Renewable Energy 204 (2023) 382–399

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Financial inclusion and energy poverty nexus in the era of globalization: Role of composite risk index and energy investment in emerging economies

Zeeshan Khan [a], Ilham Haouas [b], Hai Hong Trinh [c], Ramez Abubakr Badeeb [d,*], Changyong Zhang [e]

[a] Faculty of Business, Curtin University Malaysia, Malaysia
[b] Economics and Finance, College of Business, Abu Dhabi University, United Arab Emirates
[c] School of Economics and Finance, Massey University, Palmerston North, 4442, New Zealand
[d] Nottingham University Business School, Faculty of Arts and Social Sciences, University of Nottingham Malaysia, Malaysia
[e] Department of Accounting, Finance and Economics, Faculty of Business, Curtin University Malaysia, Malaysia

ARTICLE INFO

Keywords:
Energy poverty
Financial inclusion
Investment in energy
Emerging economies

ABSTRACT

Even in the modern era with increasing globalization and technological innovation, the issue of energy poverty is still debatable in many parts of the world. Unlike developed countries, developing countries struggle to satisfy the growing energy demand. To evaluate the role of financial inclusion and its impact on energy poverty in six representative emerging economies including Brazil, China, India, Indonesia, Mexico, and Russia from 2004 to 2019, this paper examines the role of the composite risk index (a combination of political, economic, and financial risk), investment in energy with public-private participation, gross domestic product, human capital, globalization, and renewable energy. This study first constructed a multidimensional index to measure the weighted average energy poverty and composite energy poverty index along with a novel index for financial inclusion. Moreover, this study uses novel panel data approaches such as Westerlund's cointegration and cross-sectionally augmented autoregressive distributed lags model (CS-ARDL). The study established long-run cointegrating relationship between energy poverty and its detereminants, i.e., financial inclusion, globalization, investment in energy, human capital index, income and composite risk index. The empirical results found that financial inclusion, renewable energy electricity, globalisation, income, human capital index and energy investment are the key determinants of energy poverty in emerging economies. Furthermore, financial inclusion is found to curb energy poverty. Human capital index and globalization also help to reduce energy poverty. Given the empirical results of the nexus and impacts of financial inclusion on energy poverty using the multidimensional proxies, the study provides critical implications to researchers and policymakers in mitigating the consequences of energy poverty and the development of financial systems and their co-movement with energy poverty-related issues.

1. Introduction

Humans never stop exploiting energy to produce goods and services. Energy has become a key input factor in boosting productivity and accelerating the global economy. The World Bank demonstrated that energy use (kg of oil equivalent per capita) has been increasing since decades ago. That is, energy use has increased by 44% from 1337 kg of oil equivalent per capita in 1971 to 1922 in 2014. This rising energy use has been supporting global economic growth by 38%, from US$ 66,163 trillion in 2010 to US$84,705 trillion in 2020. Unfortunately, the rising economic growth does not guarantee people will receive sufficient energy access. This situation is acknowledged as energy poverty, where people lack choices to access proper and affordable energy prices.

Energy poverty is known as a situation when individuals and businesses cannot access sustained energy products and services (World Economic Forum, 2010). The prevalence of energy poverty is

* Corresponding author.
E-mail addresses: zee8447@gmail.com, Zeehan.Khan@student.curtin.edu.au, zeeshankhan@postgrad.curtin.edu.my (Z. Khan), Ilham.haouas@adu.ac.ae (I. Haouas), H.H.Trinh@massey.ac.nz (H.H. Trinh), r-badeeb@hotmail.com (R.A. Badeeb), changyong.zhang@curtin.edu.my (C. Zhang).

https://doi.org/10.1016/j.renene.2022.12.122
Received 16 April 2022; Received in revised form 23 December 2022; Accepted 30 December 2022
Available online 6 January 2023

widespread. According to the European Commission (2020), around 50–125 million people cannot acquire sufficient indoor heaters in Europe. Furthermore, according to International Energy Agency (2020), around 905 million people in sub-Saharan Africa cannot afford clean cooking fuels and 578 million people lack access to electricity. Ashagidigbi et al. (2020) reveal that energy poverty is lower in urban areas than in rural areas. Energy poverty has devastating consequences on human life, such as health, psychology, and development quality. Hence, eradicating energy poverty is a top goal in the UN sustainable development goals. More importantly, understanding factors reducing energy poverty is essential to support the successful eradication policy.

There are many factors affecting energy poverty. [48] investigate the determinants of energy poverty in 27 European countries. Their findings show that some affecting variables include bilateral trade, globalization, and bureaucracy. Globalization is closely connected with the energy market, which affects energy poverty. The market matters because, through globalization, the energy market will determine the movement of supply and demand of energy, which influences energy prices. If energy prices are too high, this will not be affordable and will trigger energy poverty to rise. Another factor affecting energy poverty is climate change. Climate change can trigger environmental degradation. With worsening environmental quality, more energy is produced less and reduces the energy supply. This situation causes energy poverty to rise since less supply cannot accommodate the rising demand. The study from Essel-Gaisey and Chiang [1] is one of the studies examining this particular issue. A detailed overview of renewable energy electricity output is given below in Fig. 1 as.

Financial inclusion has been studied as a major determinant of energy poverty. However, studies understanding the nexus of financial inclusion and energy poverty are still scarce, mostly constrained by some particular proxies, samples and methodologies employed. General studies demonstrate that financial inclusion is negatively correlated with energy poverty, such as those presented in Koomson and Danquah [2], Boutabba, Diaw, Lare, and Lessoua (2020), and Allet (2016), among others. Meaning that empowering financial inclusion in society can help eradicate energy poverty. Other studies support this finding by arguing that credit financing is a crucial tool to strengthen financial inclusion and hence reduce energy poverty, such as presented in Ashagidigbi, Babatunde, Ogunniyi, Olagunju and Omotayo (2020), and Groh and Taylor (2017), among others. Specifically, the expanding banking intermediation activity can provide households with more funds to produce goods and services, earn profit, and add more income to afford sufficient energy access. Furthermore, some studies such as Morris, Winiecki, Chowdury and Cortiglia (2007); Rao, Miller, Wang and Byrne (2009); Yunus (1999), among others, emphasize microfinance as the tool to eradicate energy poverty. However, the major literature gap in the area is the narrow scope of the research, which is still limited and requires more research expansion. Also, no study has been conducted to comprehensively assess the nexus of financial inclusion and energy poverty by incorporating external factors such as financial risk, political risk, and human capital. A graphical overview of investment in energy is given below in Fig. 2 as.

This study aims to expand the literature by investigating the nexus of financial inclusion and energy poverty across six major emerging markets, including Brazil, China, India, Indonesia, Mexico and Russia over the period of 2004–2019. This study applies the cross-sectionally augmented autoregressive distributed lags (CS-ARDL) as the main method of estimation, together with some supporting tests, including the cross-sectional dependence test from Pesaran [3], the cointegration test from Pesaran and Yamagata (2008), the augmented mean group robustness test from Eberhardt and Teal (2010), and the common correlated effect mean group (CCEMG) from Pesaran [4]. This study varies from other studies in the literature in its model construction. We developed two models with different proxies for energy poverty: the weighted average of energy poverty (WAEP) and the composite energy poverty (CEP).

The focused independent variable is financial inclusion, which is proxied by five measures, including the number of commercial banking institutions, the number of commercial banks branches, the number of automated teller machines per 100,000 adults, the share of outstanding deposits in commercial banks over GDP, and the share of outstanding loans from commercial banks over GDP. In addition to financial inclusion, some control variables are also incorporated, including investment in energy, renewable energy electricity, human capital index, and globalization. The additional control also includes a composite risk index, a combination of political economic and financial risk indexes. All data are derived from World Bank development indicators. Overall, this study demonstrates that financial inclusion is negatively correlated with energy poverty in the short and long run. Furthermore, based on the Granger causality test, this study also demonstrates a causal relationship between energy poverty with financial inclusion, human capital index, and globalization. A detailed overview of the income of these selected economies is given below in Fig. 3 as.

This paper makes three contributions. First, to the best of our knowledge, this is the first paper explaining the relationship between financial inclusion and energy poverty with some additional information about energy investment, renewable energy electricity output, human capital index, globalization and composite risk index. Second, our paper also contributes to the new methodology that has not been widely implemented in the literature in the same area. This paper employs the cross-sectionally augmented autoregressive distributed lags (CS-ARDL) as the main estimation method, together with other methods such as pooled OLS regression, fixed effect regression, augmented mean group, and pooled mean group. Third, to the best of our knowledge, this is the first study employing WAEP and CEP as multiple proxies for energy poverty with five measures of financial inclusion. The empirical outcomes identified globalization, financial inclusion, investment in energy, human capital index, income and composite risk index as key determinants of energy poverty. Moreover, financial inclusion is found

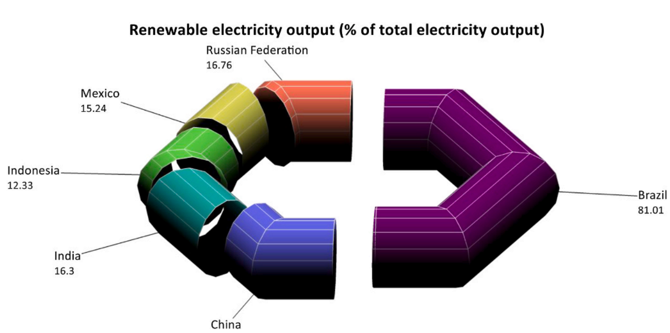

Fig. 1. Renewable energy electricity output.
Source: Author's own calculations from https://databank.worldbank.org data.

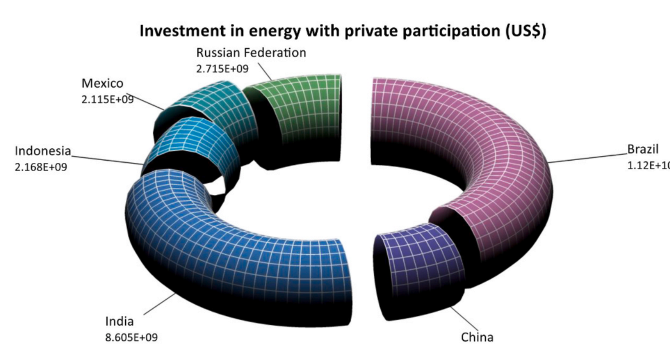

Fig. 2. Investment in energy.
Source: Author's own calculations from https://databank.worldbank.org data.

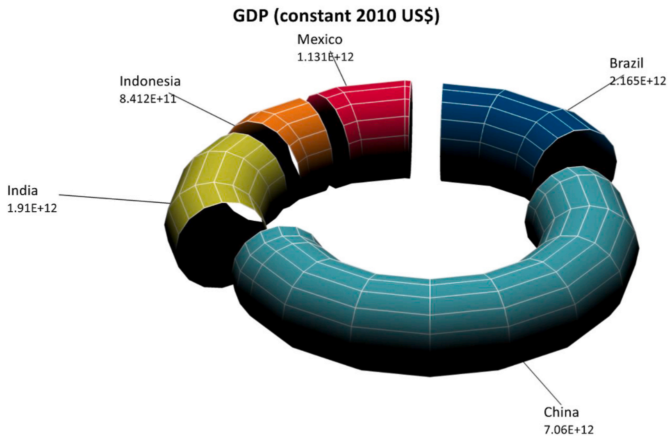

Fig. 3. Overview of selected economies income level.
Source: Author's own calculations from https://databank.worldbank.org data.

to limit energy poverty in these selected economies. Similarly, renewable energy and human capital have similar impacts on energy poverty, i.e., reducing energy poverty in these selected economies. Further, globalization also limits energy poverty; however, investment in energy does not reduce energy poverty.

This paper is organized as follows. Section 2 presents the literature and methodological review. Section 3 provides the tests for each model. Section 4 describes regression parameters and empirical findings. Section 5 analyses the result from each model, how the three models are compared to each other and empirical findings. Section 6 concludes the main findings with critical policy implications and further studies suggested.

2. Literature review

2.1. Related Studies

Energy poverty is a strategic issue that many countries are facing today. According to the European Commission (2020), around 50–125 million cannot acquire sufficient indoor heaters in Europe. Furthermore, according to International Energy Agency (2020), around 905 million people in sub-Saharan Africa are unable to afford clean cooking fuels and 578 million people lack access to electricity. Energy poverty has devastating consequences on multiple aspects of human life, such as health, psychology, and development quality. Hence, eradicating energy poverty is a top goal in the UN sustainable development goals.

World Economic Forum (2010) defines energy poverty as a situation when individuals and businesses cannot access sustainable energy products and services. This definition is also similar to that of Word Bank (2010). Grenelle II Act in France further expands the definition of energy poverty, which not only refers to a lack of access to energy but also refers to a difficult situation for individuals in paying their energy bills. Another definition is from Reddy et al. (2000), who define energy poverty as the lack of choice to access proper and affordable energy services. International Energy Agency (IEA, 2009) classifies the level of access to energy services into three groups. The first group is the lack of access to energy services that support households. The second group relates to those lacking access to energy services that support productivity, and the third group refers to those with access to energy services to live a modern lifestyle. Hence, overall, energy poverty is not related to the lack of endowment of energy resources. Rather, it relates to the lack of access for people to enjoy it. This lack of access is a focus that could occur due to multiple factors, such as income inequality, incorrect government policy, poverty, and more. These multiple factors are what make energy poverty has multiple indicators to approximate. Overall, there is no consensus regarding the best indicator or index to represent energy poverty. Similar to energy poverty, multiple indicators are used to approximate financial inclusion such that no consensus regarding the best indicator to represent financial inclusion.

Despite its strategic issue, the nexus of financial inclusion and energy poverty is studied less intensively in the literature on either financial development or the energy area. Koomson and Danquah [2] is a recent study investigating the impact of financial inclusion on energy poverty. The study was conducted in Ghana as a country sample, consisting of 22, 714 households across the country, and utilizes the multidimensional energy poverty index (MEPI). As for financial inclusion, Koomson and Danquah [2] use a multidimensional measure and linear probability model with pooled effect and found that financial inclusion negatively affects energy poverty. In other words, higher financial inclusion can reduce energy poverty.

Recent studies are developing in examining the impact of financial

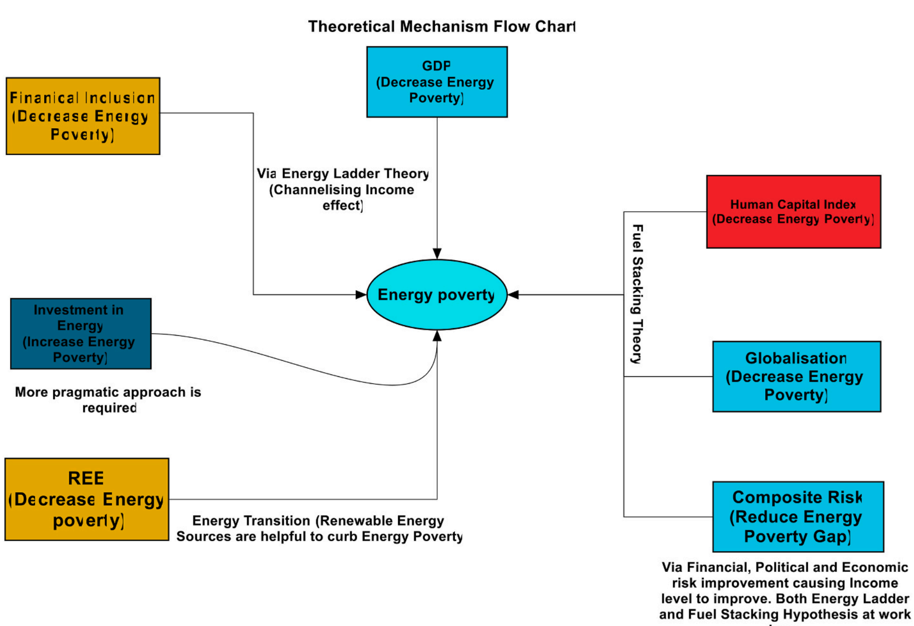

Fig. 4. Flow chart for theoretical mechanism.

inclusion on energy poverty. For example, Dogan, Madaleno and Taskin [5] also investigate the nexus of financial inclusion and energy poverty in case of Turkey using the multidimensional index as a proxy of financial inclusion. The financial inclusion contains four dimensions covering saving behavior, insurance ownership, credit card ownership and online shopping habit through the internet. The study is focused on the single year of 2018 and estimated using two-stage least squares approximation. Using this approach, the study demonstrates that financial inclusion significantly reduces energy poverty. The impact occurs through health and income channels and is particularly more impactful in female-headed households. The link between financial inclusion and energy poverty is also examined by Xia, Murshed, Khan, Chen and Ferraz [6] in the form of the impact of fiscal decentralization energy poverty in China. The study focuses on China over the period of 2005Q1-2019Q4 using multidimensional index of energy poverty. The enervy poverty indices include the dimension of accessibility, affordability, and availability of energy resources. Using the dynamic autoregessive distributed (DARDL) lag regression as the primary technique for analysis, the study demonstrates that fiscal decentralization aggravates energy poverty in the country. On the other hand, the increasing use of renewable energy and technology is associated with falling energy poverty.

Furthermore, Apergis, Polemis, and Soursou [7] also examine the impact of financial inclusion on energy poverty on the multi countries level involving 30 developing countries over the period of 2001–2016. In this study, financial inclusion is represented as education (i.e., education expenditure), while energy poverty is presented as electricity access in rural and urban areas. The study implements GMM system estimation and reveals that education has a negative impact on energy poverty. In other words, higher education is associated with better energy access to electricity. However, the study also demonstrates that carbon emission negatively impacts access to electricity. Yu and Tang [8] investigate the nexus of financial inclusion and energy efficiency. The study utilizes energy efficiency instead of energy poverty with the assumption that, with better energy efficiency, more energy can be allocated for those who need and thus reduces energy poverty. The impact of financial inclusion on energy efficiency is applied in case of 251 cities in China over the period of 2011–2015. Four of financial inclusion are utilized in the study covering the number of accounts with an age more than 15 y.o., financial institutions account ownership with age more than 15 y.o., debit card ownership with age more than 15 y.o., and credit card ownership with ager more than 15 y.o. The study uses Tobit regression to explore financial inclusion's impact on energy efficiency. The result shows that financial inclusion significantly increases energy efficiency. Thus, indirectly, the study demonstrates that financial inclusion reduces energy poverty, Essel-Gaisey and Chiang [1] investigate the relationship between financial inclusion and environmental poverty in the case of Ghana. Environmental poverty plays a major role in energy poverty since more energy can be produced when environmental issues are diminished. In this study, the author focuses on Ghana between 2010 and 2015. The study generates multidimensional indices of financial inclusion, including bank account ownership, credit access, insurance ownership, and financial remittance through mobile wallets. On the other hand, environmental poverty is approximated using a multidimensional environmental poverty index. Using 2-stage least squared regression as the main thecnique of analysis, the study demonstrates that financial inclusion significantly reduces environmental poverty. Consequently, lower environmental poverty can help poor people to access more energy, that is, lower energy poverty. [48] investigate the determinants of energy poverty in European countries. The study involves 27 European countries in the period 2000–2019. The study implements cross-sectional autoregressive distributed lag (CS-ARDL), common correlated effects generalized method of moments (CCE-GMM), and instrumental variable as the main methodology. The dependent variable in the regression is energy expenses, which proxies energy poverty. In contrast, the independent variables include access to clean fuels, bilateral trade, GDP, economic globalization, service trade and institutional quality as the determinants of energy poverty. The study demonstrates bilateral trade reduces energy poverty or increases energy access. Furthermore, economic globalization is also found to be significant in increasing energy expenses and thus drives up energy poverty.

[49,51] investigate the impact of energy poverty on human capital development in the case of India. The study is based on a survey of India human development survey (IHDS) conducted in 2004–2005 and 2011–2012. Energy poverty, as the regressor, in the study is approximated using the multidimensional energy poverty index score (MEPI), which consists of five dimension: cooking, lighting, household appliances, communication, and entertainment. On the other hand, human capital includes child health and child education. Using instrumental variable approach, the study demonstrates that energy poverty adversely impacts children's health and educational attainment. [50] investigate the relationship between renewable energy consumption and energy poverty. The study involves multi-development countries consisting of 64 countries over the period of 2000–2014. Energy poverty is represented by the global energy poverty index, which comprises six components following World Bank.

On the other hand, renewable energy consumption is proxied using the share of renewable energy consumption to the final total energy consumption. Utilizing te differential GMM and system GMM, the study demonstrates that renewable energy poverty by increasing energy efficiency. Among the sample countries, the negative association between renewable energy and energy poverty is obvious in European countries.

Zhang, Raza, Huang, and Wang [9] also investigate China's determinants of energy poverty during 1990–2019. By implementing fully modified ordinary least square, the study examines the factors affecting the country's energy poverty. Four indicators present energy poverty: total population with access to electricity, access to clean fuels and technologies for cooking, TPES per capita, and TFEC per capita. The factors tested include GDP, investment in energy, renewable energy consumption, technological innovation, composite risk index (political, financial and economic risk) and globalization. The study found that GDP and investment in energy with a public-private partnership can help reduce energy poverty. On the other hand, renewable energy consumption, composite risk index and globalization increase energy poverty in the country. Hassan, Batool, Zhu, and Khan [10] investigate the impact of energy poverty on carbon emission in BRICS region over the period 1989–2016. The study applies fully modified ordinary least squares regression and a continuously biased correction approach to estimate the impact. Energy poverty in the study is defined as access to electricity as the share of the population. In addition to energy poverty, some control variables are added, including economic growth (per capita GDP), education as primary school enrollment, and Gini coefficient to measure income inequality. The result demonstrates that energy poverty increases carbon emissions in the region.

Anton [11] investigates the impact of temperature increase on firm profitability in the case of European countries. The investigation is taken from 2009 to 2016 covering 147 European firms that are publicly listed. Firm profitability in the study is approximated using operating profit margin, EBIT margin, and return on equity. As for the temperature, annual temperature data corresponds to the average monthly observation from World Bank. Using the quantile regression as the primary method, the study demonstrates that temperature increase positively impacts firm profitability. Furthermore, the study also demonstrates that form profitability has other determinants other than temperature increase, which includes cash flow, leverage, firm size, market opportunities and net asset turnover. Anton and Nucu [12] investigate the impact of financial development on renewable energy consumption in the case of European Union. The countries sample includes 28 countries during 1990–2015. The study presents renewable energy as the share of renewable energy in total final energy consumption. Financial development covers the banking sector, bond market and capital market. The regressors include income (as per capita GDP), consumer price index, domestic credit as the share of GDP, and stock market turnover ratio. Using the panel fixed effect regression, the study demonstrates that financial development positively impacts renewable energy consumption.

Boutabba, Diaw, Lare, and Lessoua (2020) also investigate the role of microfinance in providing broader energy access that involves 639 households in districts of Lome, Togo. The study utilizes credit ownership in traditional banks, so-called microfinance, as a measure of financial inclusion. Furthermore, the study aggregates two binary indexes to approximate the energy poverty measure and utilizes an index to examine other social factors that affect an individual's access to energy. Based on the propensity score matching method applied in the study, the study reveals that access to microfinance can help households diversify their portfolios and eradicate their energy poverty. This finding is similar to that of Koomson and Danquah [2] in that financial inclusion negatively impacts energy poverty. The finding from Koomson and Danquah [2] is also similar to the study from Allet (2016), who emphasizes a need to facilitate synergies between the worlds of microfinance and energy since the lack of energy access in Africa is mainly due to a lack of financial resources.

Credit access is also utilized to represent financial inclusion in a study about estimating factors affecting energy poverty among households in Nigeria from Ashagidigbi, Babatunde, Ogunniyi, Olagunju and Omotayo (2020). In their study, the authors approximate energy poverty by a single multidimensional index constructed from several weighted indicators such as the use of traditional energy sources, the use of the same residential house for cooking or no kitchen, traditional stove/firewood, the type of energy used for lighting, and a situation where there are no radio, tape, TV or satellite dish. Based on the Tobit regression model, the study demonstrates that household income and credit access negatively affect energy poverty. This finding is in line with the findings from Koomson and Danquah [2] and Boutabba, Diaw, Lare, and Lessoua (2020), among others, who reveal a negative relationship between financial inclusion and energy poverty. In addition, Ashagidigbi et al. (2020) also reveal that energy poverty is found to be lower in urban areas than in urban areas.

The finding from Ashagidigbi et al. (2020), revealing that energy poverty is higher in rural area support previous studies emphasizing the importance of microfinance to alleviate energy poverty. Microfinance, as an instrument of financial inclusion, is also utilized by Groh and Taylor (2017) in understanding the effectiveness of microfinance for energy access. The study argues that opportunities for microfinance to engage in energy access are enormous. The study also suggests that the role of microfinance in supporting energy access is more substantial when long-term financing is available. Groh and Taylor (2017) also defend the essential role of microfinance in enforcing renewable power generation such as solar, small-scale hydro, wind, and biodiesel in rural area. Through its ability to penetrate the remote area, microfinance can help improve rural households' financial resources and make energy more affordable. This way, energy access in rural areas can be widened and energy poverty can be alleviated. The importance of microfinance has been a major focus in some studies, such as Morris, Winiecki, Chowdury and Cortiglia (2007); Rao, Miller, Wang and Byrne (2009), among others. However, from a banking theory, the use of microfinance as a catalyst to gain more energy access invites many consequences. The banking principle explains that credit intermediation can only work through the support of sufficient funding activities. Hence, encouraging more micro-lending to deliver more energy access requires other financial inclusion indicators to improve as well, such as the need to involve more people to deposit in banks, more technology to ease people to access banks, and more banking policy to diversify more assets as collateral, among others. Overall, the development of all these indicators will support a negative relationship between energy poverty and financial inclusion.

2.2. Literature review summary

Energy poverty is broadly defined as the lack of access to sustainable energy and the difficulty of financial resources to afford the energy bill. Using various measures of financial inclusion and energy poverty, most scholars in the area of financial inclusion deliver a negative relationship between this measure with energy poverty. Meaning that financial inclusion can help reduce energy poverty, giving more access for people to enjoy more energy. See, for example, Koomson and Danquah [2], Dogan, Madaleno and Taskin [5], Apergis, Polemis, and Soursou [7], Yu and Tang [8], Essel-Gaisey and Chiang [1], among others. Among others, credit access in the form of loans or microfinance is the most popular financial inclusion metric related to energy poverty. See, for example, Boutabba, Diaw, Lare, and Lessoua (2020), Babatunde, Ogunniyi, Olagunju and Omotayo (2020), Groh and Taylor (2017), Morris, Winiecki, Chowdury and Cortiglia (2007), Rao, Miller, Wang and Byrne (2009), among others, Also, rural areas tend to be more exposed to more severe energy poverty issues than urban areas, see Ashagidigbi et al. (2020).

2.3. Research gap

The impact of financial inclusion on energy poverty is a popular topic in energy economics. This popularity particularly happens because of the multidimensional definition of financial inclusion or energy poverty. Consequently, one study presented multiple indicators of financial inclusion, which can lead to different, if not conflicting, results. There is no consensus on the best indicator to represent financial inclusion. For example, some studies use bank account ownership, saving behavior, use of credit cards and the habit of online shopping [5,8]; among others). Other studies also involve credit access and insurance ownership to approximate financial inclusion [1]; among others). Likewise, some studies approximate energy poverty using access to electricity and cooking technologies [6]. Other studies utilize the energy development index (EDI), the compound energy poverty indicator (CEPI), and the multidimensional energy poverty index (MEPI), as presented in Apergis, POlemis, and Soursou [7], among others. Hence, the wide choice of indicators to represent financial inclusion and energy poverty is a research gap concerning this study.

Another research gap derived from the literature review is the presence of mediating variable that connects financial inclusion and energy poverty. Some studies present the potential of incorporating mediating variables in the model, such as energy efficiency or environmental degradation to approximate financial inclusion's impact on energy poverty. See, for example, the study from Yu and Tang [8] and Essel-Gaisey and Chiang [7], among others. Finally, another research gap among past literature is a need for financial inclusion's impact on energy poverty to be classified into short- and long-term impacts. Given that financial inclusion requires time to realize its impact, the estimated model can ideally capture both short and long term impact. From our reviewed literature, only the study from Xia and Mursheed et al. [6] presents both long and short run impacts in the estimated model. Thus, more studies are required to present the short and long run impact.

3. Theoretical framework

The theoretical mechanism through which financial inclusion affect energy poverty is explained in this section. Koomson and Danquah [2] illustrate three main channels through which financial inclusion affects energy poverty. The first channel is household income, poverty and inequality. This channel explains that increases in FI tends to increase income for low-income households. This happens particularly because financial inclusion provides households with greater capital. Given the greater capital, more goods and services can be produced, corresponding to greater profit and higher income. Given the higher income, the energy ladder theory explains that the increased income will encourage households to consume more superior energy sources for cooking and heating, such as from firewood to coal or from coal to LPG or electricity. Following the energy ladder theory, the ability of households to improve its energy consumption through higher income can reduce energy poverty, particularly in low-income households [13–15], among others. Also, on the aggregate level, higher income can incentivize private energy firms to invest and provide more energy resources for people to purchase. Hence, with a higher ability to purchase, energy becomes more affordable and energy poverty can be reduced. Furthermore, the higher income also influences income distribution in society. Given that a fraction of higher-income households can now enjoy energy consumption, the number of households under poverty becomes less, despite increased income inequality. Thus, financial inclusion can also affect energy poverty through income inequality [16,17]; among others). The role of income as the channel between financial inclusion and energy poverty is also described as income theory perspective, as described in Burgess and Pande [13], Chibba [18], Churchill and Marisetty [19], Koomson et al. (2020a), Koomson and Ibrahim [20], among others.

The second channel through which financial inclusion affects energy poverty is through education, health and labour outcomes. This channel explains that financial inclusion can encourage households to invest more in education and health, which in turn impose positive impact on labour outcomes and thus result in higher income. Higher investment in education corresponds to less energy poverty, although the impact is insignificant [21,22]; and [23]. Furthermore, better education investment, which corresponds to higher income, will increase the household's socio-economic status and living standard. Following a fuel stacking theory, it is explained that economic growth is not the only factor that affects households to change their energy use behavior; other impacting factors include living standards, environmental pressure, urbanization level and technology. Hence, an upper change in living standards, due to education and health investment can help households improve their energy sources to more superior choices, gradually reducing energy poverty. Through education, financial inclusion also improves people's financial literacy level. Financially literate people can manage their present energy consumption to avoid excessive energy bills in the future, which can help them not to be trapped in arrears on utility bills. When more people are financially literate, energy poverty can be diminished. Not only stopping at personal understanding, financial inclusion can also encourage people to invest more in education. For instance, people can save money on education insurance and claim it to achieve a better education level (e.g., undergraduate). With better education, people can earn more understanding to conserve energy and consume it wisely. This way, the probability of them being trapped in energy poverty can be reduced. Sharma [23] investigated the relationship between education and energy poverty in India and found that the two are negatively associated, meaning that higher expenditure on education corresponds to reduced energy poverty. Furthermore, Crentsil et al. [22] also demonstrate that higher education investment corresponds to reduced energy poverty.

Economic growth and energy efficiency are the last channels through which financial inclusion affects energy poverty. Koomson and Danquah [2] argue that financial inclusion influences economic growth by accumulating and allocating savings and investments to productive sectors. Higher economic growth corresponds to higher income. With the same level of population, higher economic growth also corresponds to higher income per capita. According to the energy ladder theory, it is explained that household starts consuming different types of fuel at higher-ranked of the ladder when income experiences an increase. Thus, according to this theory, energy poverty should be reduced since per capita income increases. Some studies demonstrate how financial inclusion benefits low-income economies through economic growth channels; see, for example, Sharma [23], Demirguc-Kunt et al. [24], among others. Not only economic growth, and financial inclusion can also affect energy poverty through energy efficiency. The mechanism is that financial inclusion, which delivers higher income for households, incentivizes households to pursue cleaner and more efficient energy. This behavior is consistent with fuel stacking theory, where households with higher socio-economic status and higher income tend to mix their energy use with more superior fuels. These superior fuels are determined based on some indicators, one of which is the fuel's energy efficiency. Hence, financial inclusion can affect energy poverty through energy efficiency. Yu and Tang [8] investigate the nexus of financial inclusion and energy efficiency. The study utilizes energy efficiency instead of energy poverty with the assumption that, with better energy efficiency, more energy can be allocated for those who need and thus reduces energy poverty. The result shows that financial inclusion significantly increases energy efficiency, which thus reduces energy poverty. A flowchart for theory is provided below in Fig. 4.

4. Data and Model Specification

Based on the aforementioned theoretical background, this paper employs two measures for Energy Poverty [52]. The two measures are the weighted average of energy poverty (WAEP) and the composite energy poverty index (CEP). The main independent variable is Financial Inclusion (FI). The study controls for the following variables: Investment in Energy, Renewable Energy Electricity, Human Capital Index (HCI), Globalisation, GDP, and Composite Risk Index. Data on these indicators are obtained from World Bank [55], Penn World Table 10.0, [56], KOF Globalisation [57], International Country Risk Guide (ICRG), PRS [58].

We first construct the Weighted Average of Energy Poverty – WAEP as follows:

$$\mathrm{WAEPI_{year}} = \sum\Big(\mathrm{W_1} * \text{Access to electricity}_{\mathrm{n}} + \mathrm{W_2} * \text{Access to modern fuel}_{\mathrm{n}} + \mathrm{W_3} * \mathrm{TFEC_{pc,n}} + \mathrm{W_4} * \mathrm{TPES_{pc,n}}\Big) \tag{1}$$

The WAEP value implies the scale of the needs of the population's fulfilled energy representing the level of energy availability, affordability, and accessibility. We compute the Composite Energy Poverty (CEP) index as follows

$$\text{A country}'\text{s CEP} = 100 - \text{WAEP} \tag{2}$$

We eliminate WAEP from 100 to attain CEP as the proxy for the energy gap that a country needs to fulfill given its current population. CEP measures the energy poverty level and captures the existing gap in energy affordability and availability in a certain country.

Regarding the literature on financial inclusion [25,26, 53]. We obtain five measures of financial inclusion including the institution of commercial banks (FI_1), branches of commercial banks (FI_2), number of automated teller machines (ATMs) per 100,000 adults (FI_3), outstanding deposits with commercial banks (% of GDP) (FI_4), outstanding loans from commercial banks (% GDP) (FI_5). Data on financial inclusion indicators are obtained from International Monetary Fund (IMF) [54]. We employ the standardization function of z-score normalization for each financial inclusion measure as follows:

$$Z - score = \frac{X_i - \overline{X}}{\sigma} \tag{3}$$

where:

$\overline{X}$ = group average
σ = standard deviation

We first estimate the Z-core for each of the five financial inclusion measures. We then take the standardized function of each financial inclusion's Z-score. Finally, the composite financial index is estimated by taking the average value of all five financial inclusions' Z-scores for each country *i* at year *t*.

To estimate the effects of financial inclusion on energy poverty, the study proposes the following two baseline models:

$$\text{Energy Poverty}_{i,t} = f\left(\begin{array}{c}\text{Financial Inclusion}_{i,t};\text{Investment in Energy}_{i,t};\text{Renewable Energy Electricity}_{i,t};\\ \text{Human Capital Index}_{i,t};\text{Globalization}_{i,t}\end{array}\right) \tag{4}$$

$$\text{Energy Poverty}_{i,t} = f\left(\begin{array}{c}\text{Financial Inclusion}_{i,t};\text{Composite risk index}_{i,t};\\ \text{Investment in Energy with Public Private Partnership}_{i,t};\text{Renewable Energy Electricity}_{i,t}\end{array}\right) \tag{5}$$

While the cross-sections of Eq. (4) are specified as "i" for each country including Brazil, China, India, Indonesia, Mexico, and Russia; "t" is for the period from 2004 to 2019. The regression model for Eq. (4) is presented as follows:

$$\begin{aligned}\text{Energy Poverty}_{i,t} &= \delta_{1i,t} + \delta_{2i,t}\text{Financial Inclusion}_{i,t}\\ &+ \delta_{3i,t}\text{Investment in Energy}_{i,t} + \delta_{4i,t}\text{Renewable Energy Electricity}_{i,t}\\ &+ \delta_{5i,t}\text{Human Capital Index}_{i,t} + \delta_{6i,t}\text{Globalisation}_{i,t} + \alpha_i + \varphi_{i,t}\end{aligned} \tag{6}$$

Where the characters of *i* and *t* denote country *i* at year *t*. $\textit{Energy Poverty}_{i,t}$ is the dependent variable measured by either the average value of WAEP or CEP. $\textit{Investment in Energy}_{i,t}$ Investment in energy with private participation (current US$). $\text{Renewable Energy Electricity}_{i,t}$ is the renewable energy consumption (% of total final energy consumption) We also control for $\text{Human Capital Index}_{i,t}$ and $\textit{Globalisation}_{i,t}$.

Similar to Eq. (4) with "i" for each country, including Brazil, China, India, Indonesia, Mexico, and Russia; "t" is for the period from 2004 to 2019. The regression model for Eq. (5) is presented as follows:

$$\begin{aligned}\text{Energy Poverty}_{i,t} &= \delta_{1i,t} + \delta_{2i,t}\text{Financial Inclusion}_{i,t} + \delta_{3i,t}\text{GDP}_{i,t}\\ &+ \delta_{4i,t}\text{Composite risk index}_{i,t_{i,t}}\\ &+ \delta_{5i,t}\text{Investment in Energy with Public Private Partnership}_{i,t}\\ &+ \delta_{6i,t}\text{Renewable Energy Electricity}_{i,t} + \alpha_i + \varphi_{i,t}\end{aligned} \tag{7}$$

All the things stay consistent as those used in Eq. (6) for the main dependent variable of energy poverty and the main independent of financial inclusion. However, for Eq. (5), we control for $\text{Composite Risk Index}_{i,t}$ as a combination of political, economic and financial risk index. We also control Investment in Energy with public-private Partnerships and Renewable Energy Electricity.

5. Estimation

5.1. Unit Root Testing

The study starts by examining cross-sectional dependence (CD). Examining the cross-section dependence between the units prior to the unit root procedure is critical to utilize panel unit roots from 1st, 2nd, and 3rd generation tests to cope with cross-sectional dependence. Diverse components, including financial and economic associations, the interrelation of residuals, various regular shocks such as the global financial crisis, oil price shocks, observed and omitted common components, and globalization, are related to cross-sectional dependence. It might lead to unexpected outcomes in empirical analysis, such as biased stationery, size distortion, and spurious outcomes if testing cross-sectional dependence (CD) is ignored [27,28]. We use the test CD test of Pesaran [3] to investigate the existence of cross-sectional dependence issues. We then examine the unit root or stationary process of panel data once we have the outcomes of cross-sectional dependence. Many scholars have dealt with the non-stationary issues in the panel data.[1] The previous literature on the non-stationary panel data is classified into three dominant groups, i.e., 1st generation, 2nd generation, and 3rd generation unit root tests. These main groups can be further categorized based on the nature of various issues solved by each method. For instance, the issue of non-stationary in homogenous panel data is solved by Maddala and Wu [29], Choi [37], Levin et al. [31], and in the heterogenous panel is dealt with by Im et al. [32]. Likewise, the multiple structural breaks are dealt by Lluís Carrion-i-Silvestre, Del Barrio-Castro, and López-Bazo [38]; however, this approach is not able to solve the problem of cross-sectional dependence.

Dissimilar to the 1st generation methods of Maddala and Wu [29] and Levin et al. [31], the 2nd generation panel unit root tests introduced by Choi [4,37]; Moon and Perron [36] not only solve the problem of heterogeneity but they also overcome the issue of cross-sectional dependence between units. Nevertheless, the 2nd generation unit root tests cannot execute better with decreased power if structural breaks are present in the series due to local or global shocks. The 3rd generation unit root tests not only solve the possibility of structural breaks but also deal with the problems of cross-sectional dependence and heterogeneity in panel data [39].[2] In this study, we follow the approaches of Bai and Carrion-I-Silvestre [39] and Pesaran [40] for dealing with the issue of non-stationary with cross-sectional dependence due to the existence of cross-sectional dependence refuses application of the 1st generation unit root tests [41]. Furthermore, we also use the unit root tests of Im et al. [32] and Levin et al. [31] to facilitate the testing of unit roots between units.

5.2. Cointegration Testing

After examining the stationary in the panel, we utilize the normalized or adjusted approach introduced by Pesaran and Yamagata (2008) to test the slope homogeneity or to detect whether there is a presence of slope heterogeneity or not. The test's null hypothesis supposes homogenous and the alternative hypothesis assumes heterogeneity in slope parameters. Because of the presence of cross-sectional dependence, the 1st generation unit root tests introduced by McCoskey and Kao (1998), Larsson et al. (2001), Pedroni [33], and Westerlund (2005) are unable to generate proper estimations due to the possibility of distortion of size properties, and even Kao et al. (1999) and Pedroni (2001) hypothesize that there is no cross-sectional dependence between units for considerations. Due to the existence of cross-sectional dependence, we employ estimation approaches that suit heterogeneity, such as Westerlund and Edgerton (2008), Banerjee and Carrion-i-Silvestre (2017), and Dumitrescu & Hurlin [42]. These approaches not only deal with the mentioned problem but also detect the possibility of structural breaks that may not be likely to reject the null hypothesis of non-cointegration.

Unlike the 1st and 2nd generation methods, Westerlund and Edgerton's (2008) method not only solves the cross-sectional dependence,

[1] Including Maddala and Wu [29], Phillips and Moon [30], Levin, Lin, and Chu [31], Im, Pesaran, and Shin [32], Pedroni [33], Baltagi, Bratberg, and Holmås [34], Breitung and Pesaran [35], and Moon and Perron [36].

[2] Please read the study of [39] for more detail.

heterogeneous slope parameters, and series correlation errors but also considers the possibility of structural breaks for each cross-section in different locations. Another comparable method is applied in the existing research for detecting the cointegration among variables invented by Banerjee and Carrion-i-Silvestre (2017) based on the Common Correlated Effects Mean Group (CCEMG).[3] This method resolves weak and strong cross-section dependence, heterogeneity, non-stationary panel data, and parameters that can be measured steadily in spurious regression procedures.

5.3. Cross-Sectionally Augmented Autoregressive Distributed Lags (CS-ARDL)

Different components generate general shocks in the pattern of the global financial crisis (GFC) and oil price shocks which might induce the problem of cross-sectional dependence. This issue may generate spurious estimation outcomes if omitted components correlate with the regression model's explanatory variables. The CS-ARDL is viable to employ when a problem of cross-section dependence and slope heterogeneity exists. This approach is based on the dynamic common correlated effects estimator to deal with the mentioned problems (Coban and Topcu, 2013; Yao et al., 2019). The CS-ARDL's starting point is presented in terms Eq. (7) as below.

$$W_{i,t} = \sum_{I=0}^{P_w} \gamma_{I,t} W_{i,t-I} + \sum_{I=0}^{P_z} \beta_{I,i} Z_{i,t-I} + \varepsilon_{i,t} \tag{8}$$

Ea. (8) is the Autoregressive Distributed Lags (ARDL) model, if we follow Eq. (3), it will distribute spurious outcomes in the existence of cross-sectional dependence. Eq. (4) below is the extended model of Eq. (3) by applying the average values of cross-section for each regressor, which supports dealing with the unfitting inference regarding the presence of threshold impact induced by the cross-section dependence (Chudik and Pesaran, 2015).

$$\widehat{\pi}_{CS-ARDL,i} = \frac{\sum_{I=0}^{pz} \widehat{\beta}^{pw}_{I,i}}{1 - \sum I = 0^{\widehat{\gamma_{I,i}}}} \tag{9}$$

The mean group is presented as:

$$\widehat{\overline{\pi}}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \widehat{\pi}_i \tag{10}$$

The short-run coefficients are estimated as follows:

$$\Delta W_{i,t} = \vartheta_i \left[W_{i,t-1} - \pi_i Z_{i,t} \right] - \sum_{I=1}^{P_{w-1}} \gamma_{I,t}, \Delta_I W_{i,t-1} + \sum_{I=0}^{P_z} \beta_{I,i} \Delta_I Z_{i,t} + \sum_{I=0}^{P_x} \alpha_i^{'}, I\overline{X}_t + \varepsilon_{i,t} \tag{11}$$

Where $\Delta_I = t - (t-1)$

$$\widehat{\tau}_i = -\left(1 - \sum_{I=1}^{pw} \widehat{\gamma_{I,i}}\right) \tag{12}$$

$$\widehat{\pi}_i = \frac{\sum_{I=0}^{pz} \widehat{\beta}_{I,i}}{\widehat{\tau}_i} \tag{13}$$

$$\widehat{\overline{\pi}}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \widehat{\pi}_i \tag{14}$$

For the CS-ARDL model, it is similar to the pooled mean group (PMG) in which the term Error Correction Mechanism (ECM (−1)) implies the speed of adjustment toward the equilibrium or the time it takes for an economy to attain its equilibrium point.

5.4. Robustness Tests

With heterogeneity in slope parameters and cross-section dependence, applying traditional techniques might generate misleading outcomes (Çoban and Topcu, 2013; Yao et al., 2019). For the possibility of cross-section dependence, structural breaks, and slope heterogeneity, we utilize the Augmented Mean Group (AGM) introduced by Eberhardt and Teal (2010) and the Common Correlated Effect Mean Group (CCEMG) invented by Pesaran [4]. Because both AMG and CCEMG operate better for estimation even if there is a possibility of non-stationary common factors and omitted common factors. The CCEMG deals with time-variant observed factors with heterogeneity in slope parameters and considers the identification problem. The technique calculates the average of both dependent and control variables for all cross-sections to detach the spill-over effect generated by cross-section dependence, not solely containing trends and dummies (Liddle, 2018a, Liddle, 2018b). The technique is consistent for both strong and weak components for unlimited or limited quantities with global shocks such as financial downturns, oil price shocks, and national spill-over impacts, respectively (Chudik et al., 2011; Pesaran and Tosetti, 2011). The AMG approach operates as an alternative method to CCEMG that not only deals with cross-section dependence, heterogeneity, and structural breaks but also takes into account omitted unobservable components, including year dummies, and considers a dynamic common procedure (Eberhardt and Teal, 2010).

6. Empirical Results

Table 1 presents the descriptive statistics for all the selected variables. The weighted average of energy poverty - WAEP average is 62.5% ranging from the minimum value of 35.2% to the maximum value of 75.9%. The average value of the financial inclusion index is 0.057% ranging from −0.908 as the minimum value to 1.55 as the maximum value. Table 2 provides empirical results of Model 1 using several multiple regression approaches, including the pooled OLS, random-effects GLS and fixed (within) effects models with the use of WAEP and CEP as the main dependent variable of energy poverty, presented in Panels A and B, respectively. The empirical results of Table 2 present the overall negative relationship between financial inclusion and energy poverty; statistically speaking, given a one percent increase in overall financial inclusion – FI leads to a decrease of 1.5% in energy poverty – WAEP on average. The results are consistent when the models are applied using VCE Cluster Year, Bootstrap (replications), and VCE Jack-knife (replications), presented in Columns 2–5 of Table 2 Panel A, respectively. The results are similar when using CEP as the main proxy of energy poverty in Table 2 Panel B when using Pooled OLS regression with VCE Cluster Year, random effects GLS regressions and fixed effects (within) regression in Columns 2 and 1, respectively. It is critical to note that the relationship between energy poverty measured by CEP and financial inclusion is inversely changed when the study applies the pooled OLS regressions with no VCE cluster year, bootstrap (replications), VCE Jack-knife (replications), country and year fixed effects, presented in Column 1 of Table 2 Panel B for the pooled OLS and random effects GLS presented in Columns 1 and 3, respectively.

Table 3 presents further detailed empirical results of the Model using the pooled OLS regressions with Default standard errors, Robust, Cluster Robust by country and year, ordinary least squares (OLS), Bootstrap (replications), and Jack-knife (replications) presented in Columns 1–8, respectively. The results across all the selected models consistently show the negative relationship between energy poverty – WAEP and financial inclusion in Panel A and present the positive relationship between energy poverty measured by CEP and the financial inclusion index in Panel B for Model 1. Statistically speaking, given one percent increase in

[3] Please see the study of Banerjee and Carrion-i-Silvestre (2017) for more detail.

Table 1
Descriptive statistics.

Variable	Mean	Std. dev	Min	p25	p50	p75	Max	Skewness	Kurtosis
WAEP average	62.50129	12.32653	35.19383	54.14392	65.13173	73.99012	75.99583	−0.6208577	2.131732
WAEP1	81.52342	16.07808	45.905	70.6225	84.95443	96.50886	99.125	−0.6208577	2.131732
WAEP2	40.76171	8.03904	22.9525	35.31125	42.47721	48.25443	49.5625	−0.6208577	2.131732
WAEP3	65.21874	12.86246	36.724	56.498	67.96354	77.20709	79.3	−0.6208577	2.131732
CEP average	37.49871	12.32653	24.00417	26.00988	34.86827	45.85608	64.80617	0.6208577	2.131732
CEP1	18.47658	16.07808	0.875	3.491143	15.04557	29.3775	54.095	0.6208577	2.131732
CEP2	59.23829	8.03904	50.4375	51.74557	57.52279	64.68875	77.0475	0.6208577	2.131732
CEP3	34.78126	12.86246	20.7	22.79291	32.03646	43.502	63.276	0.6208577	2.131732
Renewable electricity output	26.86315	24.61125	10.65116	15.2988	16.28462	19.46124	88.99578	1.784798	4.332695
Renewable electricity consumption	25.14884	16.86121	3.227796	9.403937	28.13535	40.46479	49.72402	−0.0144962	1.251774
GDP	2.45E+12	2.39E+12	5.40E+11	1.14E+12	1.66E+12	2.34E+12	1.15e+13	2.299305	7.562032
HCI	2.547391	0.4218586	1.841645	2.302353	2.453174	2.719821	3.403041	0.6191346	2.60363
Globalization	64.06893	4.083821	53.24166	61.79788	63.26067	65.75183	72.38351	0.3904562	2.958124
CRI	71.48322	4.247863	62.14583	68.11458	71.36458	74.23958	80.9375	0.2273215	2.42481
IIEWPPP	4.80E+09	6.63E+09	3000000	6.87E+08	2.17E+09	5.83E+09	3.45e+10	2.390023	9.058315
FI	0.057557	0.6354152	−0.9083927	−0.4969935	−0.0185635	0.489194	1.551098	0.4375436	2.417019

financial inclusion generates a change of 1.5% in energy poverty – WAEP (decrease) and CEP (increase). The results of Table 3 further support the predicted estimations of Table 2.

Table 4 provides empirical results of Model 2 investigating the relationship between financial inclusion and energy poverty with the interactions of GDP growth, composite risk, energy investments with PPP, and renewable energy electricity output. Table 4 present a positive/negative relation between overall financial inclusion and energy poverty – WAEP/CEP presented in Panels A and B, respectively. Statically speaking, given one percent change in financial inclusion induces volatility of 6.3% in energy poverty. The results are significant at a 10% level across all the tested pooled OLS models in both Panels A and B. The results also show the significant effects of economic performance – GDP, composite risk index, energy investments with PPP, and renewable energy electricity output on energy poverty. For instance, in Panel A, a one percent increase in a country's GDP, composite risk index and energy investments with PPP and renewable energy electricity output affects the volatility of energy poverty – WAEP changed by −2.16, 1.22, −5.28, and 0.31% on average, respectively. The results stay consistent when using CEP to capture energy poverty applied in the same tested model in Panel B of Table 4.

Tables 5 and 6 report unit root test results proposed by Im et al. [32] - IPS without trend and with the trend, respectively. The header of the result tables indicates the summary of the dimension of the sample data with the null - Ho and alternative hypotheses - Ha that all panels do/do not contain unit roots, respectively. The statistic of the t-tilde-bar is comparable to the t-bar, assuming that both N and T are fixed with the exact critical values at 1%, 5%, and 10% are reported on the right of Tables 5 and 6. For Table 5 without trend, because the values of the t-bar are lower than its 1% exact critical values, the study strongly rejects the null hypothesis that all the panels contain a unit root in preference to the alternative hypothesis that a non-zero proportion of the panels exhibit its stationary for energy poverty measured by WAEP and CEP, financial inclusion, investment in energy with PPP, renewable energy electricity output and globalization. For Table 6 with the trend, the results strongly reject the null hypothesis – H_0 that all panels contain the unit root for renewable electricity output.

Table 7 presents unit-root tests introduced by Levin et al. [31] - LLC for the selected variables. The below output table synthesizes the test's exact specification for the dataset. The test permits panel-specific means without the nonconstant option. Columns 1 and 2 of Table 7 present LLC's unit root tests with no trend and with trend, respectively. For column 1 with no trend, the LLC bias-adjusted test statistics of energy poverty, financial inclusion, investment in energy with PPP, human capital index globalization and composite risk index are −5.9967, −2.0567, −2.5667, −2.8394, −3.8947 and −2.4106 that are statistically significant, respectively; hence we reject the null hypothesis that panels contain unit root about the alternative that those variables are stationary. For LLC's test with the trend in Column 2, the study rejects the null hypothesis for financial inclusion, investment in energy with PPP, renewable electricity output, globalization, and composite risk index with the bias-adjusted statistics of 2.3789–3.0829, −2.6523, −2.6128, and −3.3322.

Tables 8 and 9 provide cointegration tests introduced by Westerlund [28] with the four error-correction-based tests. The tests permit a large degree of heterogeneity detecting both the short-run dynamics, the long-run cointegration relationship between energy poverty measured by WAEP (Table 8) and CEP (Table 9), and financial inclusion and the level of dependence across the cross-sections in the panel. This test helps to consider time series dimensions and incorporate cross-section dimensions within panel data. Westerlund's [28]'s four new panel cointegration tests are developed based on structural rather than residual dynamics; hence, they do not enforce any common-factor limitation. The goal is to examine the null hypothesis – H_0 of no cointegration by concluding whether the error-correction term exists in a panel error-correction conditional model equal to zero. The new cointegration tests are normally distributed and integral sufficiently to contain short-term trends, short-term dynamics with unit-specific, slope statistics, and the dependence level of cross-sections. Two tests of G_t and G_a – group mean tests are developed to test the alternative hypothesis that there is cointegration within the whole panel, while the other two are P_t and P_a used for the panel test. According to Westerlund [28], the two tests of G_t and P_t are most robust in the case of cross-sectional correlations. Gt, Ga, and Pa tests and P_a reject the null hypothesis of no cointegration between the first difference of energy poverty measured by $\Delta WAEP$ and ΔCEP and a country's financial inclusion presented in Tables 8 and 9, respectively. Westerlund [28]'s Error Correction Model - ECM Panel Cointegration tests are used to test for Model 1 reject the null hypothesis of no cointegration between financial inclusion, and the average of energy poverty measured by WAEP and CEP presented in Tables 10 and 11, respectively.

The problem of cross-sectional dependence within a panel has increasingly become an emerging challenge in panel data analysis; hence, selecting an appropriate estimator to overcome this challenge is important in generating consistent results. Motivated by this reason, the study employs the augmented mean group (AMG) estimator proposed by Eberhardt [43]. Table 12 reports the AMG's results for Model 1, indicating the financial inclusion coefficients around 1.8 for Model 1 and 1.05 for Model presented in Tables 12 and 13, respectively. For both Tables, the negative relation is documented between investment in energy with PPP, human capital index, globalization and energy poverty – WAEP with the estimated coefficients of −8.94%, −6.815%, −0.171%, respectively. On the other hand, there is a positive relation between energy poverty – WAEP and renewable electricity output risk index with

Table 2
Model 1 using pooled OLS, random-effects GLS and fixed (within) effects models.

Panel A: Model 1 using WAEP as the main dependent (Y) variable

	Pooled OLS regression					Random effects GLS regression			Fixed effects (within) regression
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(1)
$FI_{i,t}$	−1.5269 (0.8304)	−1.5269*** (0.3049)	−1.5269*** (0.2695)	−1.5269*** (0.3128)	−1.5269*** (0.2954)	−1.526944 .8303	12.17074*** 2.139752	−1.115446 .9638843	12.17074*** (2.1397)
$IiEwPPP_{i,t}$	−2.77e-10** (9.21e-11)	−2.77e-10*** (4.75e-11)	−2.77e-10*** (5.42e-11)	−2.77e-10*** (5.49e-11)	−2.77e-10*** 4.97e-11	−2.77e-10** 9.21e-11	−3.82e-11 5.79e-11	−3.18e-10** 1.09e-10	−3.82e-11 (5.79e-11)
$REE_{i,t}$	0.2486*** (0.0251)	0.2486*** (0.0138)	0.2486*** (0.0138)	0.2486*** .013761	0.24861*** (0.0135)	.24861*** .0251559	−.3899315** .1358399	.2596376*** .0282453	−0.3899** (0.1358)
$HCI_{i,t}$	14.2554*** (2.6317)	14.2554*** (1.4065)	14.255*** (1.4641)	14.2554*** (1.3437)	14.255*** (1.4357)	14.25539*** 2.631781	−9.924481* 4.293878	11.72271*** 3.553044	−9.9244* (4.2938)
$Globalization_{i,t}$	1.0160*** (0.2658)	1.0160*** (0.0860)	1.0160*** (0.1039)	1.0160*** (0.0899)	1.0160*** (0.0950)	1.0160*** .2658454	.3596262 .2025768	1.355807*** .411445	0.3596 (0.2025)
$Constant_{i,t}$	−44.1724*** (11.7692)	−44.1724*** (4.0638)	−44.1724*** (4.7241)	−44.1741*** 4.2313	−44.1724 (4.3950)	−44.1724*** 11.76926	109.7784*** 20.05763	−57.09907 17.2424	74.6996*** (14.377)
N	96	96	96	96	96	96	96	96	96
Prob > F	0.0000	Nil	Nil	Nil	Nil	Nil	Nil	Nil	0.0000
R-squared	0.8409	0.8409	0.8409	0.8409	0.8409	0.8409	0.9513	0.8455	0.2168
VCE Cluster Year	No	Yes	Yes	Yes	Yes	No	No	No	No
Bootstrap (replications)	No	No	Yes (100)	Yes (1000)	No	No	No	No	No
VCE Jackknife (replications)	No	No	No	No	Yes (16)	No	No	No	No
Country_ID fixed effects	No	No	No	No	No	No	Yes	No	yes
Year fixed effects	No	No	No	No	No	No	No	Yes	Yes

Panel B: Model 1 using CEP as the main dependent (Y) variable

	Pooled OLS regression					Random effects GLS regression			Fixed effects (within) regression
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(1)
$FI_{i,t}$	1.526944 .8303777	−12.1707*** 2.139752	1.5269*** .304955	1.526944*** .308039	1.526944 *** .3079488	1.526944 .8303777	−12.17074*** 2.139752	1.115446 .9638843	−12.17074*** 2.139752
$IiEwPPP_{i,t}$	2.77e-10** 9.21e-11	3.82e-11 5.79e-11	2.77e-10*** 4.75e-11	2.77e-10*** 5.84e-11	2.77e-10*** 5.46e-11	2.77e-10*** 9.21e-11	3.82e-11 5.79e-11	3.18e-10** 1.09e-10	3.82e-11 5.79e-11
$REE_{i,t}$	−.2486*** .0251559	.3899315** .1358399	−.2486126*** .0138183	−.2486126*** .014847	−.2486126*** .014583	−.2486126*** .0251559	.3899315** .1358399	−.2596376*** .0282453	.3899315** .1358399
$HCI_{i,t}$	−14.2553*** 2.631781	9.924479** 4.293878	−14.25539*** 1.406597	−14.25539*** 1.333241	−14.25539*** 1.32107	−14.25539*** 2.631781	9.924479* 4.293878	−11.72271*** 3.553044	9.924479* 4.293878
$Globalization_{i,t}$	−1.016081*** .2658454	−.3596259 .2025768	−1.016081*** .086061	−1.016081*** .0839106	−1.016081*** .0910735	−1.016081*** .2658454	−.3596259 .2025768	−1.355807*** .411445	−.3596259 .2025768
$Constant_{i,t}$	144.1724*** 11.7692	−9.778444 20.05763	144.1724*** 4.063867	144.1724*** 4.263612	144.1724*** 4.50348	144.1724*** 11.76926	−9.778444 20.05763	157.0991*** 17.2424	25.30038 14.37712
N	96	96	96	96	96	96	96	96	96
Prob > F	0.0000	0.0000	Nil	Nil	Nil	Nil	Nil	Nil	0.0000
R-squared	0.8409	0.9513	0.8409	0.8409	0.8409	0.8409	0.9513	0.8455	0.2168
VCE Cluster Year	No	Yes	Yes	Yes	Yes	No	No	No	No
Bootstrap (replications)	No	No	No	Yes (100)	Yes (1000)	No	No	No	No
VCE Jackknife (replications)	No	No	No	No	No	No	No	No	No
Country_ID fixed effects	No	Yes	No	No	No	No	Yes	No	yes
Year fixed effects	No	No	No	No	No	No	Yes	Yes

Table 3
Model 1 using pooled OLS regression models.

Panel A: Model 1 using the average of $WAEP_{i,t}$ as the main (Y) dependent variable

$WAEP_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Inclusion$_{i,t}$	−1.5269 (0.8304)	−1.526944 .9487826	−1.526944 2.987927	−1.526944*** .3049551	−1.526944 .8303777	−1.526944 .8875967	−1.526944 .9304943	−1.526944 .9592934
Investment in Energy with PPP$_{i,t}$	−2.77e-10** (9.21e-11)	−2.77e-10*** 5.90e-11	−2.77e-10* 9.21e-11	−2.77e-10*** 4.75e-11	−2.77e-10** 9.21e-11	−2.77e-10*** 5.44e-11	−2.77e-10*** 6.43e-11	−2.77e-10*** 6.50e-11
Renewable Energy Electricity Output$_{i,t}$	0.2486*** (0.0251)	.2486126*** .0182788	.2486126*** .0287549	.2486126*** .0138183	.2486126*** .0251559	.2486126*** .0187876	.2486126*** .019481	.2486126*** .0191619
Human Capital Index$_{i,t}$	14.2554*** (2.6317)	14.25539*** 2.066284	14.25539* 3.943095	14.25539*** 1.406597	14.25539*** 2.631781	14.25539*** 2.065902	14.25539*** 2.059207	14.25539*** 2.123854
Globalization$_{i,t}$	1.0160*** (0.2658)	1.016081*** .2475149	1.016081 .4699268	1.016081*** .086061	1.016081*** .2658454	1.016081*** .2464649	1.016081*** .2503601	1.016081*** .2539625
Constant$_{i,t}$	−44.1724*** (11.7692)	−44.17241*** 12.08021	−44.17241 25.09983	−44.17241*** 4.063866	−44.17241*** 11.76926	−44.17241*** 11.94675	−44.17241 12.23052	−44.17241*** 12.37944
N	96	96	96	96	96	96	96	96
Prob > F	0.0000	Nil	Nil	Nil	0.0000	Nil	Nil	Nil
R-squared	0.8409	0.8409	0.8409	0.8409	0.8409	0.8409	0.8409	0.8409
Default standard errors	Yes	No	No	No	No	No	No	No
Robust	No	Yes	No	No	No	No	No	No
Cluster Robust by	No	No	Yes by ID	Yes by Years	No	No	No	No
Ordinary least squares (OLS)	No	No	No	No	Yes	No	No	No
Bootstrap (replications)	No	No	No	No	No	Yes (100)	Yes (1000)	No
Jackknife (replications)	No	No	No	No	No	No	No	Yes (96)

Panel B: Model 1 using the average of $CEP_{i,t}$ as the main (Y) dependent variable

$CEP_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Inclusion$_{i,t}$	1.526944 .8303777	1.526944 .9487827	1.526944 2.987927	1.526944*** .304955	1.526944 .8303777	1.526944 1.064804	1.526944 .9591878	1.526944 .9592936
Investment in Energy with PPP$_{i,t}$	2.77e-10** 9.21e-11	2.77e-10*** 5.90e-11	2.77e-10* 9.21e-11	2.77e-10*** 4.75e-11	2.77e-10** 9.21e-11	2.77e-10*** 6.60e-11	2.77e-10*** 6.86e-11	2.77e-10*** 6.50e-11
Renewable Energy Electricity Output$_{i,t}$	−.2486126*** .0251559	−.2486126*** .0182788	−.2486126*** .0287549	−.2486126*** .0138183	−.2486126*** .0251559	−.2486126*** .0194237	−.2486126*** .0181765	−.2486126*** .0191619
Human Capital Index$_{i,t}$	−14.25539*** 2.631781	−14.25539*** 2.066284	−14.25539* 3.943095	−14.25539*** 1.406597	−14.25539*** 2.631781	−14.25539*** 2.235608	−14.25539*** 2.146975	−14.25539*** 2.123854
Globalization$_{i,t}$	−1.016081*** .2658454	−1.016081*** .2475149	−1.016081 .4699268	−1.016081 .086061	−14.25539*** 2.631781	−1.016081*** .2638502	−1.016081*** .2625157	−1.016081*** .2539626
Constant$_{i,t}$	144.1724*** 11.76926	144.1724*** 12.08021	144.1724 25.09983	144.1724 4.063867	144.1724*** 11.76926	144.1724*** 12.80881	144.1724*** 12.79037	144.1724*** 12.37944
N	96	96	96	96	96	96	96	96
Prob > F	0.0000	Nil	Nil	Nil	0.0000	Nil	Nil	Nil
R-squared	0.8409	0.8409	0.8409	0.8409	0.8409	0.8409	0.8409	0.8409
Default standard errors	Yes	No	No	No	No	No	No	No
Robust	No	Yes	No	No	No	No	No	No
Cluster Robust by	No	No	Yes by ID	Yes by Years	No	No	No	No
Ordinary least squares (OLS)	No	No	No	No	Yes	No	No	No
Bootstrap (replications)	No	No	No	No	No	Yes (100)	Yes (1000)	No
Jackknife (replications)	No	No	No	No	No	No	No	Yes (96)

Table 4
Model 2 using pooled OLS regression models.

Panel A: Model 2 using the average of $WAEP_{i,t}$ as the main (Y) dependent variable.

	Pooled OLS regression							
$WAEP_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Inclusion$_{i,t}$	6.2736* 2.538728	6.2736* 2.655369	6.2736 9.574313	6.2736*** .9585293	6.2736* 2.538728	6.2736* 3.017036	6.2736* 2.671879	6.2736* 2.720518
GDP$_{i,t}$	−2.16e-12** 6.92e-13	−2.16e-12*** 6.10e-13	−2.16e-12 2.22e-12	−2.16e-12*** 3.63e-13	−2.16e-12** 6.92e-13	−2.16e-12** 7.57e-13	−2.16e-12*** 6.55e-13	−2.16e-12** 6.37e-13
Composite Risk Index$_{i,t}$	1.227392*** .2415891	1.227392*** .2080002	1.227392* .4592094	1.227392*** .1802884	1.227392*** .2415891	1.227392*** .2346928	1.227392*** .1982987	1.227392*** .213753
Investment in Energy with PPP$_{i,t}$	−5.28e-10** 1.66e-10	−5.28e-10*** 1.25e-10	−5.28e-10 2.13e-10	−5.28e-10*** 1.09e-10	−5.28e-10** 1.66e-10	−5.28e-10*** 1.41e-10	−5.28e-10*** 1.51e-10	−5.28e-10*** 1.33e-10
Renewable Energy Electricity Output$_{i,t}$	.3151231*** .0452168	.3151231*** .0319528	.3151231** .0665612	.3151231*** .0142507	.3151231*** .0452168	.3151231*** .0371216	.3151231*** .0347741	.3151231*** .0332955
Constant$_{i,t}$	−26.25408 17.26756	−26.25408 15.15352	−26.25408 32.90891	−26.25408 13.64956	−26.25408 17.26756	−26.25408 16.77471	−26.25408 14.39308	−26.25408 15.57061
N	96	96	96	96	96	96	96	96
Prob > F	0.0000	Nil	Nil	Nil	0.0000	Nil	Nil	Nil
R-squared	0.4295	0.4295	0.4295	0.4295	0.4295	0.4295	0.4295	0.4295
Default standard errors	Yes	No	No	No	No	No	No	No
Robust	No	Yes	Yes	Yes	No	No	No	No
Cluster Robust by	No	No	Yes by ID	Yes by Years	No	No	No	No
Ordinary least squares (OLS)	No	No	No	No	Yes	No	No	No
Bootstrap (replications)	No	No	No	No	No	Yes (100)	Yes (1000)	No
Jackknife (replications)	No	No	No	No	No	No	No	Yes (96)

Panel B: Model 2 using the average of $CEP_{i,t}$ as the main (Y) dependent variable.

	Pooled OLS regression							
$CEP_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Inclusion$_{i,t}$	−6.2736* 2.538728	−6.2736* 2.655369	−6.2736 9.574313	−6.2736*** .9585294	−6.2736* 2.538728	−6.2736* 2.841394	−6.2736* 2.797817	−6.2736* 2.720518
GDP$_{i,t}$	2.16e-12** 6.92e-13	2.16e-12*** 6.10e-13	2.16e-12 2.22e-12	2.16e-12*** 3.63e-13	2.16e-12** 6.92e-13	2.16e-12*** 6.44e-13	2.16e-12** 6.94e-13	2.16e-12** 6.37e-13
Composite Risk Index$_{i,t}$	−1.227392*** .2415891	−1.227392*** .2080002	−1.227392* .4592093	−1.227392*** .1802884	−1.227392*** .2415891	−1.227392*** .213515	−1.227392*** .2119185	−1.227392*** .213753
Investment in Energy with PPP$_{i,t}$	5.28e-10** 1.66e-10	5.28e-10*** 1.25e-10	5.28e-10 2.13e-10	5.28e-10*** 1.09e-10	5.28e-10** 1.66e-10	5.28e-10** 1.65e-10	5.28e-10*** 1.56e-10	5.28e-10*** 1.33e-10
Renewable Energy Electricity Output$_{i,t}$	3151231*** .0452168	−.3151231*** .0319528	−.3151231 .0665612	−.3151231*** .0142507	−.3151231*** .0452168	−.3151231*** .037829	−.3151231*** .0347643	−.3151231*** .0332955
Constant$_{i,t}$	126.2541*** 17.26756	126.254***1 15.15352	126.2541* 32.90891	126.2541*** 13.64956	126.2541*** 17.26756	126.2541*** 15.30745	126.2541*** 15.40175	126.2541*** 15.57061
N	96	96	96	96	96	96	96	96
Prob > F	0.0000	Nil	Nil	Nil	0.0000	Nil	Nil	Nil
R-squared	0.4295	0.4295	0.4295	0.4295	0.4295	0.4295	0.4295	0.4295
Default standard errors	Yes	No	No	No	No	No	No	No
Robust	No	Yes	Yes	Yes	No	No	No	No
Cluster Robust by	No	No	Yes by ID	Yes by Years	No	No	No	No
Ordinary least squares (OLS)	No	No	No	No	Yes	No	No	No
Bootstrap (replications)	No	No	No	No	No	Yes (100)	Yes (1000)	No
Jackknife (replications)	No	No	No	No	No	No	No	Yes (96)

Table 5
Im-Pesaran-Shin unit-root test without trend.

	t-bar	t-tilde-bar	Z-t-tilde-bar	p-value	Fixed-N exact critical values		
					1%	5%	10%
$WAEP_{i,t}$	−2.3697	−1.9438	−1.8993	0.0288	−2.330	−2.090	−1.960
$CEP_{i,t}$	−2.3697	−1.9438	−1.8993	0.0288	−2.330	−2.090	−1.960
Financial Inclusion$_{i,t}$	−1.1756	−1.0131	1.1192	0.8685	−2.330	−2.090	−1.960
Investment in Energy with PPP$_{i,t}$	−2.2347	−1.9233	−1.8328	0.0334	−2.330	−2.090	−1.960
Renewable Energy Electricity Output$_{i,t}$	−2.8096	−2.0047	−2.0968	0.0180	−2.330	−2.090	−1.960
Human Capital Index$_{i,t}$	−1.4031	−1.3233	0.1132	0.5451	−2.330	−2.090	−1.960
Globalization$_{i,t}$	−3.1136	−2.2659	−2.9438	0.0016	−2.330	−2.090	−1.960
$GDP_{i,t}$	2.1353	0.7983	6.9943	1.0000	−2.330	−2.090	−1.960
Composite Risk Index$_{i,t}$	−1.7155	−1.5457	−0.6082	0.2715	−2.330	−2.090	−1.960
AR parameter	Panel-specific						
Panel means	Included						
Time trend	Not included						
Ho	All panels contain unit roots						
Ha	Some panels are stationary						

Table 6
Im-Pesaran-Shin unit-root test with trend.

	t-bar	t-tilde-bar	Z-t-tilde-bar	p-value	Fixed-N exact critical values		
					1%	5%	10%
$WAEP_{i,t}$	−1.3115	−0.9708	1.2564	0.8955	−2.970	−2.720	−2.590
$CEP_{i,t}$	−1.3115	−0.9708	1.2564	0.8955	−2.970	−2.720	−2.590
Financial Inclusion$_{i,t}$	−1.3226	−1.1634	0.6319	0.7363	−2.970	−2.720	−2.590
Investment in Energy with PPP$_{i,t}$	−2.5839	−2.1728	−2.6421	0.0041	−2.970	−2.720	−2.590
Renewable Energy Electricity Output$_{i,t}$	−3.7243	−2.6061	−4.0474	0.0000	−2.970	−2.720	−2.590
Human Capital Index$_{i,t}$	−0.8766	−0.7706	1.9056	0.9717	−2.970	−2.720	−2.590
Globalization$_{i,t}$	−2.3092	−1.7280	−1.1993	0.1152	−2.970	−2.720	−2.590
$GDP_{i,t}$	−1.3125	−1.0059	1.1425	1.1425	−2.970	−2.720	−2.590
Composite Risk Index$_{i,t}$	−2.1096	−1.8738	−1.6723	0.0472	−2.970	−2.720	−2.590
AR parameter	Panel-specific						
Panel means	Included						
Time trend	included						
Ho	All panels contain unit roots						
Ha	Some panels are stationary						

Table 7
Levin-Lin-Chu unit-root.

	[1] No trend			[2] With trend		
	Unadjusted t	Adjusted t*	p-value	Unadjusted t	Adjusted t*	p-value
$WAEP_{i,t}$	−6.6606	−5.9967	0.0000	1.3724	3.8496	0.9999
$CEP_{i,t}$	−6.6606	−5.9967	0.0000	1.3724	3.8496	0.9999
Financial Inclusion$_{i,t}$	−3.1734	−2.0567	0.0199	−4.9109	−2.3789	0.0087
Investment in Energy with PPP$_{i,t}$	−5.3082	−2.5667	0.0051	−6.7215	−3.0829	0.0010
Renewable Energy Electricity Output$_{i,t}$	−3.4231	−1.4992	0.0669	−7.4944	−2.6523	0.0040
Human Capital Index$_{i,t}$	−3.5828	−2.8394	0.0023	−3.9282	−0.2944	0.3842
Globalization$_{i,t}$	−5.9460	−3.8947	0.0000	−4.8178	−2.6128	0.0045
$GDP_{i,t}$	3.6724	4.7253	1.0000	−2.7712	−1.3837	0.0832
Composite Risk Index$_{i,t}$	−4.9822	−2.4106	0.0080	−7.1862	−3.3322	0.0004
AR parameter	Common					
Panel means	Included					
Ho	Panels contain unit roots					
Ha	Panels are stationary					

Table 8
Westerlund [28]'s Error Correction Model Panel Cointegration test for D1WAEP and financial inclusion using their first-difference values.

Whole Panel	Statistics	Value	Z-value	P-value	Robust P-value
	Gt	−4.720	−8.022	0.000	0.000
	Ga	−41.724	−15.561	0.000	0.000
	Pt	−4.643	−1.103	0.135	0.130
	Pa	−36.894	−18.022	0.000	0.000

Table 9
Westerlund [28]'s Error Correction Model Panel Cointegration test for D1CEP and financial inclusion using their first-difference values.

Whole Panel	Statistics	Value	Z-value	P-value	Robust P-value
	Gt	−4.720	−8.022	0.000	0.000
	Ga	−41.725	−15.561	0.000	0.000
	Pt	−4.643	−1.103	0.135	0.170
	Pa	−36.894	−18.022	0.000	0.000

Table 10
Westerlund [28]'s Error Correction Model Panel Cointegration test for Model 1 using WEAP average.

Whole Panel	Statistics	Value	Z-value	P-value
	Gt	−14.555	−30.703	0.000
	Ga	−1.526	4.715	1.000
	Pt	−6.813	0.011	0.504
	Pa	−1.434	3.868	1.000

Table 11
Westerlund [28]'s Error Correction Model Panel Cointegration test for Model 1 using CEP average.

Whole Panel	Statistics	Value	Z-value	P-value
	Gt	−14.555	−30.702	0.000
	Ga	−1.526	4.715	1.000
	Pt	−6.813	0.011	0.504
	Pa	−1.434	3.868	1.000

Table 12
Augmented Mean Group (AMG) estimator for Model 1.

	Dependent variable (WAEP)	Dependent variable (CEP)
Financial Inclusion$_{i,t}$	−1.835 [4.282]	1.835 [4.282]
Investment in Energy with PPP$_{i,t}$	−8.94 [1.90]	8.94 [1.90]
Renewable Energy Electricity Output$_{i,t}$	0.008 [0.073]	−0.008 [0.0737]
Human Capital Index$_{i,t}$	−6.815 [11.448]	6.815 [11.448]
Globalization$_{i,t}$	−0.172 [0.1062]	0.1719 [0.106]
Common dynamic process	0.7612* [0.354]	0.7612* [0.354]
Trend	−0.039 [0.0892]	0.0394 [0.0891]
Constant$_{i,t}$	86.549* [39.682]	13.4508 [39.682]
Number of observations	96	96
Number of groups	6	6
Wald chi2(4)	3.17	3.17
Prob > chi2	0.5299	0.5299

Legend: *p < .05; **p < .01; ***p < .001.

Table 13
Augmented Mean Group (AMG) estimator for Model 2.

	Dependent variable (WAEP)	Dependent variable (CEP)
Financial Inclusion$_{i,t}$	−1.053 [2.653]	1.052 [2.653]
GDP$_{i,t}$	−9.80 [1.69]	9.80 [1.69]
Composite Risk Index$_{i,t}$	0.0134 [0.0219]	−0.0134 [0.0219]
Investment in Energy with PPP$_{i,t}$	−2.85 [1.84]	2.85 [1.84]
Renewable Energy Electricity Output$_{i,t}$	0.050 [0.045]	−0.050 [0.0459]
Common dynamic process	0.5943* [0.236]	0.594* [0.2362]
Trend	0.675 [0.563]	−0.6759 [0.564]
Constant$_{i,t}$	65.862*** [3.608]	34.137*** 3.608
Number of observations	96	96
Number of groups	6	6
Wald chi2(4)	1.72	3.17
Prob > chi2	0.6320	0.5299

Legend: *p < .05; **p < .01; ***p < .001.

the estimated coefficients of 0.008% and 0.013%.

Tables 14 and 15 report the pooled mean group – PMG estimations for Models 1 and 2 with the rise in the observations of time conditional on large N and long T dynamic panel data, respectively. The PMG techniques introduced by Pesaran, Shin, and Smith [44,45] are based on the composition of compiling and averaging estimated coefficients that permits for the error variance, short-run coefficients, and intercept to vary across the estimated groups but restrict the long-run coefficients to be identical across the estimated groups.[4] The results of PMG estimators further support the results of AMG estimators documenting the negative relation between energy poverty – WAEP and financial inclusion with a coefficient of −0.12% and a positive relationship between energy poverty – CEP and financial inclusion with a coefficient of 0.12% for Model 1. The negative relation between energy poverty – WAEP and investment in energy with PPP, renewable energy electricity is presented with the coefficients of −6.90% and −0.47%, statistically significant at 5% and 10%, respectively. In comparison, a positive relationship exists between energy poverty and human capital, with a one-percent significant coefficient of 51.1%. The PMG estimator for Model 2 in Table 15 reaffirms this finding for the relation between energy poverty – CEP and financial inclusion with a statically significant coefficient of 3.69%.

Tables 17 and 18 report empirical results of cross-sectional augmented auto-regressive distributed lags (CS-ARDL) for Models 1 and 2, respectively. The empirical results show that financial inclusion negatively affects energy poverty – WAEP in both the long-run and

Table 14
Pooled Mean Group (PMG) regression for Model 1.

	Dependent variable (WAEP)	Dependent variable (CEP)
Financial Inclusion$_{i,t}$	−0.1263 [4.394]	0.1263 [4.394]
Investment in Energy with PPP$_{i,t}$	−6.90e-1** [2.55e-1]	6.90e-1** [2.55e-1]
Renewable Energy Electricity Output$_{i,t}$	−0.471* [0.239]	0.4709* [0.239]
Human Capital Index$_{i,t}$	51.136*** [13.276]	−51.136*** [13.276]
Globalization$_{i,t}$	0.125 [0.198]	−0.125 [0.198]
Constant$_{i,t}$	−11.042 [13.106]	31.667 [35.854]
Number of observations	90	90
Number of groups	6	6
Log Likelihood	−9.650	−9.650

Legend: *p < .05; **p < .01; ***p < .001.

Table 15
Pooled Mean Group (PMG) regression for Model 2.

	Dependent variable (WAEP)	Dependent variable (CEP)
Financial Inclusion$_{i,t}$	26.886 [16.897]	3.697* [1.597]
GDP$_{i,t}$	−8.60e-1 [9.61e-1]	−2.88 [1.70]
Composite Risk Index$_{i,t}$	0.994 [0.725]	0.349*** [0.100]
Investment in Energy with PPP$_{i,t}$	−1.42 [9.36]	−9.74** [3.14]
Renewable Energy Electricity Output$_{i,t}$	−0.142 [0.186]	0.116* [0.058]
Constant$_{i,t}$	1.905 [1.374]	0.998 [1.306]
Number of observations	90	90
Number of groups	6	6
Log Likelihood	−11.946	−8.728

Legend: *p < .05; **p < .01; ***p < .001.

Table 16
Dynamic fixed effects regression for Model 2.

	Dependent variable (WAEP)	Dependent variable (CEP)
Financial Inclusion$_{i,t}$	−6.384 [10.427]	6.384 [10.427]
Investment in Energy with PPP$_{i,t}$	−5.08e-* [2.11e-]	5.08e-* [2.11e-]
Renewable Energy Electricity Output$_{i,t}$	0.239 [0.569]	−0.239 [0.569]
Human Capital Index$_{i,t}$	−4.588 [14.748]	4.588 [14.748]
Globalization$_{i,t}$	1.070 [0.773]	−1.070 [0.773]
Constant$_{i,t}$	0.639 [5.863]	8.904 [4.811]

Legend: *p < .05; **p < .01; ***p < .001.

[4] For more details on the estimation of nonstationary heterogenous panels with STATA, please see Blackburne and Frank [46].

Table 17
Cross-sectional Augmented Auto-regressive distributed lags (CS-ARDL) for Model 1.

CS-ARDL	Dependent variable (WAEP)		Dependent variable (CEP)	
	Short-run estimation	Long-run estimation	Short-run estimation	Long-run estimation
Energy Poverty Average	−2.563 [1.245]	−3.563 1.245	2.562 [1.244]	1.562 [1.244]
Financial Inclusion$_{i,t}$	3.087 [4.796]	0.035 [1.065]	3.089 [4.792]	−82.721 [84.23]
Investment in Energy with PPP$_{i,t}$	1.61 [2.85]	1.01e-[1.66e-]	1.61e- [2.85e-]	1774.34 [1737.00]
Renewable Energy Electricity Output$_{i,t}$	−0.0553 [0.1883]	−0.002 [0.115]	−0.0553 [0.188]	−4.813 [3.205]
Human Capital Index$_{i,t}$	−79.194 [194.32]	−77.961 [136.67]	−79.185 [194.32]	1774.343 [1737.002]
Globalization$_{i,t}$	−0.2746 [0.192]	−0.144 [0.110]	−0.274 [0.192]	−0.314 [4.973]

Legend: *p < .05; **p < .01; ***p < .001.

Table 18
Cross-sectional Augmented Auto-regressive distributed lags (CS-ARDL) for Model 2.

CS-ARDL	Dependent variable (WAEP)		Dependent variable (CEP)	
	Short-run estimation	Long-run estimation	Short-run estimation	Long-run estimation
Energy Poverty Average	−1.4264*** [0.405]	−2.426 [0.405]	1.426*** [0.405]	0.426 [0.405]
Financial Inclusion$_{i,t}$	−17.126 [9.630]	−11.548 [8.623]	−17.126 [9.630]	−461.126 [453.17]
GDP$_{i,t}$	−1.81e- [2.02e-]	−1.08e- [9.88e-]	−1.81e-[2.02e-]	−3.36e- [3.35e-]
Composite Risk Index$_{i,t}$	−0.008 [0.143]	0.043 [0.105]	−0.008 [0.143]	−10.816 [11.022]
Investment in Energy with PPP$_{i,t}$	−9.30e- [5.71e-]	−5.57e- [4.23e-]	−9.30e-[5.71e-]	2.40e- [2.49e-]
Renewable Energy Electricity Output$_{i,t}$	−0.455 [0.429]	−0.390 [0.367]	−0.455 [0.429]	−6.312 [5.585]

Legend: * p<.05; ** p<.01; *** p<.001

Table 19
Dumitrescu and Hurlin [42]'s Granger non-causality test.

	W-bar	Z-bar	Z-bar tilde
Financial Inclusion$_{i,t}$	10.247	10.100*** (0.000)	5.449*** (0.000)
Investment in Energy with PPP$_{i,t}$	–	–	–
Renewable Energy Electricity Output$_{i,t}$	1.725	1.256(0.2089)	0.646(0.517)
Human Capital Index$_{i,t}$	46.186	43.186*** (0.000)	14.854*** (0.000)
Globalization$_{i,t}$	3.590	4.487*** (0.000)	2.942** (0.003)
GDP$_{i,t}$	–	–	–
Composite Risk Index$_{i,t}$	1.418	0.724(0.468)	0.268(0.788)

Legend: *p < .05; **p < .01; ***p < .001.

short-run with the coefficients of −2.563, −3.563 and −1.426, −2.426 for Models 1 and 2, respectively. For Model 2 presented in Table 18, their coefficient of −1.426 is statistically significant at a 1% level for the short-run relation between energy poverty and financial inclusion. The results of CS-ARDL further support the estimated results of AMG, PMG, and multiple regression models above when presenting the negative relations between energy poverty – WAEP, renewable electricity output, human capital index, and globalization with the estimated coefficients of −0.055%, −79.19%, and −0.2746% for Model 1 in the short-run. It is critical to note that the magnitude of those relations is changed in the long run. For further results, please see Table 16.

Table 19 presents the estimation of the Granger non-causality test proposed by Dumitrescu and Hurlin [42] - DH to investigate the causality within the panel data and reject the null hypothesis – H_0 that there is no causality within the estimated panel. The DH's tests reported in Table 19 reject the null hypothesis for financial inclusion, human capital index, and globalization with the Z-bar tilde statistics of 5.449, 14.85, and 2.942 which are statistically significant at 1% and 5% levels, respectively.

The overall findings of this study is in line with the empirical outcomes from the studuy of Dogan et al., [5]; Koomson and Danquah [2]; Rafe et al. (2021) and Dong et al., [47]. However, the outcomes of mentioned studies are mostly single-country studies and ignore the role of multidimensional energy poverty and financial inclusion. Therefore, these findings are more robust in designing policy implications in this regard.

7. Conclusion

This study investigates the nexus and impacts of financial inclusion on energy poverty controlling for a vector of critical explanatory variables, including economic growth, investment in energy with PPP, composite risk index, and globalization. We construct and use the multidimensional proxies of energy poverty, namely composite energy poverty index (CEP) and weighted average energy poverty (WAEP), as well as a multidimensional measure for financial inclusion constructed based on a Z-score approach to mitigate the limitation when using single measures for capturing the impacts of financial inclusion on energy poverty in our sample countries for the period 2004–2020. Using multiple regression approaches including pooled ordinary least squares (OLS), random-effects (RE), and fixed-effects (FE) with robust, cluster roust, bootstrap (replication), and Jack-knife (replication); the study detects a robust negative relationship between financial inclusion and energy poverty measured by CEP, while a positive impact of financial inclusion on energy poverty measured by WAEP is presented. The results are almost statistically significant across the tested regression models at the 10% level.

For Cointegration, the study employed Westerlund [28]'s Error Correction Model Panel test, the study documents an existing cointegration between energy poverty and financial inclusion, rejecting the null hypothesis of no cointegration in the tested models. By applying the pooled mean group (PMG) and cross-sectional auto-regressive distributed lags (CS-ARDL), the study reaffirms the empirical results examined in the earlier tests and detects robust statistically significant relationships among energy poverty and financial inclusion in the short-run rather than in the long run. The results of CS-ARDL presented in Table 13 are statistically significant at the 1% level for Model 2, controlling for economic growth (GDP), investment in energy with PPP, composite risk index, and renewable electricity output. The study presents the visualization of the relation between energy poverty measured by either CEP or WAEP, and the financial inclusion index, represented in Figs. 1–3, respectively. Given the empirical results of the nexus and impacts of financial inclusion on energy poverty using the multidimensional proxies, the study provides critical implications to researchers, policymakers, and related parties in the 6 sample countries in mitigating the consequences of energy poverty as well as the development of financial systems and their co-movement with energy poverty-related issues. The study provides the following policy implications and limitations of the study.

7.1. Policy recommendations

Policymakers should effectively channel more money to people who live in poorer areas to develop innovative financing models to subsidize their energy access or enable them to pay for their energy use in installments. Energy poverty can also be limited via investment in human capital, more investment in renewable energy and opening up with the benefit of getting technologies that overcome the issue of energy poverty. More is needed to enhance public-private participation through collaborative cost, risk and resource-sharing. This may also help in reducing the cost of renewable energy technologies. Our study suggests that it is important for policymakers to tackle energy poverty problems by addressing the interplay between energy-sector regulation, financial policies, political and financial risks, and private sector participation. Ignoring any of these dimensions will result in unacceptable outcomes and inefficient policies. Finally, there is still a need for further research on financial inclusion, energy poverty, and other associated social and economic factors, particularly toward Sustainable Development Goals, to adapt the effects of climate change and global warming as urgent issues in the world in recent years.

7.2. Limitations of the study

The study is limited to specific countries; however, future studies may also use data from developing and developed economies to test the determining and limiting factors of energy poverty empirically. Furthermore, updated data should be employed to fully capture the energy poverty situation. Future studies are encouraged to test for structural shocks to see the impact of these structural shocks in terms of energy poverty.

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.

Acknowledgment

This research was supported by Curtin Malaysia Higher Degree by Research (CMHDR) Grant.

Appendix 1

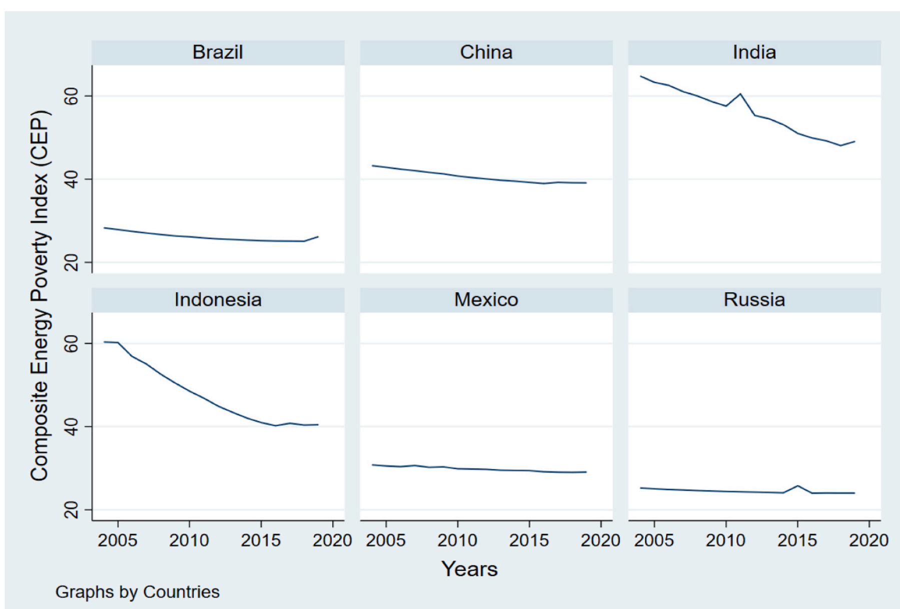

Fig. 1. Visualization of energy poverty measured by CEP across the 6 sample countries.

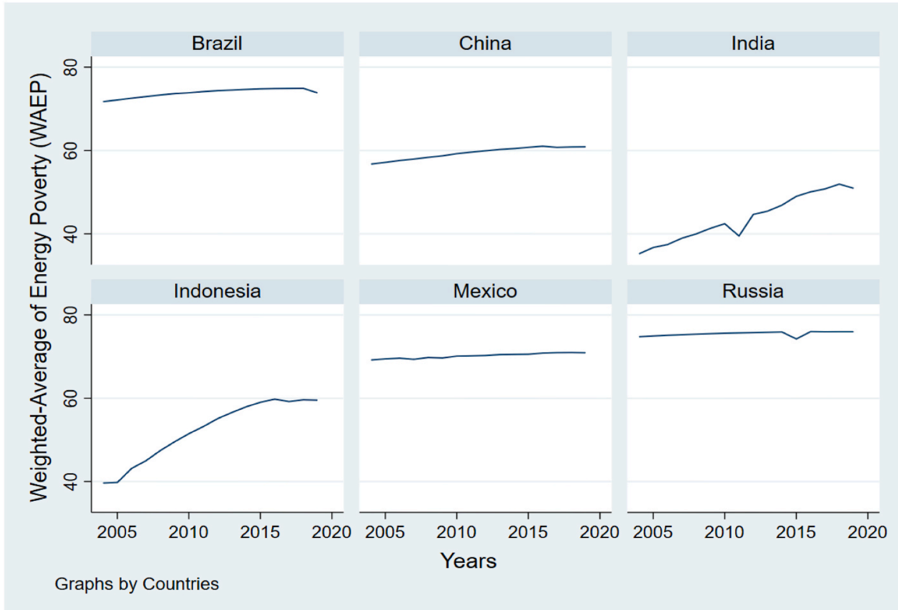

Fig. 2. Visualization of energy poverty measured by WAEP across the 6 sample countries.

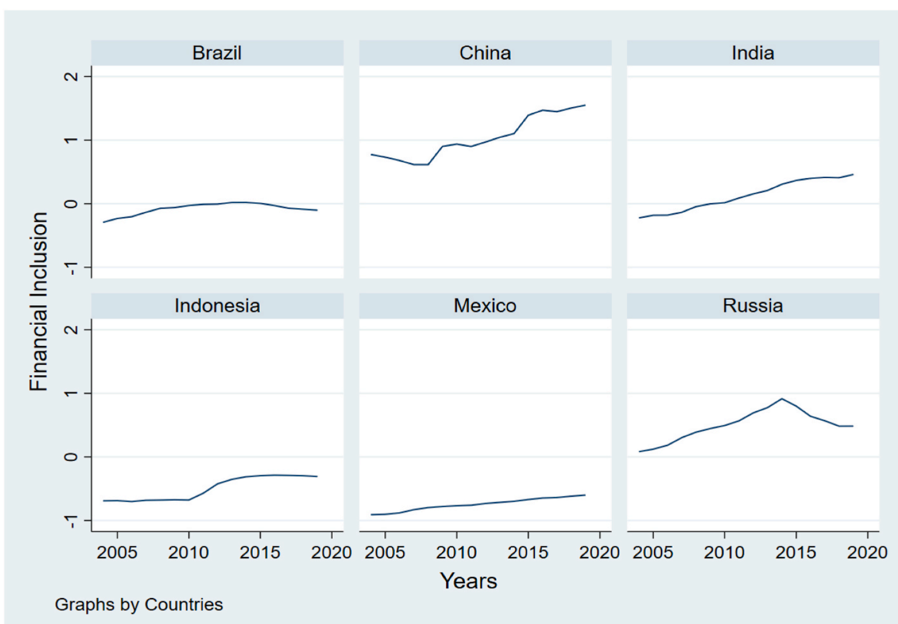

Fig. 3. Visualization of financial inclusion measured across the 6 sample countries.

References

[1] F. Essel-Gaisley, T. Chiang, Turning the tide on environmental poverty in Ghana: does financial inclusion matter? J. Sustain. Prod. Consum. 33 (2022) 88–100.
[2] I. Koomson, M. Danquah, Financial inclusion and energy poverty: empirical evidence from Ghana, Energy Econ. 94 (2021).
[3] M.H. Pesaran, Testing weak cross-sectional dependence in large panels, Econom. Rev. 34 (6–10) (2015) 1089–1117.
[4] M.H. Pesaran, Estimation and inference in large heterogeneous panels with a multifactor error structure, Econometrica 74 (4) (2006) 967–1012.
[5] E. Dogan, M. Madaleno, D. Taskin, Which households are more energy vulnerable? Energy poverty and financial inclusion in Turkey, J. Energy Econ. 99 (2021), 105306.
[6] W. Xia, M. Muntasir, Z. Khan, Z. Chen, D. Ferraz, Exploring the nexus between fiscal decentralization and energy poverty for China: does country risk matter for energy poverty reduction? J. Energy 255 (2022), 124541.
[7] N. Apergis, M. Polemis, S. Soursou, Energy poverty and education: fresh evidence from a panel of developing countries, J. Energy Econ. 106 (2022), 105430.
[8] Y. Yu, K. Tang, Does financial inclusion improve energy efficiency? J. Technol. Forecast. Soc. Change 186 (2023), 122110.
[9] J. Zhang, S.M.F. Raza, Y. Huang, C. Wang, What Affect Energy Poverty in China? A Path towards Sustainable Development, Economic Research-Ekonomska Istraživanja, 2022.
[10] S.T. Hassan, B. Batool, B. Zhu, I. Khan, Environmental complexity of globalization, education, and income inequalities: new insights of energy poverty, J. Clean. Prod. 340 (2022), 130735.
[11] S.G. Anton, The impact of temperature increase on firm profitability. Empirical evidence from the European energy and gas sectors, J. Appl. Energy 295 (2021), 117051.
[12] S.G. Anton, A.E.A. Nucu, The effect of financial development on renewable energy consumption. A panel data approach, J. Renew. Energy 147 (2020) 330–338.
[13] R. Burgess, R. Pande, Do rural banks matter? Evidence from the Indian social banking experiment, Am. Econ. Rev. 95 (3) (2005) 780–795.

[14] S.A. Churchill, R. Smyth, L. Farrell, Fuel poverty and subjective wellbeing, Energy Econ. 86 (2020), 104650.
[15] I. Koomson, R.A. Villano, D. Hadley, Effect of financial inclusion on poverty and vulnerability to poverty: evidence using a multidimensional measure of financial in- clusion, Soc. Indicat. Res. 25 (4) (2020) 375–387.
[16] S.A. Churchill, R. Smyth, Ethnic diversity, energy poverty and the mediating role of trust: evidence from household panel data for Australia, Energy Econ. 86 (2020), 104663.
[17] A.C. Sadath, R.H. Acharya, Assessing the extent and intensity of energy poverty using multidimensional energy poverty index: empirical evidence from households in India, Energy Pol. 102 (2017) 540–550.
[18] M. Chibba, Financial inclusion, poverty reduction and the millennium development goals, Eur. J. Dev. Res. 21 (2) (2009) 213–230.
[19] S.A. Churchill, V.B. Marisetty, Financial inclusion and poverty: a tale of forty-five thousand households, Appl. Econ. 1–12 (2019).
[20] I. Koomson, M. Ibrahim, Financial Inclusion and Growth of Non-farm Enterprises in Ghana. Financing Sustainable Development in Africa, Springer, 2018, pp. 369–396.
[21] R.H. Acharya, A.C. Sadath, Energy poverty and economic development: household-level evidence from India, Energy Build. 183 (2019) 785–791.
[22] A.O. Crentsil, D. Asuman, A.P. Fenny, Assessing the determinants and drivers of multidimensional energy poverty in Ghana, Energy Pol. 133 (2019), 110884.
[23] D. Sharma, Nexus between financial inclusion and economic growth: evidence from the emerging Indian economy, J. Financ. Econ. Pol. 8 (1) (2016) 13–36.
[24] A. Demirgüç-Kunt, L. Klapper, D. Singer, Financial Inclusion and Inclusive Growth: A Review of Recent Empirical Evidence, The World Bank, 2017.
[25] T.-H. Le, A.T. Chuc, F. Taghizadeh-Hesary, Financial inclusion and its impact on financial efficiency and sustainability: empirical evidence from Asia, Borsa Istanbul Review 19 (4) (2019) 310–322, 11.
[26] T.-H. Le, H.-C. Le, F. Taghizadeh-Hesary, Does financial inclusion impact CO2 emissions? Evidence from Asia, Finance Res. Lett. 34 (2020), 101451, https://doi.org/10.1016/j.frl.2020.101451.
[27] R. Salim, Y. Yao, G.S. Chen, Does human capital matter for energy consumption in China? Energy Econ. 67 (2017) 49–59.
[28] J. Westerlund, Testing for error correction in panel data, Oxf. Bull. Econ. Stat. 69 (6) (2007) 709–748.
[29] G.S. Maddala, S. Wu, A comparative study of unit root tests with panel data and a new simple test, Oxf. Bull. Econ. Stat. 61 (S1) (1999) 631–652.
[30] P.C. Phillips, H.R. Moon, Linear regression limit theory for nonstationary panel data, Econometrica 67 (5) (1999) 1057–1111.
[31] A. Levin, C.-F. Lin, C.-S.J. Chu, Unit root tests in panel data: asymptotic and finite-sample properties, J. Econom. 108 (1) (2002) 1–24.
[32] K.S. Im, M.H. Pesaran, Y. Shin, Testing for unit roots in heterogeneous panels, J. Econom. 115 (1) (2003) 53–74.
[33] P. Pedroni, Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis, Econom. Theor. (2004) 597–625.
[34] B.H. Baltagi, E. Bratberg, T.H. Holmås, A panel data study of physicians' labor supply: the case of Norway, Health Econ. 14 (10) (2005) 1035–1045.
[35] J. Breitung, M.H. Pesaran, Unit roots and cointegration in panels, in: The Econometrics of Panel Data, Springer, 2008, pp. 279–322.
[36] H.R. Moon, B. Perron, Beyond panel unit root tests: using multiple testing to determine the nonstationarity properties of individual series in a panel, J. Econom. 169 (1) (2012) 29–33.
[37] I. Choi, Unit root tests for panel data, J. Int. Money Finance 20 (2) (2001) 249–272.
[38] J. Lluís Carrion-i-Silvestre, T. Del Barrio-Castro, E. López-Bazo, Breaking the panels: an application to the GDP per capita, Econom. J. 8 (2) (2005) 159–175.
[39] J. Bai, J.L. Carrion-I-Silvestre, Structural changes, common stochastic trends, and unit roots in panel data, Rev. Econ. Stud. 76 (2) (2009) 471–501, https://doi.org/10.1111/j.1467-937X.2008.00530.x.
[40] M.H. Pesaran, A simple panel unit root test in the presence of cross-section dependence, J. Appl. Econom. 22 (2) (2007) 265–312.
[41] A. Jalil, Energy–growth conundrum in energy exporting and importing countries: evidence from heterogeneous panel methods robust to cross-sectional dependence, Energy Econ. 44 (2014) 314–324.
[42] E.-I. Dumitrescu, C. Hurlin, Testing for Granger non-causality in heterogeneous panels, Econ. Modell. 29 (4) (2012) 1450–1460.
[43] M. Eberhardt, Estimating panel time-series models with heterogeneous slopes, STATA J. 12 (1) (2012) 61–71, https://doi.org/10.1177/1536867X1201200105.
[44] M.H. Pesaran, Y. Shin, R.P. Smith, Estimating long-run relationships in dynamic heterogeneous panels, in: DAE Working Papers Amalgamated Series 9721, University of Cambridge England, 1997.
[45] M.H. Pesaran, Y. Shin, R.P. Smith, Pooled mean group estimation of dynamic heterogeneous panels, J. Am. Stat. Assoc. 94 (446) (1999) 621–634.
[46] E.F. Blackburne, M.W. Frank, Estimation of nonstationary heterogeneous panels, STATA J. 7 (2) (2007) 197–208.
[47] K. Dong, F. Taghizadeh-Hesary, J. Zhao, How inclusive financial development eradicates energy poverty in China? The role of technological innovation, Energy Econ. 109 (2022), 106007.
[48] X. Zhao, M. Ramzan, T. Sengupta, G.D. Sharma, U. Shahzad, L. Cui, Impacts of bilateral trade on energy affordability and accessibility across Europe: does economic globalization reduce energy poverty? J. Energy Build. 262 (2022), 112023.
[49] M. Rafi, M. Naseef, S. Prasad, Multidimensional energy poverty and human capital development: empirical evidence from India, J. Energy Econ. 101 (2021), 105427.
[50] J. Zhao, K. Dong, X. Dong, M. Shahbaz, How renewable energy alleviate energy poverty? A global analysis, J. Renew. Energy 186 (2022) 299–311.
[51] M. Rafi, M. Naseef, S. Prasad, Multidimensional energy poverty and human capital development: empirical evidence from India, Energy Econ. 101 (2021), 105427.
[52] Khanna, A. Rupali, Yanfei Li, Subodh Mhaisalkar, Mahesh Kumar, Liang. Lim Jia, Comprehensive energy poverty index: Measuring energy poverty and identifying micro-level solutions in South and Southeast Asia, Energy Pol. 132 (2019) 379–391.
[53] Jeleta Kebede, Athula Naranpanawa, Selvanathan Saroja, Financial inclusion: Measures and applications to Africa, Economic Analysis and Policy 70 (2021) 365–379.
[54] International Monetary Fund (IMF), International Monetary Fund - Homepage (imf.org) (2022).
[55] World Bank. https://databank.worldbank.org/.
[56] Penn World Tabl 10.0, PWT 10.0 | Penn World Table | Groningen Growth and Development Centre | University of Groningen (rug.nl) (2022).
[57] KOF Globalisation. KOF Globalisation Index – KOF Swiss Economic, Institute | ETH, Zurich, 2022.
[58] International Country Risk Guide (ICRG), The PRS Group. https://www.prsgroup.com.