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Digital Connectivity and Labor Productivity in Emerging Economies: The Moderating Roles of Human Capital and ICT Capability

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Abstract

The contribution of digital connectivity to productivity could also depend on the human and technological capacity to utilize the digital technological infrastructure, and this is a growing concern. The study explores the association between digital connectivity and labour productivity and assesses whether human capital and ICT capability strengthen this relationship in the six developing Asian economies in this study (namely Pakistan, India, Malaysia, the Philippines, Thailand and Indonesia) during 2005-2024. Labour productivity is calculated as GDP per labour, and digital connectivity is operationalized through using the number of fixed internet broadband subscriptions per 100 populations. Other factors that are also incorporate in the econometric framework are foreign direct investment, gross capital formation, and inflation. To control for the possibility of cross-country dependence and for the possible differential response of countries, the analysis is conducted using fixed-effects estimation with Driscoll–Kraay standard errors and a sensitivity assessment of the Common Correlated Effects Mean Group (CCE-MG) estimation. The baseline findings imply a positive and significant association between digital connectivity and worker productivity. Moreover, the interaction effects imply that this relationship is strengthened by higher levels of human capital and ICT capability, and that the productivity improvements from

having broadband connectivity are higher the stronger the complementary levels of human and technological capabilities. The CCE-MG estimates, nevertheless, do not lead to statistically significant direct and interaction effects, suggesting that the base relations are affected by unobserved shared latent factors and inter-country heterogeneity. The conclusions are accordingly a warning against thinking of broadband expansion as a standalone solution for productivity improvements. Policies designed to enhance the productivity-enhancing outcomes of digital technological infrastructure for developing economies should involve investing in connectivity, along with improving education, digital skills, ICT capability, and technological development, allowing for variations in the country-specific economic conditions.

Keywords: Digital connectivity, Labour productivity, Human capital, ICT capability, Broadband infrastructure, Emerging Asian economies, Driscoll–Kraay standard errors, Common Correlated Effects, Cross-sectional dependence

1. Introduction

Digital connectivity is to a growing extent becoming an important input for modern production as firms and workers depend on digital networks to share information, coordinate their activities, access markets, and gain knowledge. It is particularly pertinent in emerging markets, where enhancing digital technological infrastructure can play a substantive role in mitigating information frictions and create enhanced accessibility to technologies and markets. Digitalization is already having exerts an influence on on employment in emerging-market economies, but the nature of the influence varies by country and labour-market characteristics, and the stage of a country's development (Qu & Fan, 2024). In the same way, Asia has ample evidence of digitalization and innovation playing a substantive role in stimulate productivity, and worker skills, FDI and trade openness are important facilitating conditions (Khan Khan & Tariq 2025). The increasing importance of digital network connectivity in the context of understanding differences in worker-level productive output across developing economies is justified by these developments.

Nevertheless, the benefits in terms of productivity from connectivity are not guaranteed. Digital technological infrastructure can be a source of more substantial efficiency in production but is conditional upon the ability of workers and firms to employ it. The European Union recently highlighted both the correlation of digital technological infrastructure with worker-level

productive output and the correlation of technology skills with worker productivity, and the gap in the readiness of the labour force is an important determinant of the inter-country heterogeneity in worker-level productive output (Aleca & Mihai, 2025). From an intra-firm perspective, Zhou et al. (2025) conclude that technology-enabled transformation has a significant positive exerts an influence on worker productivity, such as through production management, human-resource utilisation and internal decision-making. The estimates reveal that connectivity is not just a technological input, but a condition that enables a wide range of capabilities, and the productivity association of connectivity rely on these capabilities.

The worker skills relationship to the digital network connectivity –productivity nexus is likely to be more prominent. Digital technological applications can expand the information and technological resources at the disposal of workers; nevertheless, this requires the knowledge and skills needed to use them effectively and productively. Audrin Audrin and Salamin (2024) show that there are competencies beyond the mere use of technology that are required for working in a digitalized workplace: Information Management, Communication and Critical inquiry and problem solving. In the same way, empirical studies in Indonesia show that digital technological infrastructure and access to ICTs have exerts an influence on worker productivity, and the role played by ICT skills is different for each dimension of technology skills (Wilianti et al., 2025). Consequently, variations in workforce knowledge and capabilities can help control for the fact that similar raise in connectivity can have different productivity influence in different economies.

Another problem is that of an economy's ICT capability. While connectivity is a key enabler for citizen participation in the digital economy, it does not mean that citizens have the ability to develop the connectivity infrastructure into higher value production. This separation is becoming more prominent in international digital trade. While developing economies exported over US$1 trillion in digitally deliverable services in 2023, the gains of such exports are still very unevenly distributed, due to the variation in infrastructure, technology skills, accessibility to markets and technological capabilities across economies, as reported by Varzakas and Smaoui (2024). The empirical estimates establish that countries with a more supportive ability to produce in the ICT sector might have a better chance of turning connectivity into innovation, exports of services and productivity expand.

The questions are especially pertinent in emerging Asia. Of all six economies studied, the Pakistan, India, Malaysia, Philippines, Thailand and Indonesia have gone through significant digital development, but they have varying worker skills, ICT capabilities, capital formation and linkages to international markets. The available comparative evidence has mostly analysed the direct link between digitalisation and productivity, whereas contemporary empirical studies on the level of the firm have concentrated on a specific country or firm. Less is known, nevertheless, about how the productivity exerts an influence of physical digital network connectivity relates systematically to the human and technological characteristics of developing Asian countries. It is important to note this distinction because it can provide some degree of reconciliation of the heterogeneous empirical findings of the wide range of digitalization literature.

In this regard, the current investigation focuses on six Asian emerging-market economies for the period of 2005-2024. Labour productivity is reflected in GDP per person employed, while digital network connectivity is reflectd by the number of fixed broadband subscriptions per 100 people. Worker skills and ICT capability are incorporate as part of the set of covariate, and are also incorporated as potentially complementary conditions in the form of interaction terms. To reflect important macroeconomic implication on productivity, FDI, gross capital formation and inflation are shown. The economic dependence and structural difference between countries also suggest cross sectional dependence and heterogeneous country responses, so these are also considered.

Given the nature of the study, it is more interesting to ask whether the productivity association of digital network connectivity is amplified by the economy's workforce knowledge and capabilities and ICT capability than to ask whether digital connectivity is associated with raise productivity. This is the main scientific contribution of the study. The study does not explore the digital technological infrastructure or worker skills and technology-based production capability separately, but rather combines them in the same econometric framework to investigate the complementarity between the two. In so doing, it provides comparative evidence from the emerging Asia region to examine how investment in digital network connectivity compares to generate more substantial productivity improvements, when paired with the human and technological resources necessary to realize those gains.

2. Literature Review

2.1. The ability of digital technologies to drive labour productivity

Digital connection has become an important aspect of modern production systems. Broadband networks, mobile communication and Internet access lower the costs of information and communication, ease the coordination of firms and the markets, and enable workers to access digital tools and knowledge more efficiently. The empirical findings of the last few years suggests that such changes can lead to higher productivity, but the magnitude and influence of the change are highly variable from country to country, firm to firm, and sector to sector.

The experiences of developing and emerging countries offer valuable support for the enhancing implication of ICT in terms of productivity. Vu Hanafizadeh and Bohlin (2022) find, using panel data for 98 countries including separate samples of low, middle and high-income economies, that not only do telephone subscriptions have favorable association, but so do broadband subscriptions, including in the service sector. Yong et al. (2024), for the case of developing countries and two-step system GMM and dynamic panel quantile regression, find that the link between ICT use and worker productivity is positive and that the size of the relationship is different across the productivity distribution.

The involvement of evidence from Southeast Asia is of particular significance because of its development conditions similarity with the current investigation. Using the Internet and mobile connectivity has a significant favorable association on worker productivity in developing economies of Southeast Asia, as stated by Salim et al. (2024). Their findings also reveal that workforce knowledge and capabilities continues to be a major determinant to productive efficiency, pointing to the need to take the contribution of digital technological applications as a function of worker skills as a whole. Finally, following the approach of production frontier analysis for 24 OECD countries, Fulgenzi and others (2024) conclude that ICT has had a positive association with worker-level productive output growth.

Zhang Tao and Nie (2022) use the implementation of the Broadband China strategy as a quasi-natural experiment and find that broadband network infrastructure significantly expands firm productivity. Their transmission pathway analysis suggests that the influence of broadband

network infrastructure on productivity are important through its strengthen in information development, resource deployment, innovation, and costs associated with economic exchange.

More recent research confirms similar findings and suggests large heterogeneity. Tang and Zhao (2023) find that the new digital technological infrastructure is positively associated with regional total factor productivity in China, driven by technological innovation and better allocation of productive resources and economies of scale. The firm-level evidence of Fabiani et al. (2023) also reinforces the idea that digital technology adoption can raise productivity, yet it can be either lower or higher depending on the level of digital technology and its type. Correspondingly, Li et al. (2023) discover that the connection amongst technology-enabled transformation and total factor productivity is optimistic, for Chinese quoted companies, so that there are measurable productivity improvements arising from the shift from traditional manufacturing to digitally powered manufacturing.

Hua, Zhang (2025) show that the Broadband China project has led to a dramatic decline in labour misallocation in regions, and that labour mobility is salient transmission mechanism in this process. Wang Xia Lan and Li (2023) also find that the raise of rural digital technological infrastructure is positively associated with employment and income through more substantial broadband penetration, suggesting that the association of connectivity extends beyond less-developed, rural labour markets.

The latest evidence reinforces the evidence for a direct association and gives better identification. In their literature, Zhao and Liu (2025) propose a difference-in-differences design that capitalize on the Broadband China policy and data from 280 cities across China to show that digital technological infrastructure has a strong implication on worker-level productive output. Correspondingly, Meng and Xu (2025) conclude that the use of digital technological infrastructure stimulates TFP of firms in their study, which is drawing upon a quasi-natural experiment approach that exploits the Big Data Pilot Zone policy. They see better information-technology capabilities, better talent matching and raise innovation as salient transmission mechanism.

Using the staggered roll-out of the Broadband China policy and firm-level data, Li et al. (2026) conclude that digital technological infrastructure stimulate corporate worker productivity. Of particular significance, they highlight the economic benefits of connectivity are grounded on firms'

capacity to absorb external digital technological infrastructure and to integrate it into production, management and investment decisions.

Nevertheless, the evidence is not entirely good. Karacuka Myovella and Haucap (2025) find the aggregate influence of digitalization on worker-level productive output to be relatively small for 40 Sub-Saharan African economies and large variations across sectors. Their findings imply a productivity paradox: just because access to digital tools is easier does not mean that productivity raise are proportional.

2.2. Human Capital as a Moderator of the Digital Connectivity–Productivity Relationship

Over the recent period, there has been a growing understanding in the literature that the capacity of workers and firms is not an independent factor of digital technological infrastructure. Connectivity is the means by which digital information, platforms and technologies are accessed, but the productivity that can be created from these resources relies on the understanding, adaptation and application of these resources by workers. Worker skills can thus be considered as a digital network connectivity complementarily factor that can change the productivity return on digital network connectivity, not just another conventional factor determining productivity.

Osei (2024) shows that, among 28 African countries from 2011 to 2019, digital technological infrastructure helps foster innovation and that the complementary association of digital technological infrastructure and worker skills matters. Examining Chinese listed companies, Zhang (2023) determines that technology-enabled transformation stimulate worker-level productive output via raise capital intensity and investment on innovation. Aleca et al. (2025) find association between digital technological infrastructure and digital competencies with worker productivity for EU economies. They also find that the productivity improvements from Internet coverage are only apparent over time, and sustaining the productivity improvements of digitalization is conditional upon ongoing investment in the development and cultivation of digital competencies and training.

Using research evidence from the faculty of universities in Pakistan, Sulehri (2024) determines that information-literacy and technology skills have positive influence on knowledge diffusion and research productivity. This evidence is in the context of higher education, but it serves as a helpful

micro-level example of the general process: Digital resources are more productive when users have the skills to effectively use them. As stated by Zhao et al. (2025), one of the ways in which Broadband China enhance worker productivity was human-capital upgrading.

All of these studies indicate that workforce knowledge and capabilities might be playing a more basic role than just as an adjustment variable. It can identify how much workers and firms can capitalize on digital connectivity to be productive. This offers a theoretical basis to explore workforce knowledge and capabilities as a moderator in the current study. Instead of just determining if human capital creates or augment worker productivity, the analysis explores whether better workforce knowledge and capabilities stimulate the productivity link of digital network connectivity.

The divide is especially significant for emerging Asia, where countries have had strong digital growth, but have varying educational levels, skills and technology preparedness. Accordingly, a similar raise in broadband connectivity can yield varying productivity results, depending on the human-capital context. The proposition is consequently tested in the current investigation in the form an interaction term between digital connectivity (DI) and human-capital (HC), whereby the influence of digital connectivity on worker productivity varies by level of HC.

2.3. The Digital Connectivity–Productivity Relationship is the second component of ICT Capability

The second component of ICT Capability is the digital network connectivity Productivity Relationship. But it's not just a complementary condition, such as worker skills, that can drive the productivity value of digital network connectivity. An additional aspect concerns the ICT capability of an economy, the ability to make ICT infrastructure technologically intensive production, digital services and internationally tradable activities. While the basis for digital participation is broadband network infrastructure, economies vary significantly in the extent of ICT's use in production and trade.

Broadband network infrastructure enhances firm productivity by increasing information development, better allocation of productive resources, innovation, and decreasing costs associated with economic exchange as demonstrated by Zhang et al. (2022). Tang et al. (2023)

also conclude that digital technological infrastructure stimulate TFP through technological innovation, allocation of factors and economies of scale, and this association is more substantial in areas characterised by high R&D and socioeconomic advancement.

Fabiani et al. (2023) conclude that the use of digital technology by firms leads to higher TFP, but the influence is larger for firms that use more technology (or more sophisticated technology bundles). In a similar vein, Li et al. (2023) conclude that there is a positive association between technology-enabled transformation and corporate TFP for Chinese listed companies. The same conclusion is reached by Zhou et al. (2025) drawing upon firm-level evidence and provides evidence of that technology-enabled transformation enhances worker productivity, in part, by business-process reengineering and using digital technological applications.

Meng et al. (2025) conclude that digital technological infrastructure stimulate the TFP of firms, in part, through enhancing their information-technology capabilities, improving firms' talent matching, and promoting innovation. The results of these studies are particularly pertinent for the current investigation because they illustrate the capability formation and technology utilization aspects of the productivity implication of infrastructure. Tang et al. (2023) find that digitally-enabled areas with more R&D activity and socioeconomic advancement and traditional infrastructure have more substantial appreciable productivity association.

Digitalization does not yield the same benefits in terms of productivity across 40 Sub-Saharan African economies, determines Karacuka et al. (2025). According to Xia and Johar (2024), the digital technological infrastructure can support organizational digital innovation through the lowering of experimenting costs and the creation of digital products and processes, as well as the modification of existing ones. The estimates reveal that the technological environment of an economy is more conducive to the promotion of innovation and productivity improvements from connectivity.

The current investigation takes this distinction a step further, by applying fixed broadband subscriptions as a measure of digital connectivity and ICT service exports as an indicator of ICT-enabled productive capability. The interaction lnDI × ICT, consequently, addresses the question of whether the connection between digital network connectivity and labour productivity is stronger in countries with higher ICT productive capability. This approach complements the recent research

that has focused on estimating the direct association of digital technological infrastructure and asks whether the productivity payoff from connectivity is related to the technology-based production capability of the economy in which connectivity is used.

There is a significant body of recent research supporting the potential of digital technological infrastructure and ICT adoption for enhancing productivity, although three areas of limitation have been identified. Firstly, the majority of the contemporary empirical evidence is limited to China, individual countries, firms or digitalization indexes at a broad level. Second, recent research shows that worker skills and technology-based production capability are complements of digital technological infrastructure; although they are frequently considered as transmission pathway, mediators, or independent determinants of the link between digital network connectivity with worker productivity, they are still rarely regarded as a moderator of the relationship. Third, contemporary empirical evidence shows that there is no universal positive or homogeneous association between digital productivity.

The current investigation aims to fulfill these gaps by focusing on Pakistan, India, Malaysia, the Philippines, Thailand and Indonesia for the period 2005-2024. It emphasises on fixed broadband connectivity and worker productivity and examines whether it is worker skills and ICT capability that mediate between the two. The study thus questions the role of digital technological infrastructure and asks what kind of conditions make its productivity implication more likely to occur.

The contribution is significant because it offers a more complex account of the divergent empirical evidence from the recent digital-productivity literature. The positive interaction between digital network connectivity and workforce knowledge and capabilities suggests that investments in worker skills should be paired with investments in infrastructure and physical capital. The econometric estimates indicate that, if ICT capability is improving the relationship, it does not seem that connectivity is enough for the economies to capitalize on digital networks, but they also require productive and technological capacity. The study then brings together the recent research on digital technological infrastructure, labour productivity, workforce knowledge and capabilities and ICT capability into a single Emerging-Asian framework.

3. Methodology

3.1. Research Design and Empirical Strategy

This study examines the association between digital network connectivity and labour productivity in selected Asian emerging-market economies and more significantly on the association between digital network connectivity and worker productivity through the lens of worker skills and ICT capabilities. The empirical approach is thus drawing upon a conditional productivity specification, not a direct-effect specification.

The idea behind this comes from recent empirical research that digital technological applications have the capacity to influence productivity by making information more accessible, communicating more effectively, entering the market, organizing production and adopting technology. Salim et al. (2024) conduct a study especially on emerging-market economies in Southeast Asia and conclude that the ICT-related variables, especially Internet use and mobile connectivity, determine the labour productivity of the emerging-market economies of Southeast Asian countries. This is particularly pertinent to the current study as several of the countries in the current sample are from the same Southeast Asian region. Additionally, more contemporary empirical evidence supports this finding, as Zhao et al. (2025) show that digital technological infrastructure is positively associated with worker productivity, and they highlight human-capital upgrading and capacity for technological innovation as one of the channels through which it provides this implication.

This complementarity inspires the two moderation hypotheses of the current investigation. Worker skills is added since workers need the right knowledge and skills to properly employ digital technological applications. ICT capability is incorporated because connectivity does not ensure the ability of an economy to use digital access to create productive economic activity through ICT. The study is not only about the importance of digital network connectivity, but also under which capability conditions the productivity association is strengthen. The econometric investigation is carried out on a balanced panel data consisting of six Asian emerging-market economies (i.e., Pakistan, India, Malaysia, Philippines, Thailand and Indonesia) for the period 2005–2024. Using

the availability of the consistent annual data set for all the variables used in the empirical specifications during the period, the sample consists of six countries.

3.2. Data and Variables

All the variables are from the World Bank's World Development Indicators (WDI) database. The single internationally harmonized database minimizes potential inconsistencies in definitions and measure across the 6 economies.

Table 1: Measurement of the variables

Variable	Symbol	Measurement	Source
Labour productivity	lnLP	GDP per person employed; natural logarithm used in estimation	World Development Indicators
Digital connectivity	lnDI	Fixed broadband subscriptions per 100 people; natural logarithm used in estimation	World Development Indicators
Human capital	HC	Secondary school enrolment, gross (%)	World Development Indicators
ICT capability	ICT	ICT service exports (% of service exports, BoP)	World Development Indicators
Foreign direct investment	FDI	FDI net inflows (% of GDP)	World Development Indicators
Gross capital formation	GCF	Gross capital formation (% of GDP)	World Development Indicators
Inflation	INF	Consumer prices, annual %	World Development Indicators

Labour productivity (LP) is operationally specified as GDP per person employed and converted to natural logarithm (lnLP). The output per person employed measures the output produced by each worker. This measure is especially suitable as the research question is about whether digital network connectivity correlates with gains in the productivity of labour, rather than simply GDP growth. This decision is also consistent with recent empirical studies on ICT-productivity link (Salim et al., 2024). Digital network connectivity is operationally specified as the number of fixed broadband subscriptions per 100 people, in log form (lnDI). The proxy measure reflects infrastructure for high-speed Internet and, consequently, has a conceptual link more similar to the physical Internet connectivity that is highlighted in the title of the study than a more general proxy measure such as Internet user penetration. The choice of digital network connectivity as the main predictor is substantiated by recent empirical research of study by (Zhao et al. 2025). Gross secondary-school enrolment is employed as a proxy of human capital. Human capital is not just

added as a traditional growth control. It is clearly formulated as a moderating variable, as the theoretical proposition of the study is: digital technological infrastructure can produce different levels of productivity, depending on the workers using it.

ICT capability is measured using ICT service exports as a percentage of service exports. In the current model, then, it is complementary to the digital connection. The availability of digital network connectivity is reflected in broadband network infrastructure, and the production capability of the economy in digital technological infrastructure is reflected in ICT capability. FDI is integrated since foreign investment can enhance the productivity through capital accumulation, technology transfer, managerial knowledge, and international production networks. Gross capital formation (GCF) is measured as a percentage of GDP. It's added the physical capital because digital technological applications require some conventional productive capital. Consequently, if there is omitted-variable bias, it is likely to arise from physical investment due to the fact that economies with higher digital network connectivity are likely to invest more in productive capital as well. Consumer prices are used to measure inflation, which is the percentage raise in consumer prices over the course of one year. Inflation(INF) is integrated to reflect macroeconomic conditions which could affect investment decisions, allocation of productive resources and productive efficiency.

3.3. Baseline Econometric Model

The baseline model is given as:

$$\ln LP_{it} = \alpha_i + \beta_1 \ln DI_{it} + \beta_2 HC_{it} + \beta_3 ICT_{it} + \beta_4 FDI_{it} + \beta_5 GCF_{it} + \beta_6 INF_{it} + \varepsilon_{it} \quad \text{(i)}$$

where $i=1,\ldots,6$ denotes the six countries and $t=2005,\ldots,2024$. In this case, α_i is the country-specific time-invariant association and ε_{it} is the country-specific interference error. The coefficient of primary interest is β_1. The first hypothesis is that:

$$H_1: \beta_1 > 0$$

The hypothesis is backed by recent empirical findings (Salim et al., 2024).

3.3.1. Human-Capital Moderation Model

The first moderation specification is a test of whether human capital is an influence on the productivity association of digital connectivity:

$$\ln LP_{it} = \alpha_i + \beta_1 \ln DI_{it} + \beta_2 HC_{it} + \beta_3 ICT_{it} + \beta_4 (\ln DI_{it} \times HC_{it}) + \beta_5 FDI_{it} + \beta_6 GCF_{it} + \beta_7 INF_{it} + \varepsilon_{it} \quad \text{(ii)}$$

The marginal association of digital connectivity is:

$$\frac{\partial ln Lp_{it}}{\partial \ln DI_{it}} = \beta_1 + \beta_4 HC_{it}$$

Consequently, the moderation hypothesis would be that:

$$H_2: \beta_4 > 0$$

The positive β_4 indicates that the association between worker-level productive output and digital network connectivity strengthens with higher levels of human capital.

It is methodologically better to consider the coefficients of digital network connectivity and human capital together due to the explicit conditional question of the research. Brambor, Clark and Golder (2006) show how interpretation should be done in terms of the conditional marginal association instead of as unconditional relationships for the individual main-effect coefficients.

3.3.2. ICT-Capability Moderation Model

$$\ln LP_{it} = \alpha_i + \beta_1 \ln DI_{it} + \beta_2 HC_{it} + \beta_3 ICT_{it} + \beta_4 (\ln DI_{it} \times ICT_{it}) + \beta_5 FDI_{it} + \beta_6 GCF_{it} + \beta_7 INF_{it} + \varepsilon_{it} \quad \text{(iii)}$$

The conditional marginal effect is equal to:

$$H_3: \beta_4 > 0$$

The rationale is simple: An economy can have broadband network infrastructure, but lack the ability to produce to turn connectivity into productivity improvements. Accordingly, the influence of connectivity could be more substantial in ICT-capable economies.

3.4. Panel Unit-Root Tests

This study employs second generation unit root tests instead of merely first generation unit root tests. To test whether slope heterogeneity and CSD exists, the variables used in the recent research were stationary and the second generation unit root test was applied. The following illustration shows why it is necessary to take an average throughout its cross-section.

$$\text{CIPS} = \frac{1}{N} \sum_{i=1}^{N} t_i \text{ (N, T)} \quad \text{(iv)}$$

Recent research has found that CIPS is more popular because of how well It controls heterogeneity and CSD. Unit root is the null hypothesis to be rejected. To determine the parameters, the test also recommends a test for cointegration to check the stationarity of the variables at the first difference.

As we have shown that variables are I(1), we can proceed to test for long-term relationships between variables. The panel co-integration test is used, drawing upon Error Correction Model (ECM) that was developed by Westerlund (2007). It is particularly suitable for data sets from South Asia because it is cross-sectional dependence and sample bias free. (Raihan et al., 2022).

3.5 Fixed Effects with Driscoll–Kraay Standard Errors

Since there is evidence of cross-sectional dependence, estimation of the main models takes place using country fixed effects with Driscoll–Kraay standard errors.

The fixed-effects specification is:

$$y_{it} = \alpha_i + X'_{it}\beta + \varepsilon_{it} \quad \text{(v)}$$

Fixed-effects standard errors may be invalidated in the presence of cross-sectional dependence and serial correlation in the errors. Driscoll and Kraay (1998) have formulated a covariance estimator which is robust to very general types of spatial and temporal dependence.

3.6. CCE-MG as a Robustness Estimator

Driscoll–Kraay inference takes dependence in the covariance structure into account, but the countries could have different sizes of underlying coefficients. It is shown by Pesaran (2006) that panel estimators can have difficulties in the case where there are unobserved shared latent factors in the regressors and these factors have a multifactor structure, which is explicitly considered in the CCE estimation.

4. Results and Discussion

4.1. Descriptive Statistics and Correlation Analysis

Table 2: Descriptive Statistics

Variable	Mean	Median	Minimum	Maximum	Std. Dev.	Probability
Labour productivity (lnLP)	2.04	1.96	-0.86	5.42	1.17	0.07
Digital connectivity (lnDI)	25.31	24.80	13.20	41.95	7.03	0.10
Human capital (HC)	72.87	77.82	22.60	124.33	20.44	0.00
ICT capability (ICT)	15.95	9.52	0.63	52.09	15.71	0
FDI	3.5	3.5	1	6	1.72	0.02
Gross capital formation (GCF)	126.17	114.90	55.78	386.80	48.017	0
Inflation (INF)	0.69	0.72	-4.79	2.86	1.50	0

Descriptive statistics for variables used in the econometric investigation are shown in table 2. Labor productivity (lnLP) has a mean of 2.0439 and a median of 1.9586, with values ranging from −0.8583 to 5.4163 and a standard deviation of 1.1664. The mean and median are relatively close, implying that the distribution is not highly skewed by extreme values. Meanwhile, the range shows significant cross country and temporal productive efficiency variations. This heterogeneity is significant for the present analysis as economies vary greatly in their capacity to translate the use of technologies into productive economic activity.

Digital connectivity (lnDI) records a mean of 25.3145 and a median of 24.8031, while its values range from 13.1993 to 41.9508. The standard deviation is 7.0286, which shows that there is a significant range in digital network connectivity between the observations. This dispersion is useful as an empirical variation to look at if there are differences in digital network connectivity that are linked to differences in labor productivity. This positive link between digital network connectivity and productivity is also substantiated by contemporary empirical studies, which found that Internet adoption, and other ICT-related infrastructure, has the potential to stimulate productivity in developing economies (Salim et al., 2024). Human capital (HC) has a mean of 72.8653 and a median of 77.8180, with a minimum of 22.6038 and a maximum of 124.3306. ICT capability has a high degree of dispersion with a mean of 15.9538, a median of 9.5210, minimum value of 0.6343 and a maximum value of 52.0883. The standard deviation of 15.7098 is nearly equal to its average, so there is a fair amount of variation in the sample with regard to ICT capability. The median value of FDI is equal to its mean value, 3.5000, with values ranging from 1.0000 to 6.0000 in the adjustment variables. Gross capital formation (GCF) has a mean of 126.1737 and a median of 114.9020, with a comparatively wide range from 55.7785 to 386.8039. Inflation (INF) has a mean of 0.6887 and a median of 0.7214, ranging from −4.7889 to 2.8629. The differences in these variables suggest that there is a great deal of differences in the macroeconomic and investment environment across the sample.

Table 3: Pairwise Correlation Matrix

Variable	lnlp	lndi	HC	ICT	FDI	GCF	INF
lnLP	1.000						
lnDI	0.754***	1.000					
HC	0.494***	0.664***	1.000				
ICT	-0.468***	-0.268***	-0.248***	1.000			
FDI	0.501***	0.215**	0.252***	-0.267***	1.000		
GCF	-0.049	0.040	0.405***	0.358***	0.204**	1.000	
INF	-0.042	0.226**	-0.063	0.439***	-0.345***	-0.113	1.000

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

The pairwise correlation coefficients of study variables are presented in Table 3. Results do not imply any causality and are only preliminary evidence of the direction and strength of the

associations among the variables. Digital connectivity is significantly (at the 1% level) and positively correlated with Lnlp (r = 0.754). This relatively strong association is consistent with the increasing empirical literature that shows that better access to digital technological applications can help in information sharing, lower costs associated with economic exchange, strengthen access to markets and knowledge, and augment more efficient production processes. Nevertheless, recent research in developing economies in Southeast Asia have found that the use of the Internet and other information and communication technologies can lead to raise worker-level productive output (Salim et al., 2024). The worker skills also have a positive link with labor productivity which is 0.494, significant at 1% level. This is consistent with the classic pro-education productivity debates that education, skills and knowledge raise workers' capacity to engage in productive activities and to take advantage of new technologies. The current investigation is especially interested in the direct association between HC and digital connectivity (0.664; significant at 1% level). The ICT capability is found to be negatively correlated with worker productivity (−0.468) and digital connectivity (−0.268) at statistically significant level. More specifically, these negative links are important because they contradict the traditional view that technology capability would be positively linked to productivity. Accordingly, caution should be exercised with the results at this stage. There is also inverse association with HC and ICT which is statistically significant (−0.248). The framework of this study does not imply a separation between ICT capability and human capital. Instead, it is hypothesized that the productivity results may vary depending on the complementary skills that are available in a given economy.

The adjustment variables are positively correlated with labor productivity (FDI: 0.501) and also positively associated with human capital (FDI: 0.252). Labor productivity is negatively correlated with gross capital formation (− 0.049), although the correlation is weak and statistically insignificant; but direct association with human capital (0.405) and ICT capability (0.358) exist. The correlation of inflation and labor productivity are statistically not significant (−0.042), and the correlation of inflation and digital network connectivity are positive and statistically significant (0.226).

4.2. Cross-Sectional Dependence

Table 4: Cross-Sectional Dependence Test

Test	Statistic	p-value	Decision
Pesaran CD	5.564*	0.000	Reject cross-sectional independence

Note: *** denotes significance at the 1% level.

The null hypothesis of cross-sectional independence is strongly rejected in the Pesaran CD test (CD = 5.564, $p<0.01$) showing that the developing economies sampled in this study are subject to and/or interdependent economic processes. This discovery suggests that the chosen countries are not independent. There may be cross-sectional common shocks, global technological change, regional economic integration, international capital flows or other unobservable that influence worker productivity and its factors simultaneously across countries.

This is a methodological result of significance as it is a set of first-generation panel procedures that assumes cross-sectional independence. The second-generation panel unit-root test namely CADF/CIPS and cross-sectionally robust estimation approach is justified due to the evidence of cross-sectional dependence. New empirical work drawing upon the CIPS and Westerlund testing also start with a diagnosis of cross-sectional dependence to choose second-generation procedures.

4.3. Panel Unit-Root Tests

Table 5: CADF and CIPS Panel Unit-Root Test Results

Variable	CADF			CIPS		
	Level	First difference	Order	Level	First difference	Order
lnLP	-1.251	-4.011*	I(1)	-1.251	-4.011*	I(1)
lnDI	-1.390	-3.752*	I(1)	-1.390	-3.752*	I(1)
HC	-1.126	-4.177*	I(1)	-1.126	-4.177*	I(1)
ICT	-1.382	-4.021*	I(1)	-1.382	-4.021*	I(1)
FDI	-3.167*	-4.958*	I(0)	-3.167*	-4.958*	I(0)
GCF	-1.599	-3.750*	I(1)	-1.599	-3.750*	I(1)
INF	-0.721	-3.654*	I(1)	-0.721	-3.654*	I(1)

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

The cross-sectionally augmented Dickey–Fuller (CADF) and cross-sectionally augmented Im–Pesaran–Shin (CIPS) panel unit-root tests are reported in table 5. These second generation tests

are used as they enable to reflect the cross sectional dependence due to cross-sectional common shocks and shared latent factors that are unobserved across the economies in the sample. The findings show that most of the study variables are non-stationary in levels but are stationary after first differencing. More specifically, the CADF statistics of labour productivity (lnLP), digital connectivity (lnDI), human capital (HC), ICT capability (ICT), gross capital formation (GCF) and inflation (INF) are statistically insignificant at levels, but their corresponding first-difference statistics are statistically significant. The findings show these variables are integrated of order 1, I(1). FDI is on the other hand stationary in levels with its CADF being statistically significant at conventional levels. The findings accordingly indicate that FDI is an I(0) variable. An important feature of the empirical specification is the inclusion of both I(0) and I(1) variables which precludes the use of procedures involving integrating all variables at the same order.

The substantive conclusion that emerges from the CIPS results in Table 4 is that the variables lnLP, lnDI, HC, ICT, GCF, and INF are I(1) variables while FDI is I(0). An important consideration with the mixture of stationary and first order integrated variables is the problem of the estimation procedures that can be used when variables have different order of integration without any variable being integrated more than I(1).

4.4. Panel Cointegration Analysis

Table 6: Westerlund ECM Panel Cointegration Test

Statistic	Value	Z-value	p-value
Gt	-1.462	3.502	1.000
Ga	-2.696	3.958	1.000
Pt	-3.081	3.001	0.999
Pa	-1.781	3.139	0.999

The results of Westerlund error-correction based panel cointegration test are presented in Table 6. The four test statistics Gt, Ga, Pt, and Pa are −1.462, −2.696, −3.081, and −1.781, respectively. The p-values for the statistics are not statistically significant and are 1.000, 1.000, 0.999, and 0.999, respectively. Consequently, the null hypothesis of no cointegration is accepted. The empirical empirical findings demonstrate that there is no stable long run association between worker-level

productive output, digital network connectivity, human capital, ICT capability, FDI, gross capital formation and inflation during the sample period.

An important implication for the following econometric identification strategy is this finding. The analysis does not assume an error-correction model and/or long-run framework of CS-ARDL because of the lack of statistical evidence for cointegration. Accordingly, the econometric investigation is conducted with fixed-effects estimation with Driscoll–Kraay standard errors. As the panel may experience heteroscedasticity, serial correlation and cross-sectional dependence, the use of the Driscoll–Kraay inference is methodologically suitable because the Driscoll–Kraay estimator is robust to fairly general forms of temporal dependence and cross-sectional dependence (Driscoll & Kraay, 1998). The estimates presented below should consequently be taken as indicative of long-term equilibrium relationships within countries, and not as proof of convergence in the long run.

The finding is also aligned with the growing evidence base that is more and more inconsistent on digitalization and productivity. The influence of digital technological applications on productivity can vary among countries and industries. For instance, Karacuka et al. (2025) identify only a moderate aggregate inverse association between digitalization and worker productivity in SSA economies, with their sectoral analysis indicating positive influence on worker-level productive output in some sectors, but a productivity paradox in services. In a similar vein, Tang et al. (2023) demonstrated that the productivity implication of digital technological infrastructure is region-specific, depending on the regional development and R&D intensity as well as traditional infrastructure. In such a case, technology-enabled transformation may offer a variety of common productivity paths in different economies with varying levels of technological development.

4.5. Baseline Estimation Results

Table 7: Fixed-Effects Estimates with Driscoll–Kraay Standard Errors: Baseline and Moderating Effects

Variables	Model 1: Baseline	Model 2: Human Capital Moderation	Model 3: ICT Capability Moderation
Digital connectivity	0.0703***	0.1129***	0.0925***
	(0.0244)	(0.0176)	(0.0235)
Human capital	0.0022	-0.0026**	0.0024
	(0.0018)	(0.0010)	(0.0019)
ICT capability	-0.0106***	-0.0091***	-0.0052**
	(0.0028)	(0.0026)	(0.0024)
Digital connectivity × Human capital	—	0.00218***	—
		(0.00025)	
Digital connectivity × ICT capability	—	—	0.00335***
			(0.00047)
FDI	0.0261***	0.0219***	0.0143*
	(0.0062)	(0.0062)	(0.0082)
Gross capital formation	-0.0063**	-0.0094***	-0.0019
	(0.0022)	(0.0023)	(0.0025)
Inflation	0.0021***	0.0026***	0.0013**
	(0.0005)	(0.0006)	(0.0006)
Constant	9.9106***	10.0771***	9.8047***
	(0.1776)	(0.1120)	(0.1845)
Country fixed effects	Yes	Yes	Yes
Driscoll–Kraay SEs	Yes	Yes	Yes
Observations	120	120	120
Number of countries	6	6	6
Within R^2	0.7339	0.8324	0.7841
F-statistic	353.55***	457.49***	239.10***
Prob. > F	0.000	0.000	0.000

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

The baseline model and two moderation models are estimated using fixed-effects with Driscoll–Kraay standard errors as presented in table 7. All three of the specifications are statistically significant at the 1% level and have F-statistics of 353.55, 457.49 and 239.10. The within-R2 values are 0.7339, 0.8324 and 0.7841 showing that the variables incorporated in the model accommodate a significant portion of the variation in worker-level productive output within the sampled countries. The panel setting is especially suitable for the use of the Driscoll–Kraay standard errors because the procedure is suitable for fairly general forms of spatial and temporal dependence (Driscoll & Kraay, 1998).

4.5.1. Effect of Digital Connectivity on Labor Productivity

The consistent finding in Table 6, is that digital connectivity exhibits a positive association with worker productivity. In the base model, the coefficient of digital connectivity is 0.0703 and statistically significant at the 1% level. The coefficient of the human-capability interaction raises to 0.1129 in the human-capital model, and is positive and statistically significant at the 1% level in the ICT-capability model with a coefficient of 0.0925. In other words, the estimated link between digital network connectivity and labour productivity is positive and statistically significant in all cases, irrespective of the specification for moderation.

This finding is an economically feasible one because broadband leads to lower information and communication costs, to more substantial ease of access to knowledge, to an enhanced accessibility to markets for firms, and to a better ability for workers and firms to coordinate economic activities efficiently. Digital network connectivity can also enable the underlying technologies that enable cloud computing, online platforms, data-centric production and other production methods using digital technological applications. There is a large amount of research evidence to support this interpretation recently. Drawing upon data from developing economies in Southeast Asia, Salim et al. (2024) have found that the use of the internet and mobile connectivity have a significant positive association with worker productivity. This is particularly pertinent for the current investigation as the geographical context is common for a number of the economies in the current sample.

Zhao et al. (2025) also report that digital technological infrastructure is a principal explanatory factor of worker productivity, using a large panel of Chinese cities. They find that a part of their transmission pathway in digital technological infrastructure is the better use of labour, capacity for technological innovation, and human-capital upgrading. This transmission pathway provides an interpretive account for the positive relation between broadband connectivity and productivity in developing economies that is useful to consider.

The evidence on the firm level agrees with this. As documented by Zhang and Deng (2024), the benefits of technology-enabled transformation incorporate technological progress, more efficient allocation of capital, and better human-capital structure. Correspondingly, Yang and Zhang (2025) present the research findings from China that digital technological infrastructure can strengthen

enterprise productivity by enabling intelligent transformation, and promoting capacity for technological innovation. These econometric estimates indicate that the productivity influence of digital technological applications is achieved via complementary enhancements in firms' technological, organizational and human resources capabilities, and not only by investing in infrastructure.

That connectivity, notwithstanding this, does not necessarily translate into productivity improvements in all countries should not be seen as an endorsement of the benefits of connectivity. The digitalization-productivity link is found to be significantly different across sectors, and a positive link is not observed in all sectors in the so-called productivity paradox as documented by Karacuka et al. (2025). This qualification is relevant for the current study because of the other estimates of the digital-connectivity coefficient reported later, which show that the average digital-connectivity coefficient is sensitive to country responses by the region.

4.5.2. Human Capital

Human Looking at the baseline specification, the coefficient of human capital is 0.0022, which is not statistically distinguishable from zero. Consequently, there is insufficient statistical evidence in the baseline model of an independent human-capital association with within-country worker productivity. But the influence of the combination of digital network connectivity and worker skills is different. In Model 2 the coefficient for human capital is −0.0026 and significant at the 5% level, while the coefficient for worker skills and the interaction coefficient is positive and highly significant (0.00218).

A negative coefficient for human capital does not mean that education or skills have a negative influence on productivity. The coefficient for human capital in an interaction model is the conditional association among human capital, when digital network connectivity is zero. So the economically significant interaction term is the positive interaction term. The coefficient 0.00218 suggests that digital network connectivity and worker productivity have a positive association, and that this relationship strengthens with higher levels of worker skills.

This discovery gives direct proof to the complementary connection in between technology and abilities. Digital technological infrastructure opens up opportunities for access to and use of digital

technological applications, but workers need to have the expertise and skills needed to turn these opportunities into productive activities. Recent research also highlights the need for a combination of human competencies for technology-enabled transformation. Salim et al. (2024) conclude that worker skills is still a significant presence in the output of developing economies in Southeast Asia in addition to the adoption of ICTs. There is also evidence from economies in Europe that digital technological infrastructure and technology skills go hand in hand and that the readiness of the workforce is a driver of the extent to which a digital technology can be used in the production process.

This outcome aligns as well with the overall hypothesis that technology-enabled transformation is an infrastructure affair. Digital technological applications demand employees who need to acquire new knowledge, skills, and understanding, and who must be able to adjust to new production techniques and methods. Research on firm-level technology-enabled transformation further suggests that technology-enabled transformation can enhance productivity partly by means of human-capital structure change (Zhang & Deng, 2024).

Accordingly, the findings from Model 2 are in accordance with the key claim of the study that connectivity and human capital are complementary determinants. Accordingly, increasing broadband availability without investing in education and workforce capacities could provide less conducive to productivity improvement outcomes than a policy that promotes digital technological infrastructure and investment in education and workforce capacities.

4.5.3. ICT Capability

ICT capability yields a more intricate pattern. The coefficient is negative and statistically distinguishable from zero in all three FE–Driscoll–Kraay specifications, and the estimates are −0.0106, −0.0091, and −0.0052 in the three. The negative coefficient seems to be inconsistent with the anticipated conducive to productivity improvement association of ICT at first sight. But this is not a complete reading. There is an increasing research that shows that investments in digital technological applications do not directly translate into immediate measurable productivity improvements. The productivity association can be linked to organizational restructuring, the skills

of the workers, the capacity of innovation, complementary investment, and time needed to restructure the production processes of firms.

Evidence of the relevance of digitalization is particularly provided by Karacuka et al. (2025) who found that the influence of digitalisation on worker productivity is weak at the aggregate level and can be negative for some sectors. The results they obtain show that the influence on productivity of digitalization is criticaly shaped by the sectoral and institutional context in which digital technological applications are implemented.

The literature on the firm level is also suggestive of a similar qualification. For technology-enabled transformation to strengthen productivity through technological advancement, capital mobilization, and human-capital structuring, the transformation of organizations is pivotal (Zhang and Deng, 2024). Consequently, the expected positive coefficient of ICT capability in a macro-panel specification should not be taken for granted and assumed to be the same across all specifications.

More important, the negative coefficient is diminishing in magnitude by the addition of digital network connectivity interaction in Model 3, from a coefficient in Model 1 of −0.0106 to a coefficient in Model 3 of −0.0052. The interaction of digital-connectivity and ICT-capability is positive and statistically distinguishable from zero as well. This mix seems to imply that the negative coefficient of ICT capability alone does not imply that ICT capability itself is adversely associated with productivity. Rather, this study shows that the productivity association of ICT capability is dependent on the overall digital context.

4.5.4. Moderating Role of Human Capital

The association between digital connectivity and human capital is statistically significant at 1% with a coefficient of 0.00218 and a standard error of 0.00025. This is one of the most significant results from the study as this is beyond just the question of digital network connectivity and productivity. The positive association indicates that the productivity value of “digital connectivity” is dependent on human capital. At the country level, it is clear that nations with more human capital tend to have a more productive use of connectivity in terms of generating economic activity.

This analysis corresponds with the complementary-capabilities analysis found in the digitalization literature. The raise productivity and worker skills upgrading are two pathways by which digital technological infrastructure strengthen worker-level productive output, as evidenced by recent research (Zhao et al., 2025).

4.5.5. Moderating Role of ICT Capability

The association between digital connectivity and ICT capability is also positive and extremely significant. The coefficient is 0.00335, the standard error is 0.00047 and it is significant at the 1% level. The coefficient on ICT capability is negative direct, suggesting an association at zero level of digital network connectivity, and positive interaction, suggesting to a growing extent favorable association with increasing levels of digital network connectivity. The finding is consistent with the general perspective of ICT as a GP technology.

Combining the direct and interaction effects (Models 2 and 3) gives a combined picture that makes the seemingly contradictory results easier to understand. The coefficients of the interaction specifications should be read as conditional main implication, and digital network connectivity, when taken alone, has a strong positive association with worker-level productive output. The positive interaction terms are an indication of the fact that the productivity payoff from digital network connectivity is higher when countries have higher levels of human capital and ICT capability. These results were backed up by evidence of larger productivity improvements when digital technological infrastructure is complemented by other technological or institutional factors. Indeed, Tang et al. (2023) conclude that the positive productivity influence of new digital technological infrastructure is more substantial in areas with more R&D activity and the level of infrastructure development.

4.5.6. Control Variables

The adjustment variables give some additional insights. All three specifications receive positive and statistically significant FDI. Both of the first two coefficients are significant at the 1% level and the third at the 10% level. In the context of the East and Southeast Asian economies, Wang and Chen (2024) highlight how human-capital factors affect the potential for conducive to productivity improvement technology spillovers from FDI. This is in accordance with the present

result, which supports the broader conclusion that increasing productivity is not necessarily a result of the influx of capital or technology but also the ability of the domestic economy to integrate them. GCF is negative and significant in Models 1 and 2, but becomes statistically insignificant in Model 3. But don't assume that a negative coefficient is necessarily a sign of a decrease in productivity from physical investment. Instead, it could simply be due to variations in the amount of investment and its productivity, or transition period associated with the capital accumulation process, or investment being directed toward less productive investments. The fact that its significance disappeared after controlling for the interaction of digital-connectivity with the ICT-capability further suggests that the estimated association is specification dependent. The coefficient of INF is positive and significant in all three models, albeit rather low.

4.6. CCE-MG Robustness and Cross-Country Heterogeneity

Tables 8 and 9 present estimates derived from the Common Correlated Effects Mean Group (CCE-MG) estimator, the results of which provide a check on the baseline and moderation results in the presence of cross sectional dependence and coefficient heterogeneities. The robustness exercise is especially applicable for the current study as the countries within the sample are unlikely to change independently of each other. Digital technological applications can have influence on multiple countries, as well as international capital movements, global inflationary pressures, technological diffusion, and international economic conditions. As a result, the CCE-MG results have a more stringent test as to whether the relationships found in the fixed-effects specifications persist once such common influences are taken into account.

Table 8: CCE-MG Estimates for the Baseline Model

Variable	Coefficient	Std. Error	z-statistic	p-value
Digital connectivity	-0.0077	0.0450	-0.17	0.863
Human capital	-0.0008	0.0009	-0.89	0.372
ICT capability	0.0012	0.0029	0.42	0.671
FDI	-0.0026	0.0033	-0.80	0.426
Gross capital formation	0.0015	0.0012	1.29	0.198

Inflation	0.0026**	0.0011	2.39	0.017

Notes: ** indicates significance at the 5% level.

One qualification to the FE estimates is revealed by the results in Table 8. The CCE-MG coefficient of digital connectivity is −0.0077, which is statistically insignificant (p = 0.863). Human capital is also insignificant (−0.0008; p = 0.372), while ICT capability is positive but insignificant (0.0012; p = 0.671).

The result of the CCE-MG is not necessarily in error because the positive FE estimate was obtained. Instead, the two estimators make different assumptions and detect different types of heterogeneity. In the fixed-effects model, both the cross-sectional variation and the time-invariant country characteristics are controlled for, while in the CCE-MG, the model can also incorporate country-specific slopes and the model can control for unobserved shared latent factors. Pesaran (2006) made the development of the CCE approach specifically for cases in which the regressors are correlated with the unobserved common components and the slope coefficients vary from unit to unit.

This means that the positive average association found in the FE model is not robust enough to stand up to the presence of shared latent factors and the different country responses and is not statistically different from zero with the CCE-MG results. This is not a negative finding as this is a substantive finding. It indicates that the benefits of digital network connectivity might yield conducive to productivity improvement outcomes in some countries and less or statistically insignificant results in others. This is in accordance with the recent productivity literature since it has been shown that the productivity within groups is heterogeneous. The productivity association of digital technological infrastructure is shown to vary using the level of socioeconomic advancement, R&D intensity, and the characteristics of the infrastructure, as documented by Tang et al. (2023). Similarly, Karacuka et al. (2025) find significant cross-sector differences in the digitalization-productivity connection. A single pooled coefficient could mask country and sector-level economic differences.

The CCE-MG conclusions are consequently more differentiated, as the study is considered to provide substantial empirical support of a positive within-country association between digital

network connectivity and worker productivity as stated by the FE–Driscoll–Kraay specification, but not necessarily as a cross-country association.

Table 9: CCE-MG Results for the ICT Capability Moderation Model

Variable	Coefficient	Std. Error	z-statistic	p-value
Centered digital connectivity	0.0579	0.0935	0.62	0.536
Centered ICT capability	-0.0084	0.0110	-0.77	0.444
Digital connectivity × ICT capability	0.0049	0.0048	1.02	0.305
Human capital	-0.0003	0.0007	-0.42	0.678
FDI	-0.0033	0.0030	-1.08	0.281
Gross capital formation	0.0008	0.0010	0.75	0.453
Inflation	0.0032*	0.0018	1.76	0.078

Notes: * denotes significance at the 10% level.

Table 9 further extends the analysis of the CCE-MG by including the interaction between centered digital network connectivity and centered ICT capability. Centering the variables is pivotal because it allows to interpret the coefficient of digital network connectivity as the association between digital connectivity and worker-level productive output at the average level of ICT capability.

Centered digital connectivity has a positive coefficient (0.0579) but this value is not statistically significant ($p = 0.536$). The negative coefficient of −0.0084 is not statistically significant ($p = 0.444$) either, with Centered ICT capability. Notably, the coefficient of the interaction term between the digital connectivity and ICT capability is still positive and equal to 0.0049. The CCE-MG specification, notwithstanding this, states that for the interaction to be considered statistically significant, its p-value must be less than 0.05, which it does not.

The positive sign is still consistent with the transmission pathway found in the fixed-effects estimates. The interaction coefficient was positive and highly significant (0.00335***) in the FE model, whereas the CCE-MG was still positive, but less so. The sign of the coefficient is thus the same, but there is insufficient statistical evidence to conclude that the moderating association is consistent across estimators.

The correct reading is consequently that CCE-MG only gives indicative empirical evidence and not statistical evidence that the association of digital network connectivity with productivity is strengthened with ICT capability. This separation should be carried over to the paper. The p-value for the CCE-MG interaction is 0.305, which is too large to conclude that there is a confirmed interaction.

This reduction of the interaction effect is informative. This implies that some of the observed strong moderation which was found in the fixed-effects model could be related to cross-sectional common shocks or different country-specific relationships. Human capital is still a negligible factor in Model 2 (–0.0003; p = 0.678). FDI (−0.0033; p = 0.281) and gross capital formation (0.0008; p = 0.453) are also statistically insignificant. The findings corroborate the general finding from the previous chapter that after taking account of the different factors and the different country responses to the same factors, the average association of the traditional macroeconomic policy variables are significantly diminished.

Inflation is again a positive coefficient with a marginal significance at the 10% level (0.0032; p = 0.078). The positive inflation in both CCE-MG specifications, as well as other insignificant variables in the samples, indicates that inflation reflects a relatively stable macroeconomic relationship in this sample. The CCE-MG estimates are statistically indistinguishable from the positive signs of the digital-connectivity coefficient and its implication on ICT capability, suggesting that the positive link observed in the fixed-effects specification is robust to cross-sectional dependence and is sensitive to the different country responses.

5. Discussion

Overall, the empirical results lead to the following three conclusions. First, digital network connectivity is positively, and significantly, related to worker productivity in the key FE–Driscoll–Kraay specifications. The coefficient is positive and statistically significant in the baseline and moderation models, which means that the central relationship is not just one specific model. This is consistent with the latest research conducted in Southeast Asia and other developing economies, which indicate that the internet and digital technological infrastructure can augment productivity

by facilitating better transmission of information, innovation, labour allocation and technology uptake (Salim et al., 2024; Zhao et al., 2025).

Second, the results underscore the need for a complementary set of capabilities for digital network connectivity to be effective. The positive and statistically significant interaction with worker skills suggests that the productivity link of connectivity is strengthen by labour-force competencies. It makes a similar difference with FE specification when the positive interaction with ICT capability. This accords with a perspective that digital technological infrastructure is not an isolated component of productivity. Instead, its economic value is conditional upon some extent on the capabilities of workers, firms and institutions.

Third, the CCE-MG analysis adds a new important qualification: the relationships are heterogeneous across countries and sensitive to shared latent factors. Under CCE-MG, the unconditional digital-connectivity (0--10) is not statistically significant and so is the interaction between ICT-capability. Consequently, it would not be methodologically suitable to attribute a universal or homogenous productivity implication to the six economies drawing upon the evidence. The results show, nevertheless, that technology-enabled transformation delivers productivity improvements under specific country context conditions.

This interpretation is a combination that is, arguably, more informative than a one-sided statement of ‘digitalization enhance productivity’. The empirical findings demonstrate that digital network connectivity is an important technological enabler, but the productivity-enhancing outcomes from this depend on supportive human and technological capacities and can differ from country to country. This finding is found in the recent research, which over the last few years has to a growing extent highlighted the fact of technology-enabled transformation potential productivity delays and paradoxes, heterogeneity and mutually reinforcing capabilities (Tang et al., 2023; Karacuka et al., 2025).

The results also have a direct policy implication for the developing Asian economies. The key to expanding broadband network infrastructure is not necessarily just to invest in infrastructure. A policy package that combines the building of digital competencies, ICT capabilities, innovation capacity and the capacity of firms and workers to adopt digital technological applications to

production is likely to have a lasting influence on productivity. The evidence gathered from recent research on digital technological infrastructure also suggests a complementary approach to investing in worker skills, innovation, and production capability, rather than to using connectivity as such as a policy tool.

6. Conclusion

This study analyzed the association between digital network connectivity and worker productivity and explored whether this relationship gets shaped by human capital and ICT capability in the selected six developing Asian economies namely Pakistan, India, Malaysia, the Philippines, Thailand and Indonesia – between 2005 and 2024. The study was conducted because the significance of digital technological infrastructure for productive economic performance is increasing and it has been unclear why the productivity improvements from connectivity can vary between developing economies.

Several important insights can be derived from the empirical findings. The Driscoll–Kraay fixed effects estimation with the standard errors shows positive and statistically significant association between digital network connectivity and worker productivity. The econometric estimates indicate that, controlling for the other variables incorporate in the model and country-specific association, more substantial penetration of fixed-broadband is statistically associated with higher output per employed person. The results also suggest that the association of productivity and connectivity is positive and statistically significant and that the association of the human capital is stronger at higher levels of human capital. The same holds true for the connection of digital network connectivity to ICT capability, which is also positive and statistically significant in the baseline specification. The results confirm the main thesis of this study: digital technological infrastructure cannot be viewed separately; being able to benefit from the productivity it offers is conditional upon the capacities of the actors utilizing it and exploiting it.

There is, nevertheless, an important qualification to the sensitivity analysis: The CCE-MG estimates do not give statistically significant findings on the direct association between digital and the interaction effects. This difference implies that there are common correlated factors and heterogeneous country responses that influence the baseline relationships. The results are thus

inconclusive as to support the interpretation that digital connectivity has a uniform influence on productivity across all six economies. Rather, they propose that the productivity association of digital network connectivity can be conditional on contextual characteristics.

The study is unique in synthesizing key factors for digital network connectivity, human capital, and ICT capability within the same econometric framework for developing Asian economies. The analysis does not only ask the question about the importance of digital technological infrastructure but also asks about the influence of mutually reinforcing capabilities on the productivity association of digital technological infrastructure. This view brings together the conflicting messages in the recent research on digitalization and underscores the fact that infrastructure spending does not necessarily lead to productivity improvements.

The policy-relevant implications of the findings are for governments to adopt a digital-development policy package that incorporate investments in education, digital competencies, in ICTs for productive activities, and technological capacity development, all in the context of expanding broadband services. It may be more valuable to help make digital technological infrastructure better and more productive than to focus on connectivity expansion alone. Additionally, policies need to be tailored to the technological and human capital environments of individual countries, as the varied and estimator-specific findings suggest, and not nationalized in an emerging-economy-wide digital-productivity policy.

The overall finding of the study is that digital network connectivity is a significant part of the productivity-development process, but that the benefits of digital network connectivity are bound up in the wider capacities in which digital network connectivity is embedded. The evidence consequently suggests the need to move beyond a narrow concept of connectivity towards a more integrated approach in which digital technological infrastructure and worker skills are nurtured together with ICT capability.

7. Limitations of the Study

There were limitations to this study and these are noted below:

- Small sample size: The analysis is drawing upon six developing economies in Asia, which may restrict the extent to which the results can be applied to other emerging-market economies and developing countries.
- Measurement limitations: Digital network connectivity, human capital, ICT capability are measured through aggregated proxy measures which may not fully reflect the variation in infrastructure quality, technology skills and technology use, and capacity for innovation.
- Small panel dimension: This may mitigate the statistical power of the more complicated specifications, specifically the interaction models.
- The fixed-effects model, which estimates the Driscoll–Kraay standard errors, shows that statistically meaningful association exist while the CCE-MG results are not statistically significant. This implies the results can be vulnerable to shock frequency and nation-specific heterogeneity.
- Causal limitations: There are no definitive causal association found with the observational panel design. The digital network connectivity and labour productivity relationship might be affected by potential endogeneity and omitted factors.

Future research should address these limitations by increasing country coverage; by adopting more powerful indicators of digital and technological skills; and by introducing other identification methods to explore the underlying causal processes.

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