on within-country variation rather than a common post-2020 shock.

Figure 1 introduces the conceptual lens through which we read this question. We build on the network-society tradition (Castells, 2009), which describes contemporary

societies as dynamic sets of interconnected nodes exchanging information through digital infrastructures. We conceptualize each economic sector, such as public administration, finance, information technology, industry and logistics, trade, services, agriculture, health, education, and households, as a digital neuronal center. By this we mean a cluster of interconnected actors whose internal and external transactions are increasingly mediated by digital channels, much as neurons within a functional region of the brain fire and connect. The digital economy operates as the neural core of this system. It links the sectoral centers, and the impulses transmitted through it (faster information diffusion, lower search and transaction costs, deeper market integration) accelerate activity in every center. Conceiving each center as a neural network identifies the mechanism through which digitalization becomes growth. The denser and better connected the network within and between centers, the more efficiently and the faster each center performs its processes. As a result, transactions are completed faster, information reaches decision-makers sooner, and resources are redirected with fewer obstacles. Cumulatively, this acceleration raises GDP per capita. The framework is not merely illustrative. Each of its elements generates one of the paper's testable hypotheses. The transmission claim itself—that a country's own digital deepening raises output—is H1. The strength of transmission depends on two synaptic conditions. The funding synapse (financial development) yields H2, with complementarity predicting a positive interaction and the "too much finance" view a negative one. The absorptive synapse (human capital) yields H3, discriminating between complementarity and substitution. Finally, the network's topology (lagging centers hold the largest stock of unexploited connections) yields the convergence prediction of H4, because the marginal transmission gain should be larger in catching-up economies. What the framework adds to standard endogenous-growth reasoning is not a new mechanism but a falsifiable parameterization of an existing one. It forces the conditionality of the digital dividend to be specified ex ante (which moderator, which sign, which sub-sample) rather than asserted ex post.

Our findings run against the conventional narrative in an informative way. The digital economy shows no growth effect beyond the common global digitalization trend once country and year effects are absorbed. Yet within-country, digital deepening relative to a country's own trajectory is robustly growth-positive. Its conditional structure is equally informative because the digital dividend is smaller where private credit is most abundant (a "too much finance" pattern) and is largest where education spending is lowest. A stock-proxy check (tertiary enrollment) suggests that this moderation operates through the fiscal-input margin rather than through the skill stock itself. These results qualify the digital-complementarity narrative and reframe where the growth returns to digital policy are likely to be highest.

The study makes three contributions. Empirically, it shows that the digital economy's growth effect is conditional, not automatic, on a policy-relevant panel spanning the OECD, its accession candidates and key partners, and the EU candidate economies. Methodologically, it adapts a three-dimensional composite digital construct, aggregated using the transparent Z-score method validated against a principal-components variant, within an explicit moderation design and a robustness hierarchy that spans fixed-effects structures, sample windows, and a global external-validity panel. For policy, it identifies where the digital dividend is largest, with direct implications for sequencing digital, financial, and education strategy under SDGs 8 and 9. To develop the research ideas, the article is organized as follows: Section 2 reviews the literature and formulates the hypotheses, followed by Section 3, which describes the data and methodology. Section 4 presents the results, and Section 5 discusses them. Section 6 presents the conclusions and discusses policy implications and the study's limitations.

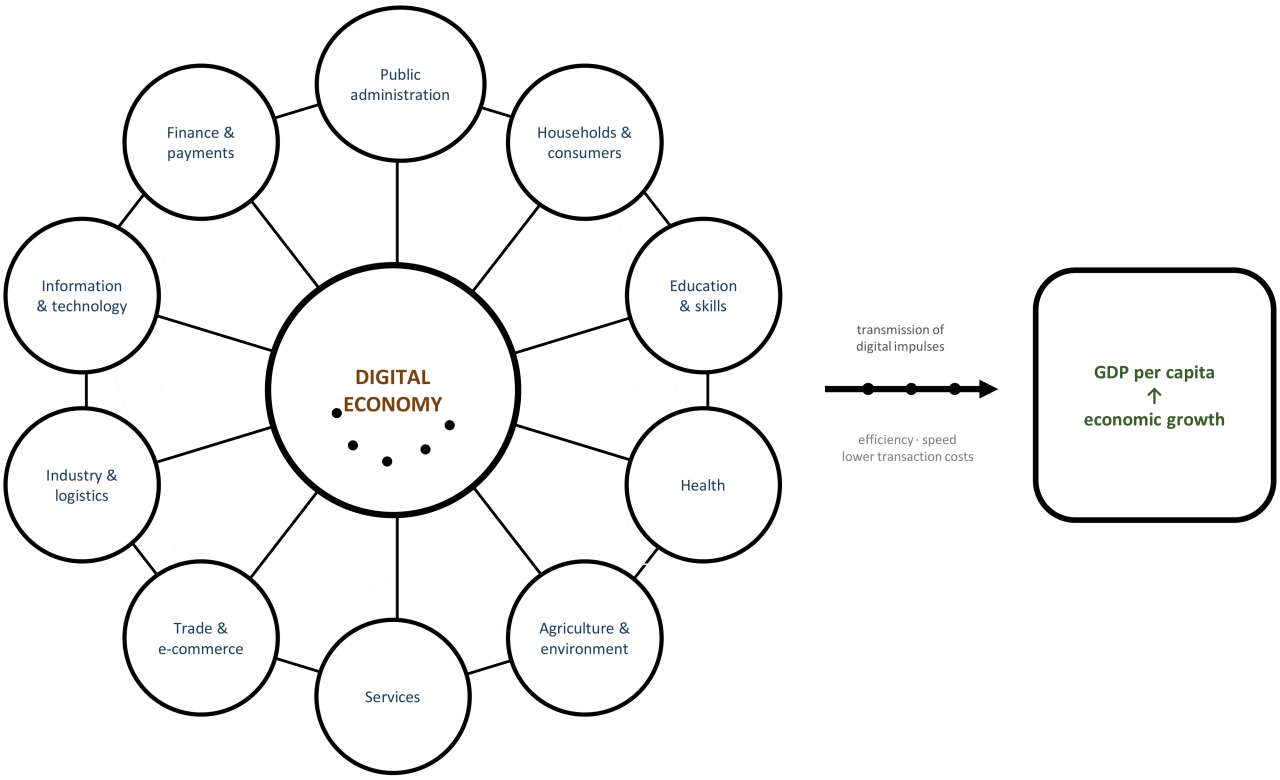


Figure 1. Conceptual framework, digital neuronal centers and the transmission of digital impulses to GDP per capita. Source: authors' conceptualization, building on the network society framework of Castells (2009).

2. Literature Review and Hypotheses

This study's research question—to what extent does the digital economy promote economic growth, and how do financial development and human-capital investment moderate that relationship? contains three logically distinct claims that the literature has frequently conflated. The first is a claim about existence that digital deepening raises growth at all, once a country is compared with its own trajectory rather than with richer, more digital neighbors. The second is a claim about conditionality: whether the size of the digital dividend depends on the complementary assets like finance and skills that a country brings to digital diffusion. The third is a claim about location: the dividend is not distributed uniformly but varies systematically between mature and catching-up economies. Each claim requires its own body of theory, generates its own testable hypothesis, and fails in its own way; this section develops them in turn, so that the four hypotheses emerge as the logical decomposition of the research question rather than as a list of candidate regressors.

Based on the research question and the arguments presented above, we formulated four hypotheses: H1 suggests that the deepening of the digital economy has a positive impact on economic growth at the national level; H2 states that financial development moderates the relationship between the digital economy and economic growth (DEI × credit ≠ 0), with a positive outcome in terms of complementarity and a negative one in terms of financial excess ("too much finance"); H3 holds that human-capital investment moderates the relationship between the digital economy and economic growth (DEI × education ≠ 0), with a positive effect from the perspective of complementarity and a negative effect from the perspective of substitutability; H4 suggests that the marginal effect of the digital economy on economic growth is greater in economies that are in the process of catching up (accession-candidate countries, key partners, and EU accession- candidate countries) than in developed OECD

member states (digital convergence). All four hypotheses refer to within-country effects on the level of real GDP per capita.

2.1. Digital Economy and Economic Growth

Why should digitalization raise growth in the first place? The theoretical case rests on two pillars. In endogenous growth theory, technology and knowledge drive long-run expansion; as a general-purpose technology, digital tools raise total factor productivity by accelerating information diffusion, lowering search and transaction costs, deepening market integration, and recombining existing knowledge into new products and processes. The second pillar is the diffusion argument: unlike frontier innovation, which is concentrated in a handful of economies, existing digital technologies are available to every country, so their growth effects should be visible across a broad panel rather than only at the technological frontier. A substantial body of empirical literature supports this expectation, linking ICT intensity, broadband penetration, high-technology trade, and digital-finance penetration to higher economic output across countries and regions (Endres & Steula, 2024; Lv et al., 2024; Öztürk & Ullah, 2022; Sarsar & Echaoui, 2026).

The methods used to measure the digital economy have also become a subject of academic research. The variety of Digital Economy Index (DEI) constructions illustrates both the development and fragmentation of the field. National statistical DEIs support a growing body of applied literature, ranging from the official index published by the China Statistics Bureau (W. Wang & Bai, 2025) to a five-indicator provincial composite constructed using National Bureau of Statistics data (Xie et al., 2024). Industry-produced city-level indices combine dozens of indicators covering infrastructure, services, government, and industrial digitalization (Z. Chen et al., 2022). Academic composite indices employ data-driven weighting schemes, such as entropy-weight TOPSIS (D. Bai et al., 2024). Other approaches use remote-sensing techniques to estimate DEI from nighttime light intensity, particularly where statistical data are costly or unavailable (Z. Chen et al., 2022; Y. Chen et al., 2024). The outcomes studied using these indices are equally diverse. Research applications include rural credit costs (W. Wang & Bai, 2025), ecosystem-service value (Y. Chen et al., 2024), green innovation spillovers (D. Bai et al., 2024), energy security (Y. Xu et al., 2026), carbon-neutrality pathways (S. Wang et al., 2025), and residents' medical costs (K. Zheng et al., 2025). A second wave extends these applications to farmers' land-transfer decisions (P. Zheng et al., 2024), labor mobility (J. Chen & Xu, 2024), and regional economic resilience, where the digital economy and financial development are examined jointly (Sun & Chen, 2025; Yuan & Zhao, 2026). Additional studies address households' financial risk-taking (Hu & Liu, 2025), the balance between carbon-emission efficiency and economic growth (C. Bai et al., 2025), green total factor productivity (Lan & Tang, 2023; H. Wang et al., 2025), urban emissions (Chang & Li, 2022; L. Wang et al., 2023), environmental coordination (Gao & Wen, 2025), the digital circular economy (Piscicelli, 2023; Xiao, 2025), marine-fishery decarbonization (Zhang et al., 2025b), and speculative bubbles in digital economy asset prices (Qin et al., 2023). Methodological surveys further consolidate approaches to index construction by combining entropy weighting with gray-target theory (Y. Xu & Li, 2022) or benchmarking entropy–TOPSIS composite indices against PCA references (Lu et al., 2025).

Cross-country applications are also beginning to emerge. An entropy-weighted DEI for the ten ASEAN countries, applied to carbon-emission intensity (Yang et al., 2025); a single-indicator digitalization measure in a study of financial development and sustainable growth across African economies (Ibrahim et al., 2024); and a fintech-adoption analysis of digital economy development in the Balkan countries, several of which belong to our EU candidate group (Radulović & Jovović, 2025); and, for Europe, a PCA-based inclusiveness index estimated with GMM over 32 countries links digitalization, governance, and human capital

to inclusive growth (Rusu & Oprean-Stan, 2023). However, studies focusing specifically on economic growth using a composite DEI remain limited. An early cross-country antecedent is the Digital Evolution Index of the Fletcher School, which ranked fifty economies on supply, demand, innovation, and institutional drivers of digital readiness (Chakravorti et al., 2015) as a benchmarking exercise rather than a growth regression. The closest antecedent to our design is Hwang (2023), who develops a principal-component-factor DEI for 18 Latin American and Caribbean countries and finds that the digital economy promotes green economic growth primarily when combined with the transition towards renewable energy. This conditional relationship was identified through threshold regression analysis. Sari and Nasrudin (2022) built an equal-weighted three-dimensional DEI for Indonesia and demonstrated, using an error-correction framework, that digitalization contributes positively to GDP in the long run but not in the short run. Similarly, Tan et al. (2022), developed a composite DEI for Malaysia as a leading indicator of digital economic activity; and, closest in spirit to our moderation design, Mansour et al. (2026) build a PCA-based DEI over four pillars for 17 EU countries and show (through mediation and moderation analyses) that national digitalization raises firm-level eco-innovation, conditional on firms' internal absorptive capabilities. That study, however, operates at the firm level with an eco-innovation outcome; the aggregate growth question remains open. Two features of this literature are particularly relevant to our research. First, existing studies are predominantly sub-national and concentrated on China, with analyses conducted at the provincial, city, or household level within a single country. Cross-country studies and single-country analyses using aggregate national data remain relatively limited (Chakravorti et al., 2015; Hwang, 2023; Sari & Nasrudin, 2022). Second, DEI is far more often deployed as an explanatory variable for sectoral or environmental outcomes than tested directly against aggregate economic growth. Where growth does appear, the effect is already reported as conditional (for instance, on the energy transition (Hwang, 2023) or on the time horizon (Sari & Nasrudin, 2022)). Yet an explicit moderation design with financial development and human-capital investment on a broad cross-country panel is missing. Together, these features define this study's space as a cross-country, annual DEI analysis that tests GDP per capita against financial development and human-capital investment as moderators.

Moreover, the same literature highlights an important concern that motivates our identification strategy. The estimated digital dividend shrinks (sometimes approaching zero) as the design moves from cross-sections to panels with country fixed effects and again when common time shocks are absorbed. The pattern suggests that a substantial share of the measured association reflects fixed national characteristics (institutions, geography, income level) and the worldwide digital trend, rather than the payoff to a country's own digital deepening. From a policy perspective, however, the within-country payoff is precisely the quantity of interest. A government cannot choose to be Denmark, but it can choose to accelerate its own digitalization. The first hypothesis (H1) therefore formulates the existence claim in its policy-relevant, within-country form (the deepening of the digital economy has a positive effect on economic growth within countries). This is deliberately the most demanding version of the claim because it must survive the absorption of everything a country permanently is and everything the world simultaneously does.

2.2. Financial Development as Moderator

If digital deepening pays off, does the payoff depend on the financial system that funds it? The affirmative case descends from the classical finance-growth nexus, from Schumpeter's banker who selects the entrepreneur (Schumpeter, 1934), through King and Levine's evidence (King & Levine, 1993) that financial depth predicts subsequent growth; financial systems are held to mobilize savings, screen projects, and allocate capital to its most

productive uses. The digital-finance literature reinforces the connection that digital finance exhibits growth-relevant spatial effects on regional development and financial inclusion (Kiraci & Mansour, 2026) and that digital economic development shapes household financial behavior (X. Xu & Lei, 2025), and in Europe specifically, fintech adoption and financial inclusion measurably reduce income inequality (evidence that the finance and technology nexus carries first-order distributional consequences in exactly the economies our panel covers) (Horobeț et al., 2025). Applied to digitalization, the complementarity prediction is direct. Digital investment is intangible-intensive, collateral-poor, and often undertaken by young firms, exactly the financing problems that deep credit markets and developed capital markets are supposed to solve. Under this view, the same digital input should yield more growth where finance is deeper, and digitalization and financial development should interact positively. We are explicit about the margin our design tests. Private credit to GDP measures the aggregate depth of intermediation, so the interaction identifies whether the digital dividend varies with how much credit the economy already extends (the depth gradient on which the two theories disagree) and not the flow of funds into digital projects, which no annual cross-country series measures.

The more recent "too much finance" literature breaks this prediction precisely where our sample remains. Beyond a threshold of financial depth that most OECD economies passed decades ago, the marginal growth return to private credit declines and can turn negative as the "too much finance" result of Arcand, Berkes and Panizza (Arcand et al., 2015), echoed in recent applied work (Azmeh & Al-Raeei, 2025; G. Xu, 2025). Thus, credit flows disproportionately into real estate and household leverage rather than productive intangibles, financial sectors bid talent away from the real economy, and boom–bust cycles destroy accumulated capabilities. If the marginal unit of credit in a saturated system no longer selects the highest-productivity projects, it has no reason to amplify the digital dividend because it may dilute it. The two traditions thus make opposite, falsifiable predictions about the same coefficient, and a credit-abundant panel such as ours is the natural arena for the contest. Financial development accordingly enters the model twice. Directly, as a standard growth covariate, and interacted with the digital index (and the second hypothesis (H2) is deliberately formulated as a two-sided test), financial development moderates the digital-economy-growth relationship (DEI × credit $\neq 0$), positive under the complementarity view and also negative under the "too much finance" view, so that the sign of a single coefficient discriminates between the two theories.

2.3. Human-Capital Investment as Moderator

The second moderator follows from the same logic applied to skills. Absorptive-capacity theory makes human capital the pivotal complementary asset for any imported technology. Converting external knowledge into domestic output requires a workforce that can adopt, operate, and build upon it. Nelson and Phelps formalized the point half a century ago (Nelson & Phelps, 1966). The return to education is highest where technology can absorb it, and the skill-biased technological change literature documents its modern form because digital technologies raise the productivity of educated workers more than others. The complementarity prediction is therefore that the digital dividend rises with human-capital investment (growth models of the digital economy assign human-capital accumulation a central role alongside creative destruction) (Liao et al., 2023). Underutilized human capital measurably depresses productivity growth (Vijaya Kumar & Balu, 2023), and cross-country evidence from samples spanning wide education ranges generally supports it.

Whether that prediction extends to a sample of advanced and near-advanced economies remains, however, an open question, and the theoretical case for the opposite sign is stronger than it may initially appear. Where baseline schooling is already high, the marginal com-

plementarity between digitalization and further education spending may be exhausted. At the same time, digital channels can provide some of the benefits that additional formal education would otherwise offer, including access to knowledge, on-demand skills, information about prices and markets, and potential customers. As a result, digitally mediated knowledge diffusion can partially substitute for conventional human-capital accumulation at the margin (Ali & Akhtar, 2023; Zhang et al., 2025a). If so, the digital dividend should be largest where education investment is lowest, because digital tools can help overcome existing limitations. As with finance, the interaction sign is the discriminating statistic, and we formulate the third hypothesis (H3) accordingly as a two-sided test. Human-capital investment moderates the digital-economy-growth relationship (DEI × education spending $\neq 0$), positive under the complementarity view, negative under the substitution view, with the verdict left to the data. We measure this moderator as the fiscal input (education expenditure) rather than the skill stock and test the stock channel separately. Section 5 shows the distinction is not semantic, because the two proxies produce different moderation results, and the difference is itself informative about the mechanism.

2.4. Structural Controls and Digital Convergence

The final element of the research question concerns where the digital dividend is located. Convergence reasoning (common to the absorptive-capacity and endogenous-growth traditions) predicts that economies further from the technological frontier capture larger incremental returns from adopting existing digital technologies. This is consistent with evidence that ICTs amplify the growth returns to global-value-chain participation in Sub-Saharan Africa (Bataka & Ossadzifo, 2023) and that the digital economy lifts export services competitiveness (Li et al., 2023). The stock of unexploited ideas is larger, the productivity gap adoption can close is wider, and leapfrogging legacy infrastructure is cheaper than replacing it. For the panel studied here, the question is not academic. The sample deliberately spans the OECD's mature members, its accession candidates and key partners, and the EU candidate countries. Economies whose accession trajectories rest, in part, on the expectation that integration accelerates their convergence. Whether digitalization is one of the levers of that convergence, and through which of its dimensions (trade participation, infrastructure, or usage), is directly relevant to the EU-enlargement and OECD-accession agenda. The fourth hypothesis (H4) formalizes the convergence claim at the level of country groups. The marginal growth effect of the digital economy is larger for catching-up economies (accession candidates, key partners, EU candidates) than for mature OECD members in digital convergence. Structural transformation and settlement structure (the declining agricultural share and the rural population share) align with development efforts so systematically that their omission would risk attributing to digitalization variation that belongs to a country's broader development stage, as would omitting the broader and drop growth fundamentals documented in the openness, innovation, and knowledge-economy literatures (Anwar et al., 2022; Deka, 2024; Mohamed et al., 2022; Seti et al., 2025); they enter all specifications as controls rather than hypothesized effects, precisely because the research question is about the digital economy, not about development at large.

3. Methodology and Data

3.1. Sample and Data Sources

We assembled a country-year panel of 58 economies. The estimation period is 2014–2022, while the Digital Economy Index is computed through 2023. The descriptive statistics and correlations reported in Section 4.1 are calculated using data from the estimation window (2014–2022) for the full 58-economy frame. Four economies (Canada, China, Montenegro, and North Macedonia) lack a complete moderator series over the

estimation window (private credit for Canada and government education expenditure for the other three) and drop automatically from the full specification estimates, which therefore cover 54 countries (446 country-year observations). The index, the descriptive statistics, and country rankings include all 58 economies. The type of DEI proposed for this article is calculated up to 2023 because all six component indicators have complete coverage up to 2023 for the 58 economies in the panel. However, the estimation window ends in 2022 because the human-capital moderator (government spending on education) is reported with a delay of several years. At the time of data collection, approximately one-fifth of countries in the panel had reported the education indicator for 2023. DEI values are calculated using Z-score parameters from 2014–2022, so the index definition is the same in both cases. The sample is a policy-driven one, not a convenience sample. It includes those 38 OECD member states, those 6 OECD accession candidates like Argentina, Bulgaria, Croatia, Peru, Romania and Thailand, then those 5 OECD key partners (Brazil, China, India, Indonesia, South Africa), those 2 EU members that are outside the OECD (Cyprus and Malta) and the 7 EU candidate countries Albania, Bosnia and Herzegovina, Georgia, Moldova, Montenegro, North Macedonia and Ukraine. Including EU candidates increases the representation of upper-middle-income economies, strengthens identification of the catching-up interaction by increasing variation in income levels and digital economy scores at the lower end of the distribution, and completes the enlargement dimension of the frame. The panel covers the full set of economies on the EU-accession and OECD-accession tracks. The starting point of the estimation window is a design choice with three justifications. First, construct comparability: from roughly 2014 onward, mass mobile-broadband diffusion makes the infrastructure and usage indicators measure the same phenomenon across mature and catching-up economies. Second, macroeconomic cleanliness: starting in 2014, the window excludes global financial crisis recovery dynamics and the euro-area sovereign-debt crisis. Third, policy alignment: 2014 marks the beginning of the current digital-policy cycle (the first edition of the European Commission's DESI and the first Global Findex wave covering digital payments). Section 4.5 shows that the conclusions are robust to extending the window back to 2012. All variables are drawn from the World Bank World Development Indicators, which were selected for their consistent cross-country definitions and broad coverage. Supranational aggregates are excluded so that every unit is a sovereign economy. The resulting panel is unbalanced (education expenditure is unavailable for Montenegro and North Macedonia throughout, so these economies are included in the specifications that do not require the human-capital moderator and in the descriptive analysis). The estimators accommodate unbalanced panels without imputation. To clarify the time windows, their uses are as follows: (1) the estimation window for every regression result in the paper (the baseline models in Table 1, and all appendix specifications in Tables A1 and A12) is the period 2014–2012, dictated by the reporting lag of the human-capital moderator; (2) the descriptive statistics and correlations (Tables 2 and 3) are computed over the same 2014–2022 window but using the full 58-economy frame (522 country-year rows), whereas the full specification regressions use the 54-country sub-sample (446 observations) described above; (3) the Digital Economy Index is computed through 2023, using the standardization parameters from the 2014–2022 window, and the country ranking uses the 2014–2022 mean for comparability with the estimates; (4) the robustness analysis additionally uses the extended 2012–2022 window (Section 4.5) and the 2012–2014 pre-window for the validation window for the instrument (Table A11); (5) the overall data coverage of the study is 2014–2023.

Table 1. Variable definitions and measurement.

Role	Variable	Measure (World Bank)	Transformation
Dependent	Real GDP per capita	GDP per capita, constant 2015 US$ (NY.GDP.PCAP.KD)	Natural log
Independent	Digital economy (DEI)	Composite of 6 indicators in 3 dimensions: participation (ICT goods imports %, ICT service exports %), infrastructure (fixed broadband/100, mobile subscriptions/100, secure Internet servers/1 M, ln), usage (Internet users %)	Z-score average within and across dimensions; standardized
Moderator 1	Financial development	Domestic credit to private sector (% GDP)	Standardized
Moderator 2	Human-capital investment	Gov. expenditure on education (% GDP)	Standardized
Control	Labor	Labor force, total	Log, standardized
Control	Structural	Agriculture value added (% GDP)	Standardized
Control	Settlement	Rural population (% of total)	Standardized

Source: Authors' processing.

3.2. Variables and Measurement

The dependent variable is the natural logarithm of GDP per capita in constant 2015 US dollars, which measures real income per person by expressing output at fixed prices and a fixed base-year exchange rate and removes both inflation and nominal exchange-rate movements from the within-country variation. A first-order concern is a panel that includes economies with large currency swings over 2014–2022 (Türkiye, Argentina, Ukraine). A variant in current PPP international dollars is used as an additional robustness check. We are explicit that the outcome is the (log) level of real income per capita, not an annual growth rate. Under country fixed effects, the coefficients are within-country semi-elasticities of the income level with respect to the regressors. Throughout the paper, "growth effect" and "digital dividend" are shorthand for these within-country income-level effects, and the hypotheses and conclusions are stated in these terms. The focal independent variable is a composite Digital Economy Index (DEI) covering participation, infrastructure, and usage, constructed as described in Section 3.3. Two moderators are used: (a) financial development, measured by domestic credit to the private sector as a share of GDP. This is the most widely used proxy for the aggregate depth of the financial system, and we interpret it strictly as a measure of the overall scale of intermediated credit, not the flow of funds into digital investment specifically or the penetration of digital finance. The moderation it identifies is therefore a depth gradient (that is, the growth return to digital deepening varies with how much credit the economy already intermediates), which is exactly the margin on which the complementarity and "too much finance" predictions disagree. Fund-flow and digital-finance penetration measures (e.g., the Global Findex digital-payment indicators or the IMF Financial Access Survey) exist only in multiyear survey waves. They cannot enter an annual panel over this window. We return to this in the Limitations section. The second moderator, (b) human-capital investment, is measured by general government expenditure on education as a share of GDP. We treat this variable as a fiscal-flow measure of the public input into human-capital formation, not a measure of the accumulated skill stock of the labor force. The two are conceptually and empirically distinct in our panel (the expenditure share correlates only weakly, $r = 0.21$, with gross tertiary enrollment), and the distinction carries interpretive weight. A moderation operating

through the fiscal input admits different readings than one operating through skills. For this reason, we use both measures: education expenditure as the fiscal flow measure in the main specifications and gross tertiary enrollment as a stock-side proxy in a dedicated robustness check (Section 4.5, Table A6), including a specification in which both measures are included simultaneously. The control vector comprises the total labor force (in logs), the agricultural share (agriculture value added as a share of GDP), which captures structural transformation, and the rural population share, which captures the settlement–structure dimension of development. We standardize all continuous regressors to have mean zero and unit standard deviation, so reported coefficients are directly comparable in magnitude. We center the interaction terms to reduce unnecessary collinearity. Table 1 summarizes the variables and their measurement.

The agricultural share warrants particular comment, because it plays three roles in the specification. First, it is the standard single-indicator proxy for the stage of structural transformation (the reallocation of output away from agriculture toward industry and services). It is therefore included to prevent the digital economy coefficient from absorbing variation that in fact reflects a country's broader level of development. Because digital-trade intensity and structural modernization are empirically entangled, omitting the agricultural share would risk an upward bias in the estimated digital–growth relationship. Conditioning on it allows the DEI to be interpreted net of development stage. Second, it provides a continuous, graded counterpart to the catching-up indicator used in the heterogeneity analysis. A larger residual agricultural sector characterizes catching-up economies, so the agricultural share captures the same developmental gradient smoothly rather than as a binary split. Third, among the agriculture-related indicators available in the source data, the agricultural share of GDP offers the cleanest interpretation as a growth control and the most complete coverage across the panel. Consistent with structural-transformation theory, it is the variable most strongly correlated with GDP per capita in the sample ($r = -0.80$) and enters the growth models with a large, negative, and highly significant coefficient throughout, providing a well-behaved structural anchor against which the study's conditional and convergence findings are identified.

3.3. Construction of a Different Model of the Digital Economy Index

Composite measures of the digital economy are well established in the literature and in policy practice. The European Commission's Digital Economy and Society Index (DESI) and its international extension I-DESI (European Commission, 2022) summarize the digital performance of EU member states and of a wider set of comparator countries. DESI was also an index whose structure, dynamics, and macroeconomic correlates (consumption, unemployment) have themselves been analyzed in panel settings, including from the perspective of candidate economies such as Ukraine that the official ranking does not yet cover (Stavytskyy et al., 2019). The World Bank's Digital Adoption Index (DAI) covers businesses, people, and governments worldwide (World Bank, 2016). A growing body of academic literature constructs country- or region-specific digital economy indices using data-driven weighting schemes, entropy-weight TOPSIS composites (D. Bai et al., 2024), statistical-bureau indicator sets (Xie et al., 2024), and night-time-light-estimated indices (Z. Chen et al., 2022; Y. Chen et al., 2024). None of these, however, meets the requirements of the present design because DESI is confined to EU member states, the DAI and survey-based digital-payment measures (Global Findex) are not produced at annual frequency, and the academic indices rarely span a policy-defined sample as heterogeneous as ours. We therefore design a dedicated index from World Development Indicators components, not to replace the established measures but to operationalize the estimation's requirements: annual coverage, 58-economy reach, and a three-dimensional structure. The digital economy is a

multidimensional construct that no single indicator captures well. Trade-side technology indicators alone capture an economy's participation in digital production networks but not the infrastructure it has built or how its population uses digital technologies. We therefore operationalize the digital economy using a well-known composite index covering three conceptually distinct dimensions, all drawn from the World Bank World Development Indicators: (1) participation, ICT goods imports (% of total goods imports) and ICT service exports (% of service exports, BoP); (2) infrastructure, fixed broadband subscriptions per 100 people, mobile cellular subscriptions per 100 people, and secure Internet servers per one million people (expressed as a natural logarithm owing to their strong right skew); and (3) usage, individuals using the Internet as a share of the population. Aggregation follows the Z-score (standard-score) method in four steps. First, each component indicator j is standardized over the estimation panel (all countries i and years t, 2014–2022):

$$z_{j,it} = \left(x_{j,it} - \bar{xj}\right)/s_j \quad (1)$$

where $\bar{xj}$ and sj are the panel-wide mean and standard deviation of indicator j, so that every indicator enters with mean zero and unit variance and no indicator dominates by scale. Second, the standardized indicators are averaged with equal weights within each of the three dimensions:

$$PART_{it} = ½ \left(z_{ICTimp,it} + z_{ICTserv,it}\right) \quad (2a)$$

$$INFR_{it} = {}^{1}/_{3} \left(z_{broadband,it} + z_{mobile,it} + z_{ln\ servers,it}\right) \quad (2b)$$

$$USE_{it} = z_{internet,it} \quad (2c)$$

Third, the scores for those three dimensions are averaged with equal weights into the DEI, ensuring that each dimension receives exactly one-third of the total weight, independent of the number of indicators it contains, as illustrated in the equation below.

$$DEI_{it}^{raw} = {}^{1}/_{3} \left(PART_{it} + INFR_{it} + USE_{it}\right) \quad (3)$$

Ultimately, the gross composite indicator is re-standardized on the estimation sample, resulting in a final index with a mean value of zero and a standard deviation of one. The DEI value is +1 and indicates a standard deviation above the sample mean (Equation (4)).

$$DEI_{it} = \left(DEI_{it}^{raw} - \text{mean}(DEI^{raw})\right)/\text{sd}(DEI^{raw}) \quad (4)$$

The equal weighting in both stages (Equations (2) and (3)) is intentional, transparent, does not impose data-driven weights that would vary from one sample to another, and follows established practice for the development of composite indices (the OECD/JRC Manual on the Development of Composite Indicators (OECD & European Commission Joint Research Centre, 2008)). Two points about this choice deserve emphasis. Equal weighting does not assume that every indicator contributes equally to growth. The weights define how digital development is measured, while the regression stage estimates the index's contribution to growth. The dimension-grouped structure discards no information (all six indicators enter the index).

In contrast, a single-principal-component index would retain only the 42% of total variance loading on the first component. That is precisely why PCA serves as a robustness check rather than the baseline. In a deliberately multidimensional construct, a modest first-component share signals that the dimensions carry distinct information, not that the index is deficient. Section 4.5 therefore stress-tests the weighting choice against two data-driven alternatives (as an entropy-weighted composite over the six indicators, standard in the applied DEI literature, and a multicomponent PCA composite that aggregates the first four components, 93% of total variance, by their variance shares) and shows the moderation

results are invariant (Table A8). For the 2023 observations used in the descriptive analysis, the same parameters ($\bar{x}_j$, s_j, and the moments of DEIraw) estimated on the 2014–2022 panel are applied, so the index definition is identical across the two uses.

As a robustness check on the aggregation method, we also extract the first principal component of the six standardized indicators. The first component accounts for 42.1% of their joint variance, and the two versions of the index correlate at r = 0.88; all baseline results are qualitatively unchanged when the PCA version replaces the z-score version (Section 4.5). The Z-score version is preferred as the primary measure because its weights are fixed by construction rather than sample-dependent and because it is computable for every country-year with at least one indicator per dimension. In contrast, listwise PCA loses observations with any missing component. Table 2 reports the index composition and the descriptive statistics of its components.

Table 2. Composition of the extended Digital Economy Index (Z-score method).

Indicator (Dimension)	N	Mean	SD	Min	Max
ICT goods imports, % of total goods imports (participation)	522	7.76	3.94	0.21	24.57
ICT service exports, % of service exports, BoP (participation)	516	11.73	10.86	0.63	62.48
Fixed broadband subscriptions per 100 people (infrastructure)	522	27.73	11.39	1.20	48.25
Mobile cellular subscriptions per 100 people (infrastructure)	522	122.85	19.39	71.94	207.28
Secure Internet servers per 1 million people, log (infrastructure)	522	8.49	2.11	2.12	12.53
Individuals using the Internet, % of population (usage)	522	78.11	15.69	13.50	99.69

Notes: There is a robust version of Principal-Component Analysis (PCA). PC1 explains 42.1% of the common variance of the six components, and the correlation with the DEI Z-score is r = 0.88.

Table 3. Descriptive statistics.

Variable	N	Mean	Std	Min	Median	Max
GDP per capita, constant 2015 US$	522	27,488	23,646	1484	18,789	110,873
GDP per capita, current US$	522	29,572	25,501	1554	20,505	134,966
Digital Economy Index (Z-score)	522	0.00	1.00	−3.44	0.16	2.30
Domestic credit to private sector (% GDP)	506	82.81	45.96	12.89	68.29	251.83
Gov. education expenditure (% GDP)	462	4.91	1.28	0.86	4.83	8.58
Labor force (millions)	521	40.54	121.97	0.20	5.14	781.19
Agriculture value added (% GDP)	521	4.09	3.85	0.19	2.77	19.24
Rural population (% of total)	522	27.09	14.36	4.40	25.90	67.77

With the index defined and its aggregation validated, the next sub-section specifies the econometric models used to estimate its growth effect and the moderating roles of financial development and human capital.

3.4. Model Specification

The basic specification of our model is a bidirectional fixed-effects model (country and year), expressed below in Equation (5):

$$ln\ GDPpc_{it} = \alpha_i + \lambda_t + \beta_1\ DEI_{it} + \beta_2\ (DEI \times M)_{it} + \gamma' X_{it} + \varepsilon_{it} \quad (5)$$

where i indexes countries and t years; αi are country fixed effects that absorb all time-invariant heterogeneity (geography, institutions, legal origin, and other fixed national characteristics); λt are year fixed effects that absorb common global shocks (including the

COVID-19 digital surge and the 2022 energy and inflation shock); *DEIit* is the extended Digital Economy Index of Equation (4); *M* denotes a moderator (financial development or human-capital investment); *Xit* is the vector of controls; and *εit* is the idiosyncratic error, clustered at the country level to allow arbitrary serial correlation within countries. Because all continuous regressors are standardized, coefficients are directly comparable in magnitude across variables and models.

We build the model sequentially to expose how the estimates respond to specification, estimating five nested models. *M*1 contains the core regressors; *M*2 adds the structural controls; *M*3–*M*5 add the interaction terms one at a time:

$$M1\text{: } ln\ GDPpc_{it} = \alpha_i + \lambda_t + \beta_1\ DEI_{it} + \beta_2\ FIN_{it} + \beta_3\ EDU_{it} + \beta_4\ ln\ LAB_{it} + \varepsilon_{it} \quad (6)$$

$$M2\text{: } M1 + \beta_5 AGR_{it} + \beta_6\ RUR_{it} \quad (7)$$

$$M3\text{: } M2 + \theta_1\ (DEI_{it} \times FIN_{it}) \quad (8)$$

$$M4\text{: } M3 + \theta_2\ (DEI_{it} \times EDU_{it}) \quad (9)$$

$$M5\text{: } M4 + \theta_3\ (DEI_{it} \times CATCH_i) \quad (10)$$

where *FINit* represents the financial development variable (domestic credit to the private sector, % of GDP, standardized), *EDUit* represents the human-capital investment indicator (government education expenditure, % of GDP, standardized), ln *LABit* is the logarithm of the labor force indicator (standardized), *AGRit* represents the agricultural share indicator, *RURit* is the rural population share indicator (both standardized), and *CATCHi* reflects a time-invariant indicator equal to one for catching-up economies (accession candidates, key partners, EU candidates, and EU non-OECD members) and zero for mature OECD members. The country's fixed effects absorb its main effect, so only the interaction is identified. The hypotheses correspond directly to the parameters: H1 refers to $\beta 1$, H2 to $\theta 1$, H3 to $\theta 2$, and H4 to $\theta 3$.

In the interacted models, the growth effect of the digital economy is not a single number. Differentiating Equation (9) with respect to DEI gives the conditional marginal effect:

$$\partial\ ln\ GDPpc_{it} / \partial\ DEI_{it} = \beta_1 + \theta_1\ FIN_{it} + \theta_2\ EDU_{it} \quad (11)$$

with delta-method standard error $se(\partial lnGDPpc/\partial DEI)$ computed from the full covariance matrix of the estimates, $se^2 = V(\beta 1) + FIN^2 \cdot V(\theta 1) + EDU^2 \cdot V(\theta 2) + 2 \cdot FIN \cdot Cov(\beta 1, \theta 1) + 2 \cdot EDU \cdot Cov(\beta 1, \theta 2) + 2 \cdot FIN \cdot EDU \cdot Cov(\theta 1, \theta 2)$. We evaluate and plot Equation (11) across the observed range of each moderator, which is more informative than the interaction coefficient alone. The interaction coefficient reports only the slope of the marginal effect, whereas the profile shows where in the moderator distribution the digital dividend is statistically distinguishable from zero.

Two robustness strategies address the principal threats to identification. First, we re-estimate the models with country-only fixed effects, which relax the common-year restriction and allow country-specific responses to global shocks; comparing the two structures shows whether the year effects are absorbing economically meaningful digital variation. Second, we examine the sample frame and estimation window. The main analysis is estimated over the 2014–2022 window. As an additional check, the baseline specifications are re-estimated over the extended 2012–2022 window, with unchanged conclusions (Section 4.5). We test the key results of the moderation analysis on a global panel of 138 countries, covering the income categories established by the World Bank, such as lower-middle income, upper-middle income, and high-income countries (presented in Section 4.5). Multicollinearity is evaluated using variance inflation factors, which do not exceed 2.5 in the raw data or 1.3 after the within transformation used by the fixed-effects estimator (Table A9). The

interaction terms are constructed from centered (standardized) variables to minimize inessential collinearity. We address reverse causality (richer countries digitalize more) and dynamics directly. Our primary identification strategy is a shift-share instrumental variable design. The DEI is instrumented using the interaction between each country's pre-sample (2012) digital position (that being the exposure component) and the leave-one-out global mean DEI each year (representing the shift component). The moderator interactions are instrumented using the corresponding interactions between the instrument and the moderators. Identification rests on the standard shift-share argument that a country's pre-sample digital position is fixed before the estimation window, the global digitalization trend is exogenous to any single country's actual growth stock (the leave-one-out construction removes the country's own contribution), and conditional on country and year fixed effects, the instrument affects growth only through its effect on the country's own digital deepening. The instrument is strong, where first-stage partial F statistics are 77–137 for the three endogenous variables under two-way fixed effects, far above conventional weak instrument thresholds. Three validation exercises probe the design beyond relevance (Table A11). A pre-trend placebo shows that, conditional on 2012 controls, the 2012 exposure does not predict pre-window growth (2012–2014; t = 0.50). The unconditional correlation reflects level convergence, which the country fixed effects absorb. Another validation exercise is permutation inference, which shows that randomly reassigning exposures across countries (500 draws) collapses the first-stage F from 277 to a placebo median of 2.9 ($p < 0.002$). Hence, the instrument's relevance is specific to the true exposure ordering. Permutation p-values for the reduced-form interactions are 0.41–0.43, so we rest the moderation inference on the clustered asymptotic tests rather than claiming permutation sharpness. The last validation exercise concerns country-specific linear trends. Adding them eliminates all effects, and we acknowledge this sensitivity explicitly. At T = 9, the exercise cannot separate the treatment effect from the underlying trend. Linear trends absorb 95% of the within-country variance of the DEI itself (median $R^2 = 0.93$) and 98% of the instruments, so the disappearance of the effects is consistent both with the estimates partly reflecting trending confounds and with the trends mechanically removing the treatment variation. Our results should therefore be interpreted as robust to the exercises described above but not to country-specific linear trends. Distinguishing between the two interpretations (and identifying the effect from deviations around country trends) requires a longer panel. As complementary evidence, all regressors are lagged by one year in a timing-robustness specification, and we estimate a two-step system GMM (Blundell–Bond) with a collapsed instrument matrix and limited lag depth. This keeps the instrument count (25) below the number of countries (54) and preserves the informativeness of the Hansen test. We also retain the Anderson–Hsiao first-difference estimator, disclosed as weakly instrumented at T = 9 (first-stage F = 4.5) and reported for completeness only. Long-run alternatives (that is, panel cointegration and error correction estimators like FMOLS, DOLS, or the common mean group) require a longer time horizon than nine years to identify level relationships and are left for future work, as data after 2023 become available. We note that multicollinearity is not a concern because all regressors are standardized, the interactions are centered, and variance inflation factors are at most 2.5 in the raw data and at most 1.3 after the within transformation that the fixed-effects estimator actually uses, being below the conventional threshold of 5. As a further check, Section 4.5 re-estimates the moderation model dropping the structural controls singly and jointly. Coefficients on interests are unaffected (Table A9). Fisher-ADF (Maddala–Wu) tests reject unit roots for the dependent variable (DEI, $p < 0.001$), and the Pesaran CD statistic on the M4 residuals (CD = −2.06, $p = 0.04$) indicates only mild residual cross-sectional dependence after the two-way structure absorbs common shocks.

4. Results

4.1. Descriptive Statistics and Correlations

Table 3 presents descriptive statistics for the estimation panel, which comprises 58 economies analyzed in the 2014–2022 period. Real GDP per capita, denominated in US dollars at 2015 constant prices, has a mean of 27,488 US dollars (with a standard deviation of 23,646), ranging from 1484 US dollars (India, 2014) up to 110,873 US dollars (Luxembourg). The nominal series is presented alongside for comparison purposes. The DEI is standardized by construction (mean 0, SD 1) and spans 3.44 to 2.30. Private credit averages 82.8% of GDP with wide dispersion (12.9–251.8%), education spending averages 4.9% of GDP, and the agricultural share averages 4.1%, low in the OECD core, but reaching 19.2% in the sample's least developed members.

The correlation matrix (Table 4) shows real GDP per capita strongly positively associated with the extended DEI (r = 0.73), financial development (r = 0.52), and human capital (r = 0.40) and strongly negatively with the agricultural share (r = −0.80) and the rural population share (r = −0.63).

Table 4. Correlation matrix.

	ln GDP pc (Real)	DEI	Fin. Dev.	Human Cap.	Labor (ln)	Agri	Rural
ln GDP pc (real)	1.00						
DEI	0.73	1.00					
Fin. dev.	0.52	0.35	1.00				
Human cap.	0.40	0.39	0.31	1.00			
Labor (ln)	−0.19	−0.19	0.22	−0.25	1.00		
Agri	−0.80	−0.65	−0.37	−0.35	0.20	1.00	
Rural	−0.63	−0.44	−0.36	−0.40	0.02	0.54	1.00

The strong raw DEI-income correlation underscores because within-country identification matters. Cross-sectional association conflates the digital economy with the broader development level, which the fixed effects design nets out. All variance-inflation factors are far below the conventional threshold of 5 (at most 2.5 in the raw data and 1.3 after the within transformation; Table A9), indicating that multicollinearity does not threaten the moderation design. A note on index stability is that the participation dimension spikes in 2020 (the pandemic-year surge in ICT trade shares) and reverts toward its mean by 2022. In contrast, infrastructure and usage rise monotonically (Figure 2).

Because the DEI averages the three dimensions and is standardized over the full window, this transitory movement shifts the index by at most a third of the participation deviation and does not disturb the country ranking. Re-estimating the baseline excluding 2020 leaves the moderation structure unchanged, and the year fixed effects absorb the common component of the shock in any case (Figure 3).

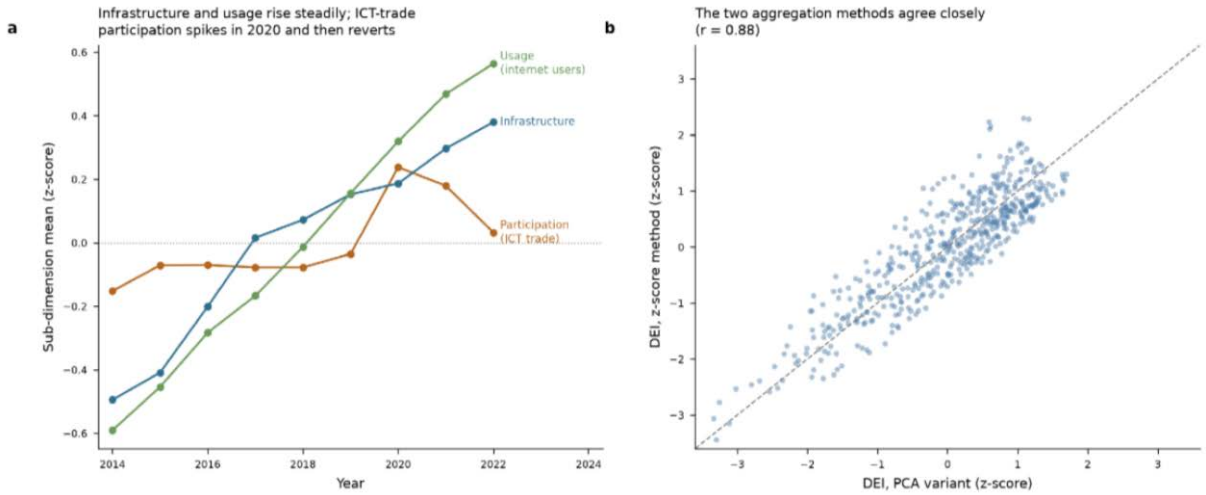


Figure 2. Extended Digital Economy Index construction. Panel (**a**) shows sample-mean trajectories of the three sub-dimensions, 2014–2022: infrastructure and usage rise steadily, while ICT-trade participation spikes in 2020 and then reverts. Panel (**b**) reflects an agreement between the Z-score aggregation and the principal-components variant (r = 0.88).

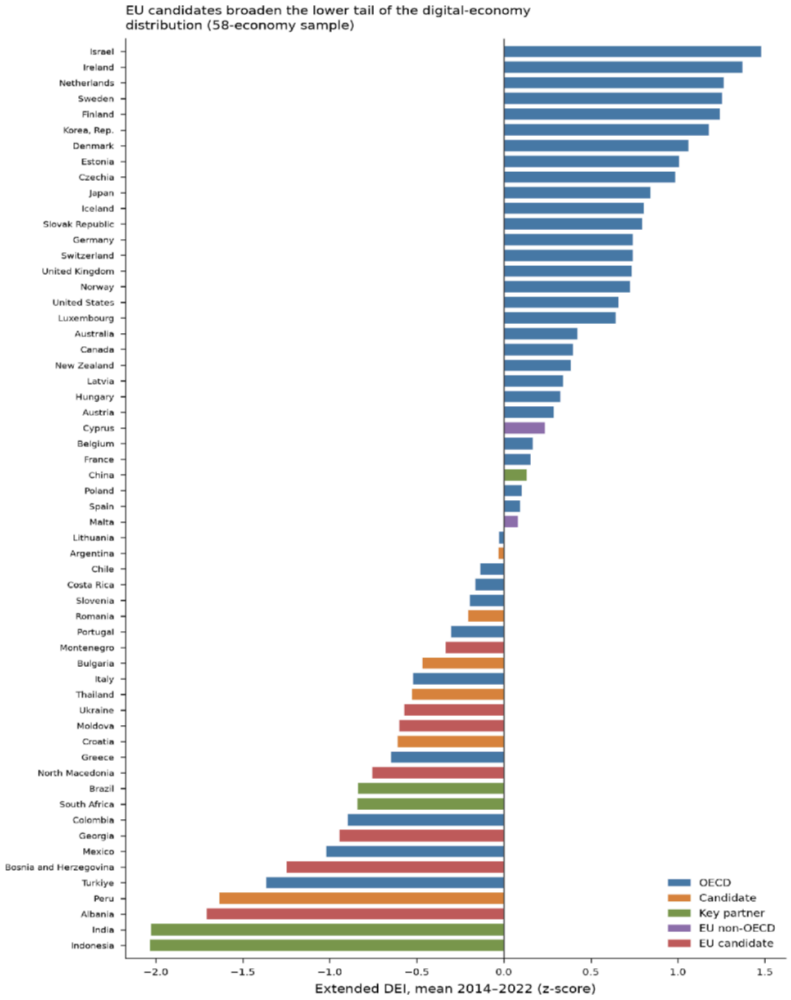


Figure 3. Country ranking by mean extended DEI, 2014–2022 (58 economy sample), colored by country group. EU candidate economies broaden the lower tail of the digital economy distribution.

4.2. Baseline Panel Estimates

We present the estimation of the bidirectional fixed effects model (Table 5), with standard errors grouped by country. The dependent variable is GDP per capita expressed in US dollars at constant 2015 prices. The DEI has a positive, significant coefficient in models M1–M3 (with values between 0.034 and 0.041, and $p < 0.05$ in M2–M3). In the interacted models M4–M5, the DEI coefficient is not an unconditional effect. Because all moderators are standardized, it measures the marginal effect of digital deepening at the sample mean for financial development and education spending. That conditional point estimate is positive but imprecise. Its statistical insignificance at the sample mean does not imply the absence of an association at other moderator values. The full marginal effect profiles (Table A10) show the effect is positive and significant where credit and education spending are below average. The association between digitalization and real income per capita therefore manifests through the conditional structure rather than as a uniform shift.

Table 5. Estimates of economic growth based on the fixed-effects model (dependent variable, ln GDP per capita).

Variable	M1	M2	M3	M4	M5
Digital economy (DEI)	0.036 * (0.019)	0.041 ** (0.019)	0.034 ** (0.017)	0.018 (0.018)	0.038 (0.025)
Financial development	−0.034 ** (0.016)	−0.026 * (0.014)	−0.036 ** (0.015)	−0.037 ** (0.015)	−0.041 *** (0.016)
Human-capital investment	−0.015 (0.018)	−0.021 (0.018)	−0.014 (0.015)	−0.019 (0.016)	−0.018 (0.015)
Labor force (log)	−0.516 (0.365)	−0.270 (0.333)	−0.175 (0.303)	−0.077 (0.277)	−0.083 (0.289)
Agriculture (% GDP)		−0.117 *** (0.031)	−0.115 *** (0.032)	−0.124 *** (0.028)	−0.128 *** (0.029)
Rural population (%)		0.075 (0.058)	0.034 (0.054)	0.085 * (0.051)	0.061 (0.056)
DEI × Financial development			−0.022 ** (0.011)	−0.017 * (0.010)	−0.018 * (0.009)
DEI × Human capital				−0.025 ** (0.010)	−0.026 *** (0.010)
DEI × Catching-up					−0.022 (0.027)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	446	446	446	446	446
Countries	54	54	54	54	54
Within R^2	0.142	0.227	0.289	0.353	0.362

Notes: Dependent variable, ln GDP per capita denominated in US dollars, constant 2015 prices. Standardized coefficients. Clustered standard errors (by country) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All models include country and year fixed effects. The regression sample is 54 of the 58 panel economies. Canada (no private credit series), China, Montenegro, and North Macedonia (there is no education expenditure series) drop automatically from the specifications that require both moderators (Section 3.1)—M1 baseline. M2 adds agricultural and rural shares. M3 adds DEI × financial development. M4 adds DEI × human capital. M5 adds the catching-up interaction. Diagnostics reveal that Fisher-ADF rejects unit roots for the dependent variable and the DEI ($p < 0.001$); Pesaran CD on M4 residuals = −2.06 ($p = 0.04$); all VIFs < 5.

Financial development enters negatively and significantly in the interacted models ($\beta = -0.037$, $p < 0.05$ in M4). This within-country pattern, where contemporaneous real per-capita output gains did not match episodes of rapid credit expansion over the sample window, is consistent with the "too much finance" literature for financially deep economies. The agricultural share remains the strongest structural correlate ($\beta \approx -0.12$, $p < 0.01$ throughout), anchoring the structural transformation control.

4.3. Moderation Analysis

Models M3–M5 introduce the interaction terms that test the study's central conditional-effects hypotheses. The DEI × financial-development interaction is negative and significant on entry ($\theta 1 = -0.022$, $p < 0.05$ in M3; -0.017, $p < 0.10$ in M4), and the DEI × human-capital interaction is negative and significant ($\theta 2 = -0.025$, $p < 0.05$ in M4; -0.026, $p < 0.01$ in M5) Figure 4. With real income as the dependent variable, the human-capital investment moderation is now significant under the two-way structure as well. The marginal effect profiles indicate that the association is conditional on both moderators. Across the credit distribution, the marginal effect of the DEI decreases steadily with financial depth. At the 5th percentile of private credit (29% of GDP), it is 0.038 (t = 1.85) under two-way fixed effects and 0.096 (t = 5.55) under country fixed effects, falling to −0.011 (t = −0.45) and 0.037 (t = 1.72), respectively, at the 95th percentile (164% of GDP). Thus, it represents a depth gradient (Table A10) that is the precise empirical content of the "too much finance" reading. Across the education spending distribution, the association between DEI and real GDP per capita is stronger and statistically significant at lower education spending, while it becomes statistically indistinguishable from zero at higher levels.

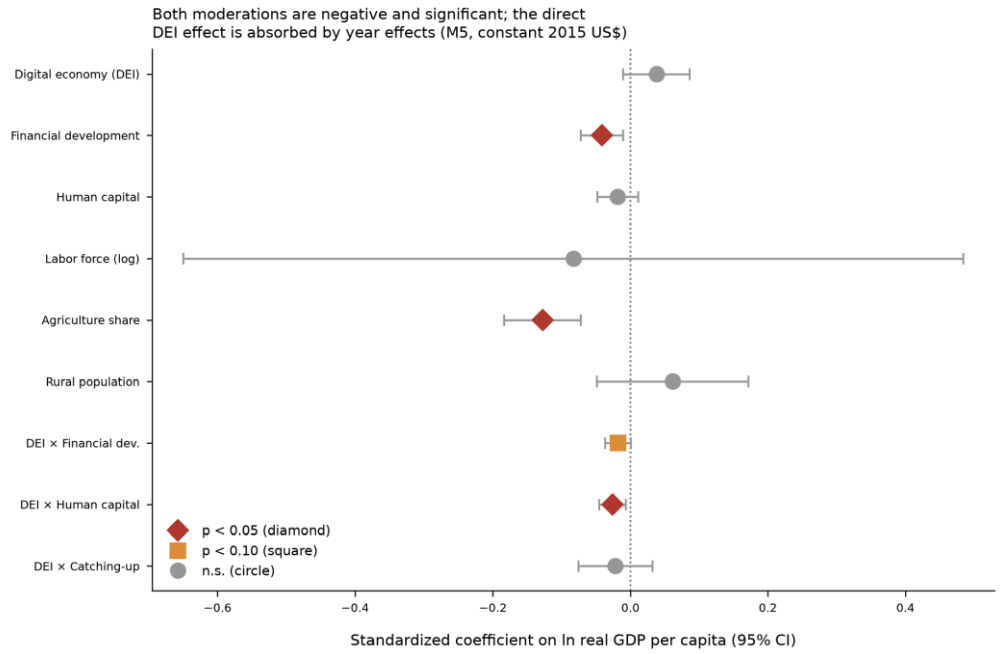


Figure 4. Standardized coefficients for ln GDP per capita expressed in US dollars in constant 2015 prices, with 95% confidence intervals. Model M5 is a bidirectional fixed-effects model. Statistical significance is indicated by both color and marker shape. Red diamonds for $p < 0.05$, orange for $p < 0.10$, and gray circles for non-significant results.

To interpret the human-capital interaction, Figure 5 plots the marginal effect of the digital economy on ln real GDP per capita across the observed range of education spending. The digital dividend is largest in countries with below-average education spending. At the 5th percentile of government education spending, the marginal effect is 0.054 (t = 3.29), while at the 95th percentile it is −0.032 (t = 0.097), which is statistically indistinguishable from zero at conventional levels ($p > 0.10$). When fixed effects are included only at the country level, the profile takes values from 0.105 (t = 7.07) up to 0.026 (t = 1.13).

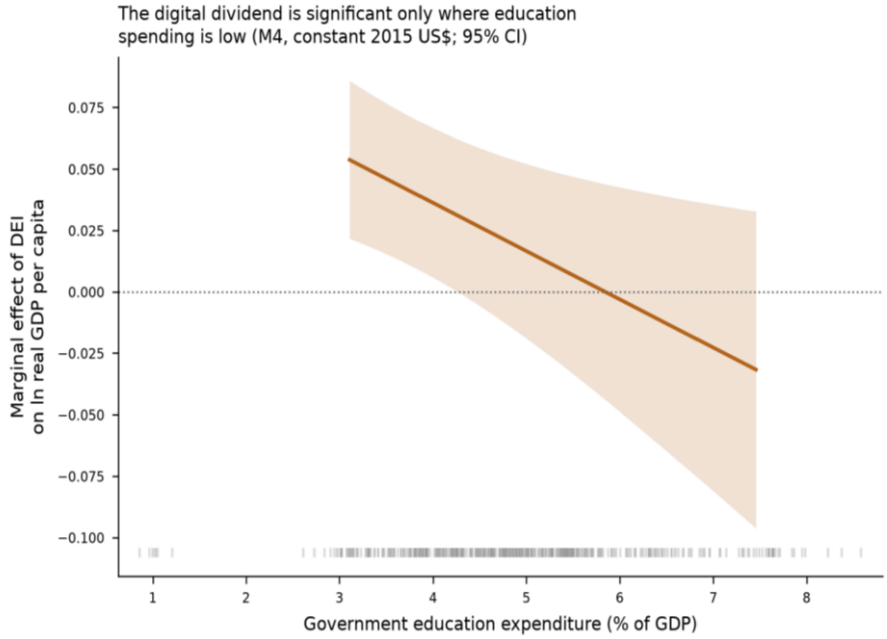


Figure 5. Marginal effect of the Digital Economy Index on ln real GDP per capita, conditional on human capital (education spending), Model M4. Shaded band with 95% confidence interval. Rug marks show observed values.

The expenditure margin moderation is thus robust in direction and, with the real-income measure, statistically sharper than with the nominal one.

4.4. Heterogeneity Across Country Groups

Model M5 adds an interaction between the DEI and a catching-up indicator (equal to one for non-OECD accession candidates, key partners, EU candidates, and EU-non-OECD economies). With the extended, multidimensional DEI and the real-income dependent variable, the interaction is not statistically significant under the two-way structure ($\theta 3 = -0.022$) and negative under country-only fixed effects (-0.047, $p < 0.05$). There is no evidence of a convergence premium for digitalization more broadly. If anything, the country-only model suggests that mature economies convert within-country digital deepening into real income somewhat more effectively. This sharpens the contrast with the trade-side DEI of earlier drafts, which produced a positive premium. The suggestive heterogeneity appears to relate to digital trade participation specifically, not to infrastructure or usage accumulation. For the composite index, the interaction is not significant under two-way fixed effects. H4's convergence prediction is therefore not supported for the composite index, a finding we return to in the Discussion.

4.5. Robustness Checks

We generate ten scenarios that support the baseline conclusions. Full tables are reported in Appendix A. First, the dependent variable. Re-estimating with current-PPP international dollars leaves the moderation structure intact (Table A1), and the earlier current-US$ estimates are qualitatively similar but noisier, as expected when nominal series mix real growth with exchange-rate movements. Second, replacing the two-way structure with country-only fixed effects (Table A3) strengthens the direct DEI effect to 0.072–0.096 ($p < 0.01$) and both interactions to conventional significance, indicating that year effects absorb the common global component of digital deepening. Third, using aggregation, we replace the Z-score index with its principal-components variant (r = 0.88 between the two), with an entropy-weighted composite over the six indicators (r = 0.78), or

with a multicomponent PCA composite aggregating the first four components (93% of total variance, so no dimension information is discarded) by their variance shares (r = 0.81), leaving all signs and significance patterns unchanged. The human-capital investment interaction is −0.019 to −0.029 ($p < 0.05$ or better in every case) and the financial development interaction is −0.016 to −0.026 (significant in five of six specifications) across all three alternatives and both fixed-effects structures (Table A8). Fourth, the results are robust to the extended 2012–2022 window. Fifth, timing: lagging all regressors by one year (Table A2) preserves the moderation structure and the within-country DEI effect, so current income cannot be driving past digitalization. Sixth, dynamics: a two-step system GMM (Blundell–Bond) with a collapsed instrument matrix (25 instruments, 54 countries, Hansen $p = 0.90$, AR(2) $p = 0.42$, Table A12) yields a well-specified but imprecise model, as expected with T = 9 (the financial development interaction retains its negative sign, −0.023, while the human-capital investment interaction is positive but statistically insignificant with 0.031 and z = 0.66). The Anderson–Hsiao specification (Table A4) is reported with its weak first stage disclosed. The static fixed-effect estimates, supported by stationarity diagnostics and the instrumental-variable evidence presented below, remain the primary evidence. The first-differenced interaction estimates in Table A4, including the positive sign on Δ(DEI × education), which reverses the headline moderation, inherit the same unreliability at T = 9 and should not be read against the fixed-effects evidence. Seventh, the moderation pattern extends to the 138-country global panel by income class (Table A5). The financial development interaction is negative and significant only among high-income economies (−0.016, $p < 0.05$, with the values near zero, and insignificant in the lower-middle, −0.07, and upper-middle, 0.004, groups), and the education interaction is negative in all three groups but significant only in the upper-middle-income group (−0.073, $p < 0.001$). The results are insensitive to the exclusion of Montenegro and North Macedonia (no education data) and Ukraine's 2022 war-shock observation. Eighth, the human-capital proxy: replacing education expenditure (a fiscal flow) with tertiary enrollment (a stock proxy) yields a DEI × tertiary interaction that is small, positive, and insignificant in every specification (0.008–0.018, n.s.; Table A6), when pitted directly against both moderating variables in a competitive model, the spending interaction effect remains robust (−0.026, $p < 0.01$, two-way FE; −0.027, $p < 0.01$, country FE) while the tertiary interaction remains null. The moderation therefore appears to operate on the fiscal-input margin, not on the skill stock, a distinction the Discussion develops. Ninth, using an identification approach by instrumenting the DEI and both interactions with the shift-share instrument described in Section 3.4 (where first-stage partial F = 77–137, Table A7), the moderation structure remains. DEI × financial development is at −0.018 ($p < 0.10$) and DEI × human capital investment at −0.049 ($p < 0.05$) under two-way fixed effects, and under country fixed effects the direct DEI effect is positive and significant (0.039, $p < 0.05$) with DEI × financial development at −0.035 ($p < 0.01$). The exogenous component of digital deepening (the part that is driven by the global digitalization wave and interacts with pre-sample position) thus reproduces the conditional-dividend pattern, which addresses the concern that reverse causality drives the baseline results. The tenth represents the control-variable approach. Thus, dropping the structural controls (agriculture, rural share) singly and jointly, and reducing the model to the moderators alone, moves the DEI × financial development coefficient only between −0.017 and −0.021, confirming that the moderation results are not an artifact of collinearity among the controls.

5. Discussion

5.1. Empirical Support and Model Contradictions

We summarize the findings for the hypothesis in Table 6. This sub-section examines these findings critically, because the pattern of support is more informative than the count of confirmations. The within-country digital dividend (H1) is supported, but its size depends decisively on the variation used to identify it. Under country-only fixed effects, which compare each economy with its own trajectory, a one-standard-deviation increase in the DEI is associated with 7.2–9.6-log-points higher real GDP per capita ($p < 0.01$). Under the two-way fixed-effects structure, which additionally accounts for the common global digitalization trend, the coefficient falls to 0.034–0.041 ($p < 0.05$ in M2–M3) and loses statistical significance once the interaction terms are included. The critical interpretation is that a large share of the apparent digital dividend may reflect the worldwide trend rather than country-specific digital deepening, an attenuation that single-country studies and cross-sectional designs may not adequately capture. We regard the two-way estimates as the conservative benchmark, while noting that, for a policymaker deciding whether to accelerate national digitalization, the within-country coefficient is the relevant quantity. The pattern also reflects findings from single-country studies. For instance, in Indonesia, a comparable equal-weighted DEI raises GDP only in the long run (Sari & Nasrudin, 2022), consistent with our interpretation that the growth payoff to digital deepening accrues through slow-moving within-country accumulation rather than short-run fluctuations.

Table 6. Summary of hypothesis tests.

#	Hypothesis	Outcome	Evidence
H1	Digital economy deepening raises growth within countries	Supported (within-country)	DEI 0.072–0.096, $p < 0.01$ under country FE; 0.034–0.041, $p < 0.05$ in two-way FE M2–M3; absorbed once interactions enter; robust to lagged regressors
H2	Financial development moderates the digital–growth link	Supported—negative ("too much finance")	DEI × Finance −0.022 ** on entry; −0.017 * full model; −0.032 *** under PPP; robust to lags and FE structure; significant among high-income economies in the global panel
H3	Human capital moderates the digital–growth link	Supported—expenditure-margin substitution	DEI × Human capital (spending) −0.025 **/−0.026 *** (two-way), −0.023 *** (country FE), −0.030 *** lagged; stock proxy (tertiary) does not moderate (0.008–0.018, n.s., Table A6); dividend significant only at low education spending (ME 0.054, t = 3.29 at p5)
H4	Digital dividend larger in catching-up economies	Not supported (channel-specific only)	Insignificant (two-way); −0.047 ** under country FE; positive only with trade-side DEI (convergence attaches to digital) trade participation

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; n.s. = not significant at conventional levels ($p > 0.10$). Significance based on standard errors clustered by country. Coefficients cited in the Evidence column are the standardized estimates from Table 4 and the corresponding appendix tables (A1–A6); ME denotes the marginal effect of the DEI at the stated percentile of the moderator.

The financial-development moderation (H2) is a robust result. The interaction coefficient is $\theta 1 = -0.022$ ($p < 0.05$) when first introduced in M3 and −0.017 to −0.018 ($p < 0.10$) in the full models with the real-income measure. It strengthens to −0.032 ($p < 0.01$) under the current-PPP measures and remains stable across fixed-effects structures and lag timing. In the global panel, the interaction is significant precisely among high-income economies and statistically indistinguishable from zero in both middle-income groups. The complementarity prediction (that deeper credit markets amplify digital returns) is therefore rejected in its own home territory, the financially deepest economies. Interpreted

through the "too much finance" lens, the result suggests that in credit-saturated systems the marginal unit of finance no longer selects the digital projects with the highest growth payoff. Two limitations qualify these findings. First, private credit measures the quantity of intermediation, not its quality or allocation, so the channel (misallocation, crowding-out of digital-intensive intangibles, or diminishing returns to credit itself) cannot be separated with these data. Second, the within-estimator identifies effects over a nine-year window, so slower-moving complementarities between financial institutions and digitalization may not be captured. The pairing of these two forces is itself an emerging area of research. Recent work examines the digital economy and financial development jointly as determinants of regional economic resilience (Sun & Chen, 2025; Yuan & Zhao, 2026), and our results suggest that, for the income-level margin in credit-abundant economies, deeper finance attenuates rather than amplifies the digital association.

The human-capital moderation (H3) is, with the real-income dependent variable, significant in both fixed-effects structures, with $\theta 2 = -0.025$ ($p < 0.05$) under the two-way design and -0.023 ($p < 0.01$) under country fixed effects, and robust to lagging all regressors (-0.030, $p < 0.01$). The marginal-effect profile is the economically meaningful object: at the 5th percentile of education spending, the digital dividend is 0.054 (t = 3.29), while at the 95th percentile it is -0.032 (t = -0.97, $p > 0.10$), statistically indistinguishable from zero. Under country fixed effects, the corresponding profile runs from 0.105 (t = 7.07) to 0.026 (t = 1.13). The stock-proxy check sharpens what this moderation is and is not. Replacing expenditure with tertiary enrollment (Table A6), we find no significant DEI × stock interaction in any specification; when we include both moderators together, the expenditure interaction does not change, while the stock interaction stays at zero. The honest summary is therefore not "digitalization substitutes for human capital", but the dividend is independent of the skill stock and concentrated where the fiscal input to education is thin. This interpretation carries fewer concerning implications for policy. Digitalization does not devalue skills. The pattern is consistent with digital channels partially standing in for public education spending at the margin, plausibly by lowering the cost of information diffusion and skill acquisition outside formal channels. Two fiscal mechanisms could generate this pattern, and our design does not separate them. Low education spending may serve as a proxy for smaller overall fiscal capacity, in which case the digital dividend is largest where the public sector has limited capacity to invest and digital channels relieve a binding constraint. Or it may reflect direct budget reallocation within a given fiscal envelope, in which case the interaction captures a substitution choice that governments actively make. Distinguishing the two requires conditioning the interaction on general government size or fiscal headroom, an extension we flag for future work, since the potential confounding role of overall fiscal capacity would temper the reallocation interpretation without overturning the expenditure-margin result itself. The substitution interpretation should not be extrapolated to low-income settings (in the global panel, the education interaction is negative in every income class, though statistically significant only in the upper-middle-income group) because absorptive-capacity constraints at much lower education levels may reassert complementarity below the range observed here. The firm-level evidence points in the same direction. Within the EU, the eco-innovation returns to national digitalization accrue disproportionately to firms with stronger internal absorptive capabilities (Mansour et al., 2026). Absorptive capacity conditions the dividend at the micro level just as education spending conditions it here at the macro level, though in our high-schooling sample the aggregate margin points toward substitution rather than complementarity.

The convergence hypothesis (H4) is not supported for the composite index, and the null is itself a finding. With the extended, multidimensional DEI and real income, the catching-up interaction is insignificant under the two-way structure ($\theta 3 = -0.022$, SE = 0.027) and

negative under country fixed effects (-0.047, $p < 0.05$). The comparison localizes the convergence mechanism (infrastructure and usage accumulate at broadly similar within-country rates in mature and catching-up economies), and mature economies appear to convert that accumulation into real income somewhat more effectively, while what differentiates the catching-up group is integration into digital trade, the participation dimension. Estimating the moderation model separately on the three sub-dimensions reinforces this decomposition. The infrastructure dimension carries both moderations (interaction with credit -0.022, $p < 0.05$; with education spending -0.026, $p < 0.01$), usage shows the same pattern more weakly (-0.018 and -0.021, $p < 0.10$), and the trade-participation dimension moderates through neither channel; its role is confined to the convergence margin, exactly where the composite-index evidence locates it. For the EU candidates, which occupy the lower tail of the DEI distribution (Albania at -1.7 to Montenegro at -0.3 standard deviations), the policy content is concrete. The convergence lever is not connectivity alone, which is already converging, but participation in digital goods and services trade. Regional evidence reinforces this reading; in Balkan economies, fintech adoption (a participation channel) rather than infrastructure endowment differentiates digital economy development (Radulović & Jovović, 2025). A suspicious reader might argue that the zero interaction reflects the small sample size rather than a true absence of large-scale convergence. We cannot rule out this possibility, and the 2012–2022 period, which yields the same zero result, only partially addresses this issue.

5.2. Interpreting the Three Core Findings

Three results reshape how we should read the digital-economy-growth relationship for advanced and near-advanced economies. First, in the two-way fixed-effects specification, the unconditional DEI coefficient is not statistically distinguishable from zero at the sample-mean values of the moderators, while the marginal effect analysis shows positive and statistically significant associations at lower levels of financial depth and education expenditure. Within-country digital deepening is robustly growth-positive when countries are compared with their own trajectories. This reconciles the broad positive association reported in cross-sectional work (Endres & Steula, 2024; Lv et al., 2024; Öztürk & Ullah, 2022; Sarsar & Echaoui, 2026) and the conditional, long-run-only effects found in the few DEI-growth studies available (Hwang, 2023; Sari & Nasrudin, 2022) with the more skeptical within-country evidence. Much of the cross-sectional association reflects fixed country characteristics and common global trends, especially the post-2020 digital surge, and the two-way structure absorbs precisely that component. With a multidimensional index whose infrastructure and usage components trend smoothly worldwide, year effects mechanically absorb more of the digital variation. The country-fixed-effects estimate identifies the component relevant for a country deciding whether to accelerate its own digitalization.

Second, the growth effect of the digital economy is conditional, but not in the direction the complementarity literature predicts. The negative DEI × human capital investment interaction and the marginal-effect profile in Figure 5 imply that the digital dividend is largest where education spending is lowest. One interpretation is that, among already-advanced economies with high baseline schooling, the evidence is consistent with a moderating effect at the public education-expenditure margin (this does not establish substitution between digital investment and human-capital formation). Where formal education investment is comparatively low, digitally mediated diffusion of skills, information, and market access may provide a larger incremental growth boost. By contrast, where education spending is already high, the marginal complementarity may be exhausted. This aligns with absorptive-capacity theory, given the sample's high baseline education levels, and complements evidence that digital transformation and human capital can act as partial

substitutes in specific institutional settings (Ali & Akhtar, 2023; Zhang et al., 2025a). The pattern generalizes in sign (the education interaction is negative in every World Bank income class in the global external-validity panel) but reaches statistical significance only in the upper-middle-income group, so the generalization is directional rather than uniform.

Third, the finance results contrast with the modest complementarity reported for trade-side digital measures; with the multidimensional DEI, the moderation is negative and significant, and the digital dividend is smallest where private credit is most abundant. Combined with the negative direct credit effect, this deepens the "too much finance" reading (Arcand et al., 2015), echoed in (Azmeh & Al-Raeei, 2025; G. Xu, 2025). In credit-saturated economies, further financial depth neither adds growth directly nor amplifies the returns to digital deepening. The global panel sharpens the interpretation. The negative moderation is significant only among high-income economies (upper-middle-income economies show the same negative sign without significance), while in both middle-income groups the interaction is statistically indistinguishable from zero, which is consistent with the substitution setting in only as financial systems mature and deepen, though the global panel can neither confirm nor reject complementarity at lower income levels. Convergence, in turn, is suggestive rather than established. The composite index interaction with the catching-up indicator is not significant, and the evidence that the premium attaches to digital-trade participation comes from the original trade-based index and the sub-dimension analysis rather than from a significant interaction in the headline specification. We therefore read the digital-trade convergence channel as a hypothesis our data are consistent with (echoed in regional evidence that participation-side adoption, not infrastructure endowment, differentiates digital development among the Balkan economies (Radulović & Jovović, 2025)) not as a demonstrated premium. The overall picture is not that digitalization fails to matter but that its returns are concentrated where the traditional engines of growth (deep finance, high education spending) are weaker.

5.3. Policy Implications

These findings carry concrete implications for aligning digital, financial, and education strategy with SDGs 8 and 9. For catching-up economies (including the EU candidate countries, which occupy the lower tail of the DEI distribution) and for economies with comparatively low education spending, targeted digital economy investment offers a relatively high growth return and can serve as a convergence lever. The evidence that this premium operates specifically through integration into digital trade is suggestive (Section 5.2) and should be read as a working hypothesis for the policy design rather than a demonstrated premium. This aligns digital economy policy for the candidate countries with emerging regional evidence that participation-side channels such as fintech adoption, rather than connectivity alone, drive digital economy development in the Balkans (Radulović & Jovović, 2025). For mature, high-education OECD members with deep financial systems, the marginal growth return to further digital volume is smaller, implying that digital strategy there should emphasize the quality and diffusion of digital technologies and their complementarity with national innovation systems, rather than volume alone.

The results also caution against a common assumption in national digital strategies that investment in digitalization and education investment are automatically complementary. In advanced economies, the two may compete at the margin for the same fiscal envelope, and the evidence here suggests that the growth-maximizing mix is context-dependent. Where education spending is already high, additional digital investment adds relatively little, whereas where it is lower, the measured association suggests a higher marginal return to digital investment. Sequencing therefore matters, and blanket policy recommendations that treat digitalization as universally beneficial are likely to misallocate resources. For the

EU-enlargement and OECD-accession agenda specifically, the concentration of the digital dividend where credit and education spending are below average supports prioritizing digital-capacity building in candidate and partner economies. At the same time, the results provide suggestive evidence of heterogeneity in the participation-side digital channel among catching-up economies without establishing a statistically significant convergence premium for the composite DEI. The expenditure-margin finding sharpens this caution because the moderation operates on the fiscal input rather than the skill stock; recommending a reallocation from education budgets toward digital investment would overstate what the data establish, especially where fiscal space is tightest. Yet the absence of a significant interaction with the skill stock is consistent with skills themselves remaining productive, so any potential substitution may be limited to the diffusion-and-access functions of education spending, rather than human capital formation itself.

5.4. Limitations

Several limitations constrain interpretation and point to directions for future research. Although the extended DEI now covers participation, infrastructure, and usage, some dimensions of the digital economy remain unmeasured at annual frequency. Digital-payment adoption (Global Findex) is surveyed only triennially, and composite government-digitalization measures (Digital Adoption Index, GovTech Maturity Index) are not produced annually, so they could not enter the index. Incorporating them as they become available would further broaden construct validity. The within-estimator identifies short-run, within-country variation over a nine-year window rather than long-run structural effects, and potential endogeneity of the digital economy is addressed primarily through the shift-share instrumental-variable strategy (Table A7), while dynamic specifications are treated as complementary robustness exercises because the Anderson–Hsiao first-stage instrument is weak in this short panel, as credible external instruments for digitalization at the country-year level remain elusive. Longer panels would sharpen the dynamic evidence. A further constraint relates to how comparable the data remain across the DEI literature because composite digital economy indices differ in components, weighting, and geographic scale (from entropy-weighted sub-national systems (D. Bai et al., 2024; Y. Xu & Li, 2022) to remote-sensing proxies (Z. Chen et al., 2022; Y. Chen et al., 2024)), coefficient magnitudes are not directly transferable across studies, and comparisons should be made at the level of qualitative patterns (sign, conditionality, channel) rather than point estimates. Third among these, the human-capital moderator is measured by government education expenditure, a fiscal flow, not a skill stock. The tertiary-enrollment robustness check (Table A6) resolves the sharpest version of this concern. We find no significant interaction with the stock proxy, while the expenditure interaction survives their joint inclusion. This locates the measured moderation on the expenditure margin. It does not rule out a moderating role of skills that a single enrollment-based proxy may fail to capture. One final consideration remains, however. Gross enrollment is an imperfect stock measure (it captures current flows into tertiary education rather than the accumulated attainment of the workforce), so replication with Barro–Lee means years of schooling (Barro & Lee, 2013) or the World Bank Human Capital Index would further strengthen this interpretation. Finally, while the key moderation results replicate in a 138-country global panel, the primary sample is deliberately policy-defined (OECD, accession, enlargement), so the magnitudes reported here are most directly informative for that sample. A further measurement limitation concerns the financial moderator. Private credit to GDP captures aggregate depth, not the allocation of credit to digital investment or the penetration of digital finance. The depth-gradient evidence (Table A10) supports the "too much finance" reading at the aggregate margin, but the allocation mechanism behind it (whether saturated credit systems misallocate the marginal

unit of finance away from high-payoff digital projects) cannot be identified with these data. Fund-flow and digital finance measures such as the Global Findex digital-payment indicators or the IMF Financial Access Survey are available only in multiyear waves. As their coverage accumulates, replicating the moderation with a digital-finance penetration measure is a direct extension.

6. Conclusions

This study examined whether the digital economy raises the level of real GDP per capita (the "growth" outcome, understood in the within-country, income-level sense defined in Section 3.2) and how financial development and human-capital investment moderate that relationship. The sample covers 58 OECD, partner, and EU candidate economies over the period 2014–2022. We used a three-dimensional Digital Economy Index (DEI) that covers participation, infrastructure, and usage. The baseline index uses Z-score aggregation, and a principal-component analysis (PCA) variant serves as a robustness check. We estimated two-way fixed-effects panel models of real GDP per capita (constant 2015 US$). At sample-mean values of the moderators, the DEI coefficient is not statistically distinguishable from zero under two-way fixed effects, although the marginal effect is positive and significant at below-average levels of financial depth and education spending. Within-country digital deepening, by contrast, is robustly growth-positive. The digital dividend is smallest where private credit is most abundant and largest where education spending is lowest. The education result reflects an expenditure-margin effect: a tertiary-enrollment stock proxy does not moderate the relationship. This conditional pattern survives lagged-regressor timing checks and alternative definitions of the dependent variable. The returns to digitalization are real but conditional, concentrated where the traditional engines of growth (financial depth and education spending) are weaker. On convergence, the evidence does not support H4 for the composite index. The DEI × catching-up interaction is not statistically significant in the baseline specification. The sub-dimension analysis links any catching-up heterogeneity to digital-trade participation rather than to infrastructure accumulation, but this evidence remains suggestive.

The study makes three contributions. Empirically, using a policy-relevant panel that spans the OECD, its accession candidates and key partners, and the EU candidate economies, it documents that the digital economy's growth effect is conditional rather than automatic. This fills a gap in the literature on digital economy indices. That literature is rich in sub-national and sectoral applications (Hwang, 2023; Mansour et al., 2026; Sari & Nasrudin, 2022) but, to our knowledge, has not yet tested a composite digital economy index against aggregate growth, under an explicit moderation design, on a broad cross-country panel. Methodologically, the study develops a transparent three-dimensional composite index of the digital economy, validated against a PCA variant, and embeds it in an explicit moderation design with layered robustness checks. These checks cover fixed-effects structures, aggregation methods, sample windows, and a global external-validity panel. We report one sensitivity explicitly: the results do not survive country-specific linear trends, which, with $T = 9$, absorb most of the within-country variation in the index itself. The robustness claim is therefore bounded by this limit rather than universal (Section 3.4, Table A11). Future research should incorporate measures of digital payments and government digitalization as annual data coverage improves. It should also use stronger instrumental variables to identify the dynamics of the relationship between digitalization and growth. Future research should incorporate digital-payment and government-digitalization measures as annual coverage becomes available and bring stronger instruments to bear on the dynamics of the digital–growth relationship. Subject to those extensions, the central message is robust. The benefits of the digital economy are real, but they may vary across countries, regions, sectors,

and social groups. Therefore, we argue that policies that treat these benefits as uniform will misjudge both their scope and their location.

Author Contributions: R.B.—conceptualization and revising the text, B.M.—methodology, R.Ș.—formal analysis and writing the initial draft. All authors have read and agreed to the published version of the manuscript.

Funding: This research did not receive any external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this article are freely available on the World Bank's World Development Indicators website. The variable descriptions and basis code can be obtained from the authors upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

OECD	Organization for Economic Co-operation and Development
DEI	Digital Economy Index
GDP	Gross Domestic Product
SDG	Sustainable Development Goal
PPP	Purchasing Power Parity
DESI	Digital Economy and Society Index

Appendix A. Robustness Tables

Table A1. PPP variant, fixed-effects estimates, dependent variable ln GDP per capita, PPP (current international $), two-way fixed effects, 2014–2022.

Variable	M1	M2	M3	M4	M5
Digital economy (DEI)	0.003 (0.025)	0.009 (0.026)	−0.002 (0.025)	−0.017 (0.024)	−0.022 (0.028)
Financial development	−0.064 ** (0.026)	−0.054 ** (0.027)	−0.072 *** (0.019)	−0.072 *** (0.018)	−0.071 *** (0.018)
Human-capital investment	−0.032 (0.027)	−0.040 (0.028)	−0.027 (0.025)	−0.032 (0.022)	−0.032 (0.022)
Labor force (log)	−1.159 ** (0.453)	−0.930 ** (0.430)	−0.770 ** (0.374)	−0.673 * (0.359)	−0.672 * (0.357)
Agriculture (% GDP)		−0.107 *** (0.036)	−0.103 *** (0.035)	−0.113 *** (0.033)	−0.112 *** (0.033)
Rural population (%)		0.105 * (0.062)	0.035 (0.078)	0.086 (0.074)	0.092 (0.086)
DEI × Financial development			−0.038 *** (0.012)	−0.032 *** (0.011)	−0.032 *** (0.012)
DEI × Human-capital investment				−0.025 *** (0.009)	−0.025 ** (0.010)
DEI × Catching-up					0.006 (0.030)
Observations	446	446	446	446	446
Within R2	0.208	0.257	0.368	0.407	0.407

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Significance based on standard errors clustered by country.

Table A2. Lagged-regressor specification. All regressors at t − 1, dependent variable ln real GDP per capita (constant 2015 US$), 2014–2022.

Variable	Two-way FE	Country FE
DEI (t − 1)	−0.007 (0.019)	0.076 *** (0.013)
Financial development (t − 1)	−0.049 *** (0.015)	−0.035 ** (0.016)
Human-capital investment (t − 1)	−0.030 ** (0.012)	−0.021 (0.013)
Labor force, log (t − 1)	−0.130 (0.248)	0.207 (0.290)
Agriculture (t − 1)	−0.136 *** (0.019)	−0.126 *** (0.020)
Rural population (t − 1)	0.056 (0.057)	0.023 (0.069)
DEI × Financial dev. (t − 1)	−0.018 * (0.009)	−0.020 * (0.011)
DEI × HC investment (t − 1)	−0.030 *** (0.010)	−0.020 ** (0.010)
Observations	446	446
Within R2	0.364	0.561

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Significance based on standard errors clustered by country.

Table A3. Fixed-effects at the country level only (excluding year effects), with the dependent variable being ln GDP per capita denominated in US dollars constant 2015 prices, for 2014–2022 period.

Variable	M1	M2	M3	M4	M5
Digital economy (DEI)	0.089 *** (0.015)	0.085 *** (0.014)	0.076 *** (0.013)	0.072 *** (0.012)	0.096 *** (0.016)
Financial development	−0.034 * (0.020)	−0.025 (0.019)	−0.037 ** (0.016)	−0.035 ** (0.014)	−0.047 *** (0.013)
Human-capital investment	−0.029 * (0.017)	−0.031 * (0.017)	−0.022 (0.015)	−0.025 * (0.013)	−0.025 ** (0.012)
Labor force (log)	0.123 (0.275)	0.347 (0.234)	0.429 ** (0.205)	0.552 *** (0.189)	0.425 * (0.216)
Agriculture (% GDP)		−0.165 *** (0.028)	−0.161 *** (0.029)	−0.169 *** (0.026)	−0.171 *** (0.027)
Rural population (%)		0.056 (0.083)	0.011 (0.056)	0.057 (0.058)	0.014 (0.053)
DEI × Financial development			−0.025 ** (0.010)	−0.020 ** (0.010)	−0.022 ** (0.009)
DEI × Human-capital investment				−0.023 *** (0.008)	−0.027 *** (0.008)
DEI × Catching-up					−0.047 ** (0.022)
Observations	446	446	446	446	446
Within R2	0.514	0.587	0.621	0.644	0.666

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Significance based on standard errors clustered by country.

Table A4. Anderson–Hsiao dynamic panel, first differences, lagged dependent variable instrumented by its second lag; year dummies included; clustered (country) standard errors.

Variable	Coefficient	Clustered SE
Lagged Δln GDPpc	−0.022	(0.254)
ΔDEI	−0.026 **	(0.012)
ΔCredit	−0.018	(0.019)
ΔEduc	0.061 ***	(0.007)
ΔlnLabor	−0.128	(0.238)
ΔAgri	−0.083 **	(0.033)
ΔRural	−0.018	(0.020)
Δ(DEI × Credit)	−0.041 ***	(0.007)
Δ(DEI × Educ)	0.038 ***	(0.004)
Observations	382	
Countries	54	
First-stage F (y, t − 2)	4.5	weak instrument

Notes: *** $p < 0.01$, ** $p < 0.05$. Significance based on standard errors clustered by country.

Table A5. Global panel by World Bank income class, specification M4, two-way fixed effects, dependent variable ln real GDP per capita (constant 2015 US$), 2014–2022.

Variable	Lower Middle	Upper Middle	High
Digital economy (DEI)	0.017 (0.053)	0.023 (0.039)	0.121 *** (0.039)
DEI × Financial development	−0.007 (0.048)	0.004 (0.017)	−0.016 ** (0.008)
DEI × Human-capital investment	−0.022 (0.019)	−0.073 *** (0.022)	−0.032 (0.026)
Observations	323	366	402
Countries	43	45	54
Within R2	0.199	0.285	0.304

Notes: *** $p < 0.01$, ** $p < 0.05$. Grouped standard errors, by country, are shown in brackets. Table A4's first-stage F statistic (4.5) is below conventional thresholds, so the dynamic estimates (including the first-differenced interaction coefficients, whose signs (e.g., the positive Δ(DEI × education)) reverse the fixed-effects results) are reported for completeness rather than inference and should not be read against the static evidence. The paper's casual identification rests on the shift-share instrumental-variable design of Table A7.

Table A6. Human-capital proxy check, tertiary school enrollment (stock) replacing and competing with education expenditure (flow); dependent variable ln real GDP per capita (constant 2015 US$), 2014–2022.

Variable	Stock, Two-Way FE	Stock, Country FE	Competitive Model Specification, Two-Way FE	Competitive Model Specification, Country FE
Digital economy (DEI)	0.063 ** (0.027)	0.086 *** (0.014)	0.027 (0.025)	0.080 *** (0.014)
DEI × Financial development	−0.019 (0.014)	−0.023 * (0.012)	−0.020 * (0.011)	−0.024 ** (0.011)
DEI × Human capital (spending flow)			−0.026 *** (0.010)	−0.027 *** (0.008)
DEI × Human capital (tertiary stock)	0.008 (0.016)	0.012 (0.013)	0.009 (0.015)	0.018 (0.011)
Observations	486	486	430	430
Within R2	0.255	0.623	0.373	0.666

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Grouped standard errors, by country, are shown in brackets. Competitive model specification includes both human-capital interactions simultaneously. The lagged variant of the stock check gives DEI × tertiary (t − 1) = 0.000 (0.016).

Table A7. Shift-share instrumental-variable estimates. DEI and both interactions instrumented by pre-sample (2012) digital position × leave-one-out global DEI trend and its moderator interactions; dependent variable ln real GDP per capita (constant 2015 US$), 2014–2022; clustered (country) standard errors.

Variable	Two-Way FE (2SLS)	Country FE (2SLS)
Digital economy (DEI)	−0.029 (0.034)	0.039 ** (0.019)
DEI × Financial development	−0.018 * (0.011)	−0.035 *** (0.012)
DEI × Human-capital investment	−0.049 ** (0.021)	−0.038 (0.027)
First-stage partial F (DEI/DEI × Fin/DEI × HC)	137.3/121.1/76.9	104.5/169.9/74.8
Observations	446	446

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. First-stage partial F statistics from the first-stage regressions of each endogenous variable on the instrument set and exogenous controls.

Table A8. Alternative weighting schemes for the Digital Economy Index. Equal weights within dimensions (baseline), entropy weighting over the six indicators, and a multicomponent PCA composite (first four components, 93% of total variance, weighted by variance shares); specification M4, dependent variable ln real GDP per capita (constant 2015 US$), 2014–2022.

Variable	Equal Weights, Two-Way FE	Equal Weights, Country FE	Entropy, Two-Way FE	Entropy, Country FE	Multi-PC, Two-Way FE	Multi-PC, Country FE
Digital economy index	0.018 (0.018)	0.072 *** (0.012)	0.016 (0.022)	0.076 *** (0.013)	0.010 (0.031)	0.107 *** (0.017)
Index × Financial development	−0.017 * (0.010)	−0.020 ** (0.010)	−0.025 * (0.015)	−0.016 (0.013)	−0.023 * (0.013)	−0.026 * (0.014)
Index × Human-capital investment	−0.025 ** (0.010)	−0.023 *** (0.008)	−0.024 *** (0.009)	−0.029 *** (0.007)	−0.027 *** (0.010)	−0.019 ** (0.008)
Observations	446	446	440	440	440	440

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; clustered (country) standard errors in parentheses. Pairwise correlations with the baseline index: entropy 0.78, multi-PC 0.81.

Table A9. Control-variable parsimony check: specification M4 re-estimated dropping structural controls singly and jointly; two-way fixed effects, dependent variable ln real GDP per capita (constant 2015 US$), 2014–2022; clustered (country) standard errors.

Specification	DEI	DEI × Fin. dev.	DEI × HC inv.	N	Within R2
Full (baseline M4)	0.018 (0.018)	−0.017 * (0.010)	−0.025 ** (0.010)	446	0.353
Drop rural	0.014 (0.018)	−0.019 * (0.010)	−0.023 ** (0.010)	446	0.343
Drop agriculture	0.018 (0.018)	−0.018 * (0.011)	−0.022 ** (0.011)	446	0.262
Drop both structural	0.016 (0.018)	−0.019 * (0.010)	−0.021 * (0.011)	446	0.258
Moderators only	0.020 (0.017)	−0.021 * (0.010)	−0.022 ** (0.011)	446	0.244

Notes: $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Variance inflation factors in the full model: at most 2.5 (raw), at most 1.3 (within-transformed).

Table A10. Marginal effect of the DEI conditional on financial depth (specification M4): delta-method marginal effects and t statistics at percentiles of the private-credit distribution; dependent variable ln real GDP per capita (constant 2015 US$), 2014–2022.

Credit Percentile	Marginal Effect, Two-Way FE	Marginal Effect, Country FE
p5 (29% of GDP)	0.038 (t = 1.85)	0.096 (t = 5.55)
p25 (48% of GDP)	0.031 (t = 1.65)	0.087 (t = 5.95)
p50 (68% of GDP)	0.024 (t = 1.33)	0.079 (t = 6.07)
p75 (112% of GDP)	0.008 (t = 0.40)	0.059 (t = 4.26)
p95 (164% of GDP)	−0.011 (t = −0.45)	0.037 (t = 1.72)

Notes: Marginal effects computed as $\partial \ln GDPpc/\partial DEI = \beta 1 + \theta 1 \cdot credit$ at the indicated percentile of the standardized credit distribution; clustered (country) covariance.

Table A11. Validation of the shift-share instrument: pre-trend placebo, permutation inference (500 random exposure reassignments), and country-specific linear trends.

Exercise	Result	Reading
Pre-trend (placebo): 2012 exposure → pre-window growth 2012–2014, bivariate	−0.010 ($t = -2.08$)	Level convergence, absorbed by country FE
Pre-trend (placebo): with 2012 controls incl. initial income	0.005 ($t = 0.50$, $p = 0.62$)	No conditional pre-trend
Permutation (500 draws): first-stage F, true vs. shuffled exposure	True F = 277 vs. placebo median 2.9; $p < 0.002$	Relevance is specific to the true exposure ordering
Permutation (500 draws): reduced-form interactions	$p = 0.41$–0.43	Permutation inference does not sharpen the moderation beyond clustered inference
Country-specific linear trends: within-country R2 of DEI on trend	median 0.93; trends absorb 95% of within variance	Treatment variation is trend-shaped at T = 9
Country-specific linear trends: M4 moderation coefficients	≈0 (n.s.); IV first-stage F for DEI falls to 2.1	Exercise uninformative: trends absorb the treatment and the instrument, not only confounds

Notes: Pre-trend regressions are cross-sectional (N = 43, limited by 2012 education-expenditure coverage) with heteroskedasticity-robust standard errors. Permutation *p*-values are two-sided shares of placebo draws exceeding the true statistic in absolute value. The country-trend row records a sensitivity, not a validation: at T = 9 country-specific linear trends remove the treatment together with potential confounds, so the elimination of the effects under trends bounds the robustness claim rather than contradicting the design (see Section 3.4). n.s. = not significant at conventional levels ($p > 0.10$).

Table A12. Two-step system GMM (Blundell–Bond), collapsed instrument matrix, dependent variable ln real GDP per capita (constant 2015 US$), 2015–2022. Windmeijer-corrected standard errors in parentheses.

Variable	Coefficient	Corrected SE	z
ln GDP per capita (t − 1)	0.835 ***	(0.196)	4.25
Digital economy (DEI)	0.093	(0.175)	0.53
Financial development	0.077 *	(0.045)	1.70
Human-capital investment	−0.019	(0.053)	−0.36
Labor force (log)	−0.035	(0.105)	−0.34
Agriculture (% GDP)	−0.109	(0.166)	−0.66

Table A12. *Cont.*

Variable	Coefficient	Corrected SE	z
Rural population (%)	−0.077	(0.076)	−1.01
DEI × Financial development	−0.023	(0.054)	−0.42
DEI × Human-capital investment	0.031	(0.047)	0.66
Year dummies	Yes		
Observations	322		
Countries	54		
Instruments (collapsed)	25		
Hansen test (p)	3.46 (0.90)		
AR(1)/AR(2) (p)	0.002/0.418		

Notes: *** $p < 0.01$, * $p < 0.10$. GMM-style instruments: lags 2–3 of the dependent variable, the DEI, and both interactions (collapsed); standard instruments with the exogenous controls and year dummies. The Hansen test does not reject the over-identifying restrictions ($p = 0.90$) and AR(2) shows no residual second-order autocorrelation ($p = 0.42$); estimates are imprecise at T = 9 and are reported as complementary evidence to the fixed-effects and instrumental-variable results (Tables 4 and A7).

References

Agrawal, S., Jain, V., & Verma, H. (2024). Navigating the circular transition: The pivotal role of dynamic capabilities in enabling circular business models and firm performance. *Circular Economy and Sustainability*, *5*(2), 751–775. [CrossRef]

Ali, L., & Akhtar, N. (2023). The effectiveness of export, FDI, human capital, and R&D on total factor productivity growth: The case of Pakistan. *Journal of the Knowledge Economy*, *15*(1), 3085–3099. [CrossRef]

Anwar, A., Malik, S., & Ahmad, P. (2022). Cogitating the role of technological innovation and institutional quality in formulating the sustainable development goal policies for E7 countries: Evidence from quantile regression. *Global Business Review*, *26*(6), 1532–1555. [CrossRef]

Arcand, J.-L., Berkes, E., & Panizza, U. (2015). Too much finance? *Journal of Economic Growth*, *20*(2), 105–148. [CrossRef]

Azmeh, C., & Al-Raeei, M. (2025). Financial development, research in finance, and economic growth. *Cogent Economics & Finance*, *13*(1), 2448220. [CrossRef]

Bai, C., Du, X., & Chua, S. (2025). The green potential of the digital economy in balancing economic growth and carbon emissions. *Scientific Reports*, *15*(1), 19365. [CrossRef]

Bai, D., Li, M., Wang, Y., Mallek, S., & Shahzad, U. (2024). Impact mechanisms and spatial and temporal evolution of digital economy and green innovation: A perspective based on regional collaboration within urban agglomerations. *Technological Forecasting and Social Change*, *207*, 123613. [CrossRef]

Barro, R., & Lee, J.-W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, *104*, 184–198. [CrossRef]

Bataka, H., & Ossadzifo, W. (2023). How ICTs moderate the effect of global value chains' participation on economic growth in Sub-Saharan Africa? *International Economic Journal*, *37*(2), 324–357. [CrossRef]

Castells, M. (2009). *The rise of the network society*. Willey. [CrossRef]

Chakravorti, B., Tunnard, C., & Chaturvedi, R. (2015, February 19). Where the digital economy is moving the fastest. *Harvard Business Review*. Available online: https://hbr.org/2015/02/where-the-digital-economy-is-moving-the-fastest (accessed on 23 August 2026).

Chang, X., & Li, J. (2022). Effects of the digital economy on carbon emissions in China: A spatial Durbin econometric analysis. *Sustainability*, *14*(24), 16624. [CrossRef]

Chen, J., & Xu, Z. (2024). The impact of the digital divide on labor mobility and sustainable development in the digital economy. *Sustainability*, *16*(22), 9944. [CrossRef]

Chen, Y., Wang, L., Yu, P., & Cheng, C. (2024). Linkages between digital economy and ecosystem services: Revealing the spatiotemporal relationship based on U-shaped effect. *Technological Forecasting and Social Change*, *207*, 123601. [CrossRef]

Chen, Z., Wei, Y., Shi, K., Zhao, Z., Wang, C., Wu, B., Qiu, B., & Yu, B. (2022). The potential of nighttime light remote sensing data to evaluate the development of digital economy: A case study of China at the city level. *Computers, Environment and Urban Systems*, *92*, 101749. [CrossRef]

Deka, A. (2024). The role of natural resources rent, trade openness and technological innovations on environmental sustainability—Evidence from resource-rich African nations. *Resources Policy*, *98*, 105364. [CrossRef]

Endres, J., & Steula, M. (2024). The impact of fixed and mobile broadband adoption on economic growth. *Journal of Telecommunications and the Digital Economy*, *12*(4), 20–44. [CrossRef]

European Commission. (2022). *Digital economy and society index (DESI), methodological note*. Directorate-General for Communications Networks, Content and Technology. Available online: https://digital-strategy.ec.europa.eu/en/library/digital-economy-and-society-index-desi-2022 (accessed on 23 August 2026).

Fatimah, Y., Kannan, D., Govindan, K., & Hasibuan, Z. (2023). Circular economy e-business model portfolio development for e-business applications: Impacts on ESG and sustainability performance. *Journal of Cleaner Production*, *415*, 137528. [CrossRef]

Gao, L., & Wen, H. (2025). Digital economy and environmental sustainability: Analysis of cross-country coordination. *Sustainability*, *17*(5), 1840. [CrossRef]

Ghazal Masri, S., & El-Fadel, M. (2026). Governance of digital transformation for sustainable development: Aligning digital innovation with the sustainable development goals. *Frontiers in Sustainable Cities*, *8*, 1743552. [CrossRef]

Guandalini, I. (2022). Sustainability through digital transformation: A systematic literature review for research guidance. *Journal of Business Research*, *148*, 456–471. [CrossRef]

Horobeț, A., Dalu, M., Marinescu, I., Belaşcu, L., Dumitrescu, S., & Kostakis, I. (2025). Financial inclusion, technology, and income inequality in Europe. *Amfiteatru Economic*, *27*(68), 93–110. [CrossRef]

Hu, S., & Liu, D. (2025). Digital economy, financial literacy, and financial risk-taking in rural households. *International Review of Economics and Finance*, *98*, 103922. [CrossRef]

Hwang, Y. (2023). The synergy effect through combination of the digital economy and transition to renewable energy on green economic growth: Empirical study of 18 Latin American and Caribbean countries. *Journal of Cleaner Production*, *148*, 138146. [CrossRef]

Ibrahim, R., Alomair, A., & Al Naim, A. (2024). How financial development heterogeneity, macroeconomic volatility, domestic investment, and digital economy are driving sustainable economic growth in Africa. *Sustainability*, *16*(21), 9281. [CrossRef]

King, R., & Levine, R. (1993). Finance and growth: Schumpeter might be right. *Quarterly Journal of Economics*, *108*(3), 717–737. [CrossRef]

Kiraci, A., & Mansour, F. (2026). The spatial effects of digital finance: Implications for economic growth, regional development, and financial inclusion. *International Econometric Review*, *17*(2), 52–78. [CrossRef]

Kumar, S., & Shah, P. (2025). Digital ESG as a catalyst for achieving the sustainable development goals: A systematic review and bibliometric analysis of digital transformation for a resilient future. *Sustainable Futures*, *10*, 101458. [CrossRef]

Lan, Q., & Tang, W. (2023). Research on the impact of digital economy on industrial green total factor productivity—Analysis based on Chinese provinces. *Economic Research-Ekonomska Istraživanja*, *36*(3), 2271033. [CrossRef]

Li, H., Han, J., & Xu, Y. (2023). The effect of the digital economy on services exports competitiveness and ternary margins. *Telecommunications Policy*, *47*(7), 102596. [CrossRef]

Liao, L., Qin, X., Li, X., & Gong, L. (2023). Creative destruction, human capital accumulation, and growth in a digital economy. *Macroeconomic Dynamics*, *28*(5), 1206–1230. [CrossRef]

Lu, J., Chuah, S.-C., Xia, D.-M., & Gary, J. (2025). The development of the modern logistics industry and its role in promoting regional economic growth in China's underdeveloped northwest, driven by the digital economy. *Economies*, *13*(9), 261. [CrossRef]

Lv, J., Li, S., Zhu, M., & Huang, W. (2024). Can the digital economy development limit the size of the informal economy? A nonlinear analysis based on China's provincial panel data. *Economic Analysis and Policy*, *83*, 896–921. [CrossRef]

Magazzino, C., Laureti, L., Costantiello, A., Leogrande, A., & Gattone, T. (2025). Innovating trade: How high-tech exports, ICT services and R&D expenditure shape global trade patterns with advanced machine learning insights. *Journal of Economic Studies*, *52*(9), 193–214. [CrossRef]

Mansour, M., Saleh, M., Jaradat, Z., AL-Hawamleh, A., Al Zobi, M., & Marei, A. (2026). Digital economy development and firm level sustainability performance in Europe. *Discover Sustainability*, *7*, 322. [CrossRef]

Mohamed, M., Liu, P., & Nie, G. (2022). Do knowledge economy indicators affect economic growth? Evidence from developing countries. *Sustainability*, *14*(8), 4774. [CrossRef]

Nelson, R., & Phelps, E. (1966). Investment in humans, technological diffusion, and economic growth. *American Economic Review*, *56*(1/2), 69–75. Available online: https://www.jstor.org/stable/1821269 (accessed on 23 August 2026).

OECD & European Commission Joint Research Centre. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. OECD Publishing. Available online: https://www.oecd.org/en/publications/handbook-on-constructing-composite-indicators-methodology-and-user-guide_9789264043466-en.html (accessed on 23 August 2026).

Öztürk, İ., & Ullah, S. (2022). Does digital financial inclusion matter for economic growth and environmental sustainability in OBRI economies? An empirical analysis. *Resources Conservation and Recycling*, *185*, 106489. [CrossRef]

Pietrulla, F. (2022). Private firm support for circular economy regulation in the EU policy context. *Sustainability*, *14*(14), 8427. [CrossRef]

Piscicelli, L. (2023). The sustainability impact of a digital circular economy. *Current Opinion in Environmental Sustainability*, *61*, 101251. [CrossRef]

Qin, M., Mirza, N., Su, C.-W., & Umar, M. (2023). Exploring bubbles in the digital economy: The case of China. *Global Finance Journal*, *57*, 100871. [CrossRef]

Radulović, D., & Jovović, N. (2025). Fintech as an enabler of digital economy development in the Balkan countries. *Journal of Central Banking Theory and Practice*, *14*(3), 185–203. [CrossRef]

Rusu, R., & Oprean-Stan, C. (2023). The impact of digitalisation and sustainability on inclusiveness: Inclusive growth determinants. *Economic Computation and Economic Cybernetics Studies and Research*, *57*(4), 209–224. [CrossRef]

Sari, D., & Nasrudin, N. (2022). Constructing Indonesian digital economy index in determining economic policy priorities amidst the COVID-19 pandemic. *Economics and Finance in Indonesia*, *68*(1), 62–74. Available online: https://scholarhub.ui.ac.id/efi/vol68/iss1/5 (accessed on 23 August 2026). [CrossRef]

Sarsar, L., & Echaoui, A. (2026). The moderating role of digital transformation in the effect of energy transition on economic growth: An empirical investigation using panel data of 134 countries. *Journal of the Knowledge Economy*, *17*(3), 8443–8466. [CrossRef]

Schumpeter, J. (1934). *The theory of economic development*. Harvard University Press. Available online: https://www.researchgate.net/publication/272398717_Schumpeter_JA_1934_2008_The_Theory_of_Economic_Development_An_Inquiry_into_Profits_Capital_Credit_Interest_and_the_Business_Cycle_New_Brunswick_USA_and_London_UK_Transaction_Publishers#fullTextFileContent (accessed on 23 August 2026).

Seti, T., Mazwane, S., & Christian, M. (2025). Financial openness, trade openness, and economic growth nexus: A dynamic panel analysis for emerging and developing economies. *Journal of Risk and Financial Management*, *18*(2), 78. [CrossRef]

Stavytskyy, A., Kharlamova, G., & Stoica, E. (2019). The analysis of the digital economy and society index in the EU. *Baltic Journal of European Studies*, *9*(3), 245–261. [CrossRef]

Sun, Y., & Chen, C. (2025). Digital rural construction, financial development and regional economic resilience: Mechanism analysis and empirical test. *International Review of Economics and Finance*, *101*, 104146. [CrossRef]

Tan, T.-H., Kueh, J., & Wong, S. (2022). Constructing digital economy index: Case of small open economy. *International Journal of Nonlinear Analysis and Applications*, *13*(2), 69–82. [CrossRef]

Varriale, V., Camilleri, M. A., Cammarano, A., Michelino, F., Muller, J., & Strazzullo, S. (2024). Unleashing digital transformation to achieve the sustainable development goals across multiple sectors. *Sustainable Development*, *33*(1), 565–579. [CrossRef]

Vijaya Kumar, M., & Balu, B. (2023). Estimating the impact of human capital underutilization on the productivity and economic growth in India. *Journal of the Knowledge Economy*, *15*(1), 5018–5042. [CrossRef]

Vitolla, F., L'Abate, V., Petruzzella, F., Raimo, N., & Salvi, A. (2023). Circular economy disclosure in sustainability reporting: The effect of firm characteristics. *Sustainability*, *15*(3), 2200. [CrossRef]

Wang, H., Wu, D., & Zeng, Y. (2025). Digital economy, market segmentation and carbon emission performance. *Environment, Development and Sustainability*, *27*, 23727–23751. [CrossRef]

Wang, L., Sun, Y., & Xv, D. (2023). Study on the spatial characteristics of the digital economy on urban carbon emissions. *Environmental Science and Pollution Research*, *30*(33), 80261–80278. [CrossRef]

Wang, S., Fan, J., Feng, P., & Wei, G. (2025). The impact mechanism of the digital economy on the carbon neutrality process in resource-based cities and its contribution to urban SDGs. *Environmental and Sustainability Indicators*, *27*, 100769. [CrossRef]

Wang, W., & Bai, X. (2025). Digital economy in rural areas and credit costs: Mediating role of financial inclusion. *Finance Research Letters*, *86*, 108461. [CrossRef]

Wang, X., Lee, Z., & Xie, X. (2023). Examining the impact of high technology exports on environmental sustainability? An empirical insight. *Economic Research—Ekonomska Istraživanja*, *36*(3), 2195475. [CrossRef]

World Bank. (2016). *World development report 2016: Digital dividends*. World Bank. Available online: https://www.worldbank.org/en/publication/wdr2016 (accessed on 23 August 2026).

Xiao, D. (2025). Evaluating and prioritizing strategies to reduce carbon emissions in the circular economy for environmental sustainability. *Journal of Environmental Management*, *373*, 123446. [CrossRef]

Xie, L., Qiu, Z., Chen, S., & Lei, X. (2024). Smartphone access, digital economy, and pesticide use intensity: Evidence from China. *Science of the Total Environment*, *943*, 173867. [CrossRef]

Xu, G. (2025). KIBS clustering, digital financial inclusion, and economic growth quality. *Finance Research Letters*, *72*, 106497. [CrossRef]

Xu, X., & Lei, L. (2025). Digital economic development, financial literacy and household cultural consumption. *Finance Research Letters*, *83*, 107687. [CrossRef]

Xu, Y., & Li, T. (2022). Measuring digital economy in China. *National Accounting Review*, *4*(3), 251–272. [CrossRef]

Xu, Y., Tiwari, S., Kazemzadeh, E., Ghosh, S., & Dogan, B. (2026). How does smart cities and digital economy facilitate energy security and energy transition? Empirical evidence from China. *Energy and Buildings*, *351*, 116639. [CrossRef]

Yang, F., Li, C., & Zhang, S. (2025). Digital economy and carbon emission intensity: Evidence from ASEAN. *Sustainability*, *17*(22), 10266. [CrossRef]

Yuan, H., & Zhao, L. (2026). Digital economy, financial development and regional economic resilience. *International Review of Financial Analysis*, *109*, 104767. [CrossRef]

Zhang, Y., Hainan, L., Feng, F., & Wu, X. (2025a). Digital economy, education, human capital and urban–rural income disparity. *Finance Research Letters*, *71*, 106464. [CrossRef]

Zhang, Y., Khan, S., & Wang, Y. (2025b). The future is digital: Can the digital economy drive marine sustainability? Exploring regional impacts on fisheries' carbon emissions in coastal China. *Journal of Cleaner Production*, *506*, 145518. [CrossRef]

Zheng, K., Guo, Y., Zhang, R., Wu, J., Ma, A., He, S., Huang, Y., Wang, H., Lin, S., Li, Y., & Wang, X. (2025). Impact of digital economy on residents' medical cost: An empirical analysis based on interprovincial data from China. *Frontiers in Public Health*, *13*, 1742511. [CrossRef]

Zheng, P., Li, Y., & Li, X. (2024). The impact of the digital economy on land transfer-out decisions among Chinese farmers: Evidence from CHFS micro-data. *Scientific Reports*, *14*, 19684. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.