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Exploring non-linear causal nexus between economic growth and energy consumption across various R&D regimes: Cross-country evidence from a PSTR model

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ABSTRACT

Purpose: This study endeavors to elucidate the divergent conclusions encountered in empirical research regarding the interplay of Economic Growth (EG) and Energy Consumption (EC).
Design/methodology/approach: For this purpose, we employ the Panel Smooth Threshold Regression (PSTR) model to intricately examine the non-linear impacts of independent variables on EC and EG within a dataset encompassing 46 countries over the period from 1996 to 2021.
Findings: The outcomes of our investigation can be summarized as follows: First, the findings underscore the positive impact of the logarithm of net capital formation on EG. This impact is particularly pronounced at low levels of Research and Development (R&D), gradually waning beyond a certain threshold. Second, the ratio of capital to labor exhibits a negative influence on EC at lower R&D levels. Notably, these detrimental impacts become more pronounced as R&D levels increase. Third, trade openness contributes positively to EG, particularly evident at low R&D levels. However, with increasing R&D levels, the incremental benefits from trade diminish. Finally, our findings lend support to the feedback hypothesis. Nevertheless, the impact of R&D expenditures in countries moderates these positive effects.
Practical implications: Policymakers should strategically balance resource allocation between capital formation and research endeavors, considering diminishing returns at elevated levels of R&D spending, to ensure sustained EG.

1. Introduction

Energy stands as a fundamental cornerstone for economic advancement in both industrialized and developing nations. It is regarded as a pivotal input for propelling industrial and societal progress. The industrial sector, given its extensive reliance on machinery, accentuates the significance of energy. The interplay between Economic Growth (EG) and Energy Consumption (EC) has captivated numerous researchers due to energy's profound impact on economies. The epochal energy crises of the 1970s sparked ongoing debates among economists and policymakers regarding whether EC shapes or is shaped by EG. Realizing sustainable EG while simultaneously mitigating environmental degradation necessitates the adoption of ecologically friendly and green technologies, alongside internalizing external repercussions through the advancement of knowledge and technology (Li and Lin, 2016).

Conventional EG theories advocate for structural transformations, knowledge, and technological advancements, while contemporary growth theories emphasize the role of innovation and technological progress in fostering EG (Romer, 1986). Endogenous growth models underscore Research and Development (R&D) expenditure as a primary catalyst for long-term EG (Inekwe, 2014), highlighting the importance of R&D investments in driving technical innovation and amplified production (Grossman and Helpman, 1994). Despite the positive correlation established between R&D spending and EG in previous studies, highlighting R&D's pivotal role in enhancing the competitive edge of firms and economies, a consensus on the nature of the EC-EG correlation

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remains elusive, as reflected in comprehensive surveys by Mardani et al. (2019), S. Narayan (2016), Payne (2010), and more on this below.

The presence of conflicting outcomes in empirical analyses conducted across different nations and periods could be attributed to the intricate non-linear interplay between variables. This complexity can lead to evolving findings over time and across nations. This particular aspect, which has remained unexplored in previous investigations, stands as the central focus of this article.

The evaluation of panel data models has encountered substantial criticism due to the issue of cross-sectional heterogeneity. Neglecting parameter variations among cross-sectional units introduces biases in the analysis (Pesaran and Smith, 1995). While studies traditionally mitigate this concern by incorporating fixed or random individual effects, these methods do not ensure consistency or account for the non-linear characteristics of other parameters across nations. An alternative and more effective approach for exploring the non-linear impacts of independent variables on a specific variable emerges through the utilization of the Panel Smooth Threshold Regression (PSTR) model, introduced by Fok et al. (2005) and adopted within this study. This model identifies homogenous categories within individual observations based on a threshold variable that denotes transitions between different regimes. However, one of the core challenges associated with employing the PSTR model pertains to the selection of a suitable threshold variable. Apart from exhibiting structural disparities at the country level, this variable should possess a robust theoretical underpinning for its application in the experimental framework. As elaborated, R&D emerges as an appropriate candidate for this purpose.

To comprehensively grasp the ramifications of R&D, this research constructs an empirical model distinguishing between the direct and indirect influences of R&D expenditure on EC and EG. The study contributes by investigating factors influencing EG and EC using conventional panel models, emphasizing the direct contribution of R&D. It contrasts outcomes concerning the EG-EC relationship through inter-model and prior experimental findings comparisons. Additionally, the study offers a nuanced understanding of determinants by leveraging the non-linear panel model, PSTR, to unravel intricacies in the EG-EC connection.

To comprehensively grasp the ramifications of R&D, this research constructs an empirical model distinguishing between the direct and indirect influences of R&D expenditure on EC and EG. Several distinctive contributions characterize this study. Firstly, it strives to investigate the factors influencing EG and EC utilizing conventional panel models, specifically emphasizing the direct contribution of R&D as a key variable. Through the estimation of diverse panel models, it contrasts the outcomes concerning the EG-EC relationship and uncovers disparities in results based on inter-model comparisons and comparisons with prior experimental findings. Secondly, the study endeavors to offer a more nuanced understanding of the determinants of EC and EG by leveraging the estimation of the non-linear panel model, namely the PSTR. In this phase, an attempt is made to synthesize the considerable research gap in the empirical literature, thereby generating insights to unravel the intricacies of the EG-EC connection.

The remainder of this paper is structured into six core sections. The second section provides a brief literature review, while the third section offers an outline of our econometric modeling strategy and provides insights into the employed dataset. Subsequently, the fourth section dissects the obtained results, while the fifth section provides a discussion of the results. The final segment offers a conclusive summary of key findings, discussing the policy implications of the study's outcomes.

2. Literature review

2.1. EC-EG nexus

Scholars are increasingly intrigued by the relationship between EC and EG (Chica-Olmo et al., 2020; Shahbaz et al., 2018; Song et al., 2021). Various theories propose factors influencing a country's EG, yet overlook energy as a potential contributor. Magazzino (2014), followed by S. Narayan and Doytch (2017), Yang et al. (2020), and Mutumba et al. (2021), offer comprehensive reviews of research on the energy–-growth relationship. The complex relationship has been explored using a range of empirical methods, including, but not limited to, Granger Causality and various panel modeling approaches (Apergis & Payne, 2011; Charfeddine and Kahia, 2019; Shojaee and Seyedin, 2021). It has been studied across diverse contexts (developed, developing, and transitional economies) and time periods (Acaravci and Ozturk, 2010). Some researchers differentiate between renewable energy and nonrenewable energy (Khezri et al., 2022; Mamkhezri and Khezri, 2023; Wang et al., 2022), or between residential and industrial users (S. Narayan and Doytch, 2017). Others introduce additional explanatory variables, such as carbon emissions (Chen et al., 2019), or divide their samples by temperature and climate (Mamkhezri et al., 2022). Furthermore, certain scholars explore how different time horizons, such as short and long terms, affect the EC-EG nexus (Magazzino et al., 2021).

The literature proposes four hypotheses to describe the relationship: growth (EG ⟹ EC), conservation (EG ⟸ EC), neutrality (EC ⇎ EG), and feedback (EG ⟺ EC). According to the growth hypothesis, reducing EC regulation diminishes EG because EC serves as a causal determinant of EG. The conservation hypothesis posits that economic expansion leads to increased EC. Conversely, it suggests that economic development is not dependent on EC; hence, energy-conservation initiatives can be enacted without impeding EG. The feedback hypothesis suggests bidirectional Granger causality between EG and EC. Finally, the neutrality hypothesis contends that there is no causal link between EG and EC; consequently, neither stimulative nor counter-stimulative energy policies impact EG. A recent literature survey by Mutumba et al. (2021) reveals a lack of consensus, with the neutrality hypothesis accounting for 10.5%, growth hypothesis 43.8%, conservation 27.2%, and feedback 18.5%, of the relationship in country-specific studies. For a meta-analysis of these four hypotheses within the scholarly discourse, interested readers are referred to Bruns et al. (2014).

2.2. R&D's effect on EC-EG nexus

In theory, R&D wields the potential to influence EC through diverse mechanisms. For instance, R&D can pave the way for advancements in energy efficiency, potentially leading to diminished EC (Yao et al., 2019). According to endogenous growth theory, R&D investments can drive technological innovations that enhance energy utilization and production efficiency, thus reducing dependence on natural resources and curtailing emissions (Awaworyi Churchill et al., 2019; Dinda, 2004). Popp's research (Popp, 2001) implies that a significant portion of fluctuations in EC in the United States can be attributed to technological advancements. Nonetheless, there exists the possibility that increased R&D expenditures might inadvertently escalate EC if they trigger EG and subsequent trade expansion, ultimately boosting output and EC (Khezri et al., 2021; Newell, 2009). This scenario is particularly plausible in economies where the diminishing marginal returns on R&D investments and innovation are a result of accumulating knowledge and the challenges associated with groundbreaking discoveries. Moreover, the influence of R&D on EC becomes even more ambiguous when EC is categorized into clean and dirty energy segments. For example, Zhang et al. (2022) establish a positive connection between R&D spending and environmental degradation, whereas Hailemariam et al. (2022) arrive at the opposite conclusion. To the best of our knowledge, no prior studies have undertaken a comprehensive examination of the EG-EC nexus, taking into account the influence of the level of R&D and considering its non-linear impacts on this relationship.

2.3. Research question and studies' contributions

The primary research question driving this study is to unravel the intricate relationship between EG, EC, and key economic factors across countries, taking into consideration the non-linear impacts of R&D levels. The two main hypotheses guiding the investigation are structured as follows:

1. We hypothesis that there exists a positive relationship between EG and EC, with the level of R&D influencing this relationship.
2. We hypothesis that higher levels of R&D will lead to a reduction in the positive effects of EC on EG, thereby supporting the feedback hypothesis.

This research aims to address several gaps in the existing literature related to the intricate non-linear interplay between EG, EC, and key economic factors. We contribute to the literature by introducing the PSTR model to explore non-linear impacts. This methodological innovation categorizes observations based on R&D thresholds, providing a more nuanced approach to studying the relationships. Moreover, the study contributes by distinguishing between the direct and indirect influences of R&D on EC and EG. By doing so, it seeks to provide a more comprehensive and nuanced understanding of these complex relationships.

3. Model and data description

3.1. Empirical model

The research delves into the interrelation between EC and EG across 46 nations using longitudinal data spanning from 1996 to 2021. The selection of the countries for the study's cohort is rooted in data availability and the temporal scope of the investigation. Employing a Cobb-Douglas production function for empirical modeling constitutes a method previously harnessed by researchers like Shahbaz et al. (2013), Kahouli (2017), and Kahouli (2018), among others. This functional framework incorporates capital stocks (CAP), the labor force (LAB), and technological progress (A) as pivotal determinants shaping the model's outcomes. In an extended rendition of the Cobb-Douglas production function, the incorporation of trade openness (OPE), and R&D is endogenously determined within the research (Omri and Kahouli, 2014; Shahbaz and Lean, 2012). R&D activities facilitate and expedite the advancement and diffusion of technological innovations. The mechanism of trade openness (OPE), through labor mobility and the transfer of capital, as well as energy consumption (ENE) as a production input, contributes to the augmentation of the Gross Domestic Product (GDP). Consequently, the culmination of these factors yields the following outcomes:

$$A_t = \theta OPE_t^{\beta_4} R\&D_t^{\beta_5} \tag{1}$$

$$GDP_t = \theta ENE_t^{\beta_1}\ LAB_t^{\beta_2} CAP_t^{\beta_3} OPE_t^{\beta_4} R\&D_t^{\beta_5} e^u \tag{2}$$

The linearized production function can be expressed as follows:

$$lnGDP_t = \alpha + \beta_1 lnENE_t + \beta_2 lnLAB_t + \beta_3 lnCAP_t + \beta_4 lnOPE_t + \beta_5 lnR\&D_t + \varepsilon_t \tag{3}$$

Given our utilization of panel data for this particular examination, the conversion of Eq. (3) into a panel data structure is articulated as follows:

$$\begin{aligned} lnGDP_{it} = \alpha + \beta_1 lnENE_{it} + \beta_2 lnLAB_{it} + \beta_3 lnCAP_{it} \\ + \beta_4 INF_{it} + \beta_5 lnOPE_{it} + \beta_6 R\&\mathrm{D}_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

Various empirical models have integrated factors like EG, the labor force, the capital stock, trade openness, and total population. These variables have been extensively explored by energy economists in their research. For instance, Belke et al. (2011), Shahbaz et al. (2013), Saidi and Hammami (2015), and Kahouli (2017, 2018) have all delved into these aspects. Within our study, we consider the capital-labor ratio (K/L), an independent variable, which signifies the extent of industrialization within a country. Nations with a higher capital-to-labor ratio usually lean towards capital-intensive economies. This suggests that if an increase in labor force capital per capita leads to higher energy intensity, there exists a significant interconnection between capital and energy. Elevating this ratio is likely to result in a reduction in energy intensity. Our model aligns with the strategy employed by Liddle and Huntington (2021) and Liddle et al. (2020). These studies formulated an energy demand function that incorporates R&D as a determining factor. In this context, our proposed model harmonizes with the broader body of literature that explores the elements influencing EC, as discussed earlier.

$$lnENE_{it} = \alpha + \beta_1 lnGDP_{it} + \beta_2 \frac{lnCAP_{it}}{lnLAB_{it}} + \beta_3 lnOPE_{it} + \beta_4 R\&D_{it} + \varepsilon_{it} \tag{5}$$

3.2. Panel smooth threshold regression (PSTR)

To address non-linearity within the empirical model, an effective approach involves employing a PSTR modeling approach. Specifically focusing on a basic scenario with two distinct regimes, and a solitary transition function, the resultant PSTR models for EG and EC are formulated as follows:

$$\begin{aligned} lnGDP_t = \alpha_i + \beta_{10} lnENE_{it} + \beta_{20} lnLAB_{it} + \beta_{30} lnCAP_{it} \\ + \beta_{40} lnOPE_{it} + [\beta_{11} lnENE_{it} + \beta_{21} lnLAB_{it} \\ + \beta_{31} lnCAP_{it} + \beta_{41} lnOPE_{it}] h(R\&D_{it}; \gamma, c) \\ + \varepsilon_{it} \end{aligned} \tag{6}$$

$$\begin{aligned} lnENE_{it} = \alpha_i + \beta_{10} lnGDP_{it} + \beta_{20} \frac{lnCAP_{it}}{lnLAB_{it}} + \beta_{30} lnOPE_{it} \\ + \left[\beta_{11} lnGDP_{it} + \beta_{21} \frac{lnCAP_{it}}{lnLAB_{it}} + \beta_{31} lnOPE_{it}\right] h(R\&D_{it}; \gamma, c) + \varepsilon_{it} \end{aligned} \tag{7}$$

The threshold variable is represented as $R\&D_{it}$ in the equation. The error term ε_{it} is considered to be independent and identically distributed with a mean of 0 and a variance of σ^2. The function governing the transition, denoted as $h(R\&D_{it}; \gamma, c)$, remains limited and continuous concerning the threshold variable $R\&D_{it}$. Building upon earlier research by Granger and Teräsvirta (1993) on STAR models in time series, González et al. (2004) present the subsequent transition function.

$$h(q_{it}; \gamma, c) = \left[1 + exp\left(- \gamma \prod_{z=1}^{m} (R\&D_{it} - c_z)\right)\right]^{-1}, \gamma > 0, c_1 \le .. \le c_m \tag{8}$$

The equation is given as $c = (c_1, .., c_m)'$ represents a multi-dimensional vector denoting location parameters. The parameter γ is responsible for determining the steepness of the transition function. The impact of EC on EG (and vice versa) in Eqs. (6) and (7), within the specific country and time, is delineated by a calculated weighted average of the parameters β_{10} and β_{11}, which are derived from the extreme regimes in our analysis:

$$\frac{\partial lnGDP_{it}}{\partial lnENE_{it}} = \beta_{10} + \beta_{11} h(R\&D_{it}; \gamma, c) \forall i, \forall t \tag{9}$$

$$\frac{\partial lnENE_{it}}{\partial lnGDP_{it}} = \beta_{10} + \beta_{11} h(R\&D_{it}; \gamma, c) \forall i, \forall t \tag{10}$$

We can calculate these equations to check the effects of other independent variables of the model in Eqs. (6) and (7). This model can be viewed as an extension of Hansen's (1999) Panel Threshold Regression (PTR) model and the panel linear model with individual effects. As the parameter γ becomes exceedingly large, the transition function $h(R\&D_{it}; \gamma, c)$ approaches the indicator function $\mathbb{I}_{(R\&D_{it} \ge c)}$. Consequently, when $m = 1$ and γ approaches infinity, the PSTR model aligns with the PTR model. In the context where $m > 1$ and γ approaches infinity, there persist two identical regimes. However, the function alternates between

Table 1
Variable definitions and sources.

Variable	Source	Variable constructed
lnGDP	WDI	$lnGDP_{it} = log(GDP_{2it})$ $GDP_{it} = GDP\ (constant\ 2015\ US\$)$
lnENE	BP	$lnEN_{it} = log(EN_{it})$ $EN_{it} = Primary\ energy\ consumption\ (TWh)$
lnCAP	WDI	$lnK_{it} = log(K_{it})$ $K_{it} = Gross\ capital\ formation\ (constant\ 2015\ US\$)$
lnLAB	WDI	$lnL_{it} = log(L_{it})$ $L_{it} = Labor\ force, total$
lnOPE	WDI	$lnOPE_{it} = log(OPE_{it})$ $OPE_{it} = Trade\ Openness\ (\%of\ GDP($
R&D	WDI	$R\&D_{it} = Research\ and\ development\ expenditure\ (\%of\ GDP)$

WDI: World Development Indicator; https://datacatalog.worldbank.org/dataset/world-development-indicators
BP: Statistical Review of World Energy; https://www.bp.com/

values of zero and one at specific points c_1, c_2, and so forth. As γ approaches zero, the transition function $h(R\&D_{it}; \gamma, c)$ remains constant, resulting in a standard linear model with consistent and homogenous parameters, referred to as individual effects. Notably, González et al. (2004) propose an extension introducing $r+1$ extreme regimes. This extension termed the general additive PSTR model, is defined as follows for EG and EC:

$$\begin{aligned} lnGDP_t = {} & \alpha_i + \beta_{10} lnENE_{it} + \beta_{20} lnLAB_{it} + \beta_{30} lnCAP_{it} + \beta_{40} lnOPE_{it} \\ & + \sum_{j=1}^{r} \left[\beta_{1j} lnENE_{it} + \beta_{2j} lnLAB_{it} + \beta_{3j} lnCAP_{it} \right. \\ & \left. + \beta_{4j} lnOPE_{it}\right] h_j\left(R\&D_{it}; \gamma_j, c_j\right) + \varepsilon_{it} \end{aligned} \tag{11}$$

$$\begin{aligned} lnENE_{it} = {} & \alpha_i + \beta_{10} lnGDP_{it} + \beta_{20} \frac{lnCAP_{it}}{lnLAB_{it}} + \beta_{30} lnOPE_{it} \\ + \sum_{j=1}^{r} & \left[\beta_{1j} lnGDP_{it} + \beta_{2j} \frac{lnCAP_{it}}{lnLAB_{it}} + \beta_{3j} lnOPE_{it}\right] h_j\left(R\&D_{it}; \gamma_j, c_j\right) + \varepsilon_{it} \end{aligned} \tag{12}$$

The transition function, denoted as $h_j\left(R\&D_{it}; \gamma_j, c_j\right)$, is influenced by both the slope parameters (γ_j) and a set of m location parameters (c_j). In this broader conceptualization, the effect of EC on EG (and vice versa) in Eqs. (11) and (12), within the context of the ith country at time t, is articulated as the weighted mean of the $r+1$ coefficients acquired from the $r+1$ distinct extreme regimes:

$$\frac{\partial lnGDP_{it}}{\partial lnENE_{it}} = \beta_{10} + \sum_{j=1}^{r} \beta_{1j} h_j\left(R\&D_{it}; \gamma_j, c_j\right) \forall i, \forall t \tag{13}$$

$$\frac{\partial lnENE_{it}}{\partial lnGDP_{it}} = \beta_{10} + \sum_{j=1}^{r} \beta_{1j} h_j\left(R\&D_{it}; \gamma_j, c_j\right) \forall i, \forall t \tag{14}$$

Expanding on the equations denoted as (13) and (14), our objective is to conduct a more profound exploration into the ramifications stemming from R&D activities on the intricate and interconnected dynamics between EC and EG. Although certain impacts of EC and EG directly influence this relationship, the remaining effects hinge on the economic framework and the extent of R&D within a specific nation. This underscores the crucial importance of the spill-over effects embedded within our model.

Our empirical model's configuration plays a pivotal role as a foundational instrument in dissecting how the economic architectures of different countries wield influence over the mutual dependence of the variables in the model. This endeavor significantly contributes to the overarching objective driving the purpose of this paper.

Table 2
Key variables' summary statistics (1996–2021).

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
lnGDP	26.226	26.230	30.653	22.159	1.831	1147
lnENE	6.252	6.041	10.689	3.273	1.735	1147
lnCAP	24.706	24.690	29.512	19.323	1.888	1147
lnLAB	15.841	15.431	20.476	11.947	1.707	1147
lnOPE	4.325	4.351	5.531	2.753	0.507	1147
R&D	1.446	1.139	5.706	0.171	1.034	1147

Within the confines of Table 1, we present an all-encompassing elucidation of our data compilation methodology, encompassing relevant factors and resources. Complementing this, we provide a condensed representation of the data amassed from 46 countries[1] spanning from 1996 and 2021, which is outlined in Table 2. It is important to acknowledge that our analysis of the PSTR model utilized an unbalanced panel due to the varying availability of R&D data across different years. We should also highlight that comprehensive data, spanning from 1998 to 2020, was available for only 38 countries without any significant deficiencies. Consequently, this dataset was exclusively employed to estimate the linear panel model. Note that the conspicuously low standard deviations associated with a majority of variables, concerning their means, imply that these variables exhibit relatively minor fluctuations and an absence of anomalies within the model, despite the extended duration of observation.

In assessing the stationarity of the variables under consideration, this study utilized a comprehensive array of tests: the Levin-Lin-Chu test (2002), the Im-Pesaran-Shin test (2003), and the Fisher-ADF test (2001). The outcomes from these unit root tests in Table 3 revealed that a number of variables exhibited first-order integration, highlighting the dynamic nature of the data set in our analysis.

4. Estimation and analysis of the results

4.1. Estimation results of conventional panel models

Estimating Eqs. (4) and (5) necessitated the utilization of four distinct panel models. These encompassed the integration of fixed effects (FE) within the spatial domain, the incorporation of FE within the temporal domain, the simultaneous integration of FE within both spatial and temporal domains, and the utilization of Panel EGLS (two-way error component random effects). Rigorous diagnostic assessments were administered to these models, culminating in the identification of the most efficacious ones. Specifically, a comparative analysis was conducted between FE models within simultaneously spatial and temporal domains, and models featuring FE solely in either the spatial or temporal domain. The underlying null hypothesis imposed constraints on models employing FE across singular spatial or temporal domains. The empirical outcomes emanating from Table 5 and Table 6 carry a robust statistical significance, leading to the rejection of the null hypothesis. This underscores the imperative nature of incorporating both spatial and temporal domains within the estimation of the FE model.

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[1] Egypt, Arab Rep., Uruguay, Cyprus, Mexico, Romania, Costa Rica, North Macedonia, Latvia, Argentina, Cuba, Bulgaria, Lithuania, Estonia, Slovak Republic, Poland, Portugal, Belarus, India, Hungary, Spain, China, Ukraine, Italy, Russian Federation, Ireland, Czechia, Slovenia, United Kingdom, Netherlands, Canada, Austria, Belgium, France, Korea, Rep., Denmark, Germany, Iceland, United States, Japan, Finland, Israel, Moldova, Tunisia, Greece, Norway, Sweden.

Table 3
Unit root test.

		Level		First Difference	
	Method	Statistic	*p*-values	Statistic	p-values
lnGDP	LLC	−5.381***	(0.000)	−8.835***	(0.000)
	IPS	0.121	(0.548)	−11.047***	(0.000)
	Fisher-ADF	175.093***	(0.000)	542.505***	(0.000)
lnENE	LLC	−3.282***	(0.001)	−11.549***	(0.000)
	IPS	−0.940	(0.174)	−16.249***	(0.000)
	Fisher-ADF	165.717***	(0.000)	849.841***	(0.000)
lnCAP	LLC	−3.033***	(0.001)	−15.092***	(0.000)
	IPS	0.390	(0.652)	−17.456***	(0.000)
	Fisher-ADF	121.699**	(0.021)	687.219***	(0.000)
lnLAB	LLC	−6.741***	(0.000)	−4.274***	(0.000)
	IPS	−0.085	(0.466)	−9.352***	(0.000)
	Fisher-ADF	133.650***	(0.003)	517.792***	(0.000)
lnOPE	LLC	−3.377***	(0.000)	−17.471***	(0.000)
	IPS	−0.864	(0.194)	−18.393***	(0.000)
	Fisher-ADF	135.296***	(0.002)	776.981***	(0.000)
R&D	LLC	0.494	(0.689)	−9.233***	(0.000)
	IPS	3.492	(1.000)	−12.052	(0.000)
	Fisher-ADF	82.097	(0.761)	576.687***	(0.000)

Notes: The null hypothesis is that there is a unit root, while the alternative hypothesis is that there is no standard unit root in the examined variable. ***, **, and * indicate significance at <1%, 1–5% and 6–10% levsls. Source: Authors' estimations.

Furthermore, the results derived from the Hausman test highlighted the necessity of discarding the random model in favor of a model characterized by FE. With a significance level set at 1%, the null hypothesis was consistently rejected across all models, reinforcing the appropriateness of FE as a model specification. In the exploration of the factors influencing GDP growth, the coefficients estimated within the FE models, operating within simultaneously spatial and temporal domains, demonstrated significance for all variables. This significance was validated through a battery of diagnostic tests. Particularly noteworthy is the positive correlation established between an increase in EC and EG. A 1 % increment in EC corresponded to a 0.350% upswing in EG. Similarly, a 1 % augmentation in R&D expenditure corresponded to a 0.015% elevation in EG within the FE model in the simultaneously spatial and temporal domains. These favorable effects were statistically significant within the FE model situated in the spatial domain, whereas the temporal domain did not exhibit the same significance.

Investigating the factors influencing EG, in Table 4 we observed that the estimated coefficients of all variables, demonstrated significance in the FE models within both spatial and temporal contexts. This was confirmed through rigorous diagnostic assessments. Specifically, augmenting EC exhibited a favorable correlation with EG, wherein a 1 % upsurge in EC led to a 0.345% increment in EG. Furthermore, in the FE model encompassing both spatial and temporal dimensions, a mere 1 % escalation in expenditure on R&D corresponded to a 0.021% growth in EG. Notably, these positive impacts manifested significance when considering the FE model in the spatial domain, whereas their significance was not mirrored in the temporal domain.

Moreover, the influence of the fixed capital-output ratio on GDP growth has been consistently found to be positive and significant across all models. Specifically, a mere one percentage point increase in the fixed capital-output ratio leads to a notable 0.350% upsurge in GDP. However, the impact of both the logarithm of the labor force and trade openness on GDP growth yields contrasting outcomes among different model contexts. While the FE models considering both spatial and temporal dimensions as well as the sole temporal domain indicate negative effects, the FE model focusing solely on spatial dynamics reveals distinct and positive coefficients for these variables. Consequently, the interpretation of the effects of labor force and trade openness on EG hinges on the choice of the estimation model. To elaborate, an upward trajectory in labor force and trade openness over time fosters positive EG, but countries characterized by higher levels of labor force and trade openness tend to experience comparatively slower EG. The FE model within the temporal domain holds greater significance concerning these variables compared to the FE model that combines both spatial and temporal dimensions. The empirical results exhibit a positive correlation between EC and EG, where a 1% increase in EG corresponds to approximately a 1% boost in EC. Furthermore, R&D exerts a direct and favorable influence on EC.

Interestingly, an enhancement in the capital-labor ratio corresponds to a reduction in EC, implying that capital can act as a substitute for energy. Additionally, the logarithm of trade openness manifests a varying impact on EC across different models. While the FE model that considers both spatial and temporal dimensions, along with the FE model concentrating solely on spatial dimensions, indicates a negative influence, the FE model focusing solely on temporal dynamics demonstrates a positive effect. This suggests that while EC diminishes as trade openness rises over time, countries with elevated trade openness levels tend to exhibit higher EC. Consequently, linear conventional panel models fall short of offering a comprehensive comprehension of the multifaceted relationships among model variables. Depending on the chosen panel model, asymmetrical outcomes may arise. This is especially relevant in the context of the connection between EC and EG, where the comprehension of this relationship is confined to a constant coefficient. Such a coefficient's value remains contentious in empirical studies. Bridging this gap and gaining a deeper understanding of

Table 4
The estimation results for Model A1 (Eq. (4)).

	Pooled OLS	FE model in the spatial domain	FE model in the temporal domain	FE model in spatial and temporal domains	Panel EGLS	PFMOLS
lnENE	0.068***	0.131***	0.085***	0.345***	0.333	0.137***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnLAB	−0.045**	0.306***	−0.064***	−0.334***	0.113	0.219***
	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
lnCAP	0.901***	0.501***	0.901***	0.350***	0.392	0.519***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnOPE	−0.269***	0.183***	−0.290***	−0.018	0.005	0.218***
	(0.000)	(0.000)	(0.000)	(0.215)	(0.719)	(0.000)
R&D	−0.001	0.101***	−0.014	0.021***	0.02	0.087***
	(0.916)	(0.000)	(0.222)	(0.002)	(0.003)	(0.001)
LogL	26.882	977.622	50.280	1370.204		
R^2	0.984	0.998	0.985	0.999	0.931	0.998
LR − test		785.163	2639.848			
		(0.000)	(0.000)			
Hausman test					396.64	
					(0.000)	
Kao's test						−4.69
						(0.000)

Notes: ***, **, and * indicate significance at <1%, 1–5% and 6–10% levsls. Source: Authors' estimations.

experimental outcomes necessitate the adoption of a research methodology with a broader analytical scope.

In light of the identification of certain variables as integrated of order one, this analysis incorporated Kao's co-integration test across various sets of variables to delve into their long-term co-integration dynamics. The findings from these tests revealed significant co-integration among the variables across all models for EG, indicating persistent and long-term relationships. Table 5 and Table 6 proceeds to investigate the sustained effects of these variables, utilizing panel co-integrating estimators, notably the Panel Fully Modified Ordinary Least Squares (PFMOLS) approach. This method is particularly insightful for examining long-run relationships in panel data where variables are integrated. The analysis of the results from the PFMOLS model indicates that its estimation does not yield distinct outcomes, suggesting that it fails to address or resolve the previously identified issues. This continuity of challenges underscores the need for further refinement or alternative modeling approaches to effectively capture the underlying dynamics of the study. The PSTR model emerges as a viable solution. PSTR boasts dual interpretations: firstly, as a regime-switching model encompassing a few extreme regimes linked to the extreme values of a transition function, exhibiting smooth transitions; secondly, as a model accommodating a “continuum of regimes,” each characterized by distinct transition function values. PSTR's applicability in our context lies in its ability to account for cross-country disparities and temporal volatility of elasticities without mandating predefined classifications. Furthermore, utilizing the PSTR model offers the potential to enhance the reliability of estimations concerning non-stationarity. Unlike time series analysis, the effects of non-stationarity in linear panel models vary. Merging observations from cross-sections and time series mitigates residual impacts while retaining the potency of explanatory variables. This leads to consistent estimates of long-run regression coefficients (Phillips and Moon, 1999).

4.2. *Estimation results of the PSTR model*

The PSTR model necessitates the determination of the count of location parameters utilized in the transition functions, denoted as *m*. When dealing with a model featuring at least one transition function, the optimal count of location parameters is chosen using the Schwarz and Akaike criteria, as outlined in Table 7. The subsequent step involves evaluating the log-linear specification of the EC and EG models in comparison with a specification incorporating threshold effects for every optimal ‘m’ value. If the assumption of linearity is invalidated, a subsequent phase requires the identification of the quantity of transition functions essential for encompassing all nonlinearity or, equivalently, heterogeneity of EC and EG model parameters. González et al. (2004) propose a testing methodology to assess both the linearity against the PSTR model and the required count of transition functions, represented as r^* (with the actual number of extreme regimes being r^*+1).

The testing process unfolds as follows. Assuming a model with $r = r^*$, the null hypothesis $H_0 : r = r^*$ is tested against the alternative hypothesis $H_1 : r = r^* + 1$. If H_0 cannot be rejected, the process concludes. However, if H_0 is rejected, the null hypothesis $H_0 : r = r^* + 1$ is matched against the alternative hypothesis $H_1 : r = r^* + 2$. This testing sequence persists until the first failling of the null hypothesis H_0 rejection. To ensure computational manageability, our investigation is restricted to PSTR models with a maximum of four transition functions. The outcomes of these tests for linearity and the assessments of specifications devoid of remaining nonlinearity are presented in Table 6. Although previous research has indicated that the F-version of the test, referred to as LMF statistics, displays superior size properties in small sample sizes compared to asymptotic-based statistics (Dijk et al., 2002), we provide an overview of all diagnostic tests, including Wald Tests (LM), Fisher Tests (LMF), and LRT Tests (LRT).

The evaluation of potential residual nonlinearity is detailed in Table 6, yielding specifications that incorporate a minimum of one transition function. In a PSTR model, the collection of exceptional patterns effectively captures non-linear characteristics. This includes variations in independent variable parameters across different countries and over time.

Table 7 presents the parameter estimates derived from the final PSTR models. It is important to note that while the estimated parameters themselves lack direct interpretability, their signs do hold significance. Models featuring a single location parameter (m), as determined by AIC and Schwarz statistics, exhibit superior performance and form the analytical cornerstone of our findings. However, the interpretation of parameter coefficients' signs across different regimes falls short of providing comprehensive and actionable insights. To grasp the nonlinear effects of the independent research variables on EC and EG, it becomes necessary to compute Eqs. (13) and (14). This computation facilitates the estimation of weighted coefficients for each variable. Nonetheless, the nonlinear estimation of EC and EG underscores the significance of all research control variables, at the very least within one of the estimated regimes.

The application of the threshold variable has yielded varying outcomes, with certain variables outperforming others in effectively elucidating the diversity in levels and demonstrating the estimated parameters. Nevertheless, the outcomes presented in Table 6 underscore the significant capacity of R&D to account for this diversity. With the parameter estimates derived from the PSTR models, it is now viable to compute, for each country in the sample and across different time points, the dynamic influences of independent variables. These refined

Table 5
Model A2 estimation results (Eq. (5)).

	Pooled OLS	FE model in the spatial domain	FE model in the temporal domain	FE model in spatial and temporal domains	Panel EGLS	PFMOLS
lnGDP	0.786*** (0.000)	0.495*** (0.000)	0.796*** (0.000)	1.098*** (0.000)	0.95 (0.000)	0.55*** (0.000)
$\frac{lnCAP}{lnLAB}$	−6.160*** (0.000)	−1.618*** (0.000)	−6.278*** (0.000)	−4.370*** (0.000)	−3.58 (0.000)	−1.93*** (0.000)
lnOPE	0.211*** (0.000)	−0.168*** (0.000)	0.283*** (0.000)	−0.011 (0.638)	−0.011 (0.637)	−0.22*** (0.000)
R&D	0.107*** (0.000)	−0.038*** (0.009)	0.126*** (0.000)	0.015 (0.207)	0.016 (0.165)	−0.04 (0.121)
LogL	−494.555	695.574	−462.371	919.496		
R^2	0.942	0.996	0.946	0.998	0.664	0.996
$LR - test$		447.845 (0.000)	2763.733 (0.000)			
Hausman test					35.52 (0.000)	
Kao′s test						−0.24 (0.403)

Notes: ***, **, and * indicate significance at <1%, 1–5% and 6–10% levsls. Source: Authors' estimations.

Table 6
Nonlinearity tests results.

			Wald Tests (LM)		Fisher Tests (LMF)		LRT Tests (LRT)		r^*
Model B1 (Eq. 10) for EG	$m = 1$	$H_0 : r = 0$ *vs* $H_1 : r = 1$	96.354	(0.000)	25.151	(0.000)	100.643	(0.000)	2
		$H_0 : r = 1$ *vs* $H_1 : r = 2$	63.938	(0.000)	16.072	(0.000)	65.790	(0.000)	
		$H_0 : r = 2$ *vs* $H_1 : r = 3$	0.000	(1.000)	0.000	(1.000)	0.000	(1.000)	
		$H_0 : r = 3$ *vs* $H_1 : r = 4$							
	$m = 2$	$H_0 : r = 0$ *vs* $H_1 : r = 1$	181.33	(0.000)	25.65	(0.000)	197.38	(0.000)	2
		$H_0 : r = 1$ *vs* $H_1 : r = 2$	132.05	(0.000)	17.65	(0.000)	140.29	(0.000)	
		$H_0 : r = 2$ *vs* $H_1 : r = 3$	16.63	(0.034)	1.99	(0.045)	16.75	(0.033)	
		$H_0 : r = 3$ *vs* $H_1 : r = 4$							
Model B2 (Eq. (12)) for EC	$m = 1$	$H_0 : r = 0$ *vs* $H_1 : r = 1$	85.204	(0.000)	29.370	(0.000)	88.535	(0.000)	3
		$H_0 : r = 1$ *vs* $H_1 : r = 2$	21.768	(0.000)	7.042	(0.000)	21.977	(0.000)	
		$H_0 : r = 2$ *vs* $H_1 : r = 3$	14.439	(0.002)	4.628	(0.003)	14.531	(0.002)	
		$H_0 : r = 3$ *vs* $H_1 : r = 4$	14.418	(0.002)	4.608	(0.003)	14.509	(0.002)	
	$m = 2$	$H_0 : r = 0$ *vs* $H_1 : r = 1$	135.193	(0.000)	24.385	(0.000)	143.847	(0.000)	1
		$H_0 : r = 1$ *vs* $H_1 : r = 2$	8.577	(0.199)	1.367	(0.225)	8.609	(0.197)	
		$H_0 : r = 2$ *vs* $H_1 : r = 3$							
		$H_0 : r = 3$ *vs* $H_1 : r = 4$							

Source: Authors' estimations.

Table 7
The estimation results of the PSTR model for Model B1 (Eq. (11)) and Model B2 (Eq. (12)).

	Model B1 (Eq. (11)) for EG				Model B2 (Eq. (12)) for EC			
	m = 1		m = 2		m = 1		m = 2	
Parameter B10	9742.89***	(0.004)	0.438***	(0.000)	−0.747*	(0.057)	82,189.8***	(0.000)
Parameter B20	−40,389.4***	(0.000)	−0.053	(0.760)	22.949**	(0.031)	−915,864.3***	(0.000)
Parameter B30	23,076.2***	(0.000)	0.671***	(0.000)	−3.620	(0.171)	−160,501.2***	(0.000)
Parameter B40	−8660.7***	(0.050)	0.170	(0.157)				
Parameter B11	−19,484.6***	(0.004)	0.042	(0.597)	−8.328**	(0.026)	−164,378.6***	(0.000)
Parameter B21	80,776.2***	(0.000)	−0.493***	(0.001)	198.415**	(0.046)	1,831,723.4***	(0.000)
Parameter B31	−46,149.5***	(0.000)	0.348***	(0.001)	−36.127	(0.141)	321,002.01***	(0.000)
Parameter B41	17,321.1*	(0.050)	−0.167	(0.153)				
Parameter B12	0.048	(0.284)	−0.598***	(0.000)	−0.153***	(0.001)		
Parameter B22	−0.322***	(0.000)	1.699***	(0.000)	2.438*	(0.078)		
Parameter B32	0.216***	(0.000)	−0.896***	(0.000)	−0.185	(0.583)		
Parameter B42	−0.095	(0.172)	0.150	(0.233)				
Parameter B13					9.742**	(0.020)		
Parameter B23					−227.573**	(0.042)		
Parameter B33					40.019	(0.147)		
Parameter B43								
			Location Parameters c_j					
First Transition Function	−13.395		[0.402, 0.402]		2.203		[2.351, 3.3158]	
Second Transition Function	0.671		[0.081, 0.0805]		2.367			
Third Transition Function					0.078			
Slope Parameter y1	0.001		14.431		1.37		0.000	
Slope Parameter y2	9.757		0.121		2.478			
Slope Parameter y3					1.266			
AIC	−4.821		−4.829		−4.532		−4.471	
Schwarz	−4.753		−4.752		−4.455		−4.433	

Source: Authors' estimations.

individual coefficients are formulated by Eqs. (13) and (14). Subsequently, we proceeded to calculate Eqs. (15) and (16) for both models B1 and B2. The same calculations are to be extended to other variables as well.

$$\frac{\partial lnGDP_{it}}{\partial lnENE_{it}} = 0.438 + 0.042 \times h_j(R\&D_{it}; 14.431, [0.402, 0.402]) \\ -0.598 \times h_j(R\&D_{it}; 0.121, [0.081, 0.0805]) \tag{15}$$

$$\frac{\partial lnENE_{it}}{\partial lnGDP_{it}} = -0.747 - 8.328 \times h_j(R\&D_{it}; 1.37, 2.203) \\ -0.153 \times h_j(R\&D_{it}; 2.478, 2.367) + 9.742 \times h_j(R\&D_{it}; 1.266, 0.078) \tag{16}$$

Hence, the ultimate impacts of variables result from a combination of estimated coefficients and the transition function. Given the dynamic nature of the transition function over time, the effects will exhibit variations over both time and among different countries. The mean effects tied to the smoothed individual coefficients are presented in Table A1 of Appendix A. The figures in Table A1 represent the average effects at the country level based on individual estimates. Additionally, the values enclosed in parentheses denote the standard deviation of estimated coefficients for each specific country. While Table A1 offers valuable insights into the influence of model variables on EC and EG at the country level, it falls short in explaining the intricate nonlinear relationships governing the effects and the underlying reasons behind disparities in estimated parameters among countries. To comprehend these distinct effects, it becomes essential to visualize the estimated coefficients against varying levels of R&D. This visual representation can be observed in Fig. 1 for EG and Fig. 2 for EC. We calculated the average coefficients both at the country level (average parameters across different times within a particular country, as reported in Table A1) and at the time level (average parameters across different countries at a specific time).

In Fig. 1, the vertical axis displays the values of estimated parameters for each model variable, while the horizontal axis illustrates the average R&D levels across countries. Notably, while the estimated parameters each exhibit distinct positive or negative trends, the varying R&D levels

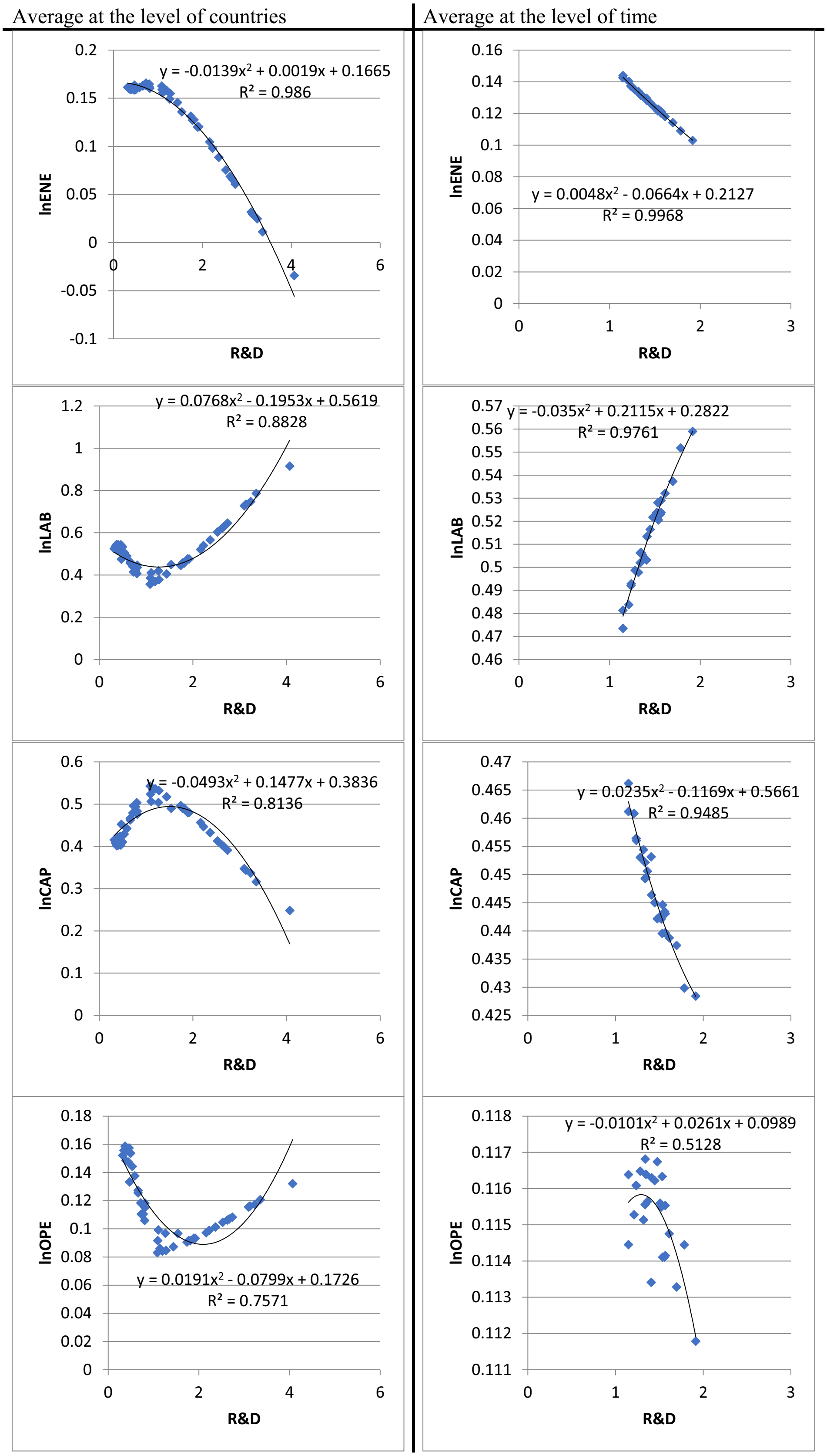
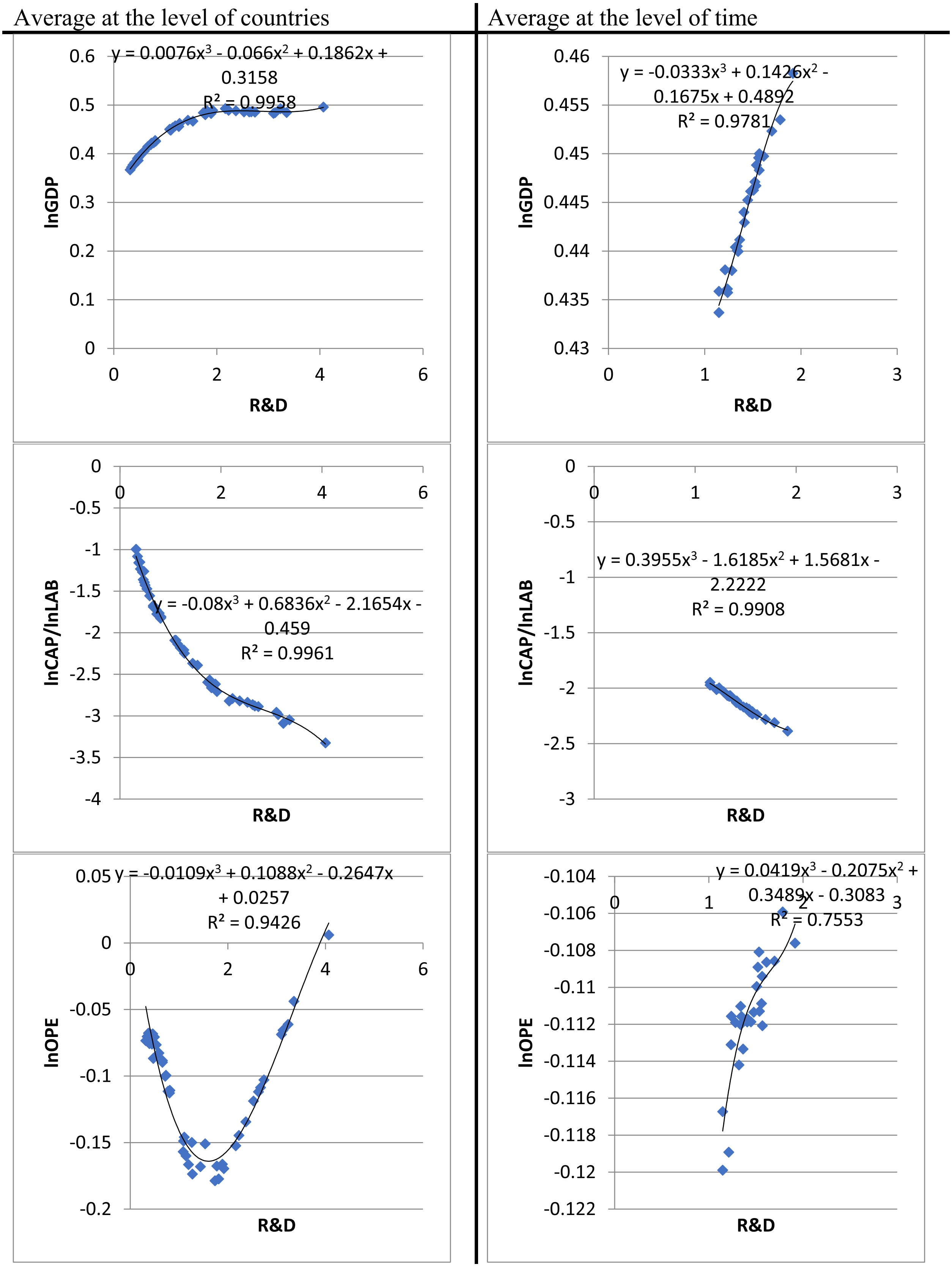


Fig. 1. The average estimated parameters of individual PSTR for Model B1 (Eq. (11)) for EG.


Average at the level of countries

Average at the level of time

Fig. 2. The average estimated parameters of individual PSTR for Model B2 (Eq. (12)) for EC.

among countries drive these effects' fluctuations. Fig. 1 illustrates that the average of estimated coefficients at both the time and country levels yield fairly similar outcomes, with the exception that the average at the time level displays lower dispersion. This discrepancy could arise due to the relatively short study period, which doesn't allow for significant temporal dispersion. However, these discrepancies are mitigated compared to the linear representation seen in Table 4 and Table 5, suggesting that employing the linear form has resolved such asymmetries.

As the results indicate, EC positively impacts EG. Nevertheless, these positive effects diminish with increasing R&D, ultimately leading to negative effects on a national average level. The logarithm of the labor force positively influences EG, and heightened R&D amplifies these positive effects, possibly indicating enhanced workforce efficiency. Notably, most panel models in linear forms revealed a negative effect for this variable, counter to our theoretical expectations. The logarithm of net capital formation and trade openness also yield positive effects on EG, with these positive effects being more pronounced at lower R&D levels and tends to either decrease or increase beyond a certain point.

The findings presented in Fig. 2 reveal that EG yields favorable impacts on EC. Notably, these beneficial effects exhibit greater prominence within countries boasting elevated R&D levels. The interplay of capital-to-labor ratio exerts asymmetric influences on EC. This parameter engenders negative effects on EC when R&D levels are low, whereas these negative effects are more severe for higher R&D tiers. Consequently, it is plausible to assert that capital can serve more as a substitute input for EC within nations characterized by advanced R&D levels, consequently leading to consumption reduction. Lastly, the extent of trade openness correlates with diminished EC, with this reduction being comparatively more restrained in countries boasting low and elevated R&D levels.

5. Discussion of results

This research delves into the intricate relationship between EG and EC across 46 countries spanning the years from 1996 to 2021. Employing diagnostic tests, we have devised a sophisticated panel model that effectively estimates model parameters. Specifically, we harnessed the power of the PSTR model to scrutinize the non-linear impacts of independent variables on both EC and EG.

The findings reveal a noteworthy insight: the logarithm of net capital formation exerts a positive influence on EG. This positive influence is particularly pronounced at lower levels of R&D, gradually tapering off beyond a certain point. It is important to underscore the pivotal role of fixed capital development in driving EG. This factor elucidates the variations in EG rates across countries, a phenomenon substantiated by previous research (Omri, 2013; Omri and Kahouli, 2014). The rationale behind the positive effects of the logarithm of net capital formation on EG lies in the augmentation of productivity and the expansion of an economy's productive capacity through capital accumulation. However, the attenuation of positive effects at elevated R&D levels could be attributed to the law of diminishing returns. This principle posits that as an economy nears the saturation point in capital utilization, the incremental benefits of additional capital formation start to dwindle. Furthermore, the dwindling positive effects beyond a certain R&D expenditure threshold might signify the diminishing marginal utility of R&D spending. In essence, while initial investments yield substantial breakthroughs, subsequent investments yield progressively fewer transformative outcomes. This underscores the significance of resource allocation optimization between capital formation and research endeavors, ensuring a sustainable and efficient trajectory of EG.

The impact of the capital-to-labor ratio on EC is not uniform and varies based on different circumstances. This factor yields negative effects on EC when R&D levels are low. Interestingly, this adverse effect becomes more pronounced as R&D levels increase. These observed outcomes stem from distinct economic dynamics related to the capital-labor ratio and EC among countries with differing degrees of R&D activity. In countries characterized by lower R&D levels, a higher capital-labor ratio often signifies a less advanced technological landscape and industrial processes. Consequently, this leads to energy-intensive production methods. Thus, an increase in the capital-labor ratio positively influences EC, as these economies heavily rely on traditional and less efficient energy-intensive production methods. Conversely, in nations with higher R&D levels, an elevated capital-labor ratio suggests a more technologically sophisticated and efficient industrial foundation. Here, increased capital investment tends to yield streamlined and energy-efficient production processes. Consequently, in such economies, a higher capital-labor ratio is more likely to result in reduced EC due to enhanced technological efficiency. This implies that capital can function as a substitute input for EC only in countries with substantial R&D efforts, leading to decreased consumption.

The impact of the logarithm of trade openness on EG is positive and is further pronounced at lower R&D levels. However, this positive effect diminishes beyond a certain point. Similarly, trade openness contributes to a reduction in EC, with this reduction being less substantial in countries with greater R&D activity. This finding aligns with Ghani's (2012) research, which demonstrates that dismantling trade barriers decreases transportation costs, ultimately leading to lower EC. Furthermore, increased trade openness introduces novel technologies and energy-efficient enhancements, thereby promoting EG. The favorable influence of trade openness on EG is attributed to the facilitation of goods and services exchange, enabling countries to access new markets, specialized resources, and technology. This, in turn, stimulates productivity and economic expansion. However, this relationship hinges on the level of R&D investment. Lower R&D levels result in more pronounced growth effects from trade openness due to potential technology spillovers and knowledge sharing from trade partners. As R&D levels rise, the incremental benefits from trade lessen, possibly due to diminishing returns in technology adoption or heightened competition. Moreover, trade openness's association with decreased EC can be explained by the import of energy-efficient technologies and the specialization of production in countries with comparative advantages, which promotes resource-efficient processes. Nonetheless, this effect is modulated by a high level of R&D, as countries with substantial R&D investments tend to swiftly innovate and adopt energy-saving technologies, thus mitigating the decline in EC resulting from trade openness.

The study's findings illuminate a significant and positive connection between EG and Enhanced EC, signifying a mutually advantageous relationship between the two factors. Moreover, the results suggest that the level of R&D exerts a notable influence on the favorable effects of EG on EC. This implies that heightened R&D endeavors amplify the positive repercussions of EG on EC. The mechanism at play here is the concept of economic complexity, wherein R&D-driven innovation leads to the enhancement of industries and products, culminating in an escalated demand for energy-intensive processes and technologies. This, in turn, bolsters overall EC. In addition, elevated investments in R&D contribute to augmented productivity and efficiency. This enables economies to harness growth opportunities with greater efficacy, thereby increasing their overall energy requisites. Thus, the interplay between R&D, EG, and EC is shaped by the dynamic interaction of innovation-driven factors and the intricacy of economic activities. Furthermore, the results demonstrate that higher levels of R&D lead to a reduction in the positive effects of EC on EG. This finding aligns with the feedback hypothesis, indicating that EC and EG are interconnected, particularly in countries with lower R&D levels. Similar findings have been reported in studies by Ajmi et al. (2013), which showed a direct relationship between EC and EG, implying that EG stimulates EC. This is also consistent with the findings of other researchers such as Kahouli (2019) and Kasman and Duman (2015) who established a significant and positive correlation between EC and EG.

These empirical outcomes can be attributed to the economic principle of diminishing returns to EC due to intensified R&D activities. As R&D efforts increase, technological advancements and innovations are likely to enhance energy utilization efficiency, fostering sustainable EG. This could mitigate the once-strong positive relationship between EC and EG, as economies become adept at achieving higher output with relatively less energy input. Consequently, the diminishing marginal utility of EC resulting from heightened R&D activities leads to a decrease in the previously pronounced positive effects of EC on EG. The transition towards more advanced and efficient technologies spurred by increased R&D efforts introduces a negative influence of EC on EG. This is because the economy becomes less reliant on energy inputs and more dependent on knowledge-driven productivity enhancements. This transformation underscores the evolving dynamics between innovation, EC, and economic development, signifying a shifting nature in their relationship. Consequently, our findings support the growth hypothesis for countries with high R&D levels. This observation aligns with prior research conducted in various countries, including the US (Bowden and Payne, 2010; Payne, 2011; Stern, 1993, 2010); Italy, France, Canada, Germany, and the UK (P. K. Narayan and Smyth, 2008); India (Jayasinghe and Selvanathan, 2021); Japan (Lee and Chien, 2010; P. K. Narayan and Smyth, 2008); Indonesia and Malaysia (Mahadevan and Asafu-Adjaye, 2007); Canada (Lee and Chien, 2010); Czech, Hungary, and Slovakia (Krkošková, 2021); Sweden (Piłatowska and Geise, 2021); 59 countries (Mamkhezri et al., 2022); among others. Our findings underscore the significance of factoring a country's economic structure as a crucial element that moderates the impact of diverse variables.

6. Conclusion and policy implications

The study's outcomes suggest a compelling need for policymakers to strategically optimize the distribution of resources between capital formation and research endeavors to ensure consistent and effective economic advancement. The role of capital accumulation in strengthening productivity and expanding the economy's productive capabilities, underscored by the favorable impacts of the natural logarithm of net capital formation on EG, emerges as a pivotal factor. However, it is crucial to take into account the diminishing advantageous effects observed at elevated levels of R&D spending, considering the principles of diminishing returns and the decreasing marginal utility associated with research expenditures.

Moreover, recognizing the asymmetric impacts of the ratio of capital to labor on EC across varying levels of R&D underlines the necessity of endorsing energy-efficient production techniques. This becomes particularly relevant for nations with elevated R&D intensities. The promotion of advanced technologies and streamlined industrial processes could lead to diminished EC, consequently enhancing overall economic performance. In addition, the affirmative correlation between trade openness and EG accentuates the pivotal role of trade as a catalyst for productivity enhancement and economic expansion. This effect is more pronounced in contexts characterized by lower levels of R&D. Hence, policymakers should concentrate on nurturing international trade relations, all the while bearing in mind the concept of diminishing returns associated with heightened trade openness. Striking the right balance between domestic innovation and knowledge transfer through trade emerges as a key consideration. Lastly, the intricate interplay between EG, EC, and R&D necessitates a nuanced approach.

The evolving relationship between EC and EG resulting from intensified R&D activities should also be a guiding factor in policy formulation. Acknowledging the shift towards knowledge-driven productivity enhancements and its subsequent implications for energy dependency adds a layer of complexity to policy considerations. Effective policy decisions demands a comprehensive understanding of the dynamic interactions between capital formation, R&D, trade openness, and their intricate impacts on EG and EC.

This study has some shortcomings that future researchers should take into account. We primarily focused on the relationship between EG, EC, and various factors across countries but may not capture country-specific nuances or contextual factors that could influence these relationships. Our study uses data from 46 countries from 1996 to 2021, potentially overlooking other countries and temporal variations (e.g., monthly) that could affect the relationships studied. Therefore, future studies should investigate these relationships using data from more countries and over a longer (more granular level) horizon when the data becomes available. Future studies may also consider including more variables such as economic complexity and uncertainty across countries in their analyses.

Funding

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Code availability

Available upon request and for replication.

Ethics approval

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Consent to participate

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Consent for publication

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CRediT authorship contribution statement

Mohsen Khezri: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation. **Jamal Mamkhezri:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Investigation, Formal analysis, Conceptualization. **Almas Heshmati:** Writing – review & editing, Validation, Methodology, Formal analysis.

Declaration of competing interest

No conflicts of interest.

Data availability

Available upon request and for replication.

Appendix A

Table A1
The average estimated parameters of individual PSTR for Model B1 and B2.

	Model B1 (Eq. (11)) for EG				Model B1 (Eq. (11)) for EG		
	lnENE	*lnLAB*	*lnCAP*	*lnOPE*	*lnGDP*	$\frac{lnCAP}{lnLAB}$	*lnOPE*
Egypt, Arab Rep.	0.164	0.474	0.452	0.133	0.386	−1.262	−0.087
	(0.003)	(0.059)	(0.043)	(0.022)	(0.034)	(0.497)	(0.018)
Uruguay	0.160	0.536	0.408	0.156	0.372	−1.082	−0.070
	(0.003)	(0.024)	(0.017)	(0.008)	(0.015)	(0.236)	(0.007)
Cyprus	0.161	0.514	0.424	0.147	0.385	−1.271	−0.076
	(0.003)	(0.057)	(0.041)	(0.021)	(0.024)	(0.349)	(0.015)
Mexico	0.159	0.545	0.402	0.159	0.377	−1.158	−0.068
	(0.001)	(0.012)	(0.008)	(0.004)	(0.011)	(0.173)	(0.003)
Romania	0.159	0.543	0.403	0.157	0.390	−1.361	−0.068
	(0.001)	(0.022)	(0.016)	(0.008)	(0.010)	(0.135)	(0.005)
Costa Rica	0.159	0.543	0.403	0.158	0.382	−1.233	−0.068
	(0.001)	(0.013)	(0.009)	(0.005)	(0.013)	(0.202)	(0.003)
North Macedonia	0.161	0.525	0.415	0.152	0.367	−0.997	−0.073
	(0.003)	(0.032)	(0.022)	(0.010)	(0.017)	(0.277)	(0.009)
Latvia	0.161	0.507	0.429	0.144	0.399	−1.472	−0.077
	(0.003)	(0.051)	(0.037)	(0.019)	(0.017)	(0.228)	(0.012)
Argentina	0.159	0.533	0.410	0.154	0.395	−1.427	−0.071
	(0.001)	(0.026)	(0.019)	(0.010)	(0.010)	(0.144)	(0.006)
Cuba	0.159	0.534	0.410	0.154	0.393	−1.393	−0.071
	(0.001)	(0.022)	(0.016)	(0.008)	(0.013)	(0.186)	(0.005)
Bulgaria	0.161	0.490	0.442	0.138	0.405	−1.556	−0.083
	(0.004)	(0.078)	(0.057)	(0.029)	(0.018)	(0.224)	(0.022)
Lithuania	0.165	0.407	0.503	0.106	0.427	−1.826	−0.113
	(0.003)	(0.069)	(0.051)	(0.026)	(0.017)	(0.200)	(0.029)
Estonia	0.149	0.419	0.504	0.097	0.456	−2.207	−0.150
	(0.019)	(0.055)	(0.035)	(0.018)	(0.029)	(0.383)	(0.040)
Slovak Republic	0.163	0.439	0.479	0.118	0.419	−1.724	−0.100
	(0.004)	(0.082)	(0.060)	(0.031)	(0.019)	(0.232)	(0.029)
Poland	0.162	0.435	0.483	0.115	0.426	−1.820	−0.111
	(0.005)	(0.066)	(0.050)	(0.027)	(0.023)	(0.266)	(0.039)
Portugal	0.156	0.411	0.506	0.099	0.448	−2.091	−0.146
	(0.009)	(0.042)	(0.033)	(0.020)	(0.027)	(0.332)	(0.045)
Belarus	0.163	0.462	0.462	0.127	0.414	−1.674	−0.090
	(0.003)	(0.058)	(0.043)	(0.022)	(0.013)	(0.157)	(0.019)
India	0.166	0.415	0.496	0.110	0.422	−1.774	−0.099
	(0.002)	(0.034)	(0.025)	(0.013)	(0.006)	(0.067)	(0.010)
Hungary	0.159	0.385	0.523	0.092	0.449	−2.091	−0.149
	(0.009)	(0.038)	(0.027)	(0.015)	(0.021)	(0.255)	(0.035)
Spain	0.159	0.371	0.534	0.086	0.453	−2.137	−0.160
	(0.006)	(0.014)	(0.008)	(0.004)	(0.014)	(0.169)	(0.026)
China	0.136	0.449	0.490	0.097	0.467	−2.392	−0.151
	(0.027)	(0.070)	(0.040)	(0.016)	(0.029)	(0.428)	(0.033)
Ukraine	0.164	0.420	0.494	0.111	0.423	−1.764	−0.111
	(0.004)	(0.082)	(0.061)	(0.032)	(0.025)	(0.316)	(0.034)
Italy	0.158	0.369	0.536	0.084	0.457	−2.181	−0.167
	(0.007)	(0.019)	(0.010)	(0.001)	(0.011)	(0.140)	(0.017)
Russian Federation	0.163	0.357	0.543	0.083	0.450	−2.092	−0.157
	(0.003)	(0.008)	(0.004)	(0.001)	(0.006)	(0.069)	(0.011)
Ireland	0.155	0.378	0.532	0.085	0.462	−2.247	−0.174
	(0.008)	(0.023)	(0.012)	(0.002)	(0.011)	(0.146)	(0.010)
Czechia	0.146	0.405	0.517	0.087	0.469	−2.368	−0.168
	(0.019)	(0.053)	(0.028)	(0.004)	(0.019)	(0.291)	(0.014)
Slovenia	0.127	0.457	0.490	0.092	0.480	−2.568	−0.168
	(0.027)	(0.076)	(0.040)	(0.007)	(0.012)	(0.246)	(0.021)
United Kingdom	0.120	0.476	0.480	0.093	0.483	−2.618	−0.166
	(0.033)	(0.093)	(0.049)	(0.008)	(0.004)	(0.169)	(0.034)
Netherlands	0.120	0.476	0.480	0.093	0.489	−2.706	−0.170
	(0.014)	(0.040)	(0.021)	(0.004)	(0.003)	(0.101)	(0.015)
Canada	0.127	0.456	0.491	0.092	0.488	−2.662	−0.177
	(0.007)	(0.021)	(0.011)	(0.002)	(0.003)	(0.077)	(0.007)
Austria	0.075	0.603	0.413	0.105	0.486	−2.837	−0.119
	(0.040)	(0.114)	(0.060)	(0.010)	(0.004)	(0.129)	(0.045)
Belgium	0.098	0.539	0.447	0.099	0.489	−2.792	−0.145
	(0.038)	(0.107)	(0.057)	(0.009)	(0.003)	(0.119)	(0.043)
France	0.105	0.521	0.457	0.097	0.493	−2.821	−0.152
	(0.005)	(0.014)	(0.008)	(0.001)	(0.000)	(0.018)	(0.006)
Korea, Rep.	0.025	0.748	0.337	0.117	0.492	−3.089	−0.061
	(0.070)	(0.200)	(0.105)	(0.018)	(0.007)	(0.285)	(0.080)
Denmark	0.069	0.623	0.403	0.106	0.486	−2.864	−0.112
	(0.030)	(0.085)	(0.045)	(0.008)	(0.004)	(0.064)	(0.034)

(*continued on next page*)

Table A1 (*continued*)

Model B1 (Eq. (11)) for EG					Model B1 (Eq. (11)) for EG		
	lnENE	*lnLAB*	*lnCAP*	*lnOPE*	*lnGDP*	$\frac{lnCAP}{lnLAB}$	*lnOPE*
Germany	0.066	0.630	0.399	0.107	0.486	−2.880	−0.109
	(0.025)	(0.072)	(0.038)	(0.006)	(0.004)	(0.042)	(0.029)
Iceland	0.089	0.566	0.433	0.101	0.488	−2.820	−0.134
	(0.026)	(0.074)	(0.039)	(0.007)	(0.004)	(0.076)	(0.029)
United States	0.061	0.645	0.391	0.108	0.485	−2.888	−0.103
	(0.022)	(0.063)	(0.033)	(0.006)	(0.002)	(0.065)	(0.026)
Japan	0.032	0.728	0.347	0.116	0.483	−2.957	−0.069
	(0.016)	(0.045)	(0.024)	(0.004)	(0.001)	(0.056)	(0.019)
Finland	0.029	0.735	0.344	0.116	0.484	−2.984	−0.066
	(0.028)	(0.078)	(0.041)	(0.007)	(0.002)	(0.108)	(0.033)
Israel	−0.034	0.915	0.248	0.132	0.496	−3.325	0.006
	(0.046)	(0.131)	(0.069)	(0.012)	(0.007)	(0.227)	(0.051)
Moldova	0.161	0.516	0.422	0.148	0.377	−1.152	−0.076
	(0.003)	(0.053)	(0.039)	(0.020)	(0.024)	(0.337)	(0.015)
Tunisia	0.163	0.456	0.466	0.125	0.415	−1.691	−0.088
	(0.002)	(0.035)	(0.025)	(0.013)	(0.006)	(0.074)	(0.008)
Greece	0.160	0.446	0.476	0.118	0.425	−1.809	−0.111
	(0.006)	(0.071)	(0.054)	(0.029)	(0.026)	(0.316)	(0.043)
Norway	0.131	0.445	0.497	0.091	0.484	−2.595	−0.179
	(0.014)	(0.040)	(0.021)	(0.004)	(0.006)	(0.140)	(0.013)
Sweden	0.011	0.786	0.317	0.121	0.485	−3.048	−0.044
	(0.013)	(0.037)	(0.019)	(0.003)	(0.002)	(0.071)	(0.016)

Notes: p-values in parentheses. Source: Authors' estimations.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107519.

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