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Research article

Assessing energy consumption and economic growth interrelations in Asia-Pacific: A multivariate approach with panel FMOLS and bootstrap Granger causality tests

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ABSTRACT

This study investigates the cointegration and causal relationship between energy consumption and economic growth using data from 16 Asian and Pacific countries from 1970 to 2010. The expanded production function is used in this investigation; this function considers not only labor but also financial resources. This study investigates whether or not a rise in energy demand is associated with a healthy economy. Human capital, in addition to material and labor resources, is taken into account by this operation. One of the first studies to adopt a multivariate method and add human capital was undertaken on the energy-growth nexus. Using the panel unit root and cointegration tests, this study confirms the existence of a long-run cointegrating connection between these variables. These studies recognize the presence of cross-sectional interdependence, according to specific reports. The significance of considering the interconnection of various countries is confirmed by comparing estimates from panel heterogeneous fully modified ordinary least squares (FMOLS) models with those from unceasingly efficient and fully modified models. Nonetheless, the bootstrap panel Granger causality test findings demonstrate that economic growth is a causal factor in rising energy consumption in the region, indicating that the relationship is not constant across countries.

1. Introduction

With a population exceeding 1.4 billion, China boasts one of the world's most extensive economic histories and currently stands as one of the fastest-growing financial powerhouses. The nation's remarkable Economic Development (ECD) journey has captivated global attention since 1979, when the government unveiled a transformative ECD plan during the 11th Central Committee of the Chinese Communist Party's Third Plenary Session. Widely recognized as the driving force behind Asia's burgeoning economy, China has embarked on ambitious initiatives such as the Belt and Road program to connect 138 nations worldwide and catalyze substantial economic and infrastructural growth.

China's ascent as an economic powerhouse is underscored by its burgeoning international trade engagements. The surge in trade agreements signed by the country in the 1980s reflects its escalating economic influence in the Asian region. Notably, China's annual trade volume surged by over 13 % yearly, skyrocketing from under $40 billion in 1980 to surpassing $135 billion by 1991. While

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outpacing global economic growth rates, China's share of global commerce has experienced a meteoric rise [1].

The General Agreement on Tariffs and Trade Secretariat has reported a significant enhancement in China's international commercial standing. Concurrently, rapid industrialization (INL), population management initiatives, and substantial reforms in economic and financial sectors have reshaped the country's landscape. However, with the surge in industrialization and commercial activities, the electricity demand has surged in tandem. In 2022, China's power consumption surged to approximately 8.7 trillion kilowatt-hours, marking a 5 to 8 percent increase from the preceding year [2].

Despite the imperative for a reliable electricity supply, many regions in China grapple with recurring outages during peak demand periods [3]. In response, the Chinese government has outlined comprehensive strategies and targets over the ensuing years to address this challenge and bolster the nation's overall energy production capacity. Initiatives are underway to diminish reliance on electricity generated from fossil fuels, with plans to expand electrical capacity significantly over the next five years. The government unveiled its 15th four-year strategy for driving growth in April 2021, aiming to elevate energy production from 2200 GW at the close of 2020–3000 GW by 2025 [4]. Rising global commodity prices underscore the imperative of safeguarding energy autonomy, prompting investments in alternative energy sources and infrastructure upgrades. As renewable energy installations increase, coal-fired power plants will continue to play a pivotal role as a flexible energy source. By 2025, China aims to modernize 200 GW of existing capacity and shutter 30 GW of inefficient coal plants [5]. Plans are also in place to augment pumped hydro capacity by 60 GW by 2025, alongside significant investments in interprovincial and territorial grid connections.

As energy consumption continues escalating, promoting Economic Development (ECD) while prioritizing energy security becomes increasingly complex for governments. To address this challenge, a thorough analysis of the factors driving China's high energy consumption and its implications is imperative [6]. This study aims to leverage ECD strategies and advanced technology to examine the impact of Industrialization (INL) and Trade Openness (TRO) on China's Renewable Energy Investment (TIN). Energy consumption has been a focal point of academic inquiry globally, owing to its critical role in sustaining economic growth while safeguarding the environment in the long term [7].

The current era's emphasis on production and energy consumption has spurred extensive academic research into the intricate interconnections among Renewable Energy Investment (REI) and key analogous variables such as Trade Openness (TRO), CO2 emissions, Foreign Direct Investment (FDI), Industrialization (INL), and Economic Development (ECD) [8]. Numerous studies have explored aspects of energy, economic development, emissions, and related factors in China, reinforcing the significance of this line of inquiry [9].

For instance, research utilizing the autoregressive distributed lag (ARDL) model has elucidated the unidirectional relationship between China's renewable energy consumption and GDP growth, highlighting a positive correlation between increasing energy usage and burgeoning economies. Factors such as population density in urban centers, import-export capacity, and levels of foreign direct investment can influence a nation's energy consumption dynamics. Studies have indicated a positive association between new energy consumption and economic expansion, urbanization rates, and total international trade volume [10]. Cointegration analyses have revealed significant connections between China's real GDP and energy consumption, with Granger causality indicating directional influence from energy consumption to GDP.

To mitigate constraints on energy consumption, swift action by the Chinese government is warranted, including initiatives to integrate national power grids, enhance urban and rural distribution networks, and promote rural electrification. Among various analytical techniques, decomposition analysis offers valuable insights into understanding energy dynamics and their context within broader socio-economic frameworks [11].

Data from 19 emerging republics were analyzed to ascertain whether a discernible decline in Renewable Energy Investment (REI) has occurred due to increasing Foreign Direct Investment (FDI), potentially catalyzing experimentation with novel technologies [12]. Previous analyses have indicated that disparities in REI across three Chinese cities can be primarily attributed to the influence of technological advancements [13]. While some argue that technological progress might negatively impact China's REI, others contend that such breakthroughs positively affect energy efficiency in the country. Stern's findings suggest that technological and human capital development may lead to an expansion of waste and pollution, based on data from 85 countries. Similarly, a study of 75 emerging nations found that while REI positively influences development and industrialization (INL), it adversely affects prosperity [14].

While existing research has predominantly focused on exploring the correlation between REI and various factors, limited attention has been paid to the impact of factors such as INL and Trade Openness (TRO) on REI. Moreover, previous studies have primarily examined short-term dynamics, whereas our study seeks to provide a broader perspective. Unlike prior research, we also employ a pathway analysis to examine the relative significance and direction of each variable's direct and mediated influences on REI [15].

The remainder of the paper is organized as follows: Literature review is presented in section 2, section 3 represents the research methodologies employed and Section 4 provides a results and discussions. Finally, Conclusion and policy recommendations are offered in section 5.

2. Literature review

2.1. Studies on Carbon Emission Efficiency

While carbon emission efficiency (CEE) has been extensively discussed in academic literature, there remains a need for consensus regarding its definition. Scholars concur that CEE entails advancing economic growth while reducing environmental impact [16]. Early research predominantly relied on single-factor measures to define CEE, despite criticism regarding their perceived complexity by academics and businesses. However, these single-factor indicators often fail to capture crucial production variables such as labor size, capital input, and energy usage [17]. Consequently, these measures were inadequate for evaluating the effects of CEE. To address this limitation, scholars have developed total factor indices that incorporate multiple inputs and outputs in manufacturing processes [18].

Regarding measurement methodologies, scholars have recently employed parametric and non-parametric approaches to assess CEE. The parametric approach typically relies on stochastic frontier analysis (SFA), a statistical technique known for its subjectivity due to the necessity of pre-determining the form of the production function [19]. Alternatively, non-parametric measures such as data envelopment analysis (DEA) utilize carbon dioxide emissions as an undesirable output to compute CEE using directional distance functions and non-radial maneuvering distance functions [20]. Regional studies on CEE have highlighted significant disparities across different geographic areas. For example [21], conducted a comparative analysis of CEE in various regions of Central and Eastern Europe, while [22] identified substantial differences in CEE between southern and northern Chinese urban areas, largely attributed to geographical factors.

Furthermore, past research has explored various approaches to enhancing CEE, including studies on industrial structure, industrial agglomeration, technological advancements, renewable energy innovation, and Foreign Direct Investment (FDI) [23,24]. [25] also contributed to this body of research by providing insights into different approaches' effectiveness to improve CEE.

2.1.1. Studies on Digital Finance

In recent years, China has witnessed the proliferation of digital technologies such as the Internet, AI, blockchain, cloud computing, and big data, leading to the emergence of digital finance facilitated by the increasing integration of economic services and numerical knowledge [26]. Digital finance, compared to traditional finance, can streamline financial processes, enhance consumer interactions with financial institutions, and extend financial services to previously underserved populations [27]. Early research by Ref. [28] suggested that integrating technology and finance could stimulate economic growth.

As digital technology becomes more pervasive in the financial sector, research has delved into the potential financial implications of digital economics. Utilizing the multiplier effect, studies such as that by Ref. [29] have indicated that digital finance can enhance financial productivity and production efficiency, contributing positively to China's economic growth. Leveraging data processing techniques like big data and blockchain, digital finance can mitigate information asymmetry in transactions, thereby expanding the reach of financial services and stimulating economic growth [30].

However, as China sets targets for reducing carbon dioxide emissions, scholars have begun examining the environmental impact of online banking. Surprisingly, research by Ref. [31] found that digital banking usage correlates with increased CO2 emissions in neighborhoods, with economic growth playing a pivotal role in this relationship. Restructuring the industrial sector could potentially mitigate CO2 emissions [32]. [33] found that while digital finance may contribute to reducing CO2 emissions, its impact is overshadowed by the energy sector due to the unequal distribution of its effects on carbon emissions. Additionally [34], found that the technological impact of digital banking may not significantly influence CO2 emissions. Some studies suggest that the expansion of information technology could reduce greenhouse gas emissions [35], while others point to the rapid technological expansion as a factor contributing to increased carbon emissions [36].

Studies have also examined how the rise of digital currency or the digital economy affects energy efficiency and greenhouse gas emissions [37].

2.1.2. Studies on Green Technology Innovation

Technological innovations enhancing environmental performance are often called "green innovations." Although there is no universally agreed-upon definition of "green innovation" in theoretical discourse, its usage persists. Technology is deemed "green" if it has a net positive impact on the environment, such as reducing pollution levels [38].

Previous research has demonstrated the difficulty of balancing economic development with carbon emissions reduction. Green Technology Innovation (GTI) may offer a means to reconcile economic expansion with mitigating carbon dioxide emissions [39]. However, valid concerns have been raised about this notion. For instance Ref. [40], asserted, without providing empirical evidence, that GTI could only address climate change on a theoretical level, sparking substantial debate within academic circles regarding the role of GTI in reducing carbon emissions. Yet, research findings on the topic have been contradictory.

Studies by Ref. [41] revealed that while patents for carbon-free energy technologies significantly reduced CO2 emissions in China, patents for green technologies had a marginal impact. Similarly, results from investigations into the effects of environmentally friendly technological advancements on CO2 emissions have been inconclusive [42]. [43] found no evidence that GTI reduced carbon emissions at the prefecture-level urban equivalent in China, with significant variations observed across different cities.

Furthermore, research by Ref. [44] suggested that the impact of GTI on CO2 emissions varied depending on the income level of the countries, with significant reductions observed in economies with income levels above a certain threshold [45]. argued that GTI could only mitigate CO2 emissions under well-functioning economic marketplaces.

In addition to examining the impact of GTI on carbon emissions, researchers have also deliberated on its effects on ecological performance or efficiency. Utilizing panel data from 72 nations [46], found that GTI significantly improved overall carbon output in economies with income levels above a certain threshold but did not affect economies with income levels below the threshold.

While the above findings have provided valuable insights, certain limitations exist. Firstly, there is limited literature discussing the impact of online banking and green technology on carbon emissions, and studies exploring the interaction between the two are even rarer. Secondly, there is variability in how Carbon Emission Efficiency (CEE) is calculated across different studies, leading to potential errors in theoretical and applied research and analysis when spatial aspects are ignored. Furthermore, the study examines the influence of GTI and digital banking on CEE using the Spatial Durbin Model (SDM) and spatial quantile regression (SQR) to analyze regional variations in the impact of these factors on CEE.

3. Data and Econometric Methodologies

3.1. Data

The data for this study were sourced from a statistical analysis of the global energy market conducted by British Petroleum in 2015 and version 8.0 of the Penn World Table [47]. The variables utilized in this research project include Gross Domestic Product (GDP), physical capital consumption, employment, human capital, and trade openness. The study period encompasses 1970 to 2010, focusing on 16 Asian and Pacific nations: Australia, Bangladesh, China, Hong Kong, Indonesia, India, Japan, Korea, Malaysia, New Zealand, Pakistan, the Philippines, Singapore, Thailand, Taiwan, and Vietnam. Historical data from 1970 to 2010 were included.

Energy consumption data (measured in millions of tons of oil equivalent) were obtained from the 2015 statistical overview of world energy published by British Petroleum. Data for real GDP (expressed in constant 2005 national currency units), physical and human capital, and labor were sourced from version 8.0 of the Penn World Table. Human capital was calculated as the product of the number of personnel and a human capital index based on years of schooling. The database utilized expected returns to education to estimate human capital. A study by Ref. [48] found that the product of these two factors determines human capital.

This section outlines the data sources and variables utilized in the analysis, providing a comprehensive foundation for the subsequent econometric methodologies employed in the study.

3.1.1. Econometric Methodologies

Below is an explanation of how we employ a human capital-enhanced neoclassical production function as in Eq. (1):

$$lnY = f(lnK, lnL, lnH, lnE) \tag{1}$$

Here, physical capital (K), labor (L), human capital (H), energy consumption (E), and final production (Y) are expressed as logarithms (lnY). Using a multivariate and panel methodology, our research investigates the cointegration and causal links between energy consumption and economic development in Asia-Pacific nations from 1970 to 2010.

First, we conduct a cross-sectional dependency test to select the most appropriate panels for unit root testing. Subsequently, we employ a panel unit root test from the second generation (Pesaran, 2007) to determine the order of series integration. This step is essential due to cross-section dependency. Next, we utilize Westerlund's test (2007), which allows for cross-section correlations, to ascertain if there is a long-run relationship among the variables when they are integrated in the same order. Finally, we assess the impact of foreign dependence by comparing coefficients obtained using a Cup-FM estimate with those derived from panel heterogeneous fully modified OLS (FMOLS) estimates. Furthermore, we employ the bootstrap panel Granger non-causality method to investigate the direction of causality between the variables, considering heterogeneity and cross-section dependency.

These econometric methodologies enable a robust analysis of the relationships between energy consumption and economic development in the Asia-Pacific region, considering the role of human capital and accounting for various statistical considerations.

3.1.2. *Cross − Sectional Dependence Tests*

Cross-sectional dependency tests, susceptible to the particular unit root tests employed, are performed first to determine which panel unit root tests are most suited. When nations and regions become more economically interdependent, new patterns of highly dependent cross-border units tend to develop [49]. Overall, there are five tests to take. Lagrange multiplier tests include the CDLM1 and CDLM2 [50,51] the CD [52], and the [53]. [54] CDLM1 test may be used for either small N or large T samples as in Eq. (2):

$$LM_1 = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 \rightarrow \chi^2\left(\frac{N(N-1)}{2}\right) \tag{2}$$

[55]CDLM2 test works for high values of N and T as in Eq. (3):

$$LM_2 = \sqrt{\frac{1}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\hat{\rho}_{ij}^2 - 1\right)\right) \rightarrow N(0,1) \tag{3}$$

The CD test developed by Ref. [56] is valid when applied to data with a large number of observations (N) and a constant temperature (T). Still, it can miss instances of dependence when the residuals exhibit considerable positive and negative correlations as in Eq. (4).

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \rightarrow N(0,1) \tag{4}$$

The test developed by Ref. [57] also applies to big N and constant T, although it suffers from the same flaw as the CD test developed by Ref. [58] as in Eq. (5).

$$FR = (T-1)\left[\frac{2}{N}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{r}_{ij}+1\right]\rightarrow\chi^2(T-1) \tag{5}$$

The test developed by Ref. [59] is reliable for big N and constant T and can accommodate the fluctuating signs of correlations as in Eq. (6).

$$FRE = \frac{N\left[\frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{r}_{ij}-\frac{1}{T-1}\right]}{SE(Q)}\rightarrow N(0,1) \tag{6}$$

The computed Spearman rank correlation coefficient $\widehat{r}_{ij}$, the correlation coefficient $\widehat{\rho}_{ij}$ The Q distribution SE (Q) standard error is shown below.

3.1.3. Panel Unit Root Tests

Panel-based unit root tests are considered more reliable than those based on a single time series. Two versions of panel unit root testing are covered in the academic literature. The first generation of panel unit root testing (1999) assumes that the panel's time series are uniformly distributed throughout the various slices. The second generation, developed by Ref. [60] and others, considers cross-sectional dependencies.

If cross-sectional dependency is established, this study employs the panel unit root test developed by Ref. [61] use cross-section averages of lagged levels and the first differences of various series to enhance the ADF regressions. This differs from prior research, which often used orthogonalization-type methods to asymptotically eliminate cross-sectional dependence before resorting to conventional unit root testing on a panel of observations.

The CADF model, a cross-sectional regression building on the strengths of the Dickey-Fuller method, is utilized as in Eq. (7):

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + d_0\overline{y}_{t-1} + \sum_{j=0}^{p} d_{j+1}\Delta\overline{y}_{t-j} + \sum_{k=1}^{p} c_k\Delta y_{i,t-k} + \varepsilon_{it} \tag{7}$$

Where $\overline{y}_t$ Represents the average value across N observations at time t. Information criteria or sequential testing may determine the appropriate lengths of the lagged first differences of $y_{i,t}$, and $\overline{y}_t$ The CIPS statistic is calculated by averaging t-statistics on the lagged value, CADFi, after performing the CADF regression for each unit as in Eq. (8).

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i. \tag{8}$$

3.1.4. Panel Cointegration Tests

Tests such as [49] and a Fisher-type test with a fundamental Johansen approach are some examples of the types of tests that may be used to evaluate whether or not panel cointegration exists [62]. Nonetheless, they proceed, assuming that the cross-section is independent of any other factor. To consider the cross-section dependency utilizing bootstrap techniques, we apply the tests only recently made public by Ref. [63]. If the panel is cointegrated as a whole in any of the twice-panel tests or if at minimum 1 element is cointegrated in either of the 2 group-mean tests, then the null hypothesis states that there is no cointegration will be rejected. The null hypothesis operates on the assumption that there is no cointegration. To be more explicit, the tests that were conducted by Ref. [64] are founded on the mistake alteration procedure that is as follows as in Eq. (9):

$$\Delta y_{it} = \delta_i' d_t + \alpha_i\left(y_{i,t-1} - \beta_i' x_{i,t-1}\right) + \sum_{j=1}^{p_i}\alpha_{ij}\Delta y_{i,t-j} + \sum_{-q_i}^{p_i}\gamma_{ij}\Delta x_{i,t-j} + e_{it} \tag{9}$$

$t = 1, \dots, T$ and $i = 1, \dots, N$, d_t represent the fixed features, whereas *pi* and *qi* reflect the variable lead and lag times across countries. Do an OLS regression on every single I in the sample first. The following step, relevant to both group-mean tests, calculates the ratio of variance estimators. $\widehat{u}_{it}$ it and Δy_{it} where $\widehat{u}_{it}$ it is computed by $\widehat{u}_{it} = \sum_{-q_i}^{p_i}\widehat{\gamma}_{ij}\Delta x_{i,t-j} + \widehat{e}_{it}$ If the standard error of $\widehat{\alpha}_i$ is written as $SE(\widehat{\alpha}_i)$ While the variance ratio is written as $\widehat{\alpha}_i(1)$. Both of these tests are group-mean tests as in Eq. (10).

$$G_\tau = \frac{1}{N}\sum_{i=1}^{N}\frac{\widehat{\alpha}_i}{SE(\widehat{\alpha}_i)}, G_\alpha = \frac{1}{N}\sum_{i=1}^{N}\frac{T\widehat{\alpha}_i}{\widehat{\alpha}_i(1)}. \tag{10}$$

The second step in conducting these two-panel tests is to estimate the standard error-correction limit by as in Eq. (11).

$$\widehat{\alpha} = \left(\sum_{i=1}^{N}\sum_{t=2}^{T}\widetilde{y}_{i,t-1}^2\right)^{-1}\sum_{i=1}^{N}\sum_{t=2}^{T}\frac{1}{\widehat{\alpha}_i(1)}\widetilde{y}_{i,t-1}\Delta\widetilde{y}_{it} \tag{11}$$

together with the margin of error by $\widehat{\alpha}$ as in Eq. (12).

$$SE(\widehat{\alpha}) = \left(\left(\frac{1}{N} \sum_{i=1}^{N} \frac{\widehat{\sigma}_i}{\widehat{\alpha}_i(1)} \right)^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} \widetilde{y}_{i,t-1}^{2} \right)^{-1/2} \tag{12}$$

where $\Delta\widetilde{y}_{it}$ it and $\widetilde{y}_{i,t-1}$ inaccuracies in the projections made by Eq. (13).

$$\Delta\widetilde{y}_{it} = \Delta y_{it} - \widehat{\delta}_i' d_t - \widehat{\lambda}_i' x_{i,t-1} - \sum_{j=1}^{p_i} \widehat{\alpha}_{ij} \Delta y_{i,t-j} - \sum_{-q_i}^{p_i} \widehat{\gamma}_{ij} \Delta x_{i,t-j} \tag{13}$$

Then as in Eq. (14).

$$\widetilde{y}_{i,t-1} = y_{i,t-1} - \widehat{\delta}_i' d_t - \widehat{\lambda}_i' x_{i,t-1} - \sum_{j=1}^{p_i} \widehat{\alpha}_{ij} \Delta y_{i,t-j} - \sum_{-q_i}^{p_i} \widehat{\gamma}_{ij} \Delta x_{i,t-j}. \tag{14}$$

Statistics for a two-group test are as in Eq. (15).

$$P_\tau = \frac{\widehat{\alpha}}{SE(\widehat{\alpha})}, P_\alpha = T\widehat{\alpha}. \tag{15}$$

3.1.5. *Panel Cointegration Regressions*

Group-mean FMOLS estimator may be used to calculate the varied cointegrating paths if a cointegrating link exists. This method allows for calculating the heterogeneous cointegrated panel member vectors, reducing the impact of endogeneity bias and serial correlation. Each of these perks is useful in its own right, but when put together, they add up to a lot that works in favor of this approach. These advantages are significant improvements over the current situation. The panel heterogeneous FMOLS estimator is defined as follows by Ref. [65] as in Eq. (16):

$$\widehat{\beta}_{GFM}^{*} = N^{-1} \sum\nolimits_{i=1}^{N} \beta_{FMi}^{*} \tag{16}$$

Where β_{FMi}* is derived from an FMOLS calculation done over time for each nation as in Eq. (17):

$$\beta_{FMi}^{*} = \left(\sum_{t=1}^{T} (\mathrm{X}_{it} - \overline{\mathrm{X}}_{i})(X_{it} - \overline{X}_i)' \right)^{-1} \sum_{t=1}^{T} ((\mathrm{X}_{it} - \overline{\mathrm{X}}_{i})(\mathrm{y}_{it} - \overline{\mathrm{y}}_{i}) - \widehat{\gamma}_i). \tag{17}$$

Here $\widehat{\gamma}_i = \widehat{\Gamma}_{21i} + \widehat{\Omega}_{21i}^{0} - \frac{\widehat{\mathrm{L}}_{21i}}{\widehat{\mathrm{L}}_{22i}}(\widehat{\Gamma}_{22i} + \widehat{\Omega}_{22i}^{0})$ and $\widehat{\mathrm{L}}_i$ Decomposes the long-run variance using a lower triangular matrix. $\widehat{\Omega}_i$.Contrarily [66], estimates do not account for cross-section dependence. To further investigate the impact of cross-sectional dependence on the parameter estimations, we turn to the Cup-FM estimates given by Ref. [58]. To do so, we subtract these two figures from one another. In this paper, we will follow the method [67] proposed to do panel regressions with cross-sectional dependency as in Eq. (18).

$$\mathrm{y}_{it} = \alpha_i + \beta \mathrm{X}_{it} + \mathrm{e}_{it} \tag{18}$$

If a factor model is used for the error term as in Eq. (19):

$$\mathrm{e}_{it} = \lambda_i' \mathrm{F}_t + \mathrm{u}_{it}. \tag{19}$$

To specify the CUP-FM estimator, one would say as in eq. (20):

$$\widehat{\beta}_{Cup} = \left[\sum_{i=1}^{N} \left(\sum_{t=1}^{T} \widehat{y}_{it}^{+}(\widehat{\beta}_{Cup})(X_{it} - \overline{X_i})' - T\left(\lambda_i'(\widehat{\beta}_{Cup})\widehat{\Delta}_{F\varepsilon i}^{+}(\widehat{\beta}_{Cup}) + \widehat{\Delta}_{u\varepsilon i}^{+}(\widehat{\beta}_{Cup})\right) \right) \right] \times \left[\sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \overline{X_i})(X_{it} - \overline{X_i})' \right]^{-1} \tag{20}$$

Where $\widehat{\mathrm{y}}_{it}^{+} = \mathrm{y}_{it} - (\widehat{\lambda_i'}\widehat{\Omega}_{F\varepsilon i} + \widehat{\Omega}_{u\varepsilon i})\widehat{\Omega}_{\varepsilon i}^{-1}\Delta\mathrm{X}_{it}$ and $\widehat{\Omega}_{F\varepsilon i}and\widehat{\Omega}_{u\varepsilon i}$ are calculated matrices of long-term correlation and $\widehat{\Delta}_{F\varepsilon i}^{+}and\widehat{\Delta}_{u\varepsilon i}^{+}$ are projections for the long-run correlation between two variables. You could get the CUP-FM by iteratively estimating the limits, longer-run covariance matrix, and stacking pending junction is touched. You may do this step as many times as you want. Monte Carlo simulations demonstrated that this method outperformed OLS and the two-step-FM estimators regarding its small-sample features.

3.1.6. *Panel Granger Non − Causality Test*

Any sign of cointegration in a system suggests Granger causality in at least one way. Granger causation in a panel setting can be done using several econometric methods. Examples include the widespread adoption and use of panel-based VECM, developed by

Ref. [68], in studies of the relationship between energy growth and economic development [69,70]. In contrast, this approach necessitates pretest to check for unit roots and cointegration, making it vulnerable to pretest bias [71]. As an added downside, it disregards the interdependence among the individual parts. Two relatively new methods that account for heterogeneity and cross-sectional dependency are [72]. As with [73], both methods permit the autoregressive coefficients to change across units. We employ the bootstrap panel Granger non-causality test future by Ref. [74]. [75] methodology relies on Meta-analysis, and the Fisher test number can be calculated using the following formula as in Eq. (21):

$$\lambda = -2\sum_{i=1}^{N} ln(p_i), i = 1, 2, \ldots, N \tag{21}$$

where p_i is the $p-$ value of the Wald figure regarding the ith element. The chi $-$ square supply with $2N$ gradations of freedom is obtained by assuming that the cross-sections are independent. When a cross-section dependence is present [76], suggest utilizing the bootstrap method to generate the Fisher test statistic empirical distribution and the related serious standards. This may be done by using a random sample of the data. The causality mechanism used in bootstrap panels may be understood as follows. Then, choose the lag orders by determining the value of maxi, the maximum instruction of addition of variables for each cross-sectional component I. Criteria for information based on the work of Kivia Schwarz or *Akaike*. Stage 2: Estimate the equation $y_{i,t} = \alpha_i + \sum_{j=1}^{k_i+dmax_i} \beta_{ij}x_{i,t-j} + \sum_{j=1}^{k_i+dmax_i} \gamma_{ij}y_{i,t-j} + e_{it}$ by OLS under the non-causality theory $\beta_{i1} = \beta_{i2} = \ldots = \beta_{iki} = 0$, and generate the residuals $\widehat{e}_{i,t}$ for each unit i. Stage 3 includes positioning the residuals. with $\widetilde{e}_{i,t} = \widehat{e}_{i,t} - (T–k–d-2)^{-1}\sum_{t=k+d+2}^{T} \widehat{e}_{i,t}$ ($k = max\ (k_i)$ *and* $d = max\ (dmax_i)$) which form the $N \times T$ medium $[\widetilde{e}_{i,t}]_{N\times T}$ To maintain the cross-covariance structure of the errors, we will randomly choose a whole column from the matrix, and then we will replace data in the appropriate places. The symbol denotes the residuals from the bootstrap. $\widetilde{e}^*_{i,t}$. Stage 4: Sample y using bootstrapping by as in Eq. (22).

$$y^*_{i,t} = \widehat{\alpha}_i + \sum_{j=k_i+1}^{k_i+dmax_i} \widehat{\beta}_{ij}x_{i,t-j} + \sum_{j=1}^{k_i+dmax_i} \widehat{\gamma}_{ij}y^*_{i,t-j} + \widetilde{e}^*_{i,t} \tag{22}$$

We use the projected values from Step 2 for $\widehat{\alpha}_i$, $\widehat{\beta}_{ij}$ and $\widehat{\gamma}_{ij}$.Stage 5: The equation in Step 2 should be estimated as deprived of impressive limits, although you should substitute $y_{i,t}$ with $y_{i,t}$. To check for Granger non-causality at the individual level, we produce Wald statistics, which have an asymptotic chi-square delivery with grades of autonomy. The Fisher test statistic derives P-values relevant to the panel non-causality test. Sixth, iteratively complete stages 3–5 to create the empirical bootstrap supply and dangerous values of the Fisher test statistics. The end outcome will be more precise because of this.

4. Results and Discussion

4.1. Cross − Sectional Dependence Test Results

The outcomes of the experiments conducted to assess cross-sectional dependency are presented in Table 1. Following these five tests, it is evident that the null hypothesis of cross-sectional independence does not withstand scrutiny. At a significance level of 1 %, the null hypothesis is rejected by the Breusch-Pagan χ-square, Pearson LM, and Pearson CD statistics. However, at the 10 % significance level, only the Friedman χ-square rejects the null hypothesis. Furthermore, with regional integration continuing to advance at its current pace, an escalation in economic interdependence and the movement of financial variables across states due to similar shocks and spillover effects can be expected. This trend persists even without anticipating a rise in regional integration. Therefore, the next step should involve applying second-generation panel unit root tests, which account for the cross-sectional dependency in the data.

4.1.1. Panel Unit Root Test Results

Due to the observed cross-sectional dependence in the panel, we employ the panel unit root test developed by Ref. [77]. Table 2 and Fig. 1 indicate that regardless of whether the model includes a trend, it is impossible to dismiss the presence of a unit root for all five variables at the level. This is because a unit root signifies a point at which a variable's value equals zero (except for the one with a trend). However, they appear stationary at first glance. Based on the findings, all series can be integrated into order one in the Asia-Pacific region.

The BG lag has been adjusted to 9, and the maximum latency is now at 4. The critical values are 2.250, 2.110, and 2.030 for the model with just the constant and 2.760, 2.620, and 2.540 for the perfect with interrupt and the tendency. These numbers represent a 1 %, 5 %, and 10 % significance level. Specify the 1 % significance level. Specify the 5 % significance threshold.

Table 1
Cross − sectional requirement examination outcomes.

< ! − − Col Count : 6 − − > Test	Breusch–Pagan χ^2	Pearson LM normal	Pearson CD normal	Friedman χ^2	Frees normal
Statistics	3221.858	234.748	−3.840	65.713	5.711
p − Value	0.098	0.05	0.103	0.164	0.043

Table 2
Panel unit root examination outcomes with the cross − sectional requirement..

	Level		First difference	
	Intercept	**Intercept trend**	Intercept	**Intercept trend**
lnGDP	−2.739	−2.863	−5.428***	−5.895***
l nK	−1.933	−3.634	−3.257**	−3.739**
lnL	−2.406	−1.713***	−3.670***	−6.889***
lnH	−2.334	−3.572	−5.165***	−5.922***
lnE	−1.114	−1.316	−6.324***	−6.610***

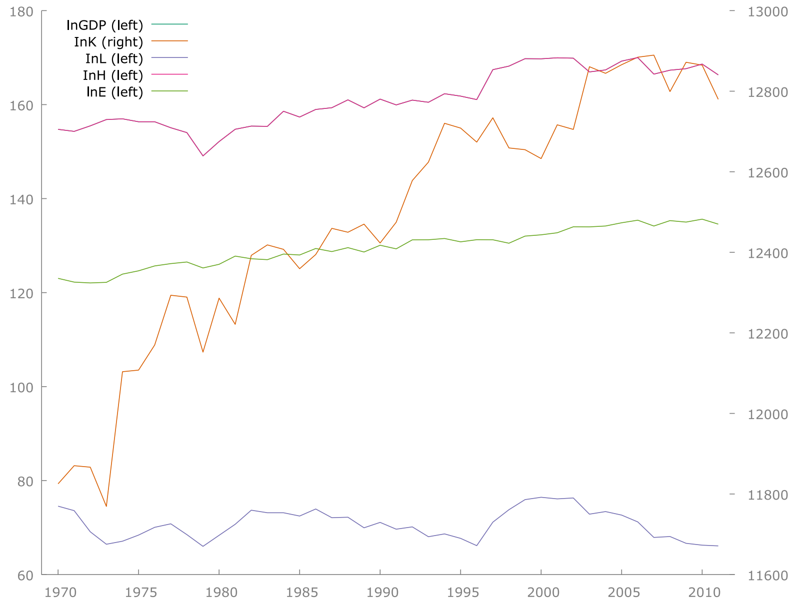

Fig. 1. *Panel unit root examination outcomes with the cross − sectional requirement..*

4.1.2. Panel Cointegration Results

Before examining the findings of the cointegration test by Ref. [78], we first conduct the standard tests by Ref. [79] to ascertain the existence of long-run equilibrium. If such equilibrium exists, we proceed to the next step. The results of each of the seven individual tests, along with their corresponding p-values, are presented in Table 3.

For the intra-dimensional tests, the null hypothesis posits the presence of standard autoregression coefficients, while for inter-dimensional tests, the null hypothesis assumes individual-varying AR coefficients. The first four tests apply to intra-dimensional assessments, whereas the last three pertain to inter-dimensional examinations. It is reasonable to reject the null hypothesis of the absence of cointegrating relationships among the five variables, as four tests suggest such a relationship.

Thus, the GDP, physical and human capital, labor, and energy consumption of the selected Asia-Pacific nations were found to be cointegrated from 1970 to 2010. The most recent year included in the analysis is 2010.

Notice that the lag duration is determined by applying the Schwarz Information Criterion to the selection process; is applied to the spectral estimate; and Newey–West is responsible for determining the bandwidth.

The results in Table 3 might need to be more accurate since they do not consider the data's cross-sectional dependence. Table 4 displays the outcomes of 4 test data for the perfect with and without an interrupt. These test statistics confirm a long-run cointegrating relationship between GDP, bodily wealth, employment, humanoid wealth, and vigor use across Asia Pacific nations. This relationship was determined by applying the bootstrap method developed by Ref. [80], which considers cross-sectional dependence. Their exclusion tests did not exclude human capital from the cointegrating space [81]. presented more evidence of the cointegration

Table 3
Panel cointegration examination outcomes without cross − sectional requirement..

Test	Panel v	Panel rho	Panel PP	Panel ADF	Group rho	Group PP	Group ADF
Statistic	1.568	1.881	−3.115	−3.493	2.891	−2.767	−3.851
p − Value	0.42	0.937	0.122	0.108	0.877	0.148	0.103

Table 4
Panel cointegration examination outcomes with the cross − sectional requirement.

Test	Gt	Ga	*Pt*	Pa
No intercept	−3.136	−8.330	−9.415	−8.279
Robust p − value	1.18	1.11	1.11	1
Intercept	−3.863	−14.821	−8.123	−21.719
Robust p − value	0.05	0.01	0.056	0.098

relationship among these 5 variables for specific nations (Malaysia, Indonesia, Thailand, Singapore, and the Philippines).

Please take note that the width of the Bartlett kernel window is determined as $4(T\ /\ 100)\ (2\ /\ 9)\ = 3$. One is selected as the lag and zero as the lead. The bootstrap error is calculated with a sample size of 100.

4.1.3. CUP − FM and FMOLS Estimates

Having established the existence of cointegration, we can next proceed to estimate the production function's parameters. We use the panel heterogeneous FMOLS supplied by Ref. [82] and the Cup − FM offered by Ref. [83], to shed light on the possible influence of cross-section dependency on the stricture estimations. Table 5 and Fig. 2 displays all of the data. According to the Cup-FM estimate, physical capital is essential to economic growth. Evidence shows that a one percent increase in physical capital in the Asia-Pacific area frequently results in a five-point five percent rise in GDP. To be more precise, we discover that the output elasticity of energy consumption is 0.04, whereas that of labor and human capital inputs is close to zero. Energy provision is also essential. As a result, the growth mechanism through investment in human capital has been unlocked, and further work should be done to encourage synergies between human capital and other factors. Look at how this differs from what is seen in endogenous growth models. Despite this, events like this are daily in works of this type. The lowest potential labor contribution to Malaysia's GDP may be found [84].

Parameter estimators for all inputs, excluding physical capital, show large degrees of bias compared to the FMOLS estimator. Specifically, due to ignoring the interdependence between nations, the energy effect estimation is optimistic. As a result, if it is utilized as a basis for policymaking, it may lead to an overemphasis on the role of energy in driving economic expansion and an exaggeration of the efficacy of the policy. The comparison shows that long-run elasticity estimates are affected by the same common factors that cause cross-sectional dependencies. We found that the size of the economy was undervalued in our example of Asian-Pacific nations, with the sum of effort resistances equal to 0.802, which was significantly lower than 0.975 from the Cup-FM estimators, in contrast to the findings of [85], who found that panel FMOLS estimates for both the aggregate economy and the disaggregate economies in Italy overestimated the size of the economy.

4.1.4. Panel Granger non − causality results

Table 6 and Fig. 3 presents the outcomes of the bootstrap panel Granger non-causality test, as proposed by Ref. [86]. Unlike the panel VECM, this analysis accounts for the data's heterogeneity and cross-sectional dependency. The Schwarz information criterion determines the lag order, and one thousand replicates are utilized to establish critical bootstrap values.

The results of the Wald test and their corresponding p-values are depicted in Columns 3 and 4 to assess the alternative hypothesis that energy consumption does not influence economic development. Furthermore, Column 5 showcases the panel-level Fisher test statistic.

The observations indicate that India, Korea, Pakistan, and Taiwan do not support the notion that energy consumption Granger-causes Gross Domestic Product (GDP) in these nations. However, the three critical values obtained from the empirical distribution surpass the Fisher test statistic of 50.912. This contradicts the hypothesis that GDP in the Asia-Pacific region correlates with energy production in the region. Tests investigating the hypothesis that GDP Granger-causes energy consumption are delineated in columns 5 and 6, labeled "Other Direction." Granger causality analyses reveal that energy consumption significantly impacts GDP in various countries, including Australia, India, and the Philippines. Additionally, these findings are significant at the 1 % regional significance level.

The results confirm the conservation hypothesis in Australia, the response result in India, and the development theory in Korea, Pakistan, and Taiwan. Furthermore, the numbers support the theory that Taiwan's population will grow much more. We found that economic progress predicts energy use for the sample of 16 Asia-Pacific nations we examined. This connection is one-way only. This research reaches a result that is at odds with that of [86,87], all of whom found support for the growth hypothesis in their respective panel samples. Nonetheless, it agrees with the results of [88], who showed the Granger causality between GDP and rising energy

Table 5
Panel estimation results..

	CUP − FM		FMOLS	
	Constant	**t − Statistics**	Constant	**t − Statistics**
lnK	1.608***	26.611	1.595***	34.571
lnL	1.312	1.882	−1.199	1.352
lnH	1.315	2.27	1.401	3.318
lnE	1.140**	3.213	1.205***	5.865

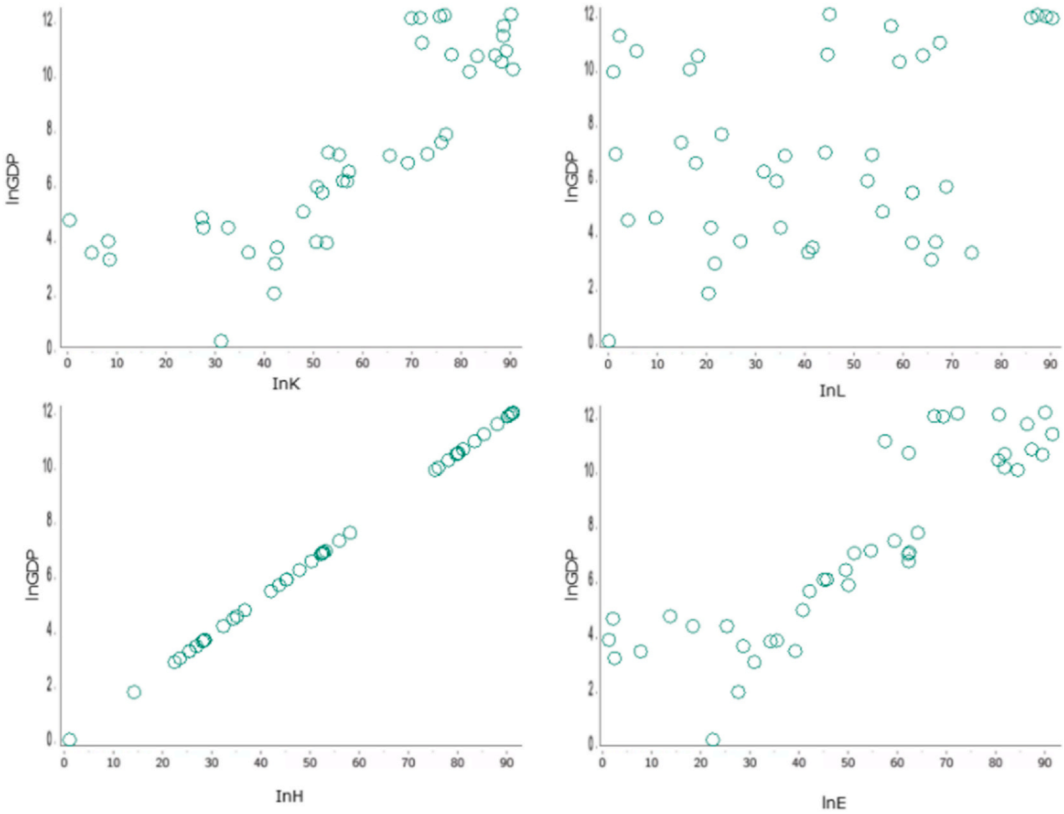

Fig. 2. Panel estimation results (Relationship of the lnGDP with Ink, InL, InH, and InE).

Table 6
Panel Granger non − causality examination outcomes..

Nation	k_i	**Energy Granger not − cause** GDP?		**GDP Granger not − cause energy**?	
		W_i	P_i	W_i	P_i
Individual countries					
Australia	3	1.897	1.771	17.493	1.100***
Bangladesh	4	7.404	1.378	4.266	1.774
China	1	2.451	2.939	1.874	1.779
Hong Kong	1	1.579	3.638	4.158	1.251
Indonesia	4	2.479	2.845	3.833	1.502
India	1	5.31	1.140**	3.281	1.141**
Japan	2	2.946	1.274	1.134	1.954
Korea	2	5.592	1.162*	1.695	1.541
Malaysia	2	1.145	1.932	1.137	1.948
New Zealand	2	1.111	1.817	1.728	1.528
Pakistan	4	11.186	1.118**	1.972	1.699
Philippines	4	2.494	1.807	8.342	1.168*
Singapore	2	1.822	1.437	3.112	1.256
Thailand	4	2.779	1.742	7.32	1.256
Taiwan	3	2.365	1.171*	1.886	1.475
Vietnam	2	2.309	1.672	1.809	1.5
Panel					
Fisher test statistic λ		50.912		61.863*	
Bootstrap critical values	***2 %	71.855		81.514	
	**4 %	63.708		71.765	
	*2 %	58.658		57.773	

consumption.

A fair expectation is that a research effort that draws from several regions, periods, data sources, and econometric methods would produce conclusions at odds with one another. Its approach, which accounts for heterogeneity and cross-sectional dependency, is one

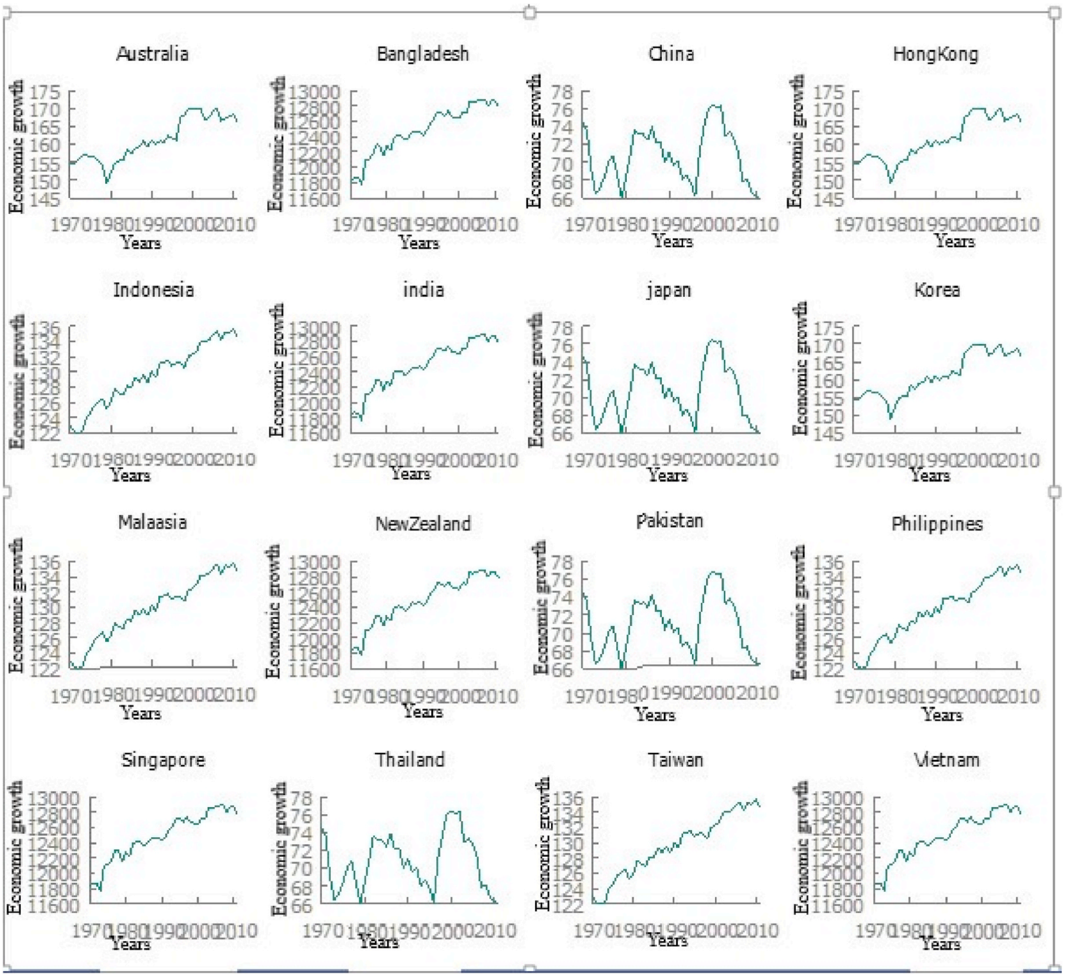

Figure 3. Panel Granger non − causality examination outcomes (The figure with each panel represents various countries and their respective economic trends or statistical data over the years)..

of the study's greatest strengths. The panel VECM test is also conducted to serve as a benchmark; its positive findings indicate that the growth hypothesis is supported throughout Asia and the Pacific in the short and long terms. Possible discrepancy causes include pre-test bias and the panel VECM model's inability to consider the impact of cross-national reliance.

5. Conclusions and Policy Implications

Using data from 16 Asian and Pacific nations between 1970 and 2010, this study investigates the relationship between energy use and economic growth. The expanded neoclassical production function incorporates humanoid investment for the first time, contrasting with the growing body of research on the energy-growth nexus. While it is well acknowledged that human capital significantly contributes to economic expansion, it has never previously been included in the industrial process. Additionally, we utilize the cointegration test and the second-generation panel unit root test developed by Pesaran to address the panel's dependence on cross-sectional data. We find that GDP, physical wealth, work, humanoid wealth, and energy consumption are combined into one sequence in log terms, confirming the presence of long-run cointegration across Asia-Pacific economies. Subsequently, we use the continuously updated, fully modified (Cup-FM) estimate to derive the cointegrating constants. According to this research, the availability of energy and physical capital is a significant factor in the growth of economies throughout Asia and the Pacific. It also shows that ignoring cross-section dependency in estimating coefficients will exaggerate energy's role in economic growth.

After controlling for heterogeneity and cross-sectional dependence, the bootstrap panel Granger causality test confirms that regional economic development Granger causes regional energy consumption, with some variation among countries. Although the test included heterogeneity and cross-sectional dependence, the same result was still obtained. This finding underlines the importance of considering international links compared to panel VECM data. The study's conclusions will have substantial policy ramifications. First, a Granger causality examination among energy consumption and financial growth suggests that an energy preservation strategy is generally viable in the Asia-Pacific region in the long run; however, separate nations are recommended to conduct further investigation, which should be based on a wide range of factors such as its economic growth phase, resource endowment, skill structure, and energy efficiency when formulating their growth-enhancing or energy policies. This is because long-term Granger causality research of the Asia-Pacific region supports the idea that an energy conservation strategy may be implemented successfully.

Moreover, research has shown that human capital has been as crucial to the growth of the regional economy as energy has been. Given the potential synergistic effect of such a strategy on energy consumption, the question of how to maximize economic growth by unlocking latent human capital is essential. Unlocking new human capital is one strategy for boosting economic growth. As a result, nations may choose to increase spending on human capital, especially in areas related to capacity development that aid in disseminating current high-tech goods and the discovery and creation of new energy-efficient goods.

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Data availability

We collected relevant data from World Bank open data available at https://data.worldbank.org/. For any further query on data, corresponding author at email address zhouxinjian@xynu.edu.cn may be approached.

CRediT authorship contribution statement

Zhou Xinjian: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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