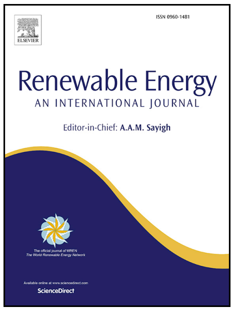

Portfolio decisions of primary energy sources and economic complexity: The world's large energy user evidence

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PII: S0960-1481(22)01690-1

DOI: https://doi.org/10.1016/j.renene.2022.11.050

Reference: RENE 17995

To appear in: *Renewable Energy*

Received Date: 20 March 2022

Revised Date: 5 November 2022

Accepted Date: 12 November 2022

Please cite this article as: Shirazi M, Fuinhas JoséAlberto, Portfolio decisions of primary energy sources and economic complexity: The world's large energy user evidence, *Renewable Energy* (2022), doi: https://doi.org/10.1016/j.renene.2022.11.050.

Credit author statement: M.S.: Writing-Original draft, Conceptualization, Validation, Data curation, Formal analysis, Visualization, and Investigation. J.A.F.: Writing-Review and editing, Supervision, Funding acquisition, Project administration, and Investigation. All authors have read and agreed to the published version of the manuscript.

Portfolio decisions of primary energy sources and economic complexity: the world's large energy user evidence

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Abstract: Sustainable energy systems are sensitive to economic complexity, i.e., the combination of knowledge, innovation, and productivity, since it affects the countries' portfolio decisions of primary energy sources, shaping geopolitics, and contributing to global energy security. This research assesses the impact of economic complexity on the performance of two energy systems measurements, e.g., diversification of primary energy demand (D.P.E.D) and non-carbon-based fuel portfolio (N.C.F.P), controlling for energy intensity, energy prices, resource supply diversity, and CO2 emissions in a panel of 25 large energy-using countries during 1998-2018. The findings support the long-run and causal relationships across energy systems using the panel cointegration methods and dynamic panel models. Specifically, economic complexity's statistically significant and positive effect on D.P.E.D and N.C.F.P is detected. Moreover, the contribution of N.C.F.P to total energy demand is more elastic than D.P.E.D when the shares of economic complexity and the control variables increase. Results also indicate that the cyclical movements of economic complexity are not related to energy systems fluctuations across large energy-consuming economies. Consequently, the role of economic complexity in sustainable energy systems is a necessary condition to overcome the barriers in achieving (i) resource abundance and equitability and (ii) a non-carbon-based fuel portfolio for large energy consumers.

Keywords: Energy Security, Economic Complexity, Energy Consumption, Dynamic Panel Model.

JEL Classification: (Q34, Q55, Q42, C26)

Acknowledgements: CeBER R&D unit funded by national funds through FCT – Fundação para a Ciência e a Tecnologia, I.P., project UIDB/05037/2020.

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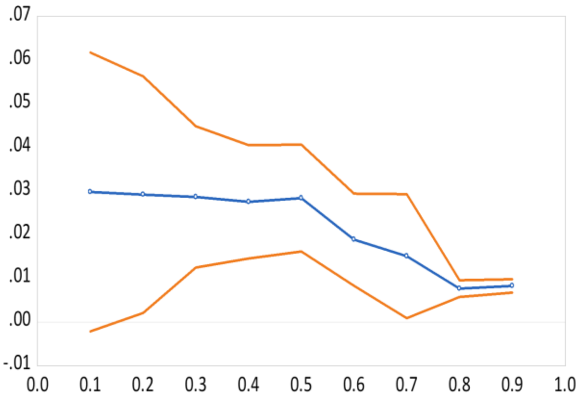
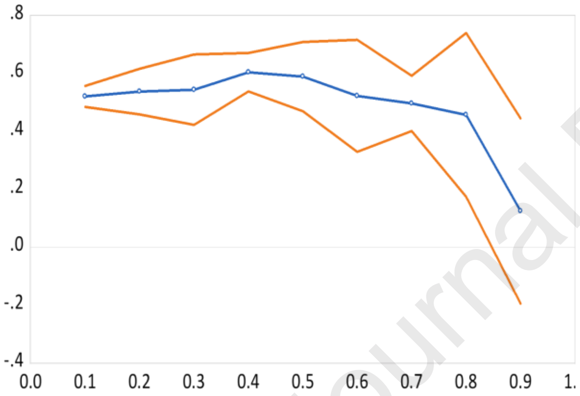
Portfolio decisions of primary energy sources and economic complexity: the world's large energy user evidence

Graphical Abstract



Economic Complexity & Diversification of Primary Energy Demand



Economic Complexity & Non-Carbon-Based Fuel Portfolio

Panel cointegration and dynamic models are applied to explore how energy systems are affected through economic complexity in large energy-users

Economic complexity develops portfolio decisions of primary energy sources

Resource abundance and equitability are more challenging to achieve through energy systems dynamics

Economic complexity lowers the barriers in achieving (i) diversification of primary energy demand , and (ii) non-carbon-based fuel portfolio

Abstract

Sustainable energy systems are sensitive to economic complexity, i.e., the combination of knowledge, innovation, and productivity, since it affects the countries' portfolio decisions of primary energy sources, shaping geopolitics, and contributing to global energy security. This research assesses the impact of economic complexity on the performance of two energy systems measurements, e.g., diversification of primary energy demand (D.P.E.D) and non-carbon-based fuel portfolio (N.C.F.P), controlling for energy intensity, energy prices, resource supply diversity, and CO2 emissions in a panel of 25 large energy-using countries during 1998-2018. The findings support the long-run and causal relationships across energy systems using the panel cointegration methods and dynamic panel models. Specifically, economic complexity's statistically significant and positive effect on D.P.E.D and N.C.F.P is detected. Moreover, the contribution of N.C.F.P to total energy demand is more elastic than D.P.E.D when the shares of economic complexity and the control variables increase. Results also indicate that the cyclical movements

of economic complexity are not related to energy systems fluctuations across large energy-consuming economies. Consequently, the role of economic complexity in sustainable energy systems is a necessary condition to overcome the barriers in achieving (i) resource abundance and equitability and (ii) a non-carbon-based fuel portfolio for large energy consumers.

Keywords: Energy Security, Economic Complexity, Energy Consumption, Dynamic Panel Model.

JEL Classification: (Q34, Q55, Q42, C26)

abbreviations and acronyms

E.C	economic complexity	E.I	energy intensity
S	energy systems	E.E	energy efficiency
E.S	energy security	E.R.P.M	energy resource portfolio measurements
E.T	energy trilemma	D.P.E.D	diversification of primary energy demand (consumption)
E.P	energy prices	D.P.E.S	diversification of the primary energy supply
E	CO_2 emissions	P.D.P.E.S	portfolio decisions of primary energy source
C.P.I	consumer price index	L.E.C.E	large energy-consuming economies
P.E.D	primary energy demand	N.C.F.P	non-carbon-based fuel portfolio
P.E.S	primary energy source	H.P	Hodrick-Prescott
A.R	auto-regressive	J.F	Johansen-Fisher
L.T.T	long-term trends	N.R.E	new & renewable energy sources
S.T.F	short-term fluctuations	A.T.S	actual time-series
L.L.C	Levin, Lin & Chu	S.E.D	sustainable economic development
P.E.G	Pedroni's Engle-Granger	P.F.M.L.S	panel fully modified least squares
C.D	cross-sectional dependency	P.D.L.S	panel dynamic least squares
A.B	Arellano-Bond	V.I.F	variance inflation factor
Δ	first difference	G.M.M	generalized methods of movements
P.Q.R	panel quantile regression	S.J	Sargan J

1. Introduction

The development of energy systems, i.e., technological dynamics, social complexity, and energy safety, needs to focus on energy security, energy equity, and environmental sustainability, called the energy trilemma [1]. Currently, energy systems are trapped in carbon-based fuel portfolios [1], which is the motivation for energy security change [2-4]. Therefore, this paper aims to assess the impact of economic complexity and controlling variables, including energy intensity, energy prices, diversification of primary energy supply, and CO_2 emissions on the portfolio decisions of primary energy sources, e.g., diversification of primary energy demand and non-carbon-based fuel portfolio, in respect of the energy trilemma [5], leading to greater reliability, safety, and efficiency of energy systems and hence, economic vulnerability reduction [4].

The Gas Act 1992 and Electricity Act 1992 offer the legislative structure and requirements for energy safety from supply to end use. Both laws aim to protect the workers and public and to prevent property destruction from supply to end use of energy sources. In this regard, the issue of energy security is considered that covers a wide range of aspects [6], from the classic definition, i.e., reliable and affordable flow of oil supply [7], to contemporary dimensions, e.g., accessibility and environmental acceptability, of energy resources in the economies [8]. Energy security includes immediate physical availability, price affordability, transportation, transmission accessibility, and environmental, political, and social acceptability dimensions of primary energy resources [9]. Specifically, in terms of immediate physical availability, the energy source is available if it is abundant enough to go on an important recoverable resource. The affordability of energy resource acquisition explains the economic dimension of energy security.

Furthermore, the accessibility dimension of energy security refers to transportation and transmission barriers, e.g., geopolitical factors, "long-term sales contracts", and massive infrastructure investments. Finally, regarding environmental acceptability and energy safety, energy security reflects the economy's success in switching from a carbon-intensive- to a non-carbon-based fuel portfolio to lower potential environmental degradation [10-11]. Particularly, energy safety requires the energy systems primarily to modernize, reinforce, and expand the extent of transparency of the responsibility regime [4].

Hence, as the need for utilization of fossil fuels and biomass energy sources for sustainable economic development, a dynamic analysis of the portfolio decisions of primary energy sources is important for policymakers in both energy-exporting- and importing countries to adopt comprehensive dynamic energy policies and, therefore develop their energy securities [12]. However, the role of energy security (sustainable demand) in resource- and non-resource sectors, capital formation, technology improvements, and economic growth of the energy-exporting countries is inevitable since they are vulnerable to external market shocks [13]. On the other hand, as the economy is dependent on the imported primary energy source to cover its primary energy demand, there is a limited possibility of meeting its energy consumption through domestic supply sources, which leads to higher risks and lower resilience, i.e., capability to respond to disruptions, of the country's energy supply security (sustainable supply).

The energy systems dynamics are analyzed through the behavior of economic agents, objects, e.g., infrastructures, technologies, energy safety, and the environment [1]. Based on [5], one of the main factors affecting energy systems resilience is economic complexity [14-15].

Specifically, economic complexity illustrates the combination of knowledge, innovation, productive structure, structural changes, and capabilities of the economic systems, shaping the sector- and source-based energy consumption patterns of the economies [15]. Conversely, economic complexity is mentioned as the quality of the gross domestic product [16]. Also, the theoretical connectedness between energy consumption and economic growth explains economic complexity in energy systems, where productivity plays an intermediate-affecting role in innovation and technological improvements [17].

Consequently, exploring driving forces and resistances of portfolio decisions of primary energy sources, e.g., diversification of primary energy demand and non-carbon-based fuel portfolio, leads to lower economic costs of transforming energy sources into production, greater reliability, safety, and efficiency of energy systems, and hence facilitates sustainable economic development [4,18]. Accordingly, this research focuses on the impact of economic complexity on portfolio decisions of primary energy sources across a large energy user panel framework. To this end, energy intensity, energy prices, diversification of primary energy supply, and CO_2 emissions are also applied as the major control variables. Notably, energy intensity refers to energy conservation, production costs, energy safety, and CO_2 emissions provide information on cleaner technologies, energy systems decarbonization, and energy safety [4,16]. The higher energy prices can cause higher diversification of primary energy supply that relates to the issue of technological complexity, i.e., "technological diversification", "spare production capacities", "diverse suppliers stockpiling", and "emergency plans" [5,14-15], which enhance the resource equitability and abundance, energy safety, and energy systems decarbonization [19]. Specifically, we analyze to how and what extent diversification of primary energy demand and non-carbon-based fuel portfolio react to the changes in the economic complexity, energy intensity, energy prices, diversification of primary energy supply, and CO_2 emissions in 25 large energy-consuming economies with diverse energy security risk scores [20], monitoring for a chain of country-specific energy systems characteristics to be less vulnerable in response to the market shocks of energy resources.

Accordingly, and in order to take the line of energy security development, abundance and equitability dimensions of the resource diversification, as well as non-carbon-based fuel portfolio, can be adopted by the policymakers through the comprehensive and connectedness energy terms and regulations in respect of technical, social, environmental and economic dynamics of the energy systems. In this regard, it is no doubt necessary for the countries to devise their energy policies to mitigate energy systems vulnerability, especially through economic complexity, which is not explicitly focused on by researchers as the determinant of energy systems measurements.

Hence, this article contributes to filling in the knowledge gap found in the field literature of energy security as follows. First, and based on [10] classifications, the current time series of three behavioral indices, e.g., diversification of primary energy- demand and supply, and non-carbon-based fuel portfolio, are calculated for the 25 large energy-consuming economies during 1998-2018 to analyze the behavior of the cross-country portfolio decisions of primary energy sources. Second, the time-series of the short-term fluctuations and long-term trends of the actual energy resource portfolio measurements, e.g., diversification of primary energy- demand and supply and non-carbon-based fuel portfolio, are extracted using the Hodrick-Prescott filter [21] suggested by [22]. This decomposition helps to recognize the long-term trends and the intensity, time duration, and the number of short-term fluctuations (ups and downs) of the mentioned indices to follow the behavioral characteristics, e.g., risk and resilience, of the cross-energy systems.

Also, the existence of a potential endogeneity is mentioned as an issue in the relationship between diversification of primary energy demand as well as non-carbon-based fuel portfolio and economic complexity with the major controlling factors, e.g., energy intensity, energy prices, resource supply diversity, and CO_2 emissions. Specifically, regardless of the suggested determinants, any unobserved country-specific characteristics may affect the portfolio decisions of primary energy sources [23]. To this end, a threefold procedure is applied in this paper. First, a panel cointegration analysis is used to assess a non-spurious long-run relationship among diversification of primary energy demand and non-carbon-based fuel portfolio and their key factors. In the next step, the panel fixed effects, a two-step difference generalized methods of movements, and quantile regression are utilized to assess how the energy systems indices, e.g., diversification of primary energy demand and non-carbon-based fuel portfolio, react in response to the changes of the determinants. Finally, the interconnection of cyclical movements, extracted using the Hodrick-Prescott filter [21], of diversification of primary energy demand and non-carbon-based fuel portfolio and their determinants through the generalized methods of movements model is focused on exploring the potential a-cyclical, pro-cyclical, or counter-cyclical behavior [24] of the energy systems indices, in response to the short-term fluctuations of economic complexity and the controlling variables.

Accordingly, in order to understand the dynamics of portfolio decisions of primary energy sources across the world's large energy-users, the following research questions are investigated:

- What is the difference in the behavior of actual time-series, short-term fluctuations, and long-term trends of the resource portfolio indicators, e.g., diversification of primary energy- demand and supply, and non-carbon-based fuel portfolio, in the world's large energy-consuming economies?
- How are the energy systems indices, e.g., diversification of primary energy demand and non-carbon-based fuel portfolio, affected in response to the changes of economic complexity and the major control variables, including energy intensity, energy prices, resource supply diversity, and CO_2 emissions?
- How are patterns of short-term fluctuations of diversification of primary energy demand and non-carbon-based fuel portfolio formed in response to cyclical movements of the determinants? A-cyclical, pro-, or counter-cyclical pattern?

The overall findings of this paper support the long-run and causal relationships across energy systems, using the panel cointegration approach and dynamic panel data techniques. Specifically, economic complexity's statistically significant and positive effect on both energy systems indices is detected. Furthermore, from the aspect of cyclical movements, diversification of primary energy demand and non-carbon-based fuel portfolio shows a counter-cyclical and an a-cyclical pattern in response to the short-term fluctuations of economic complexity, respectively. Consequently, the comparative analysis of the findings leads to identifying the portfolio decisions of primary energy sources of the world's large energy-users in order to decline risks and promote resilience of energy systems, i.e., the abundance and equitability, energy safety, and switching to non-carbon-based fuel portfolio, by figuring out its main strengths and weaknesses.

This paper is structured as follows. First, the literature survey, energy resource portfolio measurements, and theory are presented. Then, section 3 provides material and methods. Next, section 4 explains the results and discussion. Finally, conclusions and policy implications are covered in section 5.

2. Literature Survey, Energy Resource Portfolio Measurements, and Theory

2.1 Literature Survey

The first classification of recent studies regarding availability and accessibility dimensions of energy systems (S) focuses on the impact of energy sources' regional and international trade networks on energy security (E.S) [11, 25-28]. It concludes that E.S depends significantly on reliable trade relationships throughout global trade networks of renewables and non-renewables.

The second group of articles investigates determining the risks around S, e.g., energy supply, environment, technology, geopolitical and economic factors, of individual economies and regions [29-36] and finds that energy resource diversification, renewables development, citizen commitment, the mobilization of technological and economic resources, and finally, a model of efficiency, generation, and distribution as well as the preventive- and optimizing control models have constructive roles in optimization of the security status and therefore, E.S enhancement.

The third category of literature analyzes the performance of S based on indicators [37-45]. It exhibits that strategic management, control and storage of energy supply, higher reserves of energy sources, clean energy development, optimization of the structure of terminal energy consumption, energy efficiency (E.E) improvement, and policy monitoring increase the E.S level in the countries under consideration.

The fourth sort of literature considers potential opportunities to develop E.S [46-48]. It reveals the positive effect of investment screening projects such as integrated S on E.S enhancement that is applicable through wave energy, energy hub security region, cross-border transactions in energy infrastructures, subsidizing investments in renewable energy technologies, e.g., storage technologies and shale development, and data-intensive technologies such as the digitalization of the energy sector.

Also, the comparison between the transition towards new and renewable energy sources (N.R.E) or prioritizing fossil fuels as reliable supplies is analyzed from the S dilemma [49-51]. They conclude that focusing on renewables lowers the import dependence of the economy. At the same time, reliable supplies through transmission and storage capability can mitigate the volatility and costs of the energy environment. Also, the combination of E.S perspectives and energy governance helps developing countries to overcome the difficulties of the energy transition process.

Finally, some recent articles investigate the impact of oil price shocks [52-53]; energy intensity [54-55]; geopolitics, including foreign policies and transport disruptions, energy trade shocks and non-trade shocks regarding energy reserves [56]; production disruptions, and price shocks [57]: as well as production capacities on the S [58]. However, the most related conclusion to E.S indicates that the oil shocks lead to breaks in consumption patterns. Also, they show that the development of sustainable entrepreneurship through energy stewardship has a positive impact on E.S.

Therefore, the studies above, however, show no implications for the effect of economic complexity (E.C) with the control variables, e.g., energy intensity (E.I), energy prices (E.P), resource supply diversity (D.P.E.S), and $\mathrm{CO_2}$ emissions (E), on the behavioral characteristics of diversification of primary energy demand (D.P.E.D) and non-carbon-based fuel portfolio (N.C.F.P). Hence, portfolio decisions of primary energy sources (P.D.P.E.S) are analyzed in this paper through the abundance and equitability, and acceptability dimensions of primary energy sources (P.E.S), e.g., coal, crude oil, natural gas, hydroelectric power, and N.R.E. To this end, two indices, e.g., D.P.E.D and N.C.F.P, are calculated for 25 large energy-consuming economies (L.E.C.E) to expose the importance and potential risks, and the benefits regarding the P.D.P.E.S, in response to the changes in E.C. Necessarily, the economies should utilize the efficient portfolio diversification of P.E.S throughout their S to capture long-term E.S [36].

2.2 Energy Resource Portfolio Measurements (E.R.P.M)

a. Diversification of Primary Energy Demand

D.P.E.D balances the energy mix to cope with the market shocks of energy resources that lead to volatility reduction of fuel prices contributes to energy price stability and promotes the energy safety, availability, and affordability aspects of E.S, based on the preferred objective priorities of the S [35]. The Shannon index is modified in this paper to measure the D.P.E.D, presented by the first energy resource portfolio indicator (D.P.E.D). Therefore, D.P.E.D exhibits abundance and equitability dimensions of the resource diversification of the S that is shown below:

$$D_d = -\sum_{i=1}^{T}(P_i \ln P_i), \quad (1)$$

$$D.P.E.D = \frac{D_d}{D_{d,max}} \times 100 \quad (2)$$

where, D_d is Shannon's resource demand diversity index, P_i shows the share of P.E.S i in total primary energy demand (P.E.D), $D_{d,max}$ displays the maximum value of D_d and $i = (1, 2, \ldots, T)$ is used to indicate T types of P.E.S. The calculated indicator is close to zero, so the country depends on one P.E.S. On the other hand, a value close to 100 indicates that the economy's energy consumption sources are equally distributed among the major P.E.S. Thus, a lower risk of the country's S security is concluded as a higher indicator's value is assessed. The benefits of D.P.E.D can be achieved as the energy sources would be substituted in the energy mix supported by resource availability and negative correlations among resource prices [3].

b. Non-Carbon-Based Fuel Portfolio (N.C.F.P)

The second energy resource portfolio indicator (N.C.F.P) reflects the economy's success in contributing to the environmental and energy safety that may be achieved by switching from a carbon-intensive to N.C.F.P. The second indicator implies the contribution level of hydro, nuclear, and N.R.E to total P.E.D, presented as follows:

$$N.C.F.P = \frac{\text{Hydro } P.E.D + \text{Nuclear } P.E.D + N.R.E\ P.E.D}{\text{Total } P.E.D} \times 100 \quad (3)$$

The N.C.F.P indicator quantifies the progress of each country's diversification towards alternative energy sources by improving the share of non-fossil fuel energy sources (N.R.E) applied to meet energy consumption. Therefore, a markedly potential offset to the greater decarbonization of the country's S security is concluded as a higher indicator's value is calculated. The utmost important matter is that if non-carbon-based fuel switching does not grow enough to cover the growth of future P.E.D, the associated emissions will increase. In this case, most countries will require to intensify their targeted efforts on potential CO_2 capture and storage technologies to achieve the agreed United Nations objectives on E reductions [2,10].

2.3 Theory

The interaction of knowledge, innovation, productive structure, structural changes, and capabilities of the economic systems is focused through the E.C [14-15] to explain the S dynamics that affect the sector- and source-based energy consumption patterns of the economies.

As the first possible channel, it is expected that D.P.E.D and N.C.F.P go down in response to the increase of E.C due to the rebound effects of technology on energy consumption [59] and low and median productivity levels that are caused by underdeveloped and developing technologies [5,60]. It is noted that technological improvements promote economic growth and increase efficiency, lowering the cost of energy consumption and hence, increasing energy usage, which is called the rebound effect [59]. On the other hand, higher knowledge and greater technological and economic progress lead to more levels of elasticity-income and price [59] and productivity and E.E [61] that improves D.P.E.D and N.C.F.P and encourages the energy trilemma (E.T) [1,62]. Hence, the P.D.P.E.S in respect of equitability and abundance, energy safety, and decarbonization process, may be either diminished or enhanced when the S faces higher levels of E.C. Consequently and due to the existence of two different affecting channels, it is needed to empirically examine the impact of E.C on D.P.E.D and N.C.F.P that is the aim of this research.

Besides, D.P.E.S entails restraining new energy resources and enhancing energy safety and E.S [19], which requires investments and new technologies throughout the S and presents by [35]:

$$\mathrm{D_s} = -\sum_{\mathrm{i}=1}^{\mathrm{T}}(\mathrm{P_i} \ln \mathrm{P_i}), \tag{4}$$

$$\mathrm{D.P.E.S} = \frac{\mathrm{D_s}}{\mathrm{D_{s,max}}} \times 100 \tag{5}$$

Where, $\mathrm{D_s}$ is Shannon's supply diversity index, $\mathrm{P_i}$ shows share of $\mathrm{PES_i}$ production in total primary energy supply and $\mathrm{i} = (1, 2, \ldots, \mathrm{T})$ is used to indicate T types of P.E.S. Based on the calculated values of D.P.E.S. The economy succeeds in harnessing new energy resources if the final value of D.P.E.S is closer to 100%. While a value close to zero exhibits that the country highly requires investments and new technologies throughout the S. Thus, a lower risk of (i) resource abundance and equitability, (ii) energy safety, and (iii) S decarbonization is concluded when a higher indicator's value to be assessed [10]. It is worth noting that the major factors determining benefits of D.P.E.S and hence, encouraging the E.T are classified as: (i) accessing to raw materials, (ii) environmental conditions, (iii) exploitation and production cost, (iv) technology improvement, and (v) political factors [63].

In the following, to know how E.C and D.P.E.S are matched with D.P.E.D and N.C.F.P, the behavioral characteristics of knowledge, innovation, and technology mix, and D.P.E.S are analyzed via Figs. 1 and 2[1]. Based on Fig. 1, a downward (upward) trend is found in E.C for Australia, Brazil, Russia, South Africa, Spain, and Ukraine (China, India, Indonesia, Italy, Mexico, Poland, South Africa, Thailand, and Turkey), showing they are downgraded (upgraded) in the innovation process and technological improvements in the past few years. Also, no specific upward or downward trend is exhibited for Canada, Denmark, France, Germany, Netherlands, New Zealand, Norway, the UK, and the US. Furthermore, significant changes in the intensity and number of ups and downs for short-term fluctuations (S.T.F) of E.C have been detected for all 25 countries in recent years, indicating the E.C is vulnerable to the market shocks and hence, can cause cyclical movements and uncertainty throughout the S of the L.E.C.E.

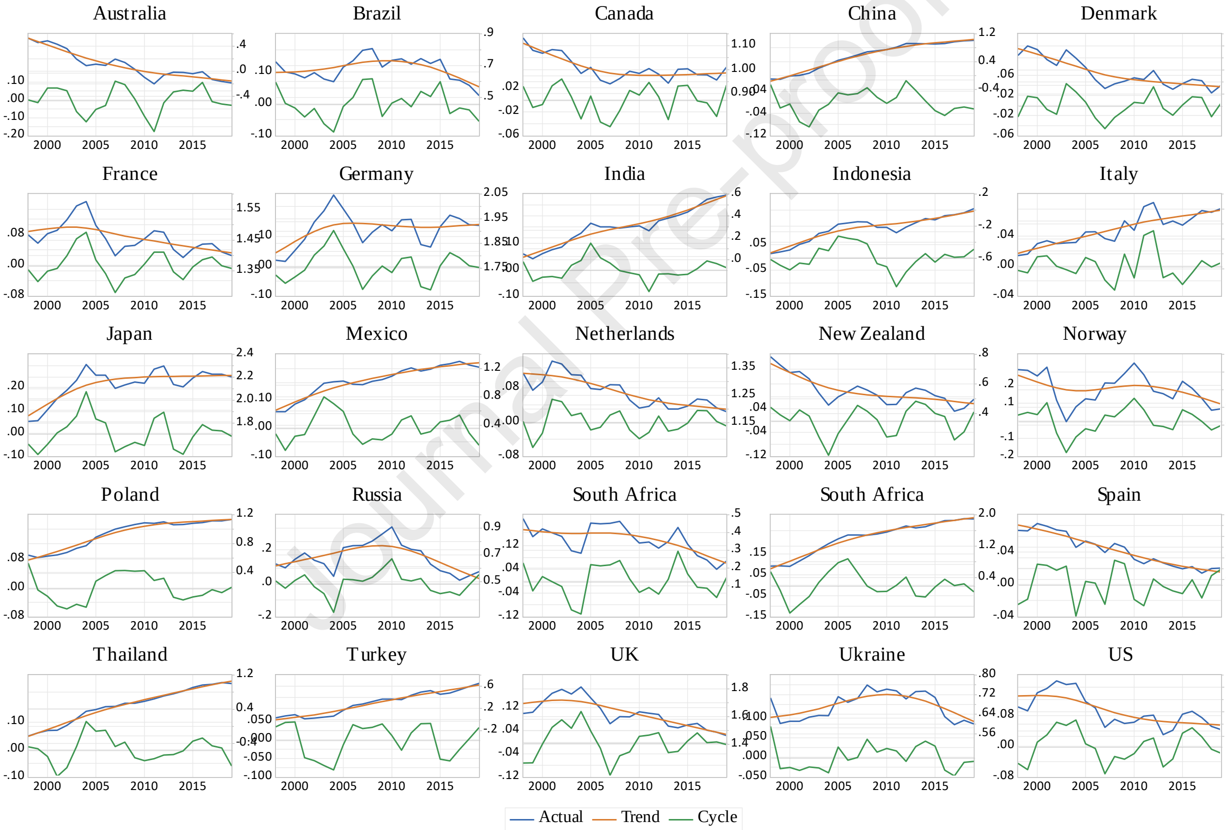


Fig. 1 Actual Time-Series, Short-Term Fluctuations, and Long-Term Trends of Economic Complexity

Also, according to Fig. 2, an upward (downward) trend is found in D.P.E.S for Brazil, China, Denmark, Japan, Mexico, Netherlands, Norway, and Poland (Canada, France, Germany, India, Indonesia, Italy, New Zealand, South Africa, South Korea, Spain, and Turkey). This behavior shows they upgraded (downgraded) the investments and new technologies for

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[1] Left vertical axes: the value of cyclical movements (S.T.F) of E.C, Right vertical axes: the value of actual time-series (A.T.S) and long-term trends (L.T.T) of E.C, and Horizontal Axes: the time period.

achieving new energy resources, especially in the past few years. Also, neither a specific upward nor particular downward trend is concluded for Australia, the UK, Ukraine, and the US. Furthermore, except for Canada, Russia, and the US, significant changes in the intensity and number of ups and downs for S.T.F of D.P.E.S have been detected for all countries in recent years, indicating the D.P.E.S is vulnerable to market shocks and can cause cyclical movements and uncertainty throughout the S of L.E.C.E.

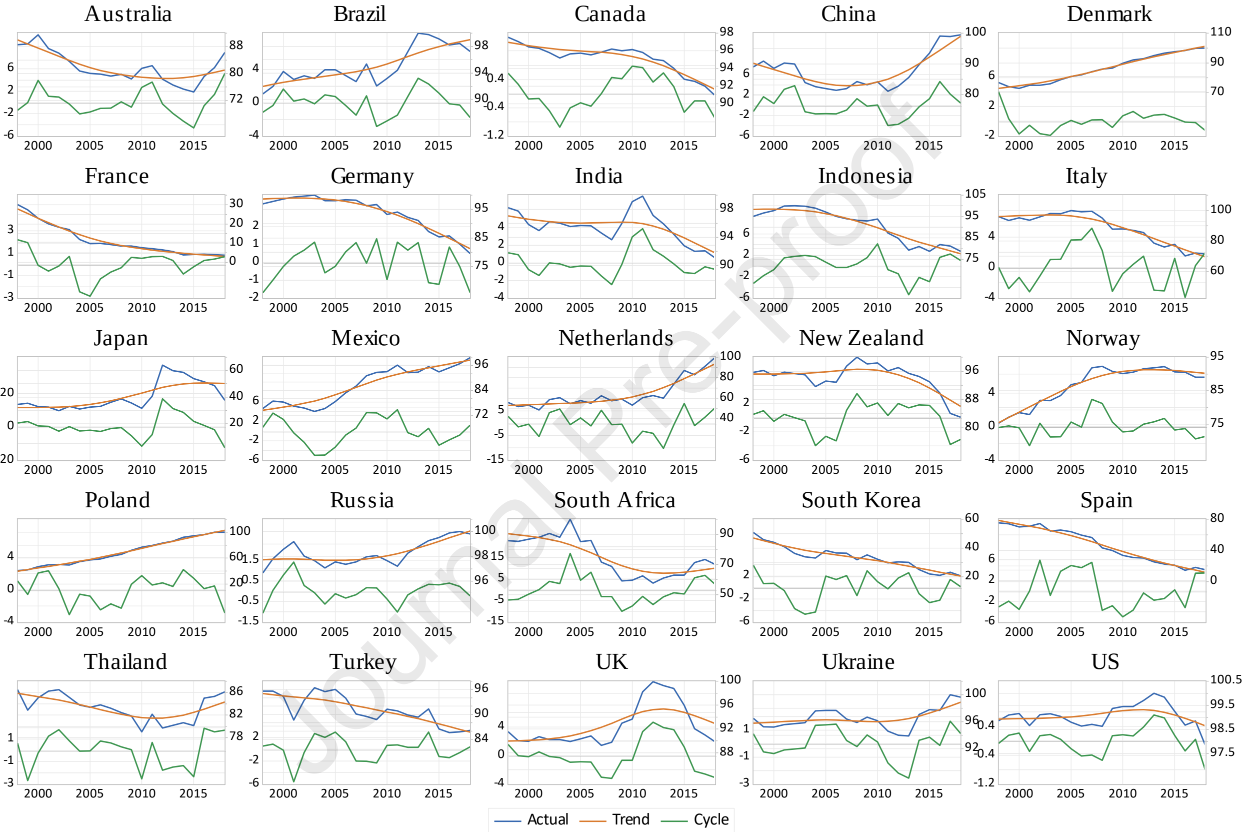

Fig. 2 Actual Time-Series, Short-Term Fluctuations, and Long-Term Trends of Diversification of Primary Energy Supply

Concerning the control variables, E.S takes into account the effect of E.P on P.D.P.E.S [36]. The higher the E.P, the higher the D.P.E.S is obtained, which entails harnessing new energy resources, which is conducive to resource equitability and abundance, energy safety, and switching to N.C.F.P [19]. Hence, it is necessary to control for E.P while studying the dynamics through the issue of E.T [37]. Therefore, the consumer price index (C.P.I) is used in this study as a representative for E.P since E.P are not available for all the economies considered in the sample. Moreover, the C.P.I indicates the fluctuations in the prices through a basket of "consumer goods and services", and has been widely applied as a proxy in respect of E.P within the recent energy literature [64-65, among others].

As the other key control factor defining the S dynamics [66], E.I is characterized by various determinants based on the structural features of the S [67]. The concept of E.I attribute to the ratio of energy consumption to economic output [68] that covers a range of aspects regarding E.S and P. D. P. E. S [69] of the S. It is important to investigate the impact of E.I on D.P.E.D and N.C.F.P, due to a potential interaction between source- and sector-based energy consumption [70], energy safety, economic competitiveness, technological innovation, and energy policies [71].

Also, the dynamics of E reduction provide information on cleaner technologies, energy safety, and S decarbonization, moderate climate change, help to upgrade the developing measures utilized throughout environmental protection, and mitigate global warming [72]. It is worth noting that energy consumption is affected in response to productivity change. Energy sources, especially non-renewables, also lead to increased emissions and ecological footprint [59]. Therefore, the switching to N.C.F.P is expected to be affected in response to the increase of E [10]. Specifically, it is applicable to develop the countries' sector- and source-based energy consumption policies in respect of global warming [73], as energy consumption is connected to productivity, E.C, E.E, energy safety, and cleaner technologies [16], and E.P as well as P.D.P.E.S [36].

3. Material and Methods

3.1 Material

In order to calculate the time-series of D.P.E.D, N.C.F.P, and D.P.E.S, the energy consumption and production data for 25 L.E.C.E, including Australia, Brazil, Canada, China, Denmark, Germany, France, India, Indonesia, Italy, Japan, Mexico, Netherlands, New Zealand, Norway, Poland, Russia, South Africa, South Korea, Spain, Thailand, Turkey, United Kingdom, Ukraine, and the United States [20] in billion cubic feet for each P.E.S, e.g., coal, natural gas, crude oil, hydroelectric power, nuclear and new and renewable energy, as well as E.I and E are collected from the US Energy Information Administration/Monthly Energy Review [63] during 1998-2018. Also, the time-series data for the C.P.I, as a proxy for E.P and E.C of the countries under consideration, are retrieved from the World Bank database and the Observatory of

Economic Complexity [74], respectively. Accordingly, a balanced panel of 25 countries covering 21 years contains 525 observations.

3.2 Methods

The method of this research follows two major steps. First, it is assessed whether D.P.E.D and N.C.F.P as the dependent variables, E.C as the explanatory variable, and E.I, E.P, D.P.E.S, and E as the controlling variables are connected through a non-spurious and long-run relationship. To this end, it is preliminary tested whether the time-series under consideration is non-stationary due to the potential existence of a unit root process. If yes, whether they follow a joint unit root process is tested by applying panel cointegration approaches. In order to test for the existence of a unit root process, the Levin, Lin, and Chu (L.L.C) unit root statistic is used that is consistent with time-trends and effects. The null hypothesis of the test suggests that all mentioned panel-series follow the non-stationary process. At the same time, the alternative assumes the fraction of panel-series that shows the stationary process is nonzero. If the dependent and independent variables are not stationary at level, it is proceeded to check for the cointegration test. Under the null hypothesis of no cointegration, Pedroni's Engle-Granger (P.E.G) technique is applied to be well-compatible with small-sample features. It is concluded that a long-run relationship within the model is not spurious, as the results reject the null hypotheses. Alternatively, the Johansen-Fisher (J.F) approach is also used to test for cointegration to show that all mentioned panels are cointegrated and check for the common time effect by subtracting the cross-section's mean from the actual series.

Subsequently, we perform panel-data-based specific residual cross-section dependence (C.D) and causality testing. To this end, least squares regressions can catch several forms, depending on assumptions made to the panel data structure. Several approaches can be considered to examine the C.D test, e.g., Breusch-Pagan LM, Pesaran scaled LM, and Pesaran C.D, as well as Granger causality tests such as stacked test and Dumitrescu-Hurlin causality test in a panel data context. Since the number of cross-sections is relatively small, it is focused on the results of the Pesaran C.D test, which is the asymptotically standard normal test [65]. In respect of the Granger causality test, if a large stacked panel-dataset is suggested, then pairwise Granger causality tests are performed in the standard form. This method supposes that all estimated coefficients are similar across all used cross-sections. The different tests of panel causality differ on the homogeneity assumptions made to the coefficients among cross-sections. Particularly, the Pairwise Dumitrescu-Hurlin panel causality test is used in this paper, which makes an extremely contrary assumption, allowing the coefficients to be dissimilar between cross-sections. Specifically, this test is performed by running the regressions through standard Granger causality method for each applied cross-section. Then, the average value of the statistics is taken to meet that the standardized form of this statistic, properly weighted in the panels, observes a standard and normal distribution [65].

The second step assesses the impact of explanatory- and control variables on D.P.E.D and N.C.F.P via regression analysis. Since it is interested in controlling the long-run elasticities of both D.P.E.D and N.C.F.P to E.C and control variables, the following equation is started to estimate:

$$\ln(\mathrm{E.R.P.M}_{i,t}) = \beta_0 + \beta_1 \ln\left(\mathrm{E.C_{i,t}}\right) + \mathrm{X}'_{\mathrm{i,t}}\beta_2 + \theta_{\mathrm{t}} + \mathrm{U_{i,t}} \quad (6)$$

Where i is the country, t is the year, X is the vector of control variables, e.g., E.I, E.P, D.P.E.S, and E, and all variables are used in natural logarithm form to remove the potential serial correlation effects. Also, θ_{t} is a year-specific effect used to capture the effect of market shocks and cycles, and finally, $\mathrm{U_{it}}$ is the stochastic error term, which is independent of the other determinants.

Based on [75], equation (6) is estimated by the panel dynamic least squares (P.D.L.S) within pooled method. The P.D.L.S technique allows us to consider the potential endogeneity and leads to asymptotically efficient and unbiased estimations through the long-run relations, even if the model encompasses endogenous regressors [76]. Additionally, in the panel-data samples with small T, the P.D.L.S method performs more comprehensively than other existing estimators, like the panel fully modified least squares (P.F.M.L.S) [77]. The mean-variance inflation factor (V.I.F) statistic is used to test for the probable existence of multicollinearity within the model [78]. As mentioned before, it is tested whether $\beta_1 > 0$ or $\beta_1 < 0$ means that a higher E.C relates to a greater or smaller level of D.P.E.D and N.C.F.P. However, some limitations might be considered through the results of the P.D.L.S model. The first possible anomaly refers to the heterogeneity issue going unanswered in the relationship between each of D.P.E.D and N.C.F.P, and the suggested determinants because of unobserved characteristics that may affect D.P.E.D and N.C.F.P and the major determinants, which further correlate with the error term lead to the biased P.D.L.S estimations. The geopolitics factors, climatic conditions, the quality and quantity of energy resources, especially crude oil, and efficiency of energy transport infrastructures are the main types of the mentioned unobserved affecting factors [60] in the 25 L.E.C.E. Therefore, in the next phase, the country fixed effects, including country-specific features, are used to account for heterogeneity issue. Then, the below equation is estimated for both measurements:

$$\ln(\mathrm{E.R.P.M}_{i,t}) = \beta_1 \ln\left(\mathrm{E.C}_{i,t}\right) + X'_{i,t}\beta_2 + \mu_i + \theta_t + \varepsilon_{i,t}, \tag{7}$$

Where μ_i indicate the country fixed effects characteristics that capture time-invariant affecting factors, which may have a potential correlation with the suggested explanatory variables, and finally, ε_{it} is considered the stochastic error term. However, the estimation of fixed effects is probably biased due to the existence of the C.D that should be considered if D.P.E.D and N.C.F.P as the dependent variables and E.C as the explanatory- and E.I, E.P, D.P.E.S, and E, as the major control variables contribute to common omitted affecting factors. Notably, subtraction through each regressor's mean value is the standard technique to account for the issue of such unobservable elements. This viewpoint is equivalent to comprising year dummies in the fixed effects estimates [23]. In order to check the existence of the C.D throughout the residual terms of the applied fixed effects regression model, the C.D statistics specified by [79] are used, which is based on a test statistic with normal distribution by the null hypothesis of no C.D. Alternatively, the equation (7) is also estimated through diverse coefficient methods, e.g., white cross-section and white period, among others, since the standard errors have been calculated in the non-parametric form and are applicable to make robustness for serial autocorrelation, heteroscedasticity, and C.D across suggested panels [80].

Then, it is considered that the previous date values may also explain D.P.E.D and N.C.F.P at time t and that S indices, E.C, and control variables can be defined simultaneously. Accordingly, a linear dynamic model of panel data series is estimated through the G.M.M method in the form of a two-step difference that accounts for simultaneity, persistence, and fixed effects, suggested by [81]. The G.M.M method covers the cause-effect relations among the variables, e.g., dependent and independent, over time, supported by lagged dependent variables as explanatory and instrumental variables. Also, we include the lagged regressors as the instrumental variables for linear equations with auto-regressive (A.R) terms to control the endogeneity. They are the internal instrumental variables since they are employed from the estimated econometric model. In addition, different forms of endogeneity, including dynamic endogeneity, unobserved heterogeneity, and simultaneity, are eliminated via internal data transformation; hence, unbiased estimations are expected through the G.M.M model [82]. The value subtraction captures the internal data transformation in each variable's past and present dates.

Furthermore, and based on [82], it is suggested that the idiosyncratic error terms are uncorrelated across individuals. Therefore, there may be no necessity for some of the determinants to be strictly exogenous. Moreover, the second-order transformation of the G.M.M model is used to avoid unnecessary data loss, recommended by [83]. The second-order transformation approach of the G.M.M method subtracts the average value of all future- and available observations of each variable via "forward orthogonal deviation" rather than subtracting the previous amounts of the variable from its present observation [82]. Then, the Arellano-Bond (A.B) test is used to check for the serial correlation in the residuals. Finally, the Sargan J (S.J) statistics examine the over-identifying restrictions of the models. Hence, and based on [61,82], the G.M.M method is used in this paper as follows:

$$\Delta\ln\left(\mathrm{E.R.P.M}_{i,t}\right) = \rho\,\Delta\ln\left(\mathrm{E.R.P.M}_{i,t-1}\right) + \beta_1\,\Delta\ln\left(\mathrm{E.C}_{i,t}\right) + \Delta X'_{i,t}\beta_2 + \Delta\varepsilon_{i,t} \tag{8}$$

It is noted that equation (8) is estimated to follow the performance of D.P.E.D and N.C.F.P in response to the first difference (Δ) of the major affecting factors. In addition, the fixed effects are removed by using Δ for all the variables through the G.M.M model, while the vector of time dummies is included to capture the impact of the macroeconomic shocks and business cycles. Also, the panel quantile regression (P.Q.R) [84] is applied and reveals no concern regarding the restrictive assumption of the identical distribution of error terms [85] and robustness with the presence of outliers [86]. Accordingly, the below equation is estimated for both S indices:

$$\ln(\mathrm{E.R.P.M}_{i,t}) = \beta_0^{\theta} + \beta_1^{\theta}\ln\left(\mathrm{E.C}_{i,t}\right) + \left(X'_{i,t}\right)\beta_2^{\theta} + \varepsilon_{i,t} \tag{9}$$

Where $B_0^{\theta}, \ldots, B_n^{\theta}$ are the estimated P.Q.R coefficients, θth is the regression quantile, which ranges from 0.1 to 0.9, and ε_t represents the random error.

Besides, the patterns of S.T.F of D.P.E.D and N.C.F.P in reaction to cyclical movements of the key determinates are captured by equation (10):

$$\varphi \ln(\mathrm{E.R.P.M}_{i,t}) = \rho\varphi \ln\left(\mathrm{E.R.P.M}_{i,t-1}\right) + \beta_1\, \varphi \ln\left(\mathrm{E.C}_{i,t}\right) + \varphi X'_{i,t}\beta_2 + \varphi\varepsilon_{i,t} \tag{10}$$

Where φ indicates the short-term fluctuations of the actual D.P.E.D and N.C.F.P, and E.C, and control variable, e.g., E.I, E.P, D.P.E.S, and E, that are extracted from their L.T.T, using the Hodrick-Prescott (H.P) filter [21].

4. Results and Discussion

4.1 Results

4.1.1 Actual Time-Series, Short-Term Fluctuations, and Long-Term Trends of Diversification of Primary Energy Demand and Non-Carbon-Based Fuel Portfolio

The P.D.P.E.S of an economy develops when the higher values of S indicators, e.g., D.P.E.D and N.C.F.P, are detected. However, the different potential reactions of D.P.E.D and N.C.F.P in response to the market shocks may be explained by the sensitivity level of renewable and non-renewable consumption for the specified indicators. Also, the different roles of oil and other mentioned energy sources should not be neglected to analyze the suggested reactions [59]. For instance, new and renewable energy technologies, e.g., wind, solar, hydro, and biomass, require investments and new technologies throughout the S [35] in respect of (i) accessing to raw materials, (ii) environmental conditions, (iii) exploitation and production cost, (iv) technology improvement, and (v) political factors [63], for vulnerability reduction of the economies to oil price shocks as the prices of renewables are insensitive to oil price shocks [87]. Accordingly, the H.P filter [21] is applied to decompose the calculated A.T.S of D.P.E.D and N.C.F.P to the S.T.F and L.T.T (Figs. 3-4)[2], finding any potential changes experienced by each country, and understanding the behavioral characteristics, e.g., risk and resilience, of the cross-systems E.S.

a. Diversification of Primary Energy Demand

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[2] Left vertical axes: the value of S.T.F of D.P.E.D and N.C.F.P, Right vertical axes: the value of A.T.S and L.T.T of D.P.E.D and N.C.F.P and Horizontal Axes: the time period

Based on Fig. 3, the calculated D.P.E.D shows a considerable upward trend in recent years for Australia, Brazil, China, Germany, Indonesia, Italy, Mexico, Netherlands, Poland, South Africa, South Korea, Spain, Thailand, Turkey, and Ukraine, indicating the energy consumption sources have been getting more equally distributed among the major P.E.S in the suggested economies. Therefore, a lower risk of resource equitability and abundance is concluded. On the other hand, the findings expose a higher-risk and fewer-resilience of S for Canada and France since a decreasing trend is detected in their D.P.E.D, while the rest of the countries show no significant change in their D.P.E.D. It is also met that the S.T.F of D.P.E.D for all countries under consideration are affected by market shocks of their S regarding intensity and the number of ups and downs, especially in the recent years.

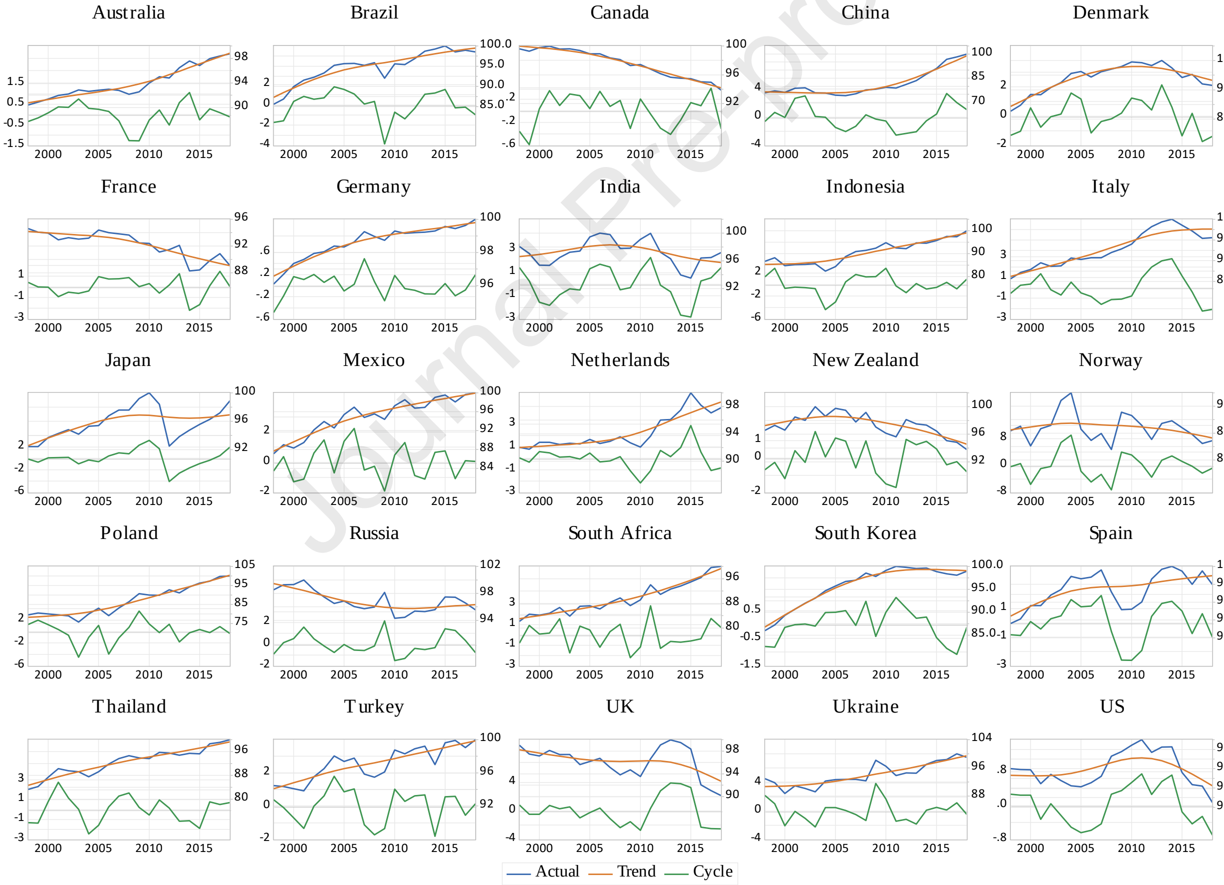

Fig. 3 Actual Time-Series, Short-Term Fluctuations, and Long-Term Trends of Diversification of Primary Energy Demand

b. Non-Carbon-Based Fuel Portfolio

The second calculated S indicator, N.C.F.P, shows a degradation in the decarbonization process for Brazil, Japan, and South Korea in the past few years, as a downward trend is found in switching from a carbon-intensive to N.C.F.P. Also, no specific upward or downward trend is met through N.C.F.P for Canada, New Zealand, Norway, and Russia. Moreover, a considerable offset in order to lower degradation in the decarbonization process of the rest of countries' S is concluded since they expose an upward trend in their N.C.F.P. Furthermore, the results indicate no significant changes in the intensity and number of ups and downs for S.T.F (resilience) of Norway's N.C.F.P in recent years. At the same time, the rest of the economies are successfully switching towards alternative energy sources by improving the share of non-fossil fuel energy sources applied to meet energy consumption (Fig. 4).

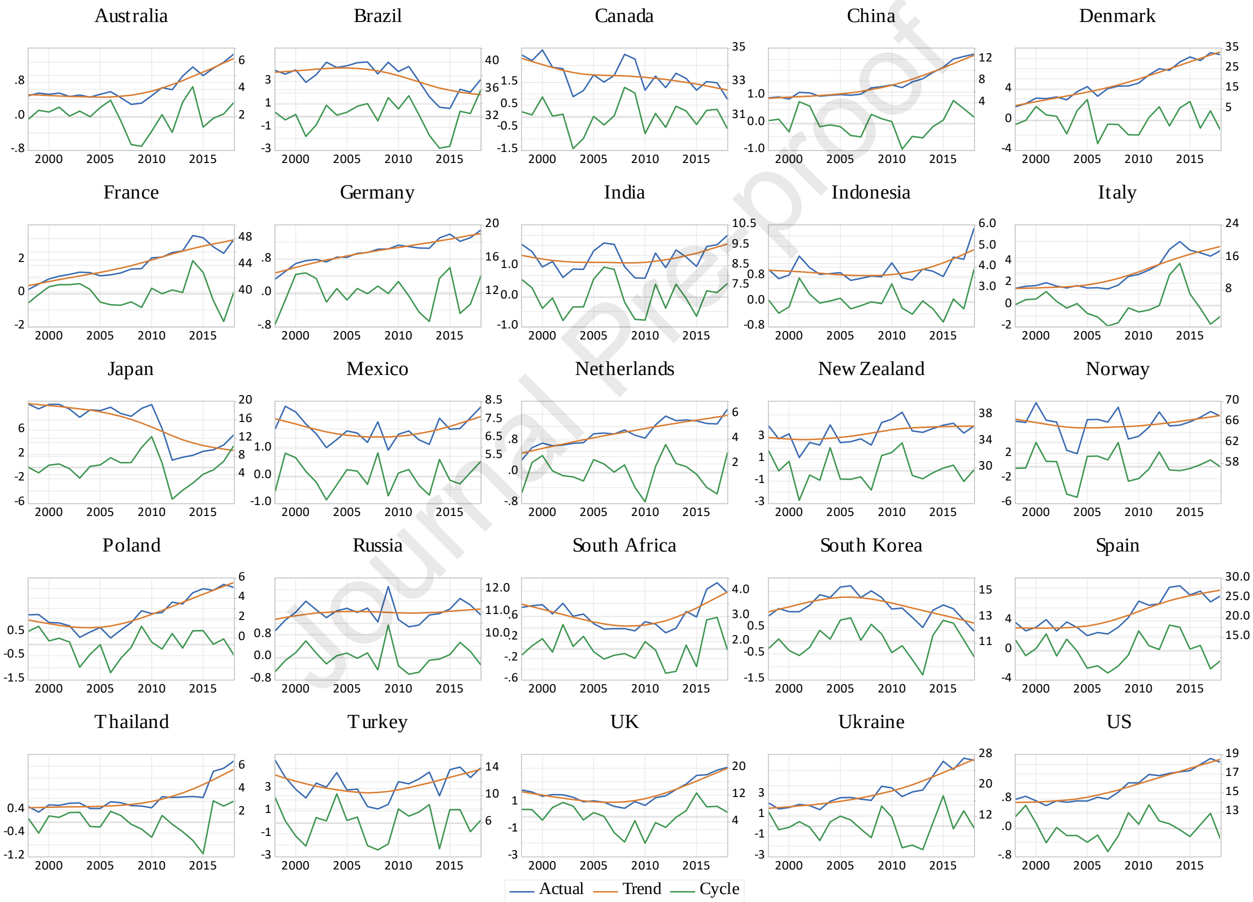
Australia Brazil Canada China Denmark
France Germany India Indonesia Italy
Japan Mexico Netherlands New Zealand Norway
Poland Russia South Africa South Korea Spain
Thailand Turkey UK Ukraine US

Fig. 4 Actual Time-Series, Short-Term Fluctuations, and Long-Term Trends of Non-Carbon-Based Fuel Portfolio

Accordingly, the potential impact of E.C and the major control factors, including E.I, E.P, D.P.E.S, and E, on the behavioral characteristics of the P.D.P.E.S, e.g., D.P.E.D and N.C.F.P, should be analyzed since the S of the L.E.C.E depends on the modes and specifications of any changes experienced by each P.E.S [1,5].

4.1.2 Descriptive Statistics, Correlations, Unit Root, Cointegration, Cross-Section Dependence, and Causality Tests

In the next step, this study investigates the descriptive statistics, correlations, unit roots, cointegration, cross-section dependence, and causality tests of the utilized variables to satisfy the pre-requisites of the applied econometric models. Specifically, and based on [87], static methods are not appropriate for S to model behavioral characteristics of D.P.E.D and N.C.F.P in response to the changes in the major determinants, as all the mentioned variables are skewed and leptokurtic via their distribution functions (Table 1). Also, the results indicate very weak correlation relationships between regressors that support no concern regarding the potential problems of multicollinearity [61].

Table 1 Descriptive Statistics and Correlations

Variable	Mean	Median	Max	Min	Std.Dev	Skewness	Kurtosis	Normality (Prob)
D.P.E.D	4.5	4.6	4.6	4.3	0.06	-1.6	5.6	0.00
N.C.F.P	2.4	2.5	4.2	-11.2	1.1	-3.7	45.1	0.00
D.P.E.S	4.3	4.5	4.6	1.3	0.5	-2.9	12.7	0.00
E.C	0.2	0.4	1.04	-14.2	0.8	-10.5	175.3	0.00
E.P	4.5	4.6	5.6	2.1	0.3	-2.2	13.9	0.00
E.I	1.6	1.5	3	0.9	0.4	0.6	2.7	0.00
E	6.13	6.06	9.3	3.5	1.2	0.04	3.6	0.00

Correlations	D.P.E.D	N.C.F.P	D.P.E.S	E.C	E.P	E.I	E
D.P.E.D	1	-	-	-	-	-	-
N.C.F.P	0.37	1	-	-	-	-	-
D.P.E.S	0.07	-0.14	1	-	-	-	-
E.C	0.23	0.23	-0.18	1	-	-	-
E.P	0.24	0.07	-0.1	0.25	1	-	-
E.I	-0.23	0.02	0.1	0.04	-0.2	1	-
E	-0.01	-0.16	-0.02	0.12	0.05	0.2	1

Notes: D.P.E.D: Diversification of Primary Energy Demand; N.C.F.P: Non-Carbon-Based Fuel Portfolio; D.P.E.S: Diversification of Primary Energy Supply; E.C: Economic Complexity; E.I: Energy Intensity; E.P: Energy Prices; E: CO_2 Emissions

Table 2 presents the results of the unit root, cointegration relationships, cross-section dependence, and causality tests. The upper part of the table shows the results of the L.L.C unit root process at the level and Δ of the utilized variables. The findings at the level exhibit that the null hypothesis is not rejected for all the variables, indicating the exitance of a unit root process in all applied panels at a 1% significance level. Besides, the results support that all the used variables are stationary at the 1% significance level in theirs Δ. It shows that equation (5) estimations using the ordinary least squares method might lead to spurious correlations. Therefore, the econometric techniques suggested in section (3.2) are more appropriate to justify the behavioral characteristics of D.P.E.D and N.C.F.P in reaction to the changes in E.C and the control variables.

The middle parts of table 2 provide the results of cointegration tests. Due to the applied sample with a small T, choose one lag and one lead for the equations (5-8). The null hypothesis of P.E.G cointegration statistics (no cointegration) is strongly rejected for both D.P.E.D and N.C.F.P. It represents that the equations (5-8) will support no spurious relationships. The J.F approach is also used to test the robustness for cointegration and the common time effect that shows all mentioned panels are cointegrated.

Further, the lower parts of table 2 show the results of the Pesaran C.D test and pairwise Dumitrescu-Hurlin panel causality test. Based on the findings, the Pesaran C.D test does not reject the null hypothesis for both applied models, e.g., D.P.E.D and N.C.F.P, at the conventional significance levels. Finally, in respect of the causality test, it is rejected the null that E.C as the explanatory variable and the rest as the major control variables do not homogeneously cause D.P.E.D and N.C.F.P orderly.

Table 2 Unit Root, Cointegration, Cross-Section Dependence, and Causality Tests

Levin, Lin & Chu Unit Root Statistics				
	Level (Individual Trend & Intercept)		First Difference (Intercept)	
Variable	Statistic	Prob	Statistic	Prob
D.P.E.D	-1.4	0.12	-8.76	0.00
N.C.F.P	1.53	0.93	-10.48	0.00
D.P.E.S	0.8	0.8	-5.9	0.00
E.C	1.41	0.92	-12.31	0.00
E.P	0.4	0.7	-4.9	0.00
E.I	-0.62	0.27	-6.06	0.00
E	-1.13	0.19	-4.72	0.00
Cointegration Tests: D.P.E.D Model				
Pedroni (Null: No Cointegration)	Statistic	Prob	Weighted Statistic	Prob
Phillips–Perron Statistic	-2.6	0.00	-2.9	0.00
Augmented Dickey-Fuller Statistic	-2.4	0.00	-2.4	0.00
Johansen-Fisher (Null: Cointegration)	Statistic (Trace)	Prob	Statistic (Max-Eigen)	Prob
Unrestricted Cointegration	54.42	0.3	54.42	0.3
Cointegration Tests: N.C.F.P Model				
Pedroni (Null: No Cointegration)	Statistic	Prob	Weighted Statistic	Prob
Phillips–Perron Statistic	-9	0.00	-4.4	0.00
Augmented Dickey-Fuller Statistic	-2.4	0.00	-3.2	0.00
Johansen-Fisher (Null: Cointegration)	Statistic (Trace)	Prob	Statistic (Max-Eigen)	Prob
Unrestricted Cointegration	45.56	0.65	45.56	0.65
Cross-Section Dependence Test (Null: No Cross-Section Dependence)			Statistic	Prob
Pesaran Cross-Section Dependence: D.P.E.D Model			0.65	0.5
Pesaran Cross-Section Dependence: N.C.F.P Model			0.28	0.7
Pairwise Dumitrescu Hurlin Panel Causality Tests: D.P.E.D Model		W-Stat	Zbar-Stat	Prob
E.C does not homogeneously cause D.P.E.D		4.03	3.08	0.00
E.P does not homogeneously cause D.P.E.D		4.3	3.6	0.00

E.I does not homogeneously cause D.P.E.D	6.9	8.4	0.00
D.P.E.S does not homogeneously cause D.P.E.D	3.7	2.5	0.00
Pairwise Dumitrescu-Hurlin Panel Causality Tests: N.C.F.P Model	W-Stat	Zbar-Stat	Prob
E.C does not homogeneously cause N.C.F.P	1.8	2	0.04
E.P does not homogeneously cause N.C.F.P	2.8	4.8	0.00
E.I does not homogeneously cause N.C.F.P	4.6	9.8	0.00
D.P.E.S does not homogeneously cause N.C.F.P	2.3	3.3	0.00
E does not homogeneously cause N.C.F.P	2.4	3.5	0.00

Notes: D.P.E.D: Diversification of Primary Energy Demand; N.C.F.P: Non-Carbon-Based Fuel Portfolio; D.P.E.S: Diversification of Primary Energy Supply; E.C: Economic Complexity; E.I: Energy Intensity; E.P: Energy Prices; E: CO_2 Emissions

4.1.3 Panel Model Estimations

Table 3 exhibits the P.D.L.S and P.F.M.L.S estimations of equation (6). The P.D.L.S estimated coefficients of E.C are positive and statistically significant for both models, e.g., D.P.E.D and N.C.F.P, showing a 1% increase in E.C leads to an average 0.06% and 0.95% increase in D.P.E.D and N.C.F.P, respectively. Moreover, and as one of the controlling extraneous variables, it is found that the E.I is negatively correlated with both D.P.E.D and N.C.F.P. The estimations also indicate that N.C.F.P lowers with the amount of E.P, D.P.E.S, and E, while D.P.E.D positively correlates with both E.P and D.P.E.S. From the aspect of explanatory power, P.D.L.S meets 96% and 98% of R-squared for D.P.E.D and N.C.F.P models, respectively that are greater than P.F.M.L.S determinations. It is noted that the results of the P.F.M.L.S and P.D.L.S models are relatively different, which may be due to a potential non-linearity throughout the models. Therefore, for the robustness test, both suggested models are re-estimated, including the squared term of the explanatory variables, indicating that non-linearity through the relationships is not a deterministic issue [61]. Hence, it is suggested that the P.D.L.S technic performs more meticulously, based on [77].

Furthermore, in accordance with [78], the models do not suffer from the multicollinearity issue since the mean V.I.F statistics meet low values, compatible with the correlation results presented in table 1 [61]. The results of both D.P.E.D and N.C.F.P models indicate that V.I.F statistics of the explanatory- and control variables and the specified mean V.I.F value are lower than the suggested standard values, which are 10 and 6, respectively [78].

Table 3 P.D.L.S vs. P.F.M.L.S Estimates of D.P.E.D and N.C.F.P

	P.D.L.S		P.F.M.L.S	
Variable	D.P.E.D Model	N.C.F.P Model	D.P.E.D Model	N.C.F.P Model

Economic Complexity	0.06 (0.00)	0.95 (0.00)	0.03 (0.03)	0.09 (0.00)
Energy Intensity	-0.05 (0.00)	-1.14 (0.00)	-0.09 (0.00)	-1.3 (0.00)
Energy Prices	0.03 (0.00)	-0.28 (0.00)	0.02 (0.00)	-0.13 (0.00)
Diversification of Primary Energy Supply	0.02 (0.00)	-0.32 (0.00)	0.04 (0.00)	0.14 (0.00)
CO_2 Emissions	-	-0.5 (0.00)	-	-0.02 (0.01)
Year dummies	Yes	Yes	Yes	Yes
R-squared	0.96	0.98	0.68	0.74
Mean V.I.F	0.0005	0.01	0.0002	0.0004
No. Observations	450	450	500	500

Notes: P.D.L.S: Panel Dynamic Least Squares; P.F.M.L.S: Panel Fully Modified Least Squares; D.P.E.D: Diversification of Primary Energy Demand; N.C.F.P: Non-Carbon-Based Fuel Portfolio; V.I.F: Multicollinearity Issue

The fixed effects estimations of equation (6) for D.P.E.D and N.C.F.P models are presented in table 4. The impact of E.C on D.P.E.D and N.C.F.P is still positive and statistically significant, but in smaller levels of effectiveness than P.D.L.S estimated values. Also, the effect of E.I on both D.P.E.D and N.C.F.P is negative and statistically significant, consistent with the P.D.L.S results. Like P.D.L.S estimations, the coefficient of E.P is positive and negative for D.P.E.D and N.C.F.P models, respectively, and is statistically significant. Particularly, it is found that a 1% increase in E.P relates to an average 0.02% increase and 0.07% decrease in D.P.E.D and N.C.F.P, respectively. Moreover, a 1% increase in D.P.E.S leads to an average 0.02% and 0.05% increase in D.P.E.D and N.C.F.P, respectively. Although N.C.F.P negatively correlates with D.P.E.S, the result is statistically insignificant. Regarding explanatory power, the fixed effects technique shows 65% and 98% of R-squared for the D.P.E.D and N.C.F.P models, respectively. The equation (7) is re-estimated through diverse coefficient methods, e.g., white cross-section and white period, among others, and no specific changes in the findings are met. Also, a potential non-linear relationship among D.P.E.D and N.C.F.P and E.C is tested. However, the results are unchanged when the squared form of E.C and the control variables is added in both regressions, indicating non-linearity through the models is not a deterministic issue [61]. Then, the C.D Pesaran test results show no C.D throughout both models. Therefore, the commonly omitted affecting factors within the models may not be relevant [83].

Table 4 Fixed Effects Estimates of D.P.E.D and N.C.F.P

Variable	D.P.E.D Model	N.C.F.P Model
Economic Complexity	0.008 (0.00)	0.01 (0.02)
Energy Intensity	-0.1 (0.00)	-0.87 (0.00)
Energy Prices	0.02 (0.00)	-0.07 (0.00)
Diversification of Primary Energy Supply	0.02 (0.00)	0.05 (0.01)
CO_2 Emissions	-	-0.04 (0.1)
Intercept	4.5 (0.00)	4.8 (0.00)
F-statistic	32.8 (0.00)	53.8 (0.00)
Year dummies	Yes	Yes
Cross-Sectional Dependency Pesaran (Prob)	0.2	0.1
R-squared	0.65	0.98
No. Observations	525	525

Notes: D.P.E.D: Diversification of Primary Energy Demand; N.C.F.P: Non-Carbon-Based Fuel Portfolio

In the following, the G.M.M method is used in the next step to estimate the parameters of the models, which covers simultaneity, persistence, and fixed effect issues [80]. Table 5 indicates the estimations of equation (8), applying the two-step difference G.M.M method. The findings show that the relationships with all suggested determinants are statistically significant when the instrumental variables are added to control past D.P.E.D and N.C.F.P values. Specifically, and consistent with the P.D.L.S and fixed-effects estimates, when the long-run growth rate of E.C increases, the growth rate of D.P.E.D and N.C.F.P develops, leading to S improvement and economic vulnerability reduction in the L.E.C.E. Specifically, a 1% increase in E.C relates to an average 0.01% and 0.2% increase in D.P.E.D and N.C.F.P, respectively. Compatible with tables 3 and 4, the estimated coefficient of E.I (E.P) in the D.P.E.D model is negative (positive), while the coefficient of E.I and E.P turn to a positive value in the N.C.F.P model that contrasts with the results driven by the P.D.L.S and fixed-effects models. This inconsistency is due to different forms of endogeneity that are eliminated via internal data transformation through the G.M.M model [82]. So, a 1% increase in the long-run growth rate of E.I and E.P causes an average 0.1% decrease and increase in D.P.E.D, and a 1.8% and 1.3% increase in N.C.F.P growth rate, respectively. Like the fixed effects model, both D.P.E.D and N.C.F.P positively correlate with D.P.E.S, which is statistically significant. Particularly, a 1% increase in D.P.E.S causes an average 0.03% and 0.7% increase in D.P.E.D and N.C.F.P, respectively.

Furthermore, the negative coefficient of E has remained for N.C.F.P, which is statistically significant through the G.M.M model. Finally, the S.J- and the A.R tests confirm that the utilized instrumenting approach is statistically valid. Furthermore, it reassures no over-identification through the models, while the latter confirms no serial correlation in the residuals. Consequently, the results provided by the G.M.M model are robust to the dynamic endogeneity, unobserved heterogeneity, and simultaneity.

Table 5 G.M.M Estimates of D.P.E.D and N.C.F.P

Variable	D.P.E.D Model	N.C.F.P Model
Diversification of Primary Energy Demand (-1)	-0.08 (0.00)	-
Diversification of Primary Energy Demand (-2)	-0.1 (0.00)	-
Non-Carbon-Based Fuel Portfolio (-1)	-	-0.7 (0.00)
Non-Carbon-Based Fuel Portfolio (-2)	-	-0.4 (0.00)
Economic Complexity	0.01 (0.00)	0.2 (0.00)
Energy Intensity	-0.1 (0.00)	1.8 (0.00)
Energy Prices	0.1 (0.00)	1.3 (0.00)
Diversification of Primary Energy Supply	0.03 (0.00)	0.69 (0.00)
CO_2 Emissions	-	-2.2 (0.00)
Year dummies	Yes	Yes
S.J Test	22.7 (0.25)	23 (0.2)
A.R (1) p-value	0.00	0.00
A.R (2) p-value	0.4	0.4
No. Instruments	25	25
No. Observations	425	425

Notes: G.M.M: Generalized Methods of Movements; D.P.E.D: Diversification of Primary Energy Demand; N.C.F.P: Non-Carbon-Based Fuel Portfolio; S.J Test: Endogeneity Issue; A.R Test: Serial Correlation Test

Although the presence of observations with unusual values is mitigated via the logarithmic form of the variables, the robustness of the findings to outliers is also tested using P.Q.R [84] since the nature of outliers might be potentially different. Accordingly, there is expected to be no concern regarding the restrictive assumption of the identical distribution of error terms [85], and the existence of outliers [86], as the explanatory variables' low-, median- and high quantiles are estimated. For space-saving, only the graphs of quantile process estimates are presented for the robustness check (Figs. 5-6)[3]. Based on Figs. 5 and 6, the impact of E.C on both D.P.E.D and N.C.F.P is still positive and statistically significant through all quantiles, which indicates a positive correlation with the E.T. Also, the effectiveness of E.I on D.P.E.D (N.C.F.P) decreases (increases) when the S move from underdeveloped- to developed S performance. Moreover, the sensitivity of D.P.E.D (N.C.F.P) in response to E.P decreases (increases) as the S experience higher quantiles. Furthermore, the results exhibit that D.P.E.D (N.C.F.P) correlates with D.P.E.S through an inverted U-shaped (U-shaped) pattern from underdeveloped- to developed D.P.E.S. Finally, the positive impact of E on N.C.F.P turns to negative when the S is trapped in the huge amounts of emissions.

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[3] Vertical axes: the P.Q.R coefficients and Horizontal Axes: the regression quantile, which ranges from 0.1 to 0.9

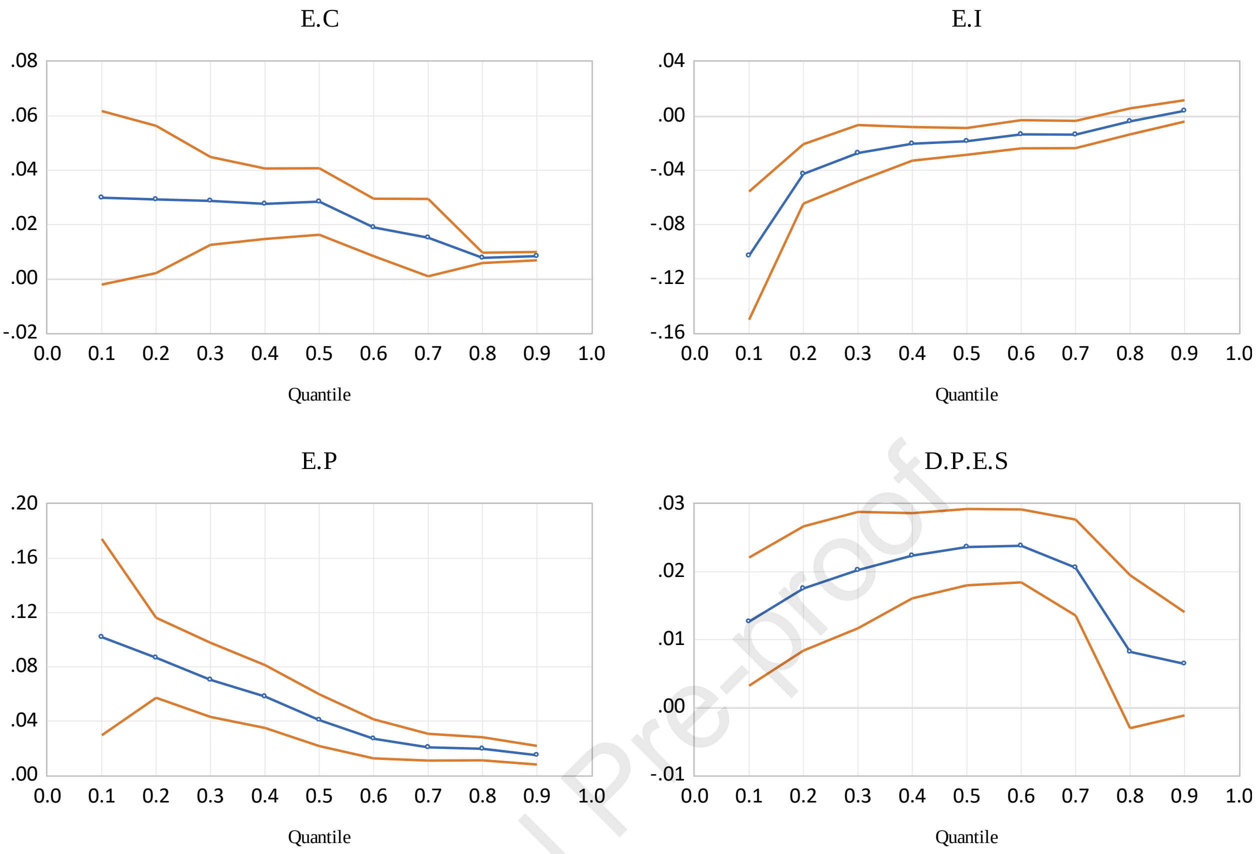

Fig. 5 Quantile Process Estimates Robust to Outliers: Diversification of Primary Energy Demand Model. Notes: E.C: Economic Complexity; E.I: Energy Intensity; E.P: Energy Prices; D.P.E.S: Diversification of Primary Energy Supply

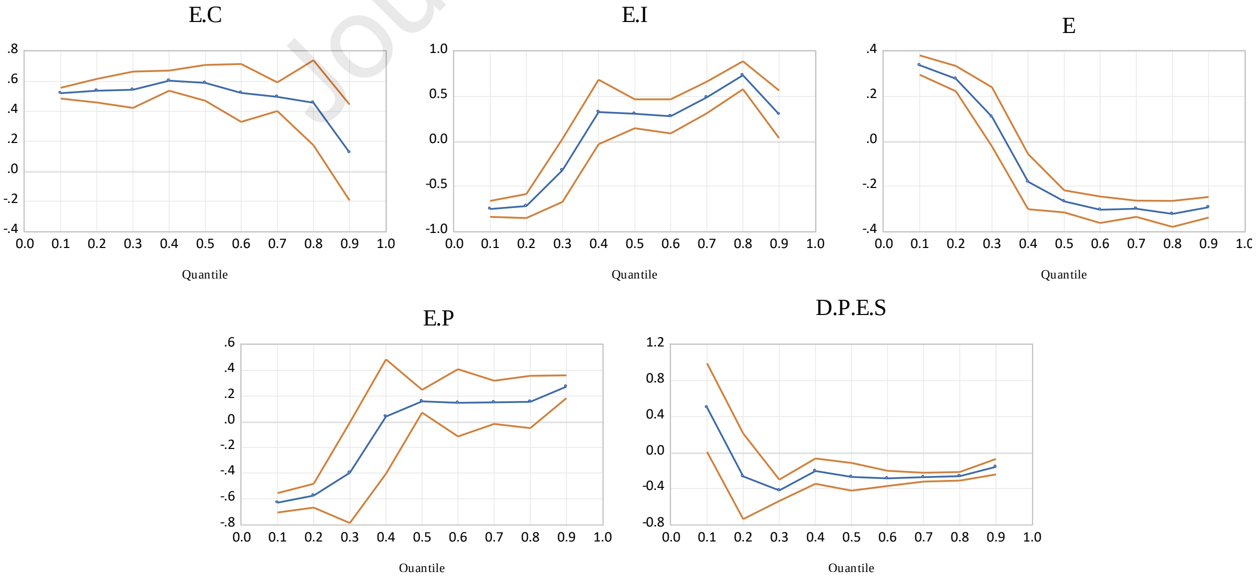

Fig. 6 Quantile Process Estimates Robust to Outliers: Non-Carbon-Based Fuel Portfolio Model. Notes: E.C: Economic Complexity; E.I: Energy Intensity; E: CO_2 Emissions; E.P: Energy Prices; D.P.E.S: Diversification of Primary Energy Supply

Finally, table 6 exhibits the patterns of S.T.F of D.P.E.D and N.C.F.P that are shaped in response to the cyclical movements of E.C and the control variables. A counter-cyclical pattern is detected for D.P.E.D when the cyclical movements of E.C and E.I take place. In contrast, D.P.E.D shows a pro-cyclical pattern in response to the cyclical movements of E.P. Moreover, N.C.F.P exposes an a-cyclical pattern within E.C. Also, a counter-cyclical behavior is found for N.C.F.P in reaction to the cyclical movements of E, while the S.T.F of E.I and E.P lead to a pro-cyclical behavior in N.C.F.P. Furthermore, the post-estimation tests of the G.M.M method, e.g., the S.J- and A.B tests, show that a proper econometric technique is utilized to examine the patterns of both D.P.E.D and N.C.F.P models. Specifically, the result of the S.J-statistic indicates that the instrumental variables included in both models are exogenous. Finally, the lagged of mentioned variables are uncorrelated with the specified error terms in both estimated equations since the results of the A.R test present no serial correlation or auto-correlation [61,82].

Table 6 G.M.M Estimates of D.P.E.D and N.C.F.P: Cycle

Variable	D.P.E.D Model	N.C.F.P Model
Diversification of Primary Energy Demand (-1)	0.4 (0.00)	-
Non-Carbon-Based Fuel Portfolio (-1)	-	-0.14 (0.00)
Economic Complexity	-0.003 (0.04)	-0.03 (0.1)
Energy Intensity	-0.16 (0.00)	2.5 (0.00)
Energy Prices	0.07 (0.00)	0.3 (0.00)
CO_2 Emissions	-	-3.6 (0.00)
Year dummies	Yes	Yes
S.J Test	21.7 (0.4)	17 (0.65)
A.R (1) p-value	0.00	0.00
A.R (2) p-value	0.7	0.3
No. Instruments	25	25
No. Observations	475	475

Notes: G.M.M: Generalized Methods of Movements; D.P.E.D: Diversification of Primary Energy Demand; N.C.F.P: Non-Carbon-Based Fuel Portfolio; S.J Test: Endogeneity Issue; A.R Test: Serial Correlation Test

4.2 Discussion

As the G.M.M method controls for main sources of endogeneity, e.g., dynamic endogeneity, simultaneity, and unobserved heterogeneity, by considering lagged values of D.P.E.D and N.C.F.P (previous performance) and utilizing an internal process of transformation, the results of the G.M.M method are not entirely similar to the results of P.D.L.S and fixed-effects techniques (Tables 3-5). For instance, a significant negative impact of D.P.E.S on the performance of N.C.F.P. is found using the P.D.L.S method. Also, both P.D.L.S and fixed-effects methods expose a significantly negative effect of E.I and E.P on the performance of N.C.F.P.

Based on the theoretical framework, there are two channels to assess the impact of knowledge, innovation, productive structure, structural changes, and capabilities of the economic systems [14-15] on the performance of D.P.E.D and N.C.F.P in order to explain the S dynamics, affecting the patterns of the sector and source-based energy consumption of the economies. As the first one, the rebound effects of technology on energy consumption [59], and low and median productivity levels [5,60] can lead to a negative response of D.P.E.D and N.C.F.P to the changes in E.C. As the second channel, higher knowledge, innovation, and greater technological and economic progress develop P.D.P.E.S, i.e., D.P.E.D and N.C.F.P, due to more levels of elasticity-income and price [59] and productivity, energy safety, and E.E [61], encouraging the E.T [1,62,88]. Based on our results in the world's L.E.C.E and consistent with [59,61-62], there is a positive nexus between E.C and S enhancement, i.e., greater resource equitability and abundance and switching to N.C.F.P. From the aspect of S.T.F, D.P.E.D and N.C.F.P show a counter-cyclical and an a-cyclical pattern with E.C respectively, indicating that the S.T.F of E.C do not relate with S fluctuations across the L.E.C.E. Consequently, the issue of E.T can be encouraged as the energy sources would be substituted in the energy mix, satisfied through the resource availability and negative correlations among resource prices [3,88].

Also, the negative and positive impact of E.I, as one of the major control variables defining S dynamics, on D.P.E.D and N.C.F.P is concluded, respectively [66-67]. Moreover, the results exhibit a counter-cyclical pattern between D.P.E.D and E.I, showing that the S.T.F of E.I do not intensify the S fluctuations of the L.E.C.E. On the other hand, a markedly pro-cyclical behavior is detected for N.C.F.P in reaction to the cyclical movements of E.I that can cause uncertainty and instability throughout the S. Therefore, the interaction of efficient source- and sector-based energy consumption [70], economic competitiveness, technological innovation, and energy policies [71] mitigate E.I, develop energy safety, leading to- higher resource diversity (D.P.E.D) and lower speed of energy transition (N.C.F.P).

Moreover, the higher the E.P, the higher the D.P.E.S is found, which entails harnessing new energy resources, which is conducive to resource equitability and abundance and switching to N.C.F.P [19,37]. Furthermore, the development of D.P.E.S encourages energy safety and E.S that enhances the E.T [19,88], which can be followed through (i) accessing raw materials, (ii) environmental conditions, (iii) exploitation and production cost, (iv) technology improvement, and (v) political factors [10,63].

Finally, it is expected that the dynamics of E reduction provide information on cleaner technologies, S decarbonization, moderate energy safety, and climate change, help to upgrade the developing measures utilized throughout environmental protection, and mitigate global warming [72]. In this regard, the estimations indicate that a decrease in the E in the world's L.E.C.E lead to higher N.C.F.P across S. Specifically, the positive effect of E on N.C.F.P turns negative when the S is trapped in the massive amounts of emissions. Thus, the countries with a greater level of E are also the economies experiencing lower environmental, political, and social acceptability [72]. Moreover, a counter-cyclical behavior is found for N.C.F.P in reaction to the cyclical movements of E, indicating that switching to N.C.F.P is not threatened in respect of risk and resilience if the S.T.F of E is intensified across S.

Following the quantile process, the positive effect of E.C on D.P.E.D and N.C.F.P lowers when the process enters into high quantiles, showing that resource equitability and abundance and switching to N.C.F.P are more sensitive to underdeveloped and developing technological complexity than developed complex technology (Figs. 5-6).

The comparative analysis demonstrates that the contribution of N.C.F.P to total P.E.D is more elastic than D.P.E.D in L.E.C.E when the shares of E.C and the control variables increase (table 5). Therefore, D.P.E.D is more challenging to satisfy than N.C.F.P through S dynamics. Hence, the opportunity costs of E.S policies in resource diversification development are high across L.E.C.E and are considered one of the reasons S has been trapped in carbon-based fuel portfolios [1].

Further, targeted P.D.P.E.S may strengthen any motives for energy safety. It is, therefore, necessary that countries consider modifications in disseminating major environmental and energy safety knowledge. It is also required to ensure that each sector is consistent with the right environmental and energy safety policies. By doing so, all sectors, even those less compatible with the suggested policies and procedures, can follow cautionary measures for the process-safety initiatives [4].

Consequently, the findings lead to identifying the P.D.P.E.S of the world's L.E.C.E and lower economic costs of transforming energy sources into production [18] in order to decline risks and promote resilience of S, i.e., resource abundance and equitability, and switching to N.C.F.P [9], via figuring out its main strengths and weaknesses.

5. Conclusions and Policy Implications

Energy security is sensitive to the energy systems dynamics, i.e., technological dynamics, social complexity, and environmental and energy safety procedures, especially for the world's large energy-consuming economies. Therefore, it needs to focus on resource diversity, affordable energies, and environmental sustainability called the energy trilemma. Accordingly, this paper explores the impact of economic complexity and the controlling variables, including energy intensity, energy prices, diversification of primary energy supply, and CO_2 emissions on the portfolio decisions of primary energy sources, e.g., diversification of primary energy demand and non-carbon-based fuel portfolio, in a panel of 25 large energy users from 1998 to 2018. The overall findings of this paper support the long-run- and causal relationships across energy systems, using the panel cointegration approach and dynamic panel data techniques. Specifically, a statistically significant and positive effect of the economic systems' knowledge, innovation, productive structure, structural changes, and economic capabilities on the diversification of primary energy demand and non-carbon-based fuel portfolio is detected. Also, diversification of primary energy demand is more challenging than non-carbon-based fuel portfolios through energy systems dynamics. Hence, the opportunity costs of energy security policies in resource diversification development are high for large energy users and are considered one of the reasons that energy systems have not been specific enough motivated to environmental and energy safety. From the aspect of cyclical movements, diversification of primary energy demand and non-carbon-based fuel portfolio show a counter-cyclical and an a-cyclical pattern with economic complexity, respectively, showing that the cyclical movements of economic complexity do not relate with energy systems fluctuations in the large energy-consuming economies. Consequently, the most important policy implications are as follows:

- Facilitate the interaction among knowledge, innovation, structural changes, and greater technological and economic progress through research and development loan guarantees to decrease the opportunity costs of energy systems development and encourage the energy trilemma.

- Promote diversification of primary energy supply to motivate energy trilemma and enhance energy security, obtained by (i) accessing raw materials, (ii) environmental and energy safety conditions, (iii) exploitation and production cost, (iv) technology improvement, and (v) political factors.
- Advance the relation between efficient source- and sector-based energy consumption, economic competitiveness, technological innovation, and energy policies to mitigate energy intensity, leading to greater resource equitability and abundance and environmental and energy safety.
- Propel the higher energy prices to a greater diversity of primary energy supply to entail restraining new energy resources, which is conducive to the diversification of primary energy demand and switching to a non-carbon-based fuel portfolio

However, the comprehensive application of economic complexity to the broad concept of energy systems dynamics asks for interdisciplinary research, e.g., economics, environmental science, engineering, social sciences, mathematics, and practical experiences, which is considered the major constraint of this research. Also, the asymmetric and time-varying analysis of behavioral regimes of diversification of primary energy demand and non-carbon-based fuel portfolio can lead to vulnerability reduction in risk and resilience, which are mentioned as the other limitations of this article and suggested to an analysis by further investigations.

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Declaration of interests

☒ 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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: