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Impact of Digital Economy, Productivity, Natural Resources and Innovation Capacity on FDI Flows in Emerging Market Countries

(Impak Ekonomi Digital, Produktiviti, Sumber Alam dan Kapasiti Inovasi terhadap Aliran FDI Negara Pasaran Baru Muncul)

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ABSTRACT

This study aims to examine the effects of digital economy (DE), natural resources (NRs), productivity and innovation capacity on foreign direct investment (FDI) flows in 24 emerging market countries (EMCs) from 2000 to 2021. Heterogeneous panel data estimates were used to analyse short- and long-term relationships between dependent and independent variables. The digital index was constructed using the principal component analysis approach. In terms of short- and long-term relationships, FDI flows, progress in DE, NRs and total factor productivity performance have a positive impact. The significance of indicators for FDI sustainability flows in EMCs is demonstrated by the multidimensional and bidirectional causal relationships between FDI and a few variables. The findings of this study provide a comprehensive empirical figure that can be used to enhance strategies for expanding the flow of FDI in short- and long-term periods, ultimately improving economic sustainability for EMCs.

Keywords: FDI; digital economy; emerging market countries; natural resources; total factor productivity

ABSTRAK

Kajian ini bertujuan untuk mengkaji kesan ekonomi digital, sumber alam, produktiviti, dan kapasiti inovasi terhadap aliran pelaburan langsung asing (FDI) di 24 negara pasaran baharu muncul dari tahun 2000 hingga 2021. Analisis hubungan jangka pendek dan jangka panjang antara pembolehubah bersandar dan bebas telah dijalankan menggunakan anggaran data panel heterogen dalam kajian ini. Selain itu, kajian ini menggunakan pendekatan analisis komponen utama (PCA) untuk membangunkan indeks digital. Kajian ini menyimpulkan bahawa, aliran FDI, perkembangan ekonomi digital, sumber alam dan prestasi faktor produktiviti menyeluruh mempunyai hubungan positif dalam jangkamasa pendek serta panjang. Kajian ini menunjukkan bahawa terdapat kesan sebab-akibat berbilang dimensi secara dua hala antara FDI dan beberapa pembolehubah, yang menunjukkan kepentingan indikator dengan aliran kelestarian FDI bagi negara pasaran baharu muncul. Secara keseluruhan, kajian ini memperkayakan gambaran empirikal yang komprehensif untuk meningkatkan strategi bagi memperluas aliran FDI dalam tempoh jangka pendek dan panjang, sekali gus memperbaiki kelestarian ekonomi bagi negara pasaran baharu muncul.

Kata kunci: FDI; ekonomi digital; negara pasaran baharu muncul; sumber alam; faktor produktiviti menyeluruh

JEL: C01, O20

INTRODUCTION

The digital economy (DE) encompasses all activities that utilise digital data, regardless of their modernity or size, as defined by the International Monetary Fund (2018). As the global economy shifts towards digital globalisation, digital content has become an integral part of it. DE's spread promotes competitiveness across boards and creates new business opportunities for small enterprises to expand their businesses. Furthermore, digital technology has had an impact on a firm's business strategies for producing goods and services throughout a region. The use of digital technology by multinational enterprises (MNEs) can reduce international transaction costs and create an efficient and transparent platform for the international market (Mckinsey Global Institute 2016). DE's impact is not limited to the technology industry, but it is shifting towards digitalisation to manage consistent development and supply chains across nations in the global economy. Long-term foreign direct investment (FDI) is significantly affected by DE, and most governments worldwide acknowledge the crucial role of digitalisation in attracting sustainable investments. The World Investment Report (2024) underlines how business facilitation and digital government solutions can create a transparent and streamlined environment that can address low investment levels. The report emphasises the significant increase in online services and information portals, which not only enhances transparency but also fosters broad digital government development, especially in developing nations.

Digital technology's transformation and growth in developed and developing countries are crucial in attracting FDI flows. According to Osano and Koine (2016), technology's efficiency and marginal cost reduction are key factors in attracting FDI. Between 2010 and 2015, the number of technology-based companies in UNCTAD's top 100 MNEs increased by more than twice. Moreover, the size of MNEs has expanded in the aspect of assets, which account for 65% of their operating profit, and in the aspect of employees, which account for 30% of their operating profit, compared with trends for other top 100 MNEs (World Investment Report 2024). Firms and consumers gain benefits from digital infrastructure, which provides an international platform to access the market, and the relationship between digital infrastructure and connectivity is strongly associated with digital transformation.

The fixed broadband subscriptions per 100 individuals in developed and developing countries from 2015 to 2023 are compared in Figure 1. Fixed broadband subscriptions in developed nations were consistently higher, with a starting rate of 31 per 100 individuals in 2015 and a progressively rising rate of 38.7 per 100 individuals by 2023. Conversely, the worldwide subscription showed a moderate increase over the years, rising from 11.4 subscriptions per 100 individuals in 2015 to 18.6 subscriptions per 100 individuals in 2023. The growth of developing countries had been minimal, with only 2 subscriptions per 100 individuals observed throughout 2015–2023. The steady increase in subscriptions in developed countries showed progress in digital connectivity, whilst stagnation in developing countries was a result of persistent challenges in infrastructure development and affordability. Figure 2 indicates that mobile broadband subscriptions worldwide consistently increased, from 40 per 100 individuals in 2015 to 87.4 per 100 individuals in 2023. By contrast, developing countries showed markedly decreased rates, with less than 20 subscriptions per 100 individuals in 2015 and a rise to 44.6 subscriptions per 100 individuals by 2023.

The gap between developing countries and the global average is large, but an upward trend is a sign of progress in connectivity. Figure 3 presents data on internet usage per 100 individuals from 2015 until 2023, which reveal a consistent pattern of high internet penetration in developed countries, moderate usage globally and limited access in developing countries. The internet usage levels of developed countries were most prominent between 2015 and 2023, with 79.4 per 100 individuals in 2015 and 93.2 per 100 individuals by 2023. More people can access and use the internet over time because of the widespread digital infrastructure, policy support and affordability in these regions. The digital divide between developed and less-developed regions is highlighted by this slow growth, as developing countries face challenges such as exorbitant costs, inadequate connectivity and suboptimal technological infrastructure that hinder broader internet accessibility.

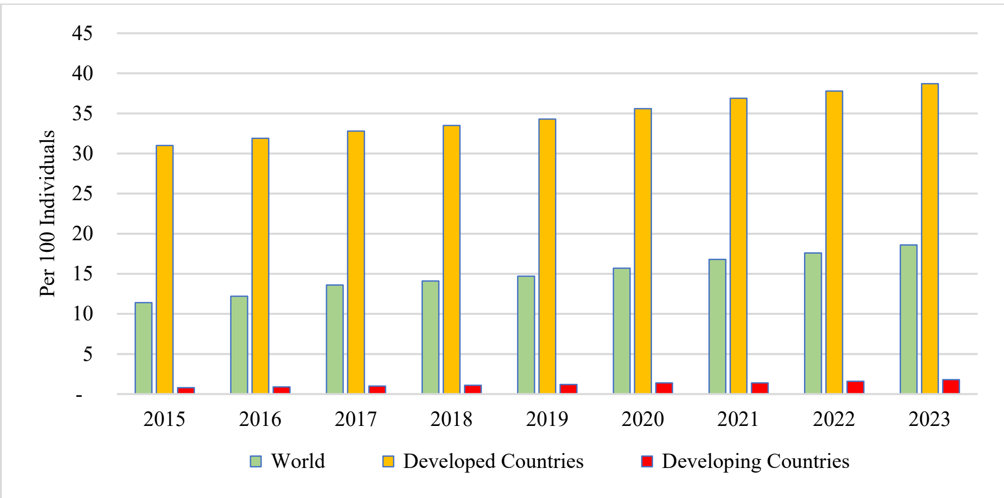

FIGURE 1. Global fixed broadband subscriptions per 100 individuals, 2015–2023
Source: International Telecommunicate Union (2024)

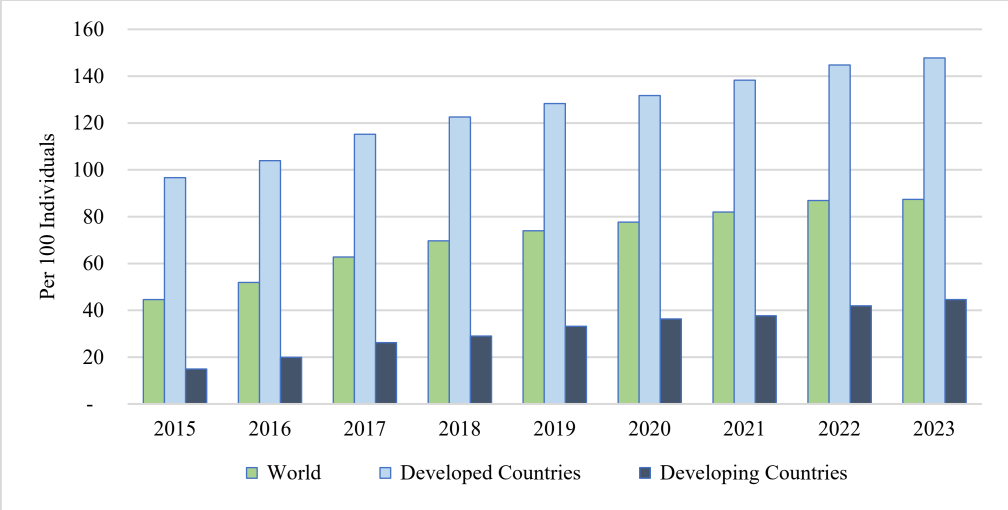

FIGURE 2. Global active mobile broadband subscriptions per 100 inhabitants, 2015–2023
Source: International Telecommunicate Union (2024)

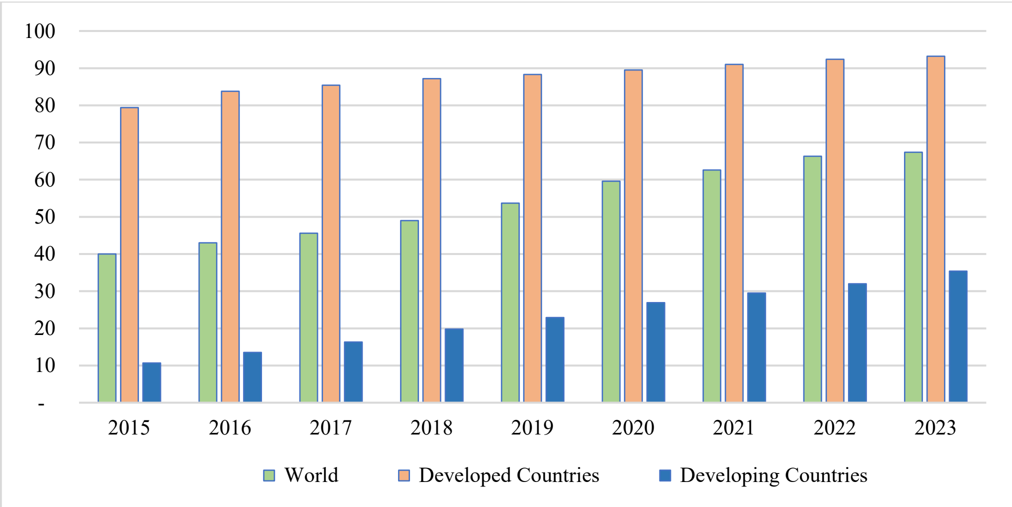

FIGURE 3. Global individuals using the internet per 100 people, 2015–2023
Source: International Telecommunicate Union (2024)

The digital revolution has contributed significantly to the economy and society. However, it has also created simultaneous difficulties, particularly for countries that are inconsiderably developed and technologically backward worldwide. The relationship between DE and digital development favours well-recognised developed countries over developing and less-developed countries with limited technological infrastructure. This gap could cause a disparity in the distribution of benefits from DE, with developed countries having more advantages than their less technologically advanced counterparts (Albiman & Sulong 2017; Malikane & Chitambara 2017). Given their varied levels of digital development, examining the impact of DE on FDI in developing countries is crucial.

FDI is positively impacted by the introduction of natural resources (NRs), such as oil, petroleum, minerals and coal. The abundance of NRs is the reason for China's FDI, as per earlier studies by Kamal et al. (2019) and Wong et al. (2020). The influence of resource-rich countries on FDI amongst emerging economies is positive, as evidenced by previous studies by Eissa and Elgammal (2019), Udi et al. (2020) and Feulefack and Ngassam (2020). The potential of FDI inflows to enhance productivity is recognised by the transfer of advanced technology, capital and management skills. FDI has a positive effect on total factor productivity (TFP) progress, as indicated by most studies by Klein et al. (2019), Makieła et al. (2021) and Negash (2020). According to Gál and Fazekas (2021), Adnan et al. (2020) and Herzer and Donaubauer (2017), FDI inflows have the potential to increase TFP levels by bringing in more investment and lowering production costs. Viglioni and Calegario (2020), Chen and Zhang (2018) and Omidi et al. (2018) have explored the dynamic causal direction between FDI and innovation (INO) in emerging economies.

Considering various issues on FDI flows worldwide, this study specifically focuses on determining the impact of DE on FDI inflows in emerging countries in short- and long-run periods, with INO capacity, TFP and total NRs as control variables. A clear connection between research questions, objectives and estimation techniques is established by this study to ensure methodological coherence and analytical rigour. The first research question explores the key factors influencing FDI inflows in emerging market countries (EMCs), with the corresponding objective focusing on evaluating the roles of

DE, productivity, NRs and INO. For capturing long-term relationships, cointegration analysis is used. The second question centres on the impact of these FDI determinants on the short- and long-term performance of FDI in EMCs. The objective is to examine the existence of heterogeneous cointegration between FDI and its determinants via cointegration analysis. In the third research question, the focus is on the direction and nature of dynamic causality between FDI and its key determinants. The objective is to use causal analysis to identify dynamic causal effects. The rest of this paper is structured as follows: Section 2 reviews the literature and past findings. Section 3 describes the empirical strategies employed in this study. Section 4 reports the empirical findings. Section 5 provides concluding remarks.

LITERATURE REVIEW

The efficiency and productivity of small and medium enterprises have been improved by digital technology, as indicated by AIR (2018), allowing them to establish their traditional business in the globalised world. UNCTAD (2017) reports that DE is the most favourable factor for promoting multinational investment, and the most enticing industries are those that utilise technology and services. Eden (2016) found that digital technology and digital infrastructure are essential factors when trying to attract investors to a host country. According to Kozlova et al. (2019), digital transformation acts as a stimulator for long-term investment attraction in Russia. Ashmarina et al. (2020) investigated the investment behaviour under the new economic model and found that the use of digital technology expands the investment market and improves the efficiency of economic implementation. Nurainy and Adipati (2018) observed that FDI flows in Asian countries are facilitated by the accessibility of digital technology in the host country. Drahokoupil and Fabo (2020) noted that digital skills for production lines in Slovakia are becoming remarkably popular with foreign companies. The support of the digital revolution and the production of an attractive investment environment encourages foreign capital inflow and increases economic growth in Ukraine (Tkalenko et al. 2019). Tang et al.'s (2020) study revealed a correlation between inward FDI and technological advancement, leading most foreign investors to choose China considering its advanced technology.

Numerous studies have proven that the size and availability of NRs in host countries play a crucial role in attracting FDI inflows. Using a panel data set, Bokpin et al. (2015) found that NR measurements exert a positive impact on FDI flows. Aleksynska and Havrylchyk (2013) discovered that these countries possess enriched NRs that can attract FDI, regardless of their institutional quality. According to Kang (2018), natural resource endowment is the key to attracting FDI flows in terms of the security of the resource supply chain in the long run, but the attraction of NRs is still restricted by institutional quality. Hayat (2018) examined the impact of NRs on FDI inflows and economic growth in low-, middle- and high-income countries globally and found that FDI flows have a significant positive impact on economic growth. The impact is influenced by the size of natural resource sectors and the category of countries. Kilicarslan (2019) concluded that renewable energy production and FDI inflows amongst BRICS countries and Turkey are significantly linked over time. Wall et al. (2018) research suggests that tax incentives and renewable portfolio standards are the most effective means of motivating FDI inflows.

In empirical literature, the relationship between productivity and FDI has been extensively studied. Habib et al. (2019) discovered a positive connection between TFP and FDI, which they believe is the primary factor responsible for boosting productivity growth in BRIC and Central and Eastern European countries. According to Desbordes and Franssen (2019), foreign firms have an advantage in using and managing human and physical capital, and further exploration of the international market revealed that the presence of FDI can improve productivity and export volumes. The presence of FDI, as indicated by Xie and Xue (2019), increases market competition in the local industry and stimulates the productivity of the Chinese industry, which indirectly improves the quality of export products. Meniago and Lartey (2020) discovered that TFP in most African countries is negatively affected by FDI flows.

On the contrary, according to Asongu et al. (2020), FDI has a positive impact on TFP in sub-Saharan countries, as demonstrated through GMM estimates. Improving employee skills and ensuring a good work environment are necessary for the government to attract foreign capital. Ramasamy et al. (2016) found that FDI increased TFP in 3 distinct regions in 28 states in India. Lin et al. (2020) examined the TFP in the forest product industry in China after discovering that FDI is motivating the wood industry because of its impact on FDI. In 77 low- and middle-income countries, Abdullah and Chowdhury (2020) found that FDI and TFP do not have a significant connection, with absorption capacity being essential for determining the impact of FDI on TFP.

Zhang et al. (2024) revealed that digitalisation directly attracts FDI inflows, particularly in low-income cities. Indeed, the development of technologies tends to be attractive to foreign investors as they lower operating costs, increase corporate efficiency and stimulate INO. Technological advances increase FDI inflows, which improve economic growth in the host country and enhance productivity and INO amongst OECD countries, according to Marasco et al. (2024). However, Yasin et al. (2024) discovered that FDI has a negative impact on TFP through the R&D spillovers from multinational corporations (MNCs). The reason for this effect is that competition between domestic and foreign firms results in market rivalry, rather than productivity level enhancement. The East Asia and Pacific region are most benefitted by large firms with external market links, whereas high-growth enterprises struggle to absorb FDI spillovers or improve productivity, as found by Sokhanvar (2025).

FDI plays a significant role in a country's need to increase R&D and INO activities by enabling host countries to create value-added products and improve national income through export revenues. According to Erdal and Gocer (2015), a causal link exists between FDI flow and INO capacity in Asian countries. In countries with high income, FDI flows have a positive impact on economic growth; by contrast, in poor countries, they do not have a positive impact on economic performance. The relationship between FDI and economic growth in emerging economies is influenced by technological INO, as demonstrated by these empirical results. Chen and Zhang (2018) investigated the factors that impact patent applications in China and discovered that FDI and INO patents have a positive correlation. In Brazil, Viglioni and Calegario (2020) analysed the factors that influence local INO performance and found that the presence of FDI has a positive impact on local INO.

Deng et al. (2024) investigated the effect of FDI inflows on product INO in Chinese domestic firms and determined that FDI inflows have a positive impact on product INO by broadening product scope. Local firms can benefit from knowledge spillovers through upstream vertical linkages, implying a positive impact. However, FDI has a detrimental effect on downstream industries, as foreign firms tend to rely more on imported inputs than on domestic suppliers. According to Rao et al. (2024), an adverse relationship occurs between FDI and domestic INO, which holds that firms are less motivated to innovate when there is more competition. Nonetheless, Omidi et al. (2018) reported that INO has a beneficial effect on developing countries worldwide, which is in line with Chen et al. (2020) study of 30 regions in China. Long- and short-term domestic INOs are affected by FDI, as revealed by Asunka et al. (2021). The negative correlation between FDI and INO in 211 cities in China was discovered by Jiang et al. (2020), indicating that increasing FDI has a negative impact on urban INO progress in China. Table 1 presents a selection of past studies that examined causal relationships between FDI, productivity, DE, INO and NRs.

TABLE 1. Summary of causality direction studies

Authors	Data coverage	Country	Causality direction
(A) FDI and Productivity			
Habib et al. (2019)	2007–2015	BRIC and CEE countries	FDI causes Productivity
Desbordes and Franssen (2019)	2000–2008	Emerging countries	FD causes Productivity
Xie and Xue (2019)	2001–2006	China	FDI causes Productivity
Meniago and Lartey (2020)	1980–2014	Sub-Saharan Africa countries	FDI causes Productivity
Asongu et al. (2020)	1980–2014	Sub-Saharan African countries	FDI causes Productivity
Ramasamy et al. (2017)	1993–2013	India	FDI causes Productivity
Abdullah and Chowdhury (2020)	1980–2008	Low- and middle-income countries	No causality
Lin et al. (2020).	1999–2007	China	FDI causes Productivity
(B) FDI and Digital Technology			
Kozlova et al. (2019)	2001–2017	Russia and Germany	Digital Technology causes FDI
Nurainy and Adipati (2018)	2008–2011	Asian countries	Digital Technology causes FDI
Drahokoupil and Fabo (2020)	2011–2017	Slovakia	Digital Technology causes FDI
Tkalenko et al. (2019)	1997–2017	Ukrainian	Digital Technology causes FDI
Tang et al. (2020)	2001–2009	China	FDI causes Digital Technology
(C) FDI and INO			
Erdal and Gocer (2015)	1996–2013	Asia countries	FDI causes INO
Dhrifi (2015)	1990–2012	Developed and developing countries	INO causes FDI
Chen and Zhang (2018)	2001–2007	China	FDI causes INO
Viglioni and Calegario (2020)	1998–2014	Brazil	FDI causes INO
Omidi et al. (2018)	2011–2016	Developing countries	FDI causes INO
Chen et al. (2020)	2005–2018	China	FDI causes INO
Jiang et al. (2020)	2007–2016	China	FDI causes INO
Asunka et al. (2021)	1994–2018	Middle-income countries	FDI causes INO INO causes FDI
(D) FDI and NRs			
Bokpin et al. (2015)	1980–2011	African countries	NRs cause FDI
Aleksynska and Havrylchyk (2013)	1996–2007	Developing and developed countries	NRs cause FDI
Hayat (2018)	1996–2015	Low-, middle- and high-income countries	NRs cause FDI
Kilicarslan (2019)	2007–2015	BRICS and Turkey	NRs cause FDI
Wall et al. (2018)	2005–2014	OECD and non-OECD countries	NRs cause FDI

Source: Authors' compilation

METHODOLOGY

This study made use of a secondary panel dataset that contains data of 24 EMCs from 2000 to 2021, based on the most up-to-date data availability. EMCs were the primary factor in selecting sample countries for their great engagement with the global economy, high trade volume and FDI. The classification of EMCs was based on the MSCI Market Classification Framework (2024), involving Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Türkiye and Thailand. Table 2 displays the variable specifications and data sources for this study.

TABLE 2. Variable name and data sources

Variable	Variable symbol	Variable specification	Data source
Foreign direct investment	FDI	Annual inflow of FDI measured in current USD dollars (millions)	World Bank (2024)
Digital economy index	DEI	An index created on the basis of principal component analysis that takes into account the use of fixed broadband, fixed telephone and individual internet usage	International Telecommunicate Union (2024)
Total factor productivity	TFP	The labour force participation rate expressed as a percentage of the total population aged 15–64	World Bank (2023)

Innovation capacity	INO	The number of patent applications submitted by citizens of the country	World Intellectual Property Organization (2024)
Total natural resource	NR	The proportion of natural resources as a percentage of GDP	World Bank (2024)

The use of principal component analysis (PCA) resulted in the development of a DE index by analysing three key indicators: fixed broadband subscriptions, fixed telephone subscriptions and the percentage of individuals using the internet. A dataset can be reduced in dimensionality using PCA, a multivariate statistical method that preserves as much variance as possible. Principal components are formed by transforming correlated variables into a smaller set of uncorrelated variables. Proposed by Pearson (1901) and later comprehensively developed by Hotelling (1933), PCA is widely used for creating composite indices in multivariate analysis. A covariance matrix is constructed to start the PCA process, which encompasses the variance of each variable and their interrelationships. The directions with the greatest variance are identified by calculating eigenvalues and eigenvectors from this matrix. The eigenvectors determine the weight for each principal component, which is expressed as a weighted linear combination of the original variables and can be demonstrated as follows:

$$P_1 = a_{11}x_1 + a_{12}x_2 + \dots + a_{1c}x_n$$
$$P_1 = a_{21}x_1 + a_{22}x_2 + \dots + a_{2c}x_n$$
$$\dots$$
$$P_c = a_{c1}x_1 + a_{c2}x_2 + \dots + a_{cc}x_n$$

where P_c represents the c^{th} principal component, x_i is the i^{th} variable, and a_{ci} is the weight assigned to each variable on the basis of its contribution to that component. The variance (λ) of each principal component corresponds to the eigenvalue of the covariance matrix and reflects the amount of total variance explained by that component.

This study seeks to examine the effects of DE, NRs, productivity and INO capacity on improving FDI performance. The Cobb–Douglas production function was employed, and the fundamental model of Cobb–Douglas production is outlined as

$$Y = AK^{\alpha} L^{\beta} \qquad \dots(1)$$

where Y represents the output of the country, K is the capital input, and L is the labour input. The output elasticities of labour and capital are presented by α and β, respectively. The Cobb–Douglas model has been used by Negash et al. (2020) and Jungmittag and Welfens (2020) in their studies of FDI inflows. Neoclassical economic growth theory and the Cobb–Douglas production function were extended by this study by proposing variables, which is in accordance with the extensive literature on FDI discussed earlier. The model that is central to this study can be demonstrated as follows:

$$FDI_{it} = \alpha_i + \beta_1 NR_{it} + \beta_2 DEI_{it} + \beta_3 TFP_{it} + \beta_4 INO_{it} + \varepsilon_i \qquad \dots(2)$$

The natural log transformation for dependent and independent variables was used to address heteroscedasticity issues. The estimation equation was transformed in logarithm formulation as follows:

$$InFDI_{it} = \alpha_0 + \beta_1 InNR_{it} + \beta_2 InDEI_{it} + \beta_3 InTFP_{it} + \beta_4 InINO_{it} + \varepsilon_i \qquad \dots(3)$$

where α is the intercept, β represents the coefficients of the linear panel model, and ε_i indicates the error term. This study aims to examine how productivity, digitalisation and NRs affect the ongoing FDI flow in EMCs. The cross-sectionally augmented Im–Pesaran–Shin (CIPS) and second-generation covariate-augmented Dickey–Fuller (CADF) unit root tests were utilised to examine cross-sectional correlation and heterogeneity. The next step involved implementing Pesaran (2015)'s cross-sectional dependency test and then the homogeneity test by utilising the adjusted delta of the standard dispersion statistic suggested by Pesaran and Yamagata (2008). The Westerlund (2007) cointegration test was used to examine the possibility of long-term cointegration between variables after determining the potential for homogeneity or heterogeneity in the panel dataset.

The PMG technique, developed by Pesaran et al. (1999), is appropriate for this study as it allows for heterogeneous short-run dynamics across countries whilst assuming a common long-run relationship, ideal for panels of EMCs. It is based on an ARDL framework, which makes it suitable for nonstationary data with mixed integration orders. PMG can provide robust estimates of the short- and long-run effects of FDI determinants under cross-country heterogeneity whilst being flexible and efficient. According to Pesaran et al. (1996; 2001), the panel ARDL model with symmetric conditions can be expressed in the following manner:

$$\Delta FDI_{i,t} = \beta_0 + \beta_{1i} FDI_{i,t-1} + \beta_{2i} NR_{i,t-1} + \beta_{3i} DEI_{i,t-1} + \beta_{4i} TFP_{i,t-1} + \beta_{5i} INO_{i,t-1} + \sum_{j=1}^{q-1} \delta_{1ij} \Delta FDI_{it-j} + \sum_{j=0}^{q-1} \delta_{2ij} \Delta NR_{i,t-j} + \sum_{j=0}^{q-1} \delta_{3ij} \Delta DEI_{i,t-j} + \sum_{j=0}^{q-1} \delta_{4ij} \Delta TFP_{i,t-j}$$

$$+\sum_{j=0}^{q-1}\delta_{5ij}\Delta INO_{i,t-j}+\varepsilon_{i,j} \qquad \ldots(4)$$

In Eq. (4), the long-run coefficients of the estimated PMG model are indicated by the first part, and the second part includes the first difference condition to represent short-run effects. The Schwarz information criterion was used in this study to identify the optimal lag orders of the PMG model given its small number of observations and samples. Equation (4) can be respecified with an error correction indication, according to Pesaran et al. (2001), as shown below:

$$\Delta FDI_{i,t}=\gamma_0+\sum_{j=1}^{q-1}\delta_{1i,j}\Delta FDI_{i,t-j}+\sum_{j=0}^{q-1}\delta_{2i,j}\Delta NR_{i,t-j}+\sum_{j=0}^{q-1}\delta_{3i,j}\Delta DEI_{i,t-j}+$$
$$\sum_{j=0}^{q-1}\delta_{4i,j}\Delta TFP_{i,t-j}+\sum_{j=0}^{q-1}\delta_{5i,j}\Delta INO_{i,t-j}+\phi ECT_{t-1}+\eta_{i,j}\ldots(5)$$

The elastic response corresponds to the independent variables, as depicted by the short-run coefficients of the parameter, shown as δ in Eq. (5). Negative and significant error correction terms (ECT) are indicated by the coefficient symbol ϕ. The ECT coefficient value and the speed of adjustment required determine how well the estimation can fit back into the long-term equilibrium condition. By employing the Dumitrescu and Hurlin (2012) approach, which is known as heterogeneous causalities, this study further investigated the causality between variables. This approach can contain the heterogeneity of the casual association and that of the regression model. The causality test model for DH has the following form:

$$Y_{it}=\alpha_i+\sum_{k=1}^{k}\lambda_i^k\,y_{i,t-k}+\sum_{k=1}^{k}\beta_i^k\,x_{i,t-k}+\epsilon_{i,t} \qquad \ldots(6)$$

where y_i and x_i are the observables of two fixed variables for the number of countries involved in the data coverage period of this study. The autoregressive parameters and regression coefficients are indicated as λ_i^k and β_i^k, respectively, of which the coefficients can vary across countries involved; k implies the lag order, which assumes that all cross sections of a country are measured as a balanced panel. The hypothesis for the DH test can be derived as follows:

$$\mathrm{H}_0: \beta_i = 0 \qquad \forall i = 1, \ldots, N$$
$$\mathrm{H}_1: \beta_i \neq 0 \qquad \forall i = 1, \ldots, N_1 \qquad \ldots(7)$$

All panels from all countries do not show causality if the null hypothesis is homogenous. The heterogeneous noncausality hypothesis is an alternative hypothesis proving that causality is connected to at least one country in the panel. The average Wald statistic was calculated to test the null hypothesis, as demonstrated in Eq. (8). All individual panels related to the hypothesis have an independent and identical distribution of the Wi series, as proven by the Wald statistic.

$$W_{N,T}^{HNC}=\frac{1}{N}\sum_{i=1}^{N}W_{i,T} \qquad \ldots(8)$$

RESULTS AND DISCUSSION

The first step of analysis in Table 3 is to present descriptive statistics and correlation analysis of the variables involved in this study. The INO and NR variables are the most unstable amongst variables, as indicated by the standard deviation values. With a standard deviation value of 1.067, TFP's volatility is lowest. TFP and INO have a positive bias, whereas all other variables have a negative bias. FDI has a positive correlation with DE, TFP and INO; by contrast, the correlation between NR and INO is negative, similar to the correlation between DE and TFP.

TABLE 3. Summary of descriptive statistics

	FDI	DEI	TFP	NR	INO
Minimum	16.793	−4.757	20.410	−3.994	4.110
Std. Deviation	1.326	1.555	1.067	1.671	1.751
Skewness	−0.252	−0.878	0.552	−0.925	0.854
Kurtosis	4.349	3.090	3.188	3.681	3.543
Jarque–Bera	34.763*	51.858*	21.074*	65.144*	53.853*
Shapiro–Wilk	0.462*	0.936*	0.979*	0.954*	0.855*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Shapiro–Francia (SF)	0.447*	0.937*	0.979*	0.956*	0.850*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Correlation Matrix					
FDI	1.000				

DEI	0.309*	1.000			
	(0.000)				
TFP	0.695*	0.354*	1.000		
	(0.000)	(0.000)			
NR	0.079	0.060	−0.041	1.000	
	(0.113)	(0.228)	(0.411)		
INO	0.592*	0.037	0.788*	−0.128**	1.000
	(0.000)	(0.458)	(0.000)	(0.009)	

Note: *, ** and *** are significant at 1%, 5% and 10% levels, respectively. Values in ( ) represent p-values.

The second-generation CADF test introduced by Hansen (1995) and the CIPS test by Pesaran (2007) were used to determine the integration order of the variables, with trending data measured at level and first difference to render the stationary condition. Table 4 shows the results of the CADF and CIPS tests, which indicate that all variables remain stationary at the first difference. Additionally, this study utilised the heteroscedasticity robust panel unit root tests proposed by Herwartz and Siedenburg (2008), which are crucial for advancing heteroscedasticity in small samples. Table 5 demonstrates that the variables are not stationary at the level, as demonstrated by the result. All variables at the level become stationary owing to the initial difference between constant and trend conditions, which implies that they have a unit root.

TABLE 4. Second-generation panel unit root test results

Variable	FDI	DEI	TFP	NR	INO
(A) At level					
CADF	−2.002	−2.072***	−1.757	−1.618	−2.498*
CIPS	−3.537*	−4.194*	−2.183**	−2.343*	−2.661*
(B) At first difference					
CADF	−3.943*	−3.647*	−2.569*	−3.349*	−3.194*
CIPS	−5.277*	−4.810*	−3.397*	−4.380*	−4.029*

Note: *, ** and *** are significant at 1%, 5% and 10% levels, respectively.

TABLE 5. Herwartz and Siedenburg heterogeneous panel unit root test results

Variable	At level		At first difference	
	Constant	Constant & Trend	Constant	Constant & Trend
FDI	−1.242	−1.3692***	−2.628*	−1.720*
	(0.107)	(0.085)	(0.004)	(0.004)
DEI	2.696	2.175	−2.553*	−1.496*
	(0.996)	(0.9852)	(0.005)	(0.006)
TFP	0.472	2.705	−1.3192***	−1.507***
	(0.681)	(0.996)	(0.093)	(0.065)
NR	−1.224	−0.3288	−2.628*	−1.720**
	(0.110)	(0.371)	(0.004)	(0.042)
INO	−1.8532**	−1.244	−2.667*	−1.891**
	(0.031)	(0.106)	(0.003)	(0.029)

Note: *, ** and *** are significant at 1% 5% and 10% levels, respectively.

Next, the results from panel diagnostic tests, which consisted of multicollinearity, cross-dependency and homogeneity tests, were evaluated. Table 6 shows that the tolerance is not less than 0.2, whilst the variance inflation factor (VIF) values are less than 5, which implies that all variables are not facing multicollinearity. The CD test results indicate that all variables have a significant impact of 1%, rejecting the null hypothesis of cross dependency, as demonstrated in Table 7. All variables are interdependent, and various panels are involved in every country considered in this study. Both delta values are rejected by the Pesaran and Yamagata (2008) homogeneity test, which indicates that the heterogeneous panel method should be used for this study.

TABLE 6. Test for multicollinearity effect

Variable	Collinearity statistic	VIF
TFP	0.467	2.14
INO	0.480	2.08
DEI	0.840	1.19
NR	0.874	1.14

TABLE 7. Cross-dependency and homogeneity test results

Variable	CD test	
	Statistic	p-value
FDI	24.156*	0.000
DEI	55.399*	0.000
TFP	66.024*	0.000
NR	48.556*	0.000
INO	11.884*	0.000
Pesaran–Yamagata test results		
$\tilde{\Delta}$	−2.900**	0.004
$\tilde{\Delta}$- adjusted	−3.378**	0.001

Note: *, ** and *** are significant at 1%, 5% and 10% levels, respectively.

The Westerlund (2007) cointegration test was utilised to determine if there is long-term cointegration between the variables, following the verification of the homogeneity test. Table 8 reveals the existence of an error correction for the group mean (G_t and G_α) and panel (P_t and P_α), given that the null hypothesis of no integration is rejected at less than 10% significance level. This finding confirms that FDI and other variables have a long-term association with each other, as shown by Arvin et al.'s (2021), Ahmed and Kialashaki's (2021), Asunka et al.'s (2021) and Hayat's (2018) earlier empirical findings.

TABLE 8. Bivariate Westerlund cointegration results

	G_t	G_α	P_t	P_α
FDI vs. DEI	−2.838*	−8.621***	−10.723*	−7.982*
	(0.000)	(0.092)	(0.000)	(0.000)
FDI vs. TFP	−2.541*	−10.794*	−10.496*	−7.969*
	(0.000)	(0.001)	(0.000)	(0.000)
FDI vs. NR	−2.234**	−11.538*	−10.034*	−7.818*
	(0.007)	(0.000)	(0.002)	(0.000)
FDI vs. INO	−2.848*	−12.303*	−11.996*	−9.029*
	(0.000)	(0.000)	(0.000)	(0.000)

Note: *, ** and *** are significant at 1%, 5% and 10% levels, respectively.

The short- and long-term coefficients were further investigated using the PMG estimation shown below:

$$
\begin{aligned}
FDI = {} & 1.695 + \underset{(0.058)^{*}}{0.295NR} + \underset{(0.033)^{*}}{0.111DEI} + \underset{(0.097)^{*}}{0.890TFP} - \underset{(0.062)}{0.002INO} - \underset{(0.405)^{**}}{0.887\Delta NR} + \underset{(0.150)^{***}}{0.255\Delta DEI} \\
& + \underset{(0.854)^{**}}{2.120\Delta TFP} - \underset{(0.326)}{0.060\Delta INO} - \underset{(0.000)^{*}}{0.818\gamma_{t-1}} \qquad \ldots(9)
\end{aligned}
$$

The PMG estimation results, based on an optimal ARDL (1,1,1,1) model, reveal a significant and positive relationship between FDI and DE in the short and long run. The findings are in line with the study's expectations: DE facilitates investment by decreasing transaction costs, improving market access and enhancing efficiency. Drahokoupil and Fabo (2020), Tkalenko et al. (2019) and Tang et al. (2020) have reported a positive correlation between FDI and digitalisation, which reinforces the current findings. This outcome is supported by the growth of digital infrastructure in EMCs, which is evidenced by the increase in internet and social media usage. Around 5 billion internet users exist globally, which is equivalent to 64% of the global population (Statistics 2023). TFP has a positive and significant impact on FDI in the short and long term, as expected. Foreign investors can benefit from a highly productive economy that signals efficient resource utilisation and growth potential. The results are consistent with those of Habib et al. (2019) and Asongu et al. (2020), who found that TFP enhancements resulted in an increase in FDI by 0.89% and 2.12%, respectively.

According to Kilicarslan (2019) and Hayat (2018), NRs have a positive long-term impact on FDI inflows. That is, countries with abundant and well-managed NRs will continue to attract foreign investors who are seeking resources over time. The impact of INO on FDI in the short and long run is insignificant, contrary to expectations. Whilst INO is commonly seen as a driver of investment, particularly in technology-intensive sectors, this outcome may be due to limited INO capacity or weak commercialisation frameworks in many EMCs. This finding is in line with that of Nyeadi and Adjasi (2020), who also reported the insignificance of INO indicators in South African countries, suggesting that INO may not yet be a decisive factor for FDI in these contexts. Finally, this study found that the adjustment towards long-run equilibrium is 81.8% fast, which indicates that short-term deviations from the equilibrium level of FDI are quickly corrected. The long-run relationship between FDI and its determinants is showing stability, which is a strong indication. The robustness of this finding is supported by the observation of similar patterns of rapid adjustment by Fofana (2018), Musibau et al. (2019) and Huang (2020).

The DH causality test was used to examine the causal effect between the involved variables, and Table 9 shows the results of this test. The bidirectional causal relationship between FDI and INO suggests that INO is linked to FDI, implying that expanding FDI can enhance INO and vice versa. This finding is consistent with that of Asunka et al. (2021), that is, FDI and INO have a causality effect in the short- and long-term period. A two-way causality association between DE and TFP and between TFP and INO was also observed. There is a causal link between DE and NR, DE and INO, DE and FDI, TFP and FDI and TFP and NR.

TABLE 9. DH causality test results

Variable	FDI	DEI	TFP	NR	INO
FDI		3.413	2.314	2.924	5.391*
		(0.142)	(0.882)	(0.392)	(0.000)
DEI	3.849**		4.313*	3.446***	8.344*
	(0.032)		(0.002)	(0.095)	(0.000)
TFP	4.860*	9.440*		6.820*	7.550
	(0.000	(0.000)		(0.000)	(0.000)
NR	2.098	2.203	2.273		1.965
	(0.615)	(0.723)	(0.876)		(0.484)
INO	7.213*	1.8733	3.351***	3.182	
	(0.000)	(0.367)	(0.096)	(0.169)	

Note: *, ** and *** indicate significance at 1%, 5% and 10% levels, respectively, and the p-values are presented in ( ).

CONCLUSION

In the past 20 decades, there have been many mixed results from the methods used in studies related to FDI flows. This study's empirical findings suggest that more policies encouraging FDI should be recommended given that most EMCs are currently experiencing an economic recovery period. EMCs can stimulate FDI inflows in the short- and long-term period by emphasising mapping strategies and policies that focus on advancement and improving DE. The future DE requires significant investment in digital infrastructure, such as expanding broadband connectivity, deploying 5G networks and ensuring affordable internet access in underserved regions. By simplifying business registration and licensing through digital one-stop shops and e-government services, governments can improve transparency and efficiency. For boosting investor confidence in digital markets, strong cybersecurity frameworks and data protection laws that are in line with international standards should be established. By harmonising e-commerce regulations, reducing digital tariffs and promoting digital payment systems, emerging economies can further integrate into the global digital marketplace.

Sustainable NR management can lead to FDI inflows, particularly in resource-rich emerging markets. Additional incentives for green investment, such as tax breaks for companies that use sustainable extraction practices and invest in renewable energy, should be implemented by governments. Improving environmental, social and governance compliance can ensure responsible resource use and prevent environmental degradation, which is a major concern for international investors. Promotion and improvement of a circular economy can be achieved by encouraging industries to adopt waste-to-energy projects, recycling initiatives and water conservation strategies. By ensuring ethical sourcing and reducing corruption risks, blockchain technology can help increase investor confidence in mining, agriculture and energy sectors. The importance of investing in R&D for policymakers is due to the two-way causal effect of FDI and INO capacity on attracting foreign investors to double up FDI flows between EMCs. Ensuring long-term economic transformation and attracting knowledge-intensive investments by ensuring technology INO also play a pivotal role.

To create a dynamic digital ecosystem, governments must create technology parks, incubators and INO hubs that aid local startups and scale-ups. Encouraging venture capital investment through targeted tax incentives, seed funding and regulatory support can further accelerate the growth of high-tech industries. Moreover, strengthening intellectual property rights protections is essential for creating a secure environment that encourages foreign firms to invest in R&D. Streamlined patent approval processes, robust legal frameworks for technology licensing and strengthened enforcement mechanisms can help achieve this goal. Strategic policies that reinforce human capital development, industrial modernisation and infrastructure efficiency are necessary for enhancing TFP. For equipping the workforce with the expertise needed for high-tech industries, investing in STEM education and digital skills training is crucial. A considerably competitive and knowledge-based economy can be facilitated by partnerships between universities and MNCs, which can promote technology transfer and INO-driven R&D. The adoption of automation, artificial intelligence and advanced manufacturing technologies should be encouraged by governments to accelerate industrial upgrading. The attractiveness of a country to FDI can be improved by creating special economic zones for high-tech industries and aligning regulatory frameworks with global value chains.

Additionally, improving transportation and logistics infrastructure, such as smart ports and AI-powered customs systems, can streamline trade processes, reduce operational costs for investors and boost the overall competitiveness of emerging economies. Finally, an economic slowdown has occurred in the EMCs recently due to the global pandemic and exchange instability. Improving export volume by enhancing digital facilities as part of DE platform and smoothing trading activities by increasing competitiveness and appropriate productivity levels can be achieved in this condition. The Belt and Road Initiative in China is an alternative for EMCs, as it involves more capital flows that can provide more FDI clues and increase FDI opportunities. By enhancing their transport and digital infrastructure, the emerging economies in ASEAN can reap the benefits of the ASEAN–China Free Trade Agreement, which will have an impact on the regions' FDI flows in the future.

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