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Influence of a knowledge-based economy on foreign direct investment in regional comprehensive economic partnership economies

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Influence of a knowledge-based economy on foreign direct investment in regional comprehensive economic partnership economies

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Abstract: This study examines the influence of a knowledge-based economy on foreign direct investment (FDI) among countries in the regional comprehensive economic partnership (RCEP). The knowledge-based economy is the focus of this study, with particular attention paid to digital technology, innovation, and advanced industrial capacities. Panel data from ten RCEP member states from 2008 to 2019 and the Lasso-Poisson pseudo-maximum likelihood method are used in the estimation. The results show that technological skills, similarities in technological skills, R&D, high-tech and innovative industrial activities, and access to finance between the recipient and investing countries in the RCEP positively influence FDI flows. Additionally, the economic complexity disparity across RCEP countries positively influences their FDI activities. Based on these findings, RCEP nations should accelerate their efforts to advance digital technology and innovation, increase the economic complexity of production, and promote knowledge-based economic integration.

Keywords: knowledge-based economy; digital technology and innovation; economic complexity; foreign direct investment; FDI; regional comprehensive economic partnership; RCEP.

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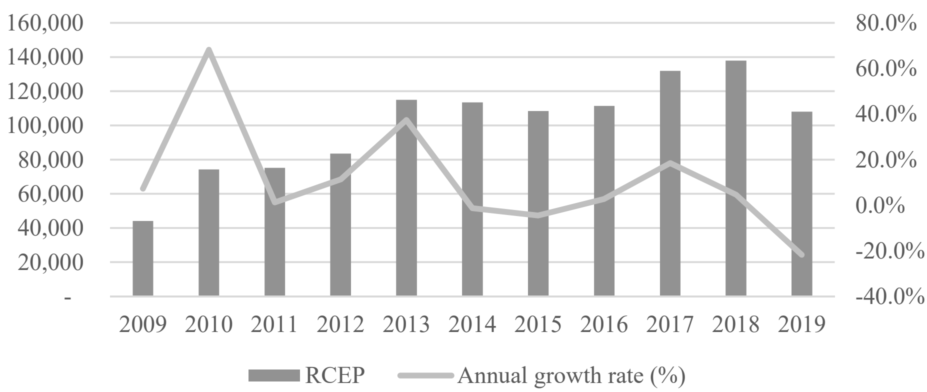
1 Introduction

The regional comprehensive economic partnership (RCEP), the world's largest free trade agreement, was signed by 15 Asian countries in 2020 and entered into force in 2022. The agreement covers the chapters dealing with trade in goods and services, investment, intellectual property, and competition. Notably, the investment chapter of the RCEP agreement contains provisions relevant to investment treatment, promotion, and facilitation, all of which have the potential to attract FDI activities across members. According to UNCTAD, the RCEP will receive roughly half (49.8%) of global FDI inflows in 2021, making it a major FDI destination. Some scholars have also anticipated that FDI liberalisation under the RCEP will boost FDI activities among RCEP members (Balistreri and Tarr, 2022; Uttama, 2021; Li et al., 2017). Bilateral inward FDI has become a crucial driver of RCEP, with a compound annual growth rate of 9.2% from 2009 to 2019 (Figure 1). According to data from the International Trade Centre (ITC), during 2009–2019, Vietnam was the largest FDI recipient (22% of all RCEP countries), followed by Indonesia, Singapore, and China. Meanwhile, Japan was the largest FDI investor (32% of RCEP), followed by Singapore, the Republic of Korea, and China. However, it is noteworthy that RCEP members comprise a wide range of economies (developed, developing, and least-developed countries). Based on this heterogeneity, opportunities for the complementarity and substitution of FDI have appeared.

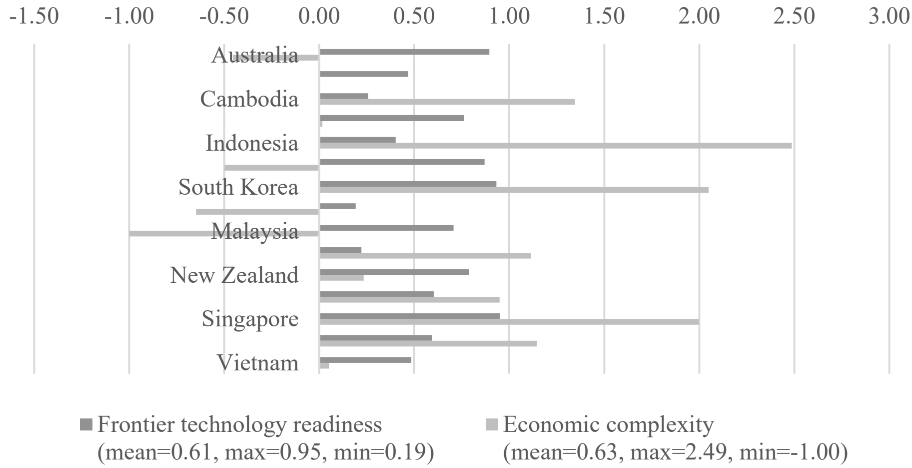
Figure 1 Bilateral FDI inflows in RCEP, 2009-2019 (Million US$)



Source: ITC (2022)

The knowledge-based economy is an essential mechanism of a country's economic development, and it has evolved in accordance with the global economic landscape. In the past, labour skills played the primary role in a knowledge-based economy; the current focus is on digital technology, innovation, and sophisticated production capabilities. Digital technology and innovation development (hereafter, 'the digital economy') have been regarded as effective knowledge-driven instruments for economic growth and development. All countries also need to explore pathways leading to a high level of digital economy (Casella and Formenti, 2018; Srinivasan and Eden, 2021). The development of the digital economy, such as digital infrastructure, technologies, ICT adoption, skills, R&D, and industry activities, can reflect the socioeconomic status and potential of a nation (Anukoonwattaka et al., 2022). In addition, the studies of Arvin et al. (2021), Jovanovic and Morschett (2022) and Moeini Gharagozloo et al. (2021) found that the digital economy had a positive influence on FDI in some groups of countries. Based on UNCTAD's frontier technological readiness index, the average degree of technological readiness in the RCEP was 0.61, which shows how the digital economy has grown (Figure 2). Singapore had the most significant digital economy, followed by South Korea, Australia, and Japan. On the frontier technological readiness index, more than half of RCEP members scored higher than the global average. The RCEP is likely to be an attractive FDI destination due to the digital economy. The greater the degree of digitalisation, the greater the foreign direct investment (FDI). The RCEP is likely to be an attractive destination for FDI, and other economic activities that use digital technology will continue to rise.

Figure 2 Frontier technology readiness and ECI s by RCEP countries in 2019



Source: UNCTAD (2022) and Growth Lab (2021)

In addition, the notion of economic complexity has been used to explain a country's economic structures and the diversity and sophistication of its productive capacities. The economic complexity index (ECI) (Hidalgo and Hausmann, 2009; Hausmann et al., 2013) was created to measure how sophisticated and knowledge-based a country's productive capabilities are. A country with a high level of economic complexity has greater productive capabilities. It also shows how much a country with a higher level of economic complexity can improve its economic activities in other countries. In 2019, Growth Lab found that the average level of economic complexity in RCEP was 0.63, and almost all RCEP countries had an ECI higher than the average for the whole world (Figure 2). Indonesia had the most extensive economic complexity, followed by South Korea, Singapore, Cambodia, and Thailand. Most countries with a high complexity index were ASEAN members who have attempted to increase FDI activities to support their economic growth and recovery. Recent studies by Ranjbar and Rassekh (2022), Gnangnon (2022) and Koch (2021) demonstrated that economic complexity improved FDI and international trade. Considering this issue, improving economic complexity illustrates the higher degree of knowledge-based economies that tend to foster FDI activities. However, only some studies have explored economic complexity's direct impact on FDI.

This study addresses the questions in light of the concerns mentioned earlier. How crucial is the knowledge-based economy for RCEP's FDI? How do differences in RCEP's knowledge-based economy levels affect intra-RCEP FDI? Moreover, what should policymakers be concerned about?

On the basis of these research questions, the purpose of this paper is to analyse the effects of the development of a knowledge-based economy on bilateral FDI in RCEP member countries and encourage a rethinking of knowledge-driven policies and actions. In doing so, this study contributes to the literature in a few ways. First, the study examines the influence of the digital economy and economic complexity as two drivers of FDI, arguably providing a more reliable picture of a country's FDI performance. Interestingly, the roles of the five building blocks of digital economy development (ICT adoption, skills, R&D activity, industry activity, and access to finance) are considered in the study. There have been a small number of studies on the linkages between the digital economy and economic complexity with FDI. The literature argues that the digital economy is the primary driver of FDI (Arvin et al., 2021; Jovanovic and Morschett, 2022). Meanwhile, Sadeghi et al. (2020) found that economic complexity has statistically influenced FDI. The results of this study would show how important it is to develop the digital economy and have a complex economy to attract FDI. Second, the study conducts a more in-depth analysis of how differences in knowledge-based economies between the recipient and home countries influence FDI in the RCEP. This study would have policy implications for RCEP nations seeking FDI in an effort to accelerate knowledge-based economic integration. Finally, despite extensive research into FDI, technology, and innovation development, a panel of specific RCEP economies was not considered. This paper endeavours to address the gap by exploring the effects of the digital economy and economic complexity on bilateral FDI in RCEP economies from 2008 to 2019. Importantly, this study uses a penalised Poisson pseudo-maximum likelihood regression estimator with an adaptive lasso for consistent variable selection to improve the reliability and validity of our estimation results. A data-driven approach that uses machine learning algorithms (Athey and Imbens, 2019; Fu et al., 2021; Mullainathan and Spiess, 2017; Portugal et al., 2018) ensures high data quality and accurate predictions.

The remainder of the paper is structured as follows: Section 2 provides a literature review. Methodology and data are described in detail in the following section. In Section 4, the empirical results are presented and discussed, and Section 5 provides the conclusion.

2 Literature review

This section describes two strands of the literature: the effects of a knowledge-based economy, i.e., digital technology and innovation and economic complexity, on FDI and the economic determinants of FDI.

2.1 Knowledge-based economy and FDI

The knowledge-based economy refers to an economic system driven by knowledge-intensive activities, which is a crucial instrument of the country's economic development. In this study, the knowledge-based economy focuses on digital technology, innovation, and sophisticated production capabilities.

2.1.1 Digital technology, innovation, and FDI

The development of digital technology and innovation, or the 'digital economy,' is part of a knowledge-based economy that has emerged as the country's primary economic driver. It can be measured by the Frontier Technology Readiness of UNCTAD. This index is to assess the country's capacity to use, adopt, and adapt its technologies to the digital economy. The readiness index has five building blocks: ICT deployment, skills, R&D activity, industry activity, and access to finance. First, ICT deployment captures the prevalence of the use of ICT and the quality of ICT infrastructure. Second, relevant skills are delivered through education, practical training, or learning by doing. Third, R&D activity emphasises the production and modification of technologies. Fourth, industry activity refers to the ongoing use, adoption, and adaptation of technologies in the industry. Lastly, access to finance offers opportunities for the availability of finance for technologies. A country with high ICT deployment, skills, R&D, industrial activity, and financial access has a higher level of a knowledge-based economy.

Several studies have analysed the relationship between FDI and the digital economy. Some of these studies support a positive relationship between the digital economy and FDI (Arvin et al., 2021; Jovanovic and Morschett, 2022; Khan et al., 2021; Latif et al., 2018; Moeini Gharagozloo et al., 2021; Nayak and Sahoo, 2021). Jovanovic and Morschett (2022) examined the relationship between Swiss and German industrial manufacturers' digital readiness and service FDI. They found that digital readiness was a key factor in the FDI decision. Similarly, Moeini Gharagozloo et al. (2021) revealed that superior digital readiness positively impacted international M&A intensity in the USA. Khan et al. (2021) studied the impact of the digital economy on venture capital investment in European nations and discovered a positive correlation between them. Their findings were similar to those of Nayak and Sahoo (2021). They indicated a significantly positive relationship between ICT and FDI in India. Arvin et al. (2021) examined the causal linkage between ICT connectivity and FDI in the G-20 countries. They found a bidirectional causal relationship between ICT (fixed telephone subscriptions and mobile cellular subscriptions) and FDI. Meanwhile, the unidirectional causality from ICT with fixed broadband subscriptions, ICT goods exports, ICT goods imports, ICT connectivity, and ICT penetration to FDI existed. Their findings contradict Latif et al. (2018), suggesting a unidirectional causality from FDI to ICT for the BRICS economies. Moreover, Gopalan et al. (2022) investigated the role of digitalisation in the global value chain (GVC) in emerging and developing countries. They revealed that digitalisation positively influenced GVC participation. Teruel et al. (2022) also investigated the effects of new digital technologies on high-growth enterprises in the EU Member States and the United Kingdom. They suggested that adopting digital technologies that led to higher internalisation positively impacted high-growth enterprises.

In sum, the aforementioned findings indicate that the influence of digital economy development on FDI can be seen in the recipient and home countries' direct access to ICT deployment and digital readiness. This review of the literature leads to the first hypothesis:

Hypothesis 1 Bilateral FDI is positively associated with the country's level of digital technology and innovation development.

2.1.2 Economic complexity and FDI

'Economic complexity' is widely used to reflect the level of complexity of a country's economy. Specifically, the ECI has become increasingly popular in recent years as a measure of a country's sophisticated and knowledge-based production capabilities (Hausmann et al., 2013). It was measured by the diversity of exported goods from various countries. A country with high economic complexity has a knowledge-based economy. Much empirical evidence has examined the economic determinants of economic complexity, such as economic growth, economic activities, and factor movements (Avom et al., 2021; Balland et al., 2022; Kamguia et al., 2021; Nguyen and Su, 2021; Ranjbar and Rassekh, 2022); and some studies have concentrated on the impact of economic complexity on economic structures (Gnangnon, 2022; Koch, 2021; Lapatinas, 2016; Maldonado et al., 2022; Nguyen, 2021; Qi, 2022; You et al., 2021). However, some pieces of literature on the effect of economic complexity on foreign investment (Antonietti and Franco, 2021; Khan et al., 2020; Ranjbar and Rassekh, 2022; Sadeghi et al., 2020).

Ranjbar and Rassekh (2022) found that countries with high economic complexity enhanced the efficacy of FDI inflows, whereas countries with low economic complexity impeded FDI inflow potential. Sadeghi et al. (2020) also revealed that economic complexity relating to knowledge intensity in production has statistically influenced FDI attraction. Khan et al. (2020) explored the causal linkage between economic complexity and FDI in China. They found that the bidirectional causal relationship between economic complexity and FDI existed in the long run. Meanwhile, the unidirectional causality from economic complexity to FDI only existed in the short run. Their findings contradicted those of Antonietti and Franco (2021), who explored the causal linkage between economic complexity and FDI in the world, high-income countries, and low-income countries. There was unidirectional causality from FDI to economic complexity in the world and in high-income countries. There is no solid empirical evidence on the causal link between economic complexity and FDI. Moreover, Nguyen et al. (2021) attempted to examine the influence of economic complexity on entrepreneurship density. They found a positive relationship between them in low- and middle-income economies but a negative linkage in high-income countries. Their findings were similar to Ajide's (2022).

In conclusion, the empirical evidence presented above demonstrates that economic complexity positively affects FDI flows through both direct and indirect effects. This review of the literature leads to the second hypothesis:

Hypothesis 2 Bilateral FDI is positively associated with the country's economic complexity.

2.2 Economic determinants of FDI

The knowledge-capital (KC) model is one of the FDI theories that sheds light on horizontal and vertical FDI motives. It suggested that the economic size of recipient and investing countries, similarity in economic size, differences in factor endowments (labour and capital), and trade costs between countries are the primary determinants driving bilateral FDI (Markusen, 2002) and sales of multinational enterprises (Carr et al., 2001). The theoretical predictions of the KC model featured two distinct strands. First, horizontal FDI exists when the recipient and investing countries have similar economic sizes and high trade costs. Horizontal FDI exists when a multinational enterprise duplicates identical production activities in different countries. Second, differences in factor endowments and low trade costs are dominated by vertical FDI. Vertical FDI exists when a multinational enterprise fragments some of its production stages abroad. The theoretical determinants of the KC model can be categorised into three groups. The first group refers to the variables of economic size that are approximated by the sum of GDP (+) and the square of the difference between countries' GDP (–), which tend to have positive and negative effects on FDI, respectively. The second group refers to the factor endowment variables approximated by the difference between countries' skill levels (+) and the interaction term between the differences in GDP and skill levels (–), which are anticipated to have positive and negative effects on FDI, respectively. The last group refers to the variables of trade costs (–). They are approximated using the interaction term between trade costs in the recipient country and squared skill differences, trade costs for the recipient and investing countries, investment costs, and distance between countries, which have an adverse effect on FDI.

The most recent empirical studies applied the KC model to investigate the motives and determinants of FDI (Behera and Mishra, 2022; Chattopadhyay et al., 2022; Cieślik, 2019; Duong et al., 2021; Schneider and Wacker, 2022). For instance, Schneider and Wacker (2022) reassessed the theoretical motives of FDI using the KC model, which incorporated cultural, institutional, and financial factors. They used a cross-validation approach and suggested that the KC determinants and the additional factors, e.g., institutional, cultural, or financial factors, had significant impacts on FDI. Nevertheless, the efficiency of the additional KC model was less potent than the original KC model. Duong et al. (2021) built the estimation model based on the KC model. They suggested that market size, the difference in factor endowment, and the formation of economic integration significantly affected FDI flows to Vietnam. Similarly, Behera and Mishra (2022) designated their estimation model to analyse FDI's push and pull factors in emerging countries. Their findings indicated that push factors, e.g., market size, efficiency, assets, trade openness, and cultural proximity of emerging countries, were significantly crucial to attracting FDI. In addition, Cieślik (2019) investigated the horizontal and vertical motives for undertaking FDI in Poland, applying the KC model in the study. He found that the difference influenced Poland's multinational enterprise activities in terms of factor endowments, similarity in market size, and EU membership. His results aligned with those of Chattopadhyay et al. (2022), dealing with the motives of FDI in BRICS countries.

Based on the theoretical analysis, the following hypothesis is proposed regarding the KC determinants of FDI:

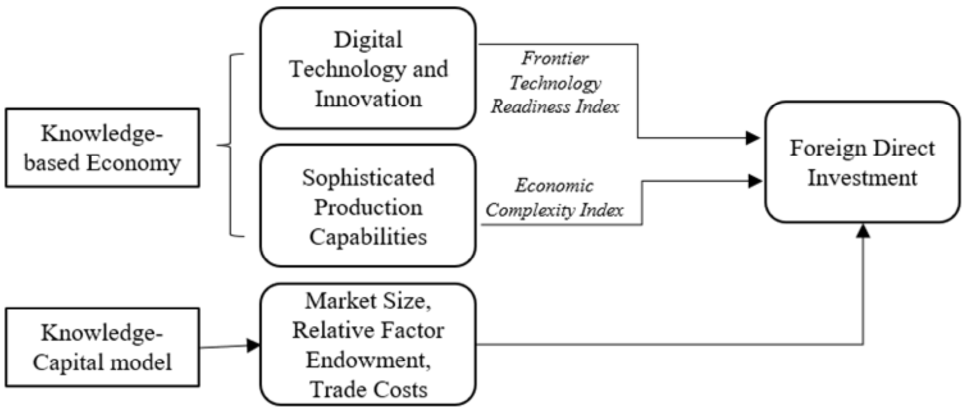
Hypothesis 3a The countries' economic sizes positively affect bilateral FDI.

Hypothesis 3b Bilateral FDI is positively influenced by the factor endowment differential between countries.

Hypothesis 3c Bilateral FDI is negatively influenced by trade costs.

The existing empirical studies have shown the significant effect of either digital technology and innovation or economic complexity on FDI. However, it still lacks a solid, comprehensive investigation regarding the influence of a knowledge-based economy on FDI and FDI in specific regions, e.g., East Asia, Southeast Asia, and South Asia. Consequently, the present study contributes to the previous literature by investigating the effects of a knowledge-based economy, focusing on the digital economy and economic complexity, on FDI in the RCEP. A conceptual framework for this study is presented in Figure 3.

Figure 3 A conceptual framework of this study



3 Research methodology

3.1 Model estimation

To analyse the effects of the knowledge-based economy development on FDI, the empirical studies regarding the digital economy and economic complexity and the KC model by Markusen (2002), described in the previous section, are the basis for the specification model. The model and selected variables are described as follows:

$$fdi_{ijt} = \propto + \underbrace{\underbrace{\beta_1 digi_{it} + \beta_3 digi_{jt}}_{\text{Digital economy effects}} + \underbrace{\beta_3 eci_{it} + \beta_4 eci_{jt}}_{\text{Economic complexity effects}} + \beta_5 difsq_{ijt}}_{\text{Knowledge-based economy effects}} + \underbrace{\beta_6 kci_{jt}}_{\text{KC model effects}} + \epsilon_{ijt} \tag{1}$$

$$digi = f(ict, sk, rd, ind, fin) \tag{2}$$

$$difsq = f(digidsq, ecidsq) \tag{3}$$

$$digidsq = f(ictdsq, skdsq, rddsq, inddsq, findsq) \tag{4}$$

$$kc = f(sgdp, gdpdsq, skdif, inter, intertc, invc, dist) \tag{5}$$

where fdi_{ijt} is the values of bilateral FDI inflow from the j^{th} home country to i^{th} recipient country in year t. The explanatory variables are divided into three groups. First, the individual variables relevant to the development of knowledge-based economy are $digi_{it}$, $digi_{jt}$, eci_{it}, and eci_{jt}. $digi_{it}$ and $digi_{jt}$ are the sets of digital economy development of recipient and home country proxied by frontier technological readiness index consisting of ICT adoption (*ict*), skills (*sk*), R&D activity (*rd*), industry activity (*ind*), and access to finance (fin). eci_{it} and eci_{jt} are the economic complexity of i^{th} recipient and j^{th} home country. They are expected to be positive signs. The higher the knowledge-based economy level, the larger the bilateral FDI is. Second, the variables of differences in the knowledge-based economy ($difsq_{ijt}$) are $digidifsq_{ijt}$ and $eecidsq_{ijt}$. $digidifsq_{ijt}$ is the difference in digital economy development between i^{th} recipient and j^{th} home country, measured by the squared difference between the two countries' frontier technological readiness index ($digidif^2 = (digi_i - digi_j)^2$). It consists of differences in ICT adoption (*ictdsq*), skills (*skdsq*), R&D activity (*rddsq*), industry activity (*inddsq*), and access to finance (*findsq*) measured as same as the difference in digital economy. $_{eecidsq}$ijt is the difference in economic complexity between i^{th} recipient and j^{th} home country, measured by the squared difference in the two countries' ECI ($ecidif^2 = (eci_i - eci_j)^2$). They are expected to be either positive or negative signs. The difference in knowledge-based economies across countries can either increase or decrease bilateral FDI. The higher the difference in the knowledge-based economy across countries, the larger the resource-seeking FDI is. Conversely, the higher the similarity in the knowledge-based economy across countries, the larger the efficiency-seeking FDI is. Moreover, it includes the interaction term between the complexity difference and the digital economy ($ecidifsq \times digi$). It is expected to be a negative sign. The similarities in knowledge-based economy level encourage an increase in FDI. Finally, the KC variables, KC_{ijt}, are economic factors of FDI with respect to the KC model consisting of the sum of gross domestic product (GDP) of the recipient and home country $sgdp = gdp_i + gdp_j$), similarity in GDP ($gdpdsq = gdpdif^2 = (gdp_i - gdp_j)^2$), difference in the share of skilled labour of a pair of countries ($skdif = (sk_j \ / \ lab_j) - (sk_i \ / \ lab_i)$) where *sk* is skilled labour and lab is total labour, interaction term of differences in two countries' GDP and share of skilled labour ($inter = gdpdif \times skdif$), interaction term of differences in share of skilled labour differenced and trade costs (*tc*) of the recipient country ($intertc = skdif^2 \times tc$), investment costs (*invc*), and distance between the recipient and the investing country (*dist*). The KC model variables are expected to have positive signs, i.e., *sgdp* and *skdif* and negative signs, i.e., *gdpdsq*, *inter*, *intertc*, *invc*, and dist. ϵ_{ijt} is an error term for $i = 1, \ldots, 15$ countries, $j = 1, \ldots, 15$ countries, $t = 2008, \ldots, 2019$, and βs are the estimated parameters.

This study applies a data-driven machine learning approach, "A Poisson pseudo-maximum likelihood with the adaptive least absolute shrinkage and selection operator method", to examine the causal inference. It can avoid data quality problems, e.g., multicollinearity, cross-sectional dependence, autocorrelation, and heteroskedasticity. First, the model is estimated using a Poisson pseudo-maximum likelihood (PPML) estimator with fixed effects, as proposed by Silva and Tenreyro (2011, 2006) as a traditional econometric analysis. The PPML is an estimator with consistent and unbiased estimates (Silva and Tenreyro, 2011). Importantly, it mitigates:

1 the Jensen's inequality ($E[\ln Y] \neq \ln E(Y)$) where E is the conditional mean

2 the trouble of zeros in the observed data $\left(\sum_{i=1}^{n}\left[Y_i - \exp\left(X_i\tilde{\beta}\right)\right]X_i = 0\right)$ where $\exp(X_i\beta)$ is the conditional expectation of Y_i given X

3 the heteroskedasticity problem by providing the assumption of the conditional mean: $E[Y_i \mid X] = \exp(X_i\beta) \propto V[Y_i \mid X]$ where $V[Y_i \mid X]$ is the conditional variance of Y_i given X (Silva and Tenreyro, 2006).

The specification model with PPML is shown below:

$$fdi_{ijt} = \exp\left[\mu_{it} + \alpha_t + \beta_1 digi_{it} + \beta_2 digi_{jt} + \beta_3 eci_{it} + \beta_4 eci_{jt} + \beta_5 difsq_{ijt} + \beta_6 kc_{ijt}\right] * \epsilon_{ijt} \tag{8}$$

where μ_{it} and α_t are country-fixed effects and time-fixed effects. Moreover, to avoid the overfitting problem that leads to inconsistent estimates of parameters, variable selection must be considered. Second, a machine-learning regularisation technique is conducted for consistent variable selection to avoid a model's overfitting bias and out-of-sample error. The regularisation algorithms can reduce overfitting and generalisation errors in the regression model (Tibshirani, 1996). This study utilises the adaptive lasso (least absolute shrinkage and selection operator) penalised (or regularisation) approach introduced by Zou (2006) to select the most decisive variables influencing the goodness fit model and at the same time shrink the irrelevant variables to precisely zero. The adaptive lasso estimates, $\hat{\beta}^{(n)}$ (*adaptive lasso*), are given by

$$\hat{\beta}^{(n)}(\textit{adaptive lasso}) = \arg\min_{\beta} \| Y - X\beta \|^2 + \underbrace{\lambda_n \sum\nolimits_{j=1}^{P} \hat{\omega}_j \left|\beta_j\right|}_{\textit{Lasso penalty}} \tag{9}$$

where λ_n denotes a non-negative regularisation parameter that varies with n and $\hat{\omega}_j$ denotes a weight vector where it is equal to $1/|\hat{\beta}^{(n)}|^{\gamma}$ when $\gamma > 0$. Finally, it is to estimate the 'post-lasso' PPML regression model using a cross-fit partialing-out lasso Poisson regression developed by Chernozhukov et al. (2018) that renders debiased estimation and inference. Finally, the Jarque-Bera normality test is performed, and the results confirm the non-normal distributions of all observed variables in the model. Hence, the lasso penalised regression approach is appropriate in model estimation (Casella et al., 2010).

3.2 Data sources

This study uses panel data for 15 RCEP member countries (Australia, Brunei Darussalam, Cambodia, China, Indonesia, Lao People's Democratic Republic, Japan, Republic of Korea, Malaysia, Myanmar, New Zealand, the Philippines, Singapore, Thailand, and Vietnam) over the 2008–2019 period. This study's selection of countries and periods depends on the availability of data. The dependent variables are inward FDI flow and stock based on the constant price of US dollars in 2010. Data for bilateral inward FDI flow and stock are drawn from the ITC. Following Dorakh (2020), the negative FDI value is transformed to 1 to avoid inconsistency in the estimation.

The primary explanatory variables are the frontier technological readiness index and the ECI, which capture the development of the country's digital technology and innovation, or degree of digital economy. The frontier technology readiness index data is gathered from the UNCTAD, and the ECI is from the Centre for International Development hosted by Harvard University (Growth Lab, 2021). As mentioned previously, the data used to construct the KC variables include GDP, skill labour, trade cost, investment cost, and distance. Data for GDPs (at constant 2010 prices) are sourced from the World Bank. Skilled labour is the sum of occupational labour categorised into groups 1 (managers), 2 (professionals), and 3 (technicians and associate professionals). Data for skilled labour is gathered from the International Labour Organization. The investment cost is proxied by deducting the investment freedom index from the ideal score of 100, and the trade cost is measured by deducting the trade freedom index from the score of 100. The investment freedom index and trade freedom index are gathered from the Heritage Foundation. Distances between the capital cities of a pair of countries are collected from the CEPII. The descriptive statistics of all variables are demonstrated in Table 1. Moreover, the results of the Jarque-Bera normality test confirm that all observed model variables in the specification model have non-normal distributions.

Table 2 displays the results of the cross-section dependence test with the null hypothesis of no cross-section dependence, as well as the first- and second-generation panel unit root tests with the null hypothesis of the presence of the panel unit root test. First, the results of the first-generation Levin-Lin-Chu unit root test (LLC) proposed by Levin et al. (2002) indicate that most variables are stationary at the level of almost all variables. Second, the statistics of the cross-section dependence (CD) test proposed by Pesaran (2021) (henceforth Pesaran-CD) demonstrate that almost all variables have cross-sectional dependence. Lastly, the results of the second-generation cross-section augmented Dickey-Fuller panel unit root test (CADF) proposed by Pesaran (2007) indicate that most panel data series are stationary at the level and that all series are stationary at the first difference level. Consequently, the Lasso-penalised regression approach is appropriate for model estimation (Casella et al., 2010).

Table 1 Descriptive statistics

Variable	*Unit*	*Obs.*	*Mean*	*Standard deviation*	*Min.*	*Max.*	*Jarque-Bera*
Dependent variables							
$fdif_{ijt}$	Million US$	2,520	470.032	1601.07	0.000	15132.1	1.1e+05*
$fdis_{ijt}$	Million US$	2,184	4656.98	13715.7	0.000	111373	5.1e+04*
Explanatory variables							
1. Individual knowledge-based economy							
$digi_{it}$	Index	2,520	0.559	0.290	0.000	0.976	157.200*
ict_{it}	Index	2,520	0.500	0.285	0.000	1.000	150.500*
sk_{it}	Index	2,520	0.513	0.265	0.112	1.000	202.000*
rd_{it}	Index	2,520	0.403	0.294	0.000	1.000	165.700*
ind_{it}	Index	2,520	0.620	0.213	0.093	0.966	150.400*
fin_{it}	Index	2,520	0.718	0.203	0.059	0.937	517.900*
$digi_{jt}$	Index	2,520	0.559	0.290	0.000	0.976	157.200*
ict_{jt}	Index	2,520	0.500	0.285	0.000	1.000	150.500*
sk_{jt}	Index	2,520	0.513	0.265	0.112	1.000	202.000*
rd_{jt}	Index	2,520	0.403	0.294	0.000	1.000	165.700*
ind_{jt}	Index	2,520	0.620	0.213	0.093	0.966	150.400*
fin_{jt}	Index	2,520	0.718	0.203	0.059	0.937	517.900*
eci_{it}	Index	2,520	0.481	1.045	–1.350	2.548	134.100*
eci_{jt}	Index	2,520	0.481	1.045	–1.350	2.548	134.100*

Notes: The Jarque and Bera (1987) test is the normality test whether the observed data has a normal distribution (Null hypothesis). * indicates significance at the 1% level.

Source: Author's calculation

Table 1 Descriptive statistics (continued)

Variable	*Unit*	*Obs.*	*Mean*	*Standard deviation*	*Min.*	*Max.*	*Jarque-Bera*
Dependent variables							
2. Difference in knowledge-based economy							
$digidifsq_{ijt}$	Index	2,520	0.177	0.201	3.6e-07	0.952	1,184.00*
$ictdsq_{ijt}$	Index	2,520	0.162	0.190	1.6e-07	1.000	1,568.00*
$skdsq_{ijt}$	Index	2,520	0.149	0.172	1.09e-07	0.788	970.200*
$rddsq_{ijt}$	Index	2,520	0.184	0.215	0.000	1.000	1,355.00*
$inddsq_{ijt}$	Index	2,520	0.095	0.116	5.8e-07	0.723	3,032.00*
$findsq_{ijt}$	Index	2,520	0.086	0.122	1.6e-08	0.761	8,978.00*
$ecidsq_{ijt}$	Index	2,520	2.331	2.691	1.3e-06	13.943	1,553.00*
$ecidifsq \times digi_{it}$	-	2,520	1.341	2.001	0.000	12.541	6,196.00*
$ecidifsq \times digi_{jt}$	-	2,520	1.341	2.001	0.000	12.541	6,196.00*
3. KC variables							
$sgdp_{ijt}$	Billion US$	2,520	2960.84	4186.58	15.157	23284.1	3,840.00*
$gdpdsq_{ijt}$	-	2,520	1.9e+07	5.2e+07	2.2e-04	3.1e+08	2.6e+04*
$skdif_{ijt}$	-	2,520	1.863	2.225	0.064	15.523	5304.00*
$inter_{ijt}$	-	2,520	294.565	8557.77	-69319.2	54068.6	2.6e+04*
$intertc_{it}$	-	2,520	2.421	6.570	0.000	88.303	1.7e+05*
$invc_{it}$	Index	2,520	0.453	0.236	0.000	0.900	111.000*
$dist_{ijt}$	Kilometres	2,520	3949.64	2881.04	315.543	11041.0	323.200*

Notes: The Jarque and Bera (1987) test is the normality test whether the observed data has a normal distribution (Null hypothesis). * indicates significance at the 1% level.

Source: Author's calculation

4 Empirical results

4.1 Baseline results

Table 3 reports the results of the effect of knowledge-based economy development (in terms of digital technology, innovation, and economic complexity) on RCEP's inward FDI flow (Model 1) and inward FDI stock (Model 2). The results of traditional Poisson Pseudo-Maximum Likelihood (henceforth PPML), the adaptive Lasso penalised regression results (henceforth Lasso), and 'Post-Lasso' PPML regression (PPML Post-Lasso) are demonstrated sequentially.

Table 2 Results of the cross-section dependence test and the first- and second-generation panel unit root tests

Testing	*LLC*		*Pesaran-CD*	*CADF*	
	Level	*First diff.*		*Level*	*First diff.*
$fdif_{ijt}$	–10.343	–21.705**	42.681*	–1.624	–2.642*
$fdis_{ijt}$	0.303	–4.657	163.710*	–1.090	–1.700
$digi_{it}$	–18.503*	–46.836*	185.693*	–2.260*	–3.408*
ict_{it}	–37.654*	–39.644*	206.719*	–2.104*	–3.198*
sk_{it}	–17.313*	–43.040*	292.934*	–1.463	–2.777*
rd_{it}	–18.914*	–45.508*	201.886*	–2.624*	–3.548*
ind_{it}	–16.826*	–42.044*	182.629*	–1.988*	–3.215*
fin_{it}	–15.967*	–48.977*	291.422*	–1.639	–2.901*
$digi_{jt}$	–18.503*	–46.836*	185.693*	–2.260*	–3.408*
ict_{jt}	–37.654*	–39.644*	206.719*	–2.104*	–3.198*
sk_{jt}	–17.313*	–43.040*	292.934*	–1.463	–2.777*
rd_{jt}	–18.914*	–45.508*	201.886*	–2.624*	–3.548*
ind_{jt}	–16.826*	–42.044*	182.629*	–1.988*	–3.215*
fin_{jt}	–15.967*	–48.977*	291.422*	–1.639	–2.901*
eci_{it}	–28.627*	–48.628*	116.543*	–1.577	–2.899*
eci_{jt}	–28.627*	–48.628*	116.543*	–1.577	–2.899*
$digidifsq_{ijt}$	–26.971*	–45.976*	86.243*	–1.877*	–3.410*
$ictdsq_{ijt}$	–42.258*	–63.127*	29.907*	–2.575*	–3.081*
$skdsq_{ijt}$	–15.429*	–31.898*	55.588*	–1.394	–2.791*
$rddsq_{ijt}$	–17.742*	–48.830*	29.859*	–2.653*	–3.866*
$inddsq_{ijt}$	–19.555*	–39.351*	26.194*	–2.097*	–3.415*
$findsq_{ijt}$	–43.482*	–60.871*	80.749*	–2.686*	–3.585*
$ecidsq_{ijt}$	–32.791*	–44.479*	44.225*	–2.056*	–3.320*
$ecidifsq \times digi_{it}$	–25.650*	–44.442*	103.529*	–2.250*	–3.451*
$ecidifsq \times digi_{jt}$	–25.650*	–44.442*	103.529*	–2.250*	–3.451*
$sgdp_{ijt}$	–16.923*	–44.823*	385.686*	–1.979*	–2.748*
$gdpdsq_{ijt}$	–5.246	–35.456*	213.900*	–1.359	–2.417*
$skdif_{ijt}$	–21.412*	–42.143*	–2.405*	–1.918*	–2.948*
$inter_{ijt}$	–14.732*	–40.917*	1.416	–0.531	–2.860*
$intertc_{it}$	–17.348*	–39.092*	48.331*	–1.806***	–2.693*
$invc_{it}$	–18.243*	–44.997*	89.643*	–2.005*	–4.259*

Notes: *, **, and *** are the level of significance at 1%, 5%, and 10%, respectively.

Source: Author's calculation

Table 3 Estimation results of inward FDI flow in RCEP countries

	Model 1			*Model 2*		
	PPML (1)	*Lasso (2)*	*PPML post-Lasso (3)*	*PPML (4)*	*Lasso (5)*	*PPML post-Lasso (6)*
A. Individual knowledge-based economy						
$digi_{it}$	7.882 (1.59)	2.269	4.399 (1.06)	5.820 (1.53)		
ict_{it}	–2.546 (–1.60)	–0.836	–1.573 (–1.06)	–1.767*** (–1.70)	–0.291	–0.363 (–1.20)
sk_{it}	–11.916* (–3.84)	–8.927	–9.630* (–5.33)	–4.359* (–2.36)	–1.827	–2.538** (–2.04)
rd_{it}	–0.502 (–0.23)	0.621	0.966 (0.60)	–2.760** (–1.98)	–1.254	–1.639** (–1.93)
ind_{it}	1.228 (0.60)	2.243	2.491 (1.47)	–1.040 (–0.80)		
fin_{it}	0.632 (0.19)			–2.948 (–1.24)		
$digi_{jt}$	–2.363 (–0.38)			0.557 (0.13)		
ict_{jt}	0.268 (0.16)			–0.448 (–0.41)		
sk_{jt}	3.685 (1.00)	2.163	2.358* (3.37)	1.127 (0.51)	0.999	1.336** (2.22)
rd_{jt}	0.777 (0.31)	0.117	0.347 (0.50)	0.570 (0.36)	1.435	1.382* (2.91)
ind_{jt}	5.359*** (1.62)	4.648	4.643* (4.16)	3.098 (1.17)	2.065	2.995*** (1.65)
fin_{jt}	3.785 (0.93)	0.331	2.240 (1.49)	–1.037 (–0.41)	0.568	0.730 (0.94)
eci_{it}	0.422 (0.64)			–0.121 (–0.34)		
eci_{jt}	0.475 (0.67)	0.212	0.083 (0.42)	–0.064 (–0.13)	0.840	0.713* (3.24)
B. Difference in knowledge-based economy						
$digidifsq_{ijt}$	6.085* (3.27)	3.429	3.930* (3.42)	0.002 (0.00)		
$ictdsq_{ijt}$	–0.911 (–1.30)			0.575 (1.14)	0.337	0.391 (1.31)
$skdsq_{ijt}$	–2.100 (–1.57)	–0.413	–1.620 (–1.46)	–0.066 (–0.13)		

Notes: The ‘PPML post-Lasso’ columns (2), (4), (6), and (8) display the PPML coefficients for variables selected by the adaptive lasso method. t-statistics are in parentheses; * significant with $p < 0.01$; ** significant with $p < 0.05$; *** significant with $p < 0.1$.

Source: Author’s calculation

Table 3 Estimation results of inward FDI flow in RCEP countries (continued)

	Model 1			*Model 2*		
	PPML (1)	*Lasso (2)*	*PPML post-Lasso (3)*	*PPML (4)*	*Lasso (5)*	*PPML post-Lasso (6)*
B. Difference in knowledge-based economy						
$rddsq_{ijt}$	–2.683* (–3.17)	–1.763	–1.795* (–3.16)	0.645 (0.75)		
$inddsq_{ijt}$	–6.497** (–2.07)	–5.998	–6.671* (–2.48)	–1.962 (–1.59)	–1.587	–2.027** (–1.90)
$findsq_{ijt}$	–8.640* (–2.79)	–8.052	–10.283* (–3.84)	–5.135* (–2.72)	–4.248	–5.332* (–4.13)
$ecidsq_{ijt}$	0.696* (3.16)	0.394	0.768* (3.93)	0.672* (4.22)	0.294	0.455* (5.98)
$ecidifsq \times digi_{it}$	–0.202 (–1.44)	–0.151	–0.260*** (–1.94)	–0.096 (–1.04)		
$ecidifsq \times digi_{jt}$	–0.469* (–2.54)	–0.149	–0.504* (–3.15)	–0.694* (–4.95)	–0.354	–0.532* (–6.31)
C. KC model determinants						
$sgdp_{ijt}$	–1.1e-04** (–2.16)	–3.9e-05	–7.2e-05* (–2.78)	1.7e-04** (2.15)	6e-05	6e-05* (3.49)
$gdpdsq_{ijt}$	2.3e-09 (0.91)			–4.2e-09 (–1.36)		
$skdif_{ijt}$	0.389 (1.30)	0.057	0.167 (1.15)	0.103 (0.55)	0.185	0.221*** (1.64)
$inter_{ijt}$	–1.9e-05** (–1.90)	–1.1e-05	–1.5e-05** (–1.95)	–8.2e-05* (–3.97)	–5e-05	–5.8e-05* (–5.19)
$intertc_{it}$	–0.104 (–1.08)			–0.100*** (–1.69)	–0.097	–0.123** (–2.21)
$invc_{it}$	–3.248* (–2.41)	–2.278	–2.859* (–2.72)	0.393 (0.46)	–0.0003	
$dist_{ijt}$	3.2e-05** (1.92)	1.9e-05	2.5e-05*** (1.62)	–3e-04* (–13.95)		–3e-04* (–14.78)
Constant	–3.194 (–0.55)	2.925	0.173 (0.07)	6.356 (1.47)		5.478* (4.17)
Country-pair fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.657		0.654	0.827		0.830
Observations	1,848		1,848	1,680		1,680

Notes: The 'PPML post-Lasso' columns (2), (4), (6), and (8) display the PPML coefficients for variables selected by the adaptive lasso method. t-statistics are in parentheses; * significant with $p < 0.01$; ** significant with $p < 0.05$; *** significant with $p < 0.1$.

Source: Author's calculation

In model 1, the results of conventional PPML estimation (column 1) demonstrate that some variables in the individual digital economy group, knowledge-based economy difference group, and KC model group statistically significantly influence inward FDI within RCEP economies. Later, the adaptive lasso penalised regression is conducted, and the coefficients that are non-zero emerge, as shown in column (2). The results of a post-Lasso PPML regression are shown in column (3). The estimated coefficient of skills for digital technology and innovation in recipient countries is negative and statistically significant at the 1% level. The development of skills for digital technology in home countries in the RCEP becomes an investment barrier for RCEP economies. Countries with high skills may change themselves to be foreign investors instead of recipients. The investing countries' skills and industry activities tend to foster their investors' desire to invest abroad, particularly in RCEP. These findings are in line with our hypothesis and the empirical literature. Higher skills and industrial activities for the digital economy help improve productive capacity and scale economies, resulting in a rise in multinational firm activities (Jovanovic and Morschett, 2022; Khan et al., 2021; Moeini Gharagozloo et al., 2021; Teruel et al., 2022). The estimated coefficients of squared differences in R&D activities, industrial activities, and financial access between recipients and home countries are negative and statistically significant at the 1% level. The greater the similarities in R&D level, industrial activity level, and financial access between countries, the greater the FDI activities in RCEP, particularly efficiency-seeking FDI. The estimated coefficient of squared difference in economic complexity between recipient and home countries is positive and statistically significant at the 1% level. The difference in economic complexity between RCEP economies attracts RCEP's investment. Intra-RCEP FDI is likely to be replaced by the development of sophisticated and productive capabilities in the recipient countries. In addition, the estimated coefficients of interaction resulting from differences in economic complexity and digital economy levels between recipient and home countries are negative and statistically significant at the 1% level. The similarities in knowledge-based economies between recipient and home countries encourage an increase in RCEP's FDI. The findings regarding digital economy development are consistent with Jovanovic and Morschett (2022), Moeini Gharagozloo et al. (2021), Khan et al. (2021), Antonietti and Franco (2021), Khan et al. (2020), Ranjbar and Rassekh (2022) and Sadeghi et al. (2020).

The estimated coefficient of the sum of GDP is positive and statistically significant at the 1%–10% levels and shows a sign that is in line with the KC model. The larger market size is likely to favour FDI between RCEP countries. The estimated coefficients of the interaction between GDP, skill differences, and investment costs are negative and statistically significant at the 1%–5% levels. They are in line with the KC model. These coefficients favour both horizontal and vertical FDI. The larger the sum of the economic sizes of the RCEP countries, the greater the horizontal FDI in RCEP. Meanwhile, the lower the interaction between GDP and relative skill endowment and investment costs, the larger the vertical FDI in RCEP. It implies that RCEP's economic factors influence horizontal and vertical FDI in RCEP members. Similar results were found by Duong et al. (2021), Behera and Mishra (2022), Cieślik (2019) and Chattopadhyay et al. (2022).

In model 2, the results of conventional PPML estimation (column 4) show that many variables in the individual digital economy group, the knowledge-based economy difference group, and the KC model group have a statistically significant effect on FDI into the RCEP. The adaptive lasso penalised regression is carried out, and the coefficients that are non-zero emerge, as shown in column (5). The results of a post-Lasso PPML regression are shown in column (6). The estimated coefficients of skills and R&D activities in recipient countries are negative and statistically significant at the 1% level. The higher the skills and R&D activities, the lower the FDI activities. Countries with high skills and R&D activities may discourage inward FDI but encourage outward FDI. The skills, R&D, industrial activities, and economic complexity of the investing countries are likely to encourage RCEP FDI. The economic complexity entailing higher productive capabilities could increase economic activities and encourage multinational firm activities (Ranjbar and Rassekh, 2022; Sadeghi et al., 2020; Nguyen et al., 2021). These main findings are consistent with Model 1. The estimated coefficients of the squared industrial activities and financial access differences are negative and statistically significant at the 1% level. In contrast, the coefficient of the squared economic complexity difference is positive and statistically significant at the 1% level. These results appear to be two sides of the same coin. The greater the similarities in digital technology and innovation and the difference in productive capabilities between pairs of countries, the greater the FDI activity among RCEP members. The similarities in knowledge-based economies between recipient and home countries still encourage an increase in RCEP's FDI. The findings are in line with Model 1.

The estimated coefficients of the sum of GDP and skill differences are positive and statistically significant at the 1%–10% levels and show signs that align with the KC model. The larger market size and factor endowment differences will likely favour horizontal and vertical FDI between RCEP countries. The estimated coefficients of the interaction between GDP and skill differences, the interaction between skill differences and trade costs, and geographical distance between countries are negative and statistically significant at 1%–5%. They are in line with the KC model. Most coefficients favour the vertical strand for FDI. Low interaction between GDP and relative skill endowment, low trade costs, and proximity between pairs of countries are associated with the motive for vertical FDI. The findings indicate that these significant economic factors influence horizontal and vertical FDI across RCEP members. Similar results were found by Duong et al. (2021), Behera and Mishra (2022), Cieślik (2019) and Chattopadhyay et al. (2022).

In sum, it is worth noting that differences in the development of the knowledge-based economy and its components, e.g., skills, R&D, industry activity, and access to finance, and differences in economic complexity between the recipient and investment countries significantly influence inward FDI in RCEP countries. Moreover, the KC variables, e.g., economic size, differences in factor endowments, and investment costs, significantly affect changes in FDI. Hence, policies regarding the development of the knowledge-based economy are needed.

4.2 Heterogeneity analysis

This study accounts for the heterogeneity analysis in our model by examining the influence of a knowledge-based economy on inward FDI from major RCEP foreign investors and inward FDI to RCEP's middle-income recipient countries.

Table 4 Heterogeneity analysis by major investors in RCEP

	Model 3			*Model 4*		
	PPML (1)	*Lasso (2)*	*PPML post-Lasso (3)*	*PPML (4)*	*Lasso (5)*	*PPML post-Lasso (6)*
A. Individual knowledge-based economy						
$digi_{it}$	7.919 (1.57)			–0.104 (–0.02)		
ict_{it}	–2.104 (–1.32)			–0.213 (–0.18)	–0.043	–0.238 (–0.76)
sk_{it}	–12.239* (–3.28)	–8.977	–9.957* (–4.56)	–3.732*** (–1.77)	–3.167	–2.921* (–4.67)
rd_{it}	3.040 (1.25)	3.255	3.957* (6.04)	2.417 (1.35)	1.754	2.859* (2.60)
ind_{it}	1.806 (0.64)	3.398	3.711*** (1.74)	1.971 (1.02)	2.283	2.686* (3.17)
fin_{it}	–0.029 (–0.01)			–4.263*** (–1.86)	–2.506	–2.809** (–2.16)
$digi_{jt}$	–4.41 (–0.61)			3.087 (0.55)		
ict_{jt}	1.245 (0.59)			–1.534 (–1.00)	–0.418	–0.672 (–1.41)
sk_{jt}	–3.187 (–0.60)			–6.812*** (–1.78)		
rd_{jt}	1.868 (0.50)	3.350	1.538*** (1.80)	–1.079 (–0.30)	–1.931	–2.230* (–2.70)
ind_{jt}	3.459 (0.51)	2.339	3.002 (1.25)	–0.141 (–0.02)	4.648	4.644* (3.03)
fin_{jt}	4.979 (0.73)			2.691 (0.53)		
eci_{it}	0.719 (1.05)			–0.345 (–0.85)	–0.141	–0.186 (–1.34)
eci_{jt}	0.468 (0.57)			0.274 (0.40)	0.627	0.583 (1.47)
B. Difference in knowledge-based economy						
$digidifsq_{ijt}$	0.872 (0.32)			–3.486*** (–1.73)		
$ictdsq_{ijt}$	–0.598 (–0.74)			0.806 (1.20)		
$skdsq_{ijt}$	3.182** (2.31)	–6.343	3.343* (5.02)	5.735* (6.94)	4.103	4.376* (10.15)

Notes: The 'PPML post-Lasso' columns (2), (4), (6), and (8) display the PPML coefficients for variables selected by the adaptive lasso method. t-statistics are in parentheses; * significant with $p < 0.01$; ** significant with $p < 0.05$; *** significant with $p < 0.1$.

Source: Author's calculation

Table 4 Heterogeneity analysis by major investors in RCEP

	Model 3			*Model 4*		
	PPML (1)	*Lasso (2)*	*PPML post-Lasso (3)*	*PPML (4)*	*Lasso (5)*	*PPML post-Lasso (6)*
B. Difference in knowledge-based economy						
$rddsq_{ijt}$	2.825*	–11.819	2.510*	4.097*	2.855	3.628*
	(2.46)		(2.80)	(4.15)		(4.66)
$inddsq_{ijt}$	–7.428	–0.523	–6.832	–1.130		
	(–1.21)		(–1.39)	(–0.34)		
$findsq_{ijt}$	–11.018**	0.435	–12.189*	–13.319*	–12.224	–13.372*
	(–1.95)		(–2.79)	(–4.60)		(4.36)
$ecidsq_{ijt}$	–0.333			–0.467		
	(–0.76)			(–1.58)		
$ecidifsq \times digi_{it}$	–0.573*	–0.523	–0.582*	–0.191***	–0.153	–0.172*
	(–2.92)		(–3.37)	(–1.64)		(–4.76)
$ecidifsq \times digi_{jt}$	0.840***	0.435	0.473*	0.508		
	(1.76)		(3.45)	(1.59)		
C. KC model determinants						
$sgdp_{ijt}$	–1.9e-04*	–9e-05	–1.5e-05*	1.6e-04**	6e-05	7e-05*
	(–3.28)		(–3.67)	(1.99)		(3.75)
$gdpdsq_{ijt}$	8.4e-09*	3.2-09	5.2e-09*	–2.3e-09 (–0.79)		
	(2.91)		(2.82)			
$skdif_{ijt}$	0.287			–0.156 (–0.77)		
	(0.78)					
$inter_{ijt}$	1.4e-05			–4e-05**	–4e-05	–4.4e-05*
	(1.12)			(–1.96)		(–2.71)
$intertc_{it}$	–0.049			–0.071	–0.092	–0.096*
	(–0.40)			(–1.04)		(–2.68)
$invc_{it}$	–3.477*	–3.423	–3.634*	–0.219		
	(–2.34)		(–3.23)	(–0.24)		
$dist_{ijt}$	–2.3e-04*	–0.0001	–2.2e-04*	–1.7e-04*	–0.0001	–1.7e-04*
	(–3.85)		(–4.67)	(–6.82)		(–6.95)
Constant	4.084	7.001	5.704**	16.655*	7.719	7.772
	(0.54)		(1.92)	(2.55)		(3.46)
Country-pair fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.682		0.669	0.838		0.832
Observations	480		480	444		444

Notes: The 'PPML post-Lasso' columns (2), (4), (6), and (8) display the PPML coefficients for variables selected by the adaptive lasso method. t-statistics are in parentheses; * significant with $p < 0.01$; ** significant with $p < 0.05$; *** significant with $p < 0.1$.

Source: Author's calculation

4.2.1 Heterogeneity analysis of major RCEP's foreign investors

The influence of a knowledge-based economy on inward FDI from four major RCEP foreign investors, i.e., Japan, Singapore, South Korea, and China (hereafter JSKC), is first considered as a heterogeneity result. Table 4 reports the results of the effect of knowledge-based economy development on JSKC's inward FDI flow (model 3) and inward FDI stock (model 4). In model 3, the estimated coefficients of R&D and industrial industries for the digital economy in recipient and home countries are positive and statistically significant at the 1%–10% levels. The estimated coefficients of skills for the digital economy in recipient countries are negative and statistically significant at the 1% level. It indicates that the development of the digital economy is essential for RCEP to attract FDI from Japan, Singapore, South Korea, and China through complementarity or substitution for FDI. These findings are consistent with the baseline results. The estimated coefficients of squared differences in skills and R&D for digital economy development are positive and statistically significant at 1%. Differences in skills and R&D between JSKC and RCEP countries encourage significant investors to invest in RCEP. On the contrary, the estimated coefficient of squared difference in access to finance between the recipient and investing countries is negative and statistically significant at the 1% level. The similarity in financial accessibility between JSKC and RCEP countries enhances JSFC's FDI in RCEP. The estimated coefficient of interaction between the difference in economic complexity and the digital economy of the recipient countries is negative and statistically significant at the 1% level. This is the same as the baseline results. Regarding the KC variables, the estimated coefficient of the sum of GDP is negative and statistically significant at the 1% level. In contrast, the coefficient of GDP squared difference is positive and statistically significant at the 1% level. These findings are in contrast to the KC model and favour vertical FDI from JSKC to RCEP. Furthermore, investment costs and bilateral distance are negative and statistically significant at the 1% level. These results align with the KC model and strengthen the case for vertical FDI from JSKC to RCEP.

In conclusion, the differences in digital economy development and economic complexity between pairs of countries and economic factors, e.g., market size, factor endowments, and trade costs of recipient countries, significantly impact the entry of multinational firms from Japan, Singapore, South Korea, and China into the RCEP. These findings support the roles of digital economy development and economic complexity in RCEP inward FDI.

4.2.2 Heterogeneity analysis of RCEP's middle-income recipient countries

Another heterogeneity analysis is the study of the influence of a knowledge-based economy on inward FDI to nine of the RCEP's middle-income recipient countries, i.e., Cambodia, China, Indonesia, Lao People's Democratic Republic, Malaysia, Myanmar, the Philippines, Thailand, and Vietnam (henceforth MIC). Table 5 demonstrates the results of the effect of knowledge-based economy development on inward FDI flow to MIC (model 5) and inward FDI stock (model 6). In Model 5, the estimated coefficients of R&D and industrial industries for the digital economy in recipient and home countries are positive and statistically significant at the 1%–10% levels. It implies that R&D and industrial activities in the digital economy are important for middle-income recipient countries in the RCEP to attract FDI from RCEP economies. These findings are consistent with the baseline results. The estimated coefficient of economic complexity in recipient countries is negative and statistically significant at the 1% level, whereas it is positive and statistically significant at the same level in home countries. The higher the home countries' sophisticated and productive capabilities, the greater the RCEP's FDI flow to its middle-income countries. Moreover, the RCEP's middle-income recipient countries with low productive capabilities still attract foreign investors. The estimated coefficient of squared differences in R&D for digital economy development is positive and statistically significant at 1%. The similarities in R&D between the recipient and home countries encourage an increase in RCEP's FDI in its middle-income recipient countries. This is the same as the baseline results. The estimated coefficient of the sum of GDP is negative and statistically significant at the 1% level. In contrast, the coefficient of GDP squared difference is positive and statistically significant at the 1% level. These findings are in contrast to the KC model and favour vertical FDI over MIC. Moreover, investment costs and bilateral distance are negative and statistically significant at the 1% level. These results align with the KC model and strengthen the case for vertical FDI from RCEP to MIC.

In summary, the knowledge-based economy significantly impacts FDI from the RCEP's middle-income countries.

Table 5 Heterogeneity analysis by middle income countries in RCEP

	Model 5			*Model 6*		
	PPML (1)	*Lasso (2)*	*PPML post-Lasso (3)*	*PPML (4)*	*Lasso (5)*	*PPML post-Lasso (6)*
A. Individual knowledge-based economy						
$digi_{it}$	–10.567***			–5.644		
	(–1.80)			(–0.52)		
ict_{it}	2.154			0.358	–0.526	–0.985**
	(1.21)			(0.13)		(–1.94)
sk_{it}	9.573			–0.306		
	(1.49)			(–0.50)		
rd_{it}	5.341**	2.582	2.599**	0.710	–2.242	–3.222*
	(1.94)		(1.87)	(0.17)		(–2.64)
ind_{it}	8.358*	4.533	4.916*	2.934		
	(3.88)		(4.32)	(1.10)		
fin_{it}	4.797			0.638		
	(1.44)			(0.24)		
$digi_{jt}$	10.586***			–9.993***	1.036	0.126
	(1.70)			(–1.75)		(0.16)
ict_{jt}	–2.821***			2.132		
	(–1.63)			(1.13)		
sk_{jt}	–3.286			3.648		
	(–0.63)			(0.99)		

Notes: The 'PPML post-Lasso' columns (2), (4), (6), and (8) display the PPML coefficients for variables selected by the adaptive lasso method. T-statistics are in parentheses; * significant with $p < 0.01$; ** significant with $p < 0.05$; *** significant with $p < 0.1$.

Source: Author's calculation

Table 5 Heterogeneity analysis by middle income countries in RCEP (continued)

	Model 5			*Model 6*		
	PPML (1)	*Lasso (2)*	*PPML post-Lasso (3)*	*PPML (4)*	*Lasso (5)*	*PPML post-Lasso (6)*
A. Individual knowledge-based economy						
rd_{jt}	–2.093	3.490	3.333*	2.310		
	(–0.89)		(5.02)	(0.81)		
ind_{jt}	–0.391			1.217		
	(–0.11)			(0.38)		
fin_{jt}	4.703	2.043	3.169	1.746		
	(1.10)		(1.48)	(0.53)		
eci_{it}	–3.018*	–2.381	–3.202*	–0.969	–0.776	0.110
	(–3.45)		(–3.90)	(–1.50)		(0.29)
ecijt	1.628**	1.269	1.409*	0.892	2.041	1.768*
	(2.16)		(4.75)	(1.30)		(7.08)
B. Difference in knowledge–based economy						
$\mathrm{digidifsq}_{ijt}$	–9.079*	–3.195	–4.924*	3.124		
	(–3.56)		(–3.00)	(0.92)		
ictdsq_{ijt}	1.138	0.601	0.894	–1.202		
	(1.24)		(1.52)	(–1.16)		
skdsq_{ijt}	4.431	1.553	2.060	–5.259**		
	(1.27)		(0.91)	(–1.92)		
rddsq_{ijt}	3.301*	1.720	2.407*	0.296		
	(3.42)		(3.05)	(0.14)		
inddsq_{ijt}	4.527			0.256		
	(1.47)			(0.15)		
findsq_{ijt}	4.236			0.505*		
	(1.26)			(0.26)		
ecidsq_{ijt}	–0.666			–1.519*	–0.248	–0.050
	(–1.33)			(–3.51)		(–0.85)
$ecidifsq \times digi_{it}$	–0.425	–0.266	–0.438	0.380		
	(–1.16)		(–1.36)	(0.92)		
$ecidifsq \times digi_{jt}$	0.770		0.055	1.211*		
	(1.48)		(0.31)	(2.68)		
C. KC model determinants						
$sgdp_{ijt}$	–0.0001*	–0.0001	–0.0001*	0.0003***	0.0001	8.36e-05*
	(–3.12)		(–3.58)	(1.87)		(4.39)
$gdpdsq_{ijt}$	5.84e-09*	5.17e-09	5.63e-09*	–4.95e-09		
	(2.34)		(0.31)	(–0.66)		
$skdif_{ijt}$	–0.024			–0.139	0.149	0.314**
	(–0.08)			(–0.61)		(2.23)

Notes: The 'PPML post-Lasso' columns (2), (4), (6), and (8) display the PPML coefficients for variables selected by the adaptive lasso method. T-statistics are in parentheses; * significant with $p < 0.01$; ** significant with $p < 0.05$; *** significant with $p < 0.1$.

Source: Author's calculation

Table 5 Heterogeneity analysis by middle income countries in RCEP (continued)

	Model 5			*Model 6*		
	PPML (1)	*Lasso (2)*	*PPML post-Lasso (3)*	*PPML (4)*	*Lasso (5)*	*PPML post-Lasso (6)*
C. KC model determinants						
$inter_{ijt}$	–3.54e-05 (–0.00)			–0.088* (–3.43)	–0.071	–0.044* (–2.42)
$intertc_{it}$	0.148*** (1.70)	0.101	0.133** (2.07)	0.005 (0.07)	–0.108	–0.181* (–3.17)
$invc_{it}$	–1.958 (–1.50)	–1.845	–2.081** (–1.89)	–0.630 (–0.66)		
$dist_{ijt}$	–0.0002* (–5.50)	–0.0002	–0.0002* (–5.50)	–0.0003* (–7.12)	–0.0003	–0.0002* (–4.74)
Constant	–9.933*** (–1.71)	–0.258	–1.276 (–0.60)	5.546 (1.07)	7.023	7.757* (16.89)
Country-pair fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.807		0.794	0.813		0.758
Observations	1008		1008	1008		1008

Notes: The 'PPML post-Lasso' columns (2), (4), (6), and (8) display the PPML coefficients for variables selected by the adaptive lasso method. T-statistics are in parentheses; * significant with p < 0.01; ** significant with p < 0.05; *** significant with p < 0.1.

Source: Author's calculation

5 Conclusions and policy implications

5.1 Conclusions

The study examines the influence of a knowledge-based economy represented by digital technology, innovation, and economic complexity on FDI in RCEP countries. For this purpose, a penalised Poisson pseudo-maximum likelihood regression with an adaptive lasso for consistent variable selection is used to capture the relationship between the variables from 2008–2019. Three hypotheses are proposed in this study to examine the relations between digital economy development, economic complexity, and economic factors. The main findings reveal that the similarities in digital economy components, e.g., skills, R&D, digital industrial activities, and access to finance, between the recipient and investing countries in RCEP positively impact bilateral FDI among RCEP members. The difference in economic complexity between the RCEP's recipient and investing countries positively affects bilateral FDI. The similarities in a knowledge-based economy negatively impact FDI activities in the RCEP. As for the KC model determinants, the results align with the KC model, favouring horizontal and vertical FDI in the RCEP.

5.2 Policy implications

In light of the above empirical results, the following policy implications can be drawn: First, the similarities in the knowledge-based economy between the RCEP's recipient and investing countries foster bilateral FDI. RCEP governments should use the RCEP trade agreement to create a knowledge-driven economy. Policies aimed at improving the knowledge-based economy should be tailored.

Second, the similarities in skills, R&D, digital industrial activities, and financial access between RCEP's countries foster bilateral FDI. The governments of RCEP should enhance the use, adoption, and adaptation of digital technologies, especially the skills, R&D activities, industry activities, and access to finance necessary to improve FDI efficiency. Firstly, the government should support digital transformation in all economic sectors, especially the industrial and service sectors. Secondly, the government should promote comprehensive digital economy development (on both the demand and supply sides) based on economic conditions.

Third, the difference in economic complexity between the RCEP's countries positively impacts bilateral FDI. The government should leverage economic complexity levels with push-pull strategies. Firstly, the government should transform the traditional local production pattern by integrating foreign trade and investment activities. It can enhance production capabilities and generate more significant FDI inflows. Secondly, the government should help the private sector stabilise the economy through smart investments and a wide range of FDIs in all parts of the economy.

Inevitably, this study has some limitations and offers possibilities for future research. First, due to the uneven statistical data on FDI, only the available data was used in this study. In future studies, complete data should be considered. Second, the frontier technological readiness proxies for the development of the digital economy may be insufficient. A new measurement of the digital economy may be conducted in future studies.

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