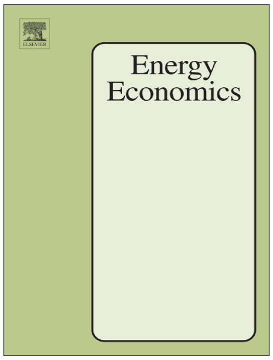

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On public policies in the energy transition: Evidence on the role of socio-technical regimes for renewable technologies

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Abstract

Our purpose is to contribute to the debate on the energy transition by investigating the role of social, technical, political, and cultural aspects in stimulating the export of renewable technologies (RTs). The literature draws attention to the need to complement public policies with a supportive socio-technical regime, even if evidence is scarce. We maintain that countries' capability in environment-related technologies, public concern and awareness of climate change, and understanding of its damaging effects are relevant drivers, alongside renewable energy policies. Moreover, we expect that such socio-technical drivers, if operating together, amplify the stimulus of policies. We test these arguments through a panel vector autoregressive (PVAR) model in first differences in the EU over the period 1996-2020. Due to heterogeneity across countries, we test the determinants on high-performing countries. Results confirm the role of public awareness and show that the export of RTs is also stimulated by increases in the share of environment-related technologies and understanding of climate change. Countries' capability in green technologies is also supported by increases in public awareness and understanding of the climate issue.

Abstract

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1. Introduction

The climate challenge has been at the forefront of the public debate since the establishment of the United Nations Paris Agreement, a legally binding international treaty signed in 2015 by nearly 200 countries to limit global warming to well below 2 (preferably 1.5) degrees Celsius. The pace of government activity in this area has recently accelerated. In terms of the European area, Sweden, the United Kingdom, France, Denmark, and Hungary have created laws that commit them to achieving net-zero emissions by 2050. The European Union (EU) and some member states have proposed legislation in the same direction and with similar timing. Finland, Austria, Iceland, Germany, Switzerland, Norway, Ireland, Portugal, and Slovenia have made stringent commitments in policy documents.

Beyond the steps already taken, there is still a long way to go. The International Energy Agency (IEA) states that by 2030 emissions must fall by 45% relative to 2010 to be on track to reach carbon neutrality (IEA, 2020). The private sector is also doing its part. Firms are reconsidering their production processes and logistic systems, designing new environmentally friendly products and services, disrupting their business models, and developing technologies that impact positively on the reduction of carbon dioxide emissions.

For several years now, renewable technologies (RTs) have played a crucial role in energy production by reducing non-renewable energy deployment and limiting carbon dioxide emissions. Photovoltaics is a well-established technology that combines the economies of scale that are possible in manufacturing with the advantage that these technologies can be deployed in very small quantities at a time. Onshore wind technology has evolved rapidly: the amount of electricity produced per megawatt of capacity installed has risen substantially and wind turbines have become bigger, with taller hub heights and larger rotor diameters. Offshore wind production is expected to grow, since the deployment of turbines in the sea will benefit from better wind resources than at land-based sites (IEA, 2021). While technological advances are important, resistance from firms and consumers can slow the adoption of RTs: some firms refuse to use renewables because they prefer the reliability of conventional power plants, and consumers may still not realise the associated benefits (Smith et al., 2005; Andrews-Speed, 2016). Understanding the socio-technical factors may allow for adopting more effective policies and attaining more consistent outcomes.

If RTs are critical, so is their export. The export of such technologies is fundamental to solving the environmental challenge at the global level, by fostering the diffusion of green technologies across countries (Chen and Lin, 2020). How to succeed in stimulating the export of RTs is debated.

It is undisputed that public policy matters. There is an extensive literature that emphasises the role played by public policies such as environmental regulations (Costantini and Crespi, 2008; Costantini and Mazzanti, 2012; Groba, 2014), renewable energy policies (Sawhney and Kahn, 2012; Groba and Cao, 2015; Kuik et al., 2019; Ogura, 2020), and R&D subsidies (Sung and Song, 2013, 2014; Kim and Kim, 2015; Sung, 2015). Nonetheless, many argue that public policies cannot be isolated from the socio-technical issues underlying the energy transition (Smith et al., 2005; Jacobsson and Lauber, 2006; Sovacool, 2009; Andrews-Speed, 2016). Despite its common sense, such a proposition finds scarce evidence (Laird and Stefes, 2009; Sung and Wen, 2018; Batel, 2020).

Our purpose is to contribute to the debate on the energy transition by investigating the role of social, technical, political, and cultural aspects in stimulating the export of RTs. The literature draws attention to the need to complement public policies with a supportive socio-technical regime: the latter shapes the context in which policies are formulated, implemented, and their outcomes. We maintain that countries' capability in environment-related technologies, public concern and awareness of climate change, and understanding of its damaging effects are relevant drivers, alongside renewable energy policies. Moreover, as stressed by Darmani et al. (2014), according to whom all factors behind the energy transition should be investigated within an integrated framework, we expect that such socio-technical drivers, if operating together, amplify the stimulus of public policies. In addition to the socio-technical variables mentioned above, two further variables are included: foreign trade, to account for external sources of technological progress, and income per capita, to control for countries' wealth and industrial modernity.

In the next section, we review the literature and illustrate in more detail the research hypotheses, which are tested using a PVAR (panel vector autoregressive) model in first differences for a panel of 28 EU member states (including the United Kingdom for the period of membership) and a sub-panel of the 14 most performing countries (which represent the ideal target of our investigation) from 1996 to 2020.

Due to heterogeneity across countries, evidence on the 28 EU members is mixed, with only a couple of results: more renewable energy policy and public awareness of the climate change promote the export of RTs. By splitting the countries based on their export performance, we test the leverage of the determinants on high performing countries. Results confirm the role of public awareness and show that the export of RTs is also stimulated by increases in the share of environment-related technologies and understanding of climate change. Countries' capability in green technologies is also supported by increases in public awareness and understanding of the climate issue, while trade openness is only relevant in low-performing countries (crucial to compensate the poor green-tech performance).

The remainder of the paper is organised as follows. Section 2 reviews the literature on the determinants of the export of RTs and sets out the research hypotheses. Section 3 presents the empirical analysis, including the model specification and the methodology, and discusses the results. Section 4 concludes this study.

2. Literature

In this section, we provide a review of the literature investigating the relationship between public policy and the export of RTs.

Initially, empirical studies adopted a descriptive approach (Lewis and Wiser, 2007). Klaassen et al. (2005) investigated the effect of public R&D policies on cost-reducing innovations for wind turbine farms and found that some governments have been able to increase their export of RTs over time. Lund (2009) suggested that policies enhancing home markets for domestic renewable sectors lead to growing industrial activities, and R&D support to related industries can also help. According to Liu and Goldstein (2013), the emblematic case is that of China, which has introduced several policies to set up an industrial base for the manufacturing of RTs: China's solar photovoltaic industry has become the largest worldwide, and its wind turbine production has experienced successful growth rates.

Gradually, the literature shifted to a more quantitative approach. Costantini and Crespi (2008) investigated environmental regulations and their impact on technological change. Using a gravity model, the authors found that such regulations represent a crucial driver of green-tech export. Jha (2009) utilised a regression model to analyse the impact of policy measures on the export of RTs. The author found evidence that the exporting country's subsidies are effective and increase the competitiveness of the industry. Sawhney and Kahn (2012) examined the US imports from a panel of countries and regressed the export of wind and solar power generation equipment on several variables. The emphasis was on the complementarities between government policy and private capital. Costantini and Mazzanti (2012) showed that environmental policies foster the export of green technologies in the EU. Sung and Song (2013) focused on technology-push policies and demonstrated that these had a positive impact on exports in the long run and that there was a short-term causal relationship between market-pull policies and exports. Moreover, in the long run an increase in government R&D expenditures increased exports, and there was a bidirectional and short-run relationship between exports and the contribution of renewable energy to the total energy supply: the latter had a negative effect on exports, whereas the former had a positive effect on renewable energy supply.

Sung and Song (2014) employed dynamic panel econometric techniques to explore the dynamic relationships between government policies and exports of RTs: biomass, solar and wind technologies exhibited different types of feedback among policy, exports, and gross domestic product (GDP) in the short and long run. Groba (2014) concentrated on solar energy technology components and tested the hypothesis by which renewable energy policies affect trade flows. The author affirmed that renewable energy policies allow for gaining a comparative advantage. Kim and Kim (2015) showed that R&D boosts the exports of RTs, there is path dependence between R&D and exports of wind power technologies and, finally, tariff incentives encourage international trade and domestic R&D. Sung (2015) analysed the effects of public policy support on the export of bioenergy technologies. In the long term, public R&D expenditures and GDP had a positive effect on the exports, while the contribution of bioenergy to the total energy supply had a negative effect. Groba and Cao (2015) examined the dynamics of exports of solar photovoltaic and wind energy technology. They confirmed the positive impact of R&D policies. Kuik et al. (2019) investigated the impact of domestic renewable energy policies on the export performance of RTs and demonstrated a positive effect: demand-pull policies, such as feed-in tariffs, foster the development of RTs. Ogura (2020) considered the effects of the interaction between innovative capacity and renewable energy policies on the export of RTs. The evidence suggested that policies in importer countries exert a robust influence, while those in exporter countries may have a negative effect. This result contradicted previous results on the effect of renewable energy policies.

To sum up, it emerges a net-positive effect of the public policy on the export of RTs (Costantini and Mazzanti, 2012, Kuik et al., 2019; Sung, 2015). Also, higher R&D subsidies as well as increasing technological capability provide support (Kim and Kim, 2015; Sung and Song, 2013; 2014). Still, in the background, there is an overall positive impact from countries' openness to trade and GDP per capita (Groba, 2014; Groba and Cao, 2015; Ogura, 2020). From the mentioned literature, we derive our first research hypothesis.

Hypothesis #1 (Hp#1): Renewable energy policies influence positively the export of RTs, given the level of trade openness and GDP per capita.

Then, as suggested by the literature on the energy transition, the attention has shifted to socio-technical regimes, which would represent the indispensable substratum for the success of the adopted policy measures (Smith et al., 2005; Sovacool, 2009; Nilsson et al., 2011). Nowadays, it is not possible to think about the effectiveness of public policies in the energy field without considering in an integrated manner the nexus between regulatory, technological, political, social, and cultural aspects (Andrews-Speed, 2016; Batel, 2020). First, the literature introduced a political-institutional dimension. Laird and Stefes (2009) emphasised the impact of the renewable energy policies taken by the German government compared with those adopted in the USA: despite starting with similar policy frameworks, the two countries were on different policy paths after 2000, with the result that Germany has moved ahead of the US in terms of the export of RTs. The authors explained how such different outcomes resulted from the distinctive institutional and social structures affecting policymaking in each country. The contribution of

Jacobsson and Lauber also concerned a similar topic (2006). According to the authors, who focused on the political process that led to the adoption of policies on RTs in Germany, the regulatory framework was designed in an ‘institutional battle’ where both the private sector and the public opinion played a role.

The social dimension was gradually introduced and the relevant variables became better defined. With regard to renewable energy deployment, Menegaki (2011) studied the link between economic growth and renewable energy, finding that perceived risks, poor information, environmental externalities, and a lack of confidence/familiarity with their technical and economic potential represent barriers. Salim and Rafiq (2012) investigated the determinants of renewable energy consumption in a panel of six major emerging economies. The evidence confirmed the expected causal relationships between renewable energy and income, and between the former and carbon dioxide emissions. Emissions have been included in the model as an important explanatory variable: higher emissions generate demand for green technologies and renewable energy. Marra and Colantonio (2021) investigated the role of socio-technical aspects such as policy stringency, lobbying, and public awareness of climate change on renewable energy consumption. The authors found that public awareness is not enough to facilitate the energy transition, while environmental policy stringency has positive direct and indirect effects. Huang et al. (2007) noted that education was positively associated with the concern about the harmful effects of non-renewables. With reference to the export of RTs, Sung and Wen (2018) included renewable energy policies, public awareness about environmental issues, lobbying from traditional and nuclear energy, public green R&D spending, and GDP levels as regressors. They demonstrated that renewable energy policy and public awareness had positive effects on exports, while R&D spending had a negative effect. In addition, Kardooni et al. (2018) and Makki and Mosly (2020) confirmed that a lack of public awareness can be a relevant barrier.

While policy support is important, lack of public concern and understanding of the climate effects can impede or slow the energy transition (Salim and Rafiq, 2012; Sung and Wen, 2018; Marra and Colantonio, 2021). The above-mentioned literature informed the identification of two further research hypotheses, the selection of the relevant variables, and the expected signs of the relationships between them. By combining the previous arguments, we put forward our second and third hypotheses.

Hypothesis #2 (Hp#2): Socio-technical issues are relevant drivers of the export of RTs, together with renewable energy policies. More specifically, under the same circumstances, an increase in the export of RTs is stimulated by:

(a) an increase in the public concern and awareness of the climate change,

(b) an increase in the understanding of the damaging effects of climate change,

(c) an increase in the countries’ capability in environmental-friendly technologies.

Hypothesis #3 (Hp#3): Socio-technical drivers, if operating together, amplify the stimulus of public policies. This means that, under the same circumstances, an increase in the export of RTs is brought (additionally and indirectly) by the interplay of socio-technical variables.

3. Empirical analysis

3.1. Model specification and methodology

Based on the recent literature, we introduce a model built on the following indicators: the export value of RTs (share of GDP, in thousands of current US $, RET); environmental policy effort approximated by the renewable electricity output (% of total electricity output, EPO); public concern and awareness measured as carbon dioxide emissions (metric tons per capita, AWA); the educational attainment level of the population (in %, EDU); patents on environment technologies (% of total, PAT); openness to foreign trade, defined as the ratio of exports plus imports over GDP (TRD); and gross domestic product per capita (in constant 2017 international $, GDP).

The name of each variable, the definition and the source are shown in Table 1.

Table 1 about here

The choice of the proxies for all the variables is in line with the literature. We choose to measure the countries' performance in terms of export of RTs for two reasons. Firstly, exports take into account the R&D, manufacturing and commercialisation of RTs: this latter phase, although often underestimated, is essential (Shakeel et al., 2017). Secondly, RET considers the success in the market and represents a tangible measure of the actual contribution of a country to the climate challenge at the global level. The data have been extracted from the United Nations Commodity Trade Statistics (UN COMTRADE) database, based on the Harmonized Commodity Description and Coding System (HS-96). The topologies of RTs and components have been provided by Jha (2009) and widely adopted in the literature (Algieri et al., 2011; Sung and Song, 2014; Sung, 2015; Kuik et al., 2019).

As policy variable we opted for the level of renewable electricity output, in accordance with a large literature (Peters et al., 2012; Sung and Song, 2014; Hille et al. 2019). EPO represents the genuine effort of a country to renewables and the attained result. This indicator, which is an indirect and output based measure of policy stringency, captures the regulatory intensity by reflecting the impact of renewable policies (Brunel and Levinson, 2016).

The level of carbon dioxide emissions per capita (AWA) summarizes the level of environmental pollution, and represents the public concern about the climate change. A high level of carbon dioxide emissions increases the demand for environmental protection and stimulates the development and use of renewables (Sadorsky, 2009; Salim and Rafiq, 2012; Sung and Wen, 2018).

EDU measures the educational attainment level (upper secondary, post-secondary non-tertiary and tertiary education) of the population aged 15 to 64 years. It is sometimes referred to as 'informal regulation', a relevant driver in raising the level of attention to environmental issues (Zarnikau, 2003; Wang and Shao, 2019). In effect, individuals too often seem to not fully appreciate (or ignore) the advantages of RTs: misunderstanding, reluctance, and even resistance may slow or impede the energy transition (Sovacool, 2009; Shahbaz et al., 2020a). A higher level of education increases the citizens' understanding of the effects of climate change (Xie et al., 2017; Neves et al., 2020; Marra and Colantonio, 2022). A strong association is expected between AWA and EDU (Dasgupta et al., 2016).

The share of patents for environment-related technologies (PAT) allows for accounting for the technological capability of a national innovation system to support RTs (Pitelis et al., 2020; Tee et al., 2021). A greater capacity to produce knowledge internally should contribute to RET (Costantini and Crespi, 2008; Hille and Möbius, 2018; Awijen et al., 2022). Looking at PAT, instead of gross domestic expenditure in R&D, reduces the 'policy' connotation usually implicit in the latter.

TRD is the sum of exports and imports of goods and services measured as a share of gross domestic product and can be interpreted as a control for the openness of a country to foreign trade, a channel by which external sources can spill inside and benefit the development of RTs (Costantini and Crespi, 2008; Jha, 2009; Nasir et al., 2021). The introduction of this variable into our framework allows for taking into account the effect of the exchange of technologies and knowledge between countries.

The level of GDP per capita can be considered a proxy for countries' industrial modernity, as widely adopted in the literature (Groba and Cao, 2015). GDP can also be used as a proxy for the political approach to the climate challenge, given the large gap between more and less advanced countries in terms of political incentives, standard settings, and R&D funding relating to the environment (de Serres et al., 2010; Cadoret and Padovano, 2016; Shahbaz et al., 2020b).

We employ a PVAR model based on a system of equations in which all the variables are treated as endogenous (Kazemzadeh et al., 2023). Such a feature assists in exploring multiple relationships between the variables, as identified in our propositions. Moreover, the PVAR enables capturing the effects of one exogenous shock of one variable on another in the system, while keeping all the others invariant. This allows for highlighting bidirectional dynamic effects and potential path dependences. The PVAR has been used in the recent literature on renewables (Acheampong et al., 2021; Charfeddine and Kahia, 2021; Zhang and Chen, 2022).
Inspired by Pham et al. (2020) and Wang et al. (2022a, 2022b), we introduce the following model with the aim of highlighting endogenous relationships between the previously defined indicators:

$$X_{i,t} = \sum_{j=1}^{P} A_j X_{i,t-j} + h_i + l_t + \varepsilon_{i,t} \quad (1)$$

In equation (1), $X_{i,t}$ is a $N \times 1$ vector of stationary variables in the i country in the t year, A_j represents a $N \times N$ matrix of the autoregressive coefficients, $X_{i,t-j}$ is the matrix of explanatory variables consisting of the lagged terms, P is the optimal lag order, h_i is a vector of individual (country in our case) fixed effects, l_t is a vector of time (year in our case) fixed effects, and $\varepsilon_{i,t}$ indicates a vector of idiosyncratic errors.

We try to explain the export of solar and wind energy technologies, focusing on socio-technical determinants, with a panel of 28 European countries, and subsequently a subset of the best-performing ones with respect to RET, using the longest time span possible from 1996 to 2020. The choice with respect to the first set of countries reflects economic and geographical criteria: the panel includes modern countries that in 2020 still belonged to the EU, thus facilitating concretely applicable policy implications. According to Bourcet (2020), 21% of the papers focusing on renewable energy deployment limit the analysis to all or some EU members.

Nonetheless, as also emphasised in the recent European Green Deal, presented in December 2019, the European Commission underlines how countries need different strategies for the deployment of renewable energy sources and technologies. Furthermore, it is useful to understand why some countries perform better than others in terms of export of RTs. Accordingly, we focus our attention on 14 member states (Austria, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, Germany, Hungary, Netherlands, Poland, Romania, Slovakia, and Slovenia) that reached higher levels of RET in the last five years which show a performance, on average, above the median. The criterion is rational and does not create any distortion for the analysis: the selected countries in the best-performing group would have been the same even if we had used the average RET over the last 10 years. Similarly, if we had considered the average value of RET over the entire period 1996–2020, only Belgium and Sweden would have replaced Bulgaria and Poland.

As highlighted by Chia et al. (2022), the PVAR allows for identifying the dynamic effect of shocks of the unobserved heterogeneity across countries and its causal effects. Moreover, since recommendations may be based on a technique that addresses the issues of cross-sectional dependence and heterogeneity, Dogan et al. (2022) underline that the outcome of a PVAR model is more reliable from a policy point of view.

Tables 2 shows the main descriptive statistics for both panels.

Table 2 about here

Over the years, the best-performing countries with respect to RET have recorded an average level of the export value of RTs (per billion GDP) of 8.65, much higher than the 5.68 of the entire group (the standard deviations were similar). Interestingly, they never showed RET values lower than 1.29 (while at the level of the whole group the worst result is close to zero). The subset of the best-performing countries also showed higher values on average in terms of EPO, AWA, EDU, and PAT: by innovating in the field of environmentally related technologies, likely stimulated by higher levels of education and awareness, such countries have also produced on average a higher percentage of electricity from renewable sources, although they are characterised by lower levels of GDP and TRD compared to the whole group.

3.2. Testing framework

The PVAR model requires the use of stationary variables to prevent spurious estimates. We have conducted different unit root tests which are conventionally divided into two sets: 'first-generation unit root tests', based on the cross-sectional independence hypothesis, and 'second-generation unit root tests', which relax the previous assumption. The former ones have been widely used in literature, despite the strong hypothesis on which they rely. Nonetheless, if the strong assumption of cross-section interdependence is not confirmed, these tests could lead to accepting by mistake the hypothesis of a unit root. It is therefore advisable to also use the latter ones, which allow for cross-section dependence. Specifically, two first-generation (Im–Pesaran–Shin and Maddala–Wu) and a second-generation unit root test (Pesaran) have been utilised to investigate the order of integration of the indicators, assuming the null hypothesis of the presence of unit roots in the panel (Im et al., 2003; Maddala and Wu, 1999; Pesaran, 2007).

The results shown in Table 3 highlight that for both panels the variables at the level are not stationary.

Table 3 about here

We have employed the first-difference transformation, which is typically used to overcome this problem (Gyimah et al., 2022; Acheampong, 2018). The above-listed unit root tests have been applied to the transformed variables and highlight the relative stationarity at conventional levels of significance (see Table 4, where Δ denotes the first difference operator).

Table 4 about here

The matrix form of the PVAR model reported in equation (1) can also be rewritten in seven equations (2) – (8), as follows:

$$\begin{aligned}\Delta RET_{i,t} &= \sum_{j=1}^{P} a_{1j}\Delta RET_{i,t-j} + \sum_{j=1}^{P} b_{1j}\Delta EPO_{i,t-j} + \sum_{j=1}^{P} c_{1j}\Delta AWA_{i,t-j} \sum_{j=1}^{P} d_{1j}\Delta EDU_{i,t-j} \\ &+ \sum_{j=1}^{P} e_{1j}\Delta PAT_{i,t-j} + \sum_{j=1}^{P} f_{1j}\Delta TRD_{i,t-j} + \sum_{j=1}^{P} g_{1j}\Delta GDP_{i,t-j} + h_{1i} + l_{1t} + \varepsilon_{1i,t}\end{aligned} \tag{2}$$

$$\begin{aligned}\Delta EPO_{i,t} &= \sum_{j=1}^{P} a_{2j}\Delta RET_{i,t-j} + \sum_{j=1}^{P} b_{2j}\Delta EPO_{i,t-j} + \sum_{j=1}^{P} c_{2j}\Delta AWA_{i,t-j} \sum_{j=1}^{P} d_{2j}\Delta EDU_{i,t-j} \\ &+ \sum_{j=1}^{P} e_{2j}\Delta PAT_{i,t-j} + \sum_{j=1}^{P} f_{2j}\Delta TRD_{i,t-j} + \sum_{j=1}^{P} g_{2j}\Delta GDP_{i,t-j} + h_{2i} + l_{2t} + \varepsilon_{2i,t}\end{aligned} \tag{3}$$

$$\begin{aligned}\Delta AWA_{i,t} &= \sum_{j=1}^{P} a_{3j}\Delta RET_{i,t-j} + \sum_{j=1}^{P} b_{3j}\Delta EPO_{i,t-j} + \sum_{j=1}^{P} c_{3j}\Delta AWA_{i,t-j} \sum_{j=1}^{P} d_{3j}\Delta EDU_{i,t-j} \\ &+ \sum_{j=1}^{P} e_{3j}\Delta PAT_{i,t-j} + \sum_{j=1}^{P} f_{3j}\Delta TRD_{i,t-j} + \sum_{j=1}^{P} g_{3j}\Delta GDP_{i,t-j} + h_{3i} + l_{1t} + \varepsilon_{3i,t}\end{aligned} \tag{4}$$

$$\begin{aligned}\Delta EDU_{i,t} &= \sum_{j=1}^{P} a_{4j}\Delta RET_{i,t-j} + \sum_{j=1}^{P} b_{4j}\Delta EPO_{i,t-j} + \sum_{j=1}^{P} c_{4j}\Delta AWA_{i,t-j} \sum_{j=1}^{P} d_{4j}\Delta EDU_{i,t-j} \\ &+ \sum_{j=1}^{P} e_{4j}\Delta PAT_{i,t-j} + \sum_{j=1}^{P} f_{4j}\Delta TRD_{i,t-j} + \sum_{j=1}^{P} g_{4j}\Delta GDP_{i,t-j} + h_{4i} + l_{4t} + \varepsilon_{4i,t}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta PAT_{i,t} &= \sum_{j=1}^{P} a_{5j}\Delta RET_{i,t-j} + \sum_{j=1}^{P} b_{5j}\Delta EPO_{i,t-j} + \sum_{j=1}^{P} c_{5j}\Delta AWA_{i,t-j} \sum_{j=1}^{P} d_{5j}\Delta EDU_{i,t-j} \\ &+ \sum_{j=1}^{P} e_{5j}\Delta PAT_{i,t-j} + \sum_{j=1}^{P} f_{5j}\Delta TRD_{i,t-j} + \sum_{j=1}^{P} g_{5j}\Delta GDP_{i,t-j} + h_{5i} + l_{5t} + \varepsilon_{5i,t}\end{aligned} \tag{6}$$

$$\begin{aligned}\Delta TRD_{i,t} &= \sum_{j=1}^{P} a_{6j}\Delta RET_{i,t-j} + \sum_{j=1}^{P} b_{6j}\Delta EPO_{i,t-j} + \sum_{j=1}^{P} c_{6j}\Delta AWA_{i,t-j} \sum_{j=1}^{P} d_{6j}\Delta EDU_{i,t-j} \\ &+ \sum_{j=1}^{P} e_{6j}\Delta PAT_{i,t-j} + \sum_{j=1}^{P} f_{6j}\Delta TRD_{i,t-j} + \sum_{j=1}^{P} g_{6j}\Delta GDP_{i,t-j} + h_{6i} + l_{6t} + \varepsilon_{6i,t}\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta GDP_{i,t} &= \sum_{j=1}^{P} a_{7j}\Delta RET_{i,t-j} + \sum_{j=1}^{P} b_{7j}\Delta EPO_{i,t-j} + \sum_{j=1}^{P} c_{7j}\Delta AWA_{i,t-j} \sum_{j=1}^{P} d_{7j}\Delta EDU_{i,t-j} \\ &+ \sum_{j=1}^{P} e_{7j}\Delta PAT_{i,t-j} + \sum_{j=1}^{P} f_{7j}\Delta TRD_{i,t-j} + \sum_{j=1}^{P} g_{7j}\Delta GDP_{i,t-j} + h_{7i} + l_{7t} + \varepsilon_{1i,t}\end{aligned} \tag{8}$$

Macroeconomic models assume a long-term equilibrium relationship between the variables: this can be highlighted by studying the cointegration between the variables. Therefore, the four cointegration tests introduced by Westerlund (2007) have been used to check for possible cross-section interdependence. The first two ($G\tau$ and $G\alpha$) investigate the alternative hypothesis that at least a unit in the panel is cointegrates; the second two ($P\tau$ and $P\alpha$) test the null hypothesis on 'no-cointegration' in the panel as a whole. The results shown in Table 5 support the choice of the first difference estimates, since the variables in level are non-cointegrated as well as non-stationary for both panels.

Table 5 about here

The correlation matrix and the variance inflation factor (VIF) have been examined to exclude collinearity and multicollinearity (specifically, VIF has been calculated by taking RET and regressing it against every other variable). The multicollinearity test results indicate that the values are lower than the usually accepted benchmark of 10 in the VIF values (Regueiro-Ferreira and Pablo Alonso-Fernández, 2023; Shan and Ren, 2023;

Kazemzadeh et al., 2023). Given the low levels of correlation, VIF and mean VIF, collinearity and multicollinearity are not a concern (see Table 6).

Table 6 about here

The final preliminary step is the lag order selection. The most common empirical strategy is to choose specific criteria and to condition on them in selecting the model. In line with the literature, the commonly used criteria are the moment Akaike information criterion (MAIC) (Akaike, 1969), the moment Bayesian information criterion (MBIC) (Akaike 1977; Rissanen 1978; Schwarz 1978), and the moment Hannan-Quinn information criterion (MHQIC), which are maximum likelihood-based selection criteria. Following Andrews and Lu (2001), the ideal lag length should minimise the moment model selection criteria MBIC, MAIC, and MHQIC. Accordingly, the optimal model for both panels is a first order PVAR (see Table 7). Analogous procedures for dealing with similar or shorter time spans have been followed by Dogan et al. (2022) with regard to annual data from 2000 to 2019 for G7 countries, Chia et al. (2022) concerning the time interval 2000-2016 for 68 developing countries, and Tzeremes et al. (2023) with respect to annual data from 2000 to 2017 for Brazil, Russia, India, China, and South Africa, the so-called BRICS countries.

Table 7 about here

The first-difference transformation allows for removing the country fixed effects in Equation 1. However, this procedure may cause the so-called Nickell bias (Nickell, 1981), with inconsistent and biased estimates using ordinary least squares (Baltagi, 2008). To overcome this problem, we have used forward mean-differencing, also referred to as the Helmert transformation (Ht), to preserve the orthogonality between lagged regressors and transformed variables (Love and Zicchino, 2006; Arellano and Bover, 1995). The model can be estimated using the generalised method of moments (GMM) and the lagged values of regressors can be used as instruments. Instead of subtracting from each variable in the model its cross-sectional mean to remove time fixed effects (Love and Zicchino, 2006, Abrigo and Love, 2016), applying the Ht to data produces the same result as applying the Ht to demeaned data (Decker, 2014).

The test of overidentifying restriction (Hansen’s J chi2) is equal to 209.05 (p-value = 0.249) for the entire set of countries, and 139,089 (p-value = 0,530) for the subset of the best-performing countries: this confirms the goodness of the models, since the null hypothesis that the over-identifying restrictions are valid is verified (the included instrumental variables are valid instruments and uncorrelated with the error term, while those instruments not included are properly excluded). With respect to the fitted models, we have calculated the modulus of each eigenvalue. Following Lutkepohl (2005), the stability of the models has been verified, as all the eigenvalues are strictly lower than 1 (see Table 8 and Figure 1, and Table 9, and Figure 2). Stability implies that the PVAR models are invertible, thus allowing bidirectional interpretations, as well as impulse-response function estimates and the variance decomposition analysis (Abrigo and Love, 2016). Furthermore, the Granger causality tests, which investigates the null hypothesis of absence of causality, has revealed bi-directional causality and confirmed the presence of endogeneity in both panels (see Tables 10 and 11).

Table 8 about here

Figure 1 about here

Table 9 about here

Figure 2 about here

Table 10 about here

Table 11 about here

3.3. Empirical results and discussion

3.3.1. Analysis on the entire panel

Table 12 shows the estimates of a first order PVAR model for the entire set of 28 EU member states.

Table 12 about here

The results show that a more vigorous renewable energy policy (increasing EPO) positively affects RET. More specifically, an increase in the production of energy from renewable sources, favoured and produced by more stringent policies, is usually followed by an increase in the manufacturing of RTs, to meet in part the domestic demand of renewable energy as well as that originating from foreign markets. This result confirms Hp#1 and is in line with most of the literature (Groba, 2014; Kuik et al., 2019), although it contrasts with the works of Sung and Song (2013) and Ogura (2020).

Hp#2, according to which socio-technical issues are relevant drivers of the export of RTs, finds scarce evidence. More specifically, an increase in the export of RTs is stimulated by raising public concern and awareness of climate change (Hp#2a). From a social point of view, increasing carbon dioxide emissions (and AWA) stimulate renewable deployment and RET (Menegaki, 2011; Marra and Colantonio, 2021; Sung and Wen, 2018). On the contrary, RET does not obtain any support from a greater understanding of the damaging effects of climate change (Hp#2b) or rises in the countries' capability in environmentally friendly technologies (Hp#2c). Both results are counterintuitive. An increase in EDU would affect the exports of RTs negatively, at least in the short term. It is likely, however, that EDU may need the long run to generate some appreciable effect (Wang and Shao, 2019; Shahbaz et al., 2020a). Moreover, we emphasise the expected positive relationship between EDU and AWA (Dasgupta et al., 2016), which implies that EDU impacts RET indirectly and may favour a more conscious transition. A growth in PAT is usually not followed by one in RET: this is at odds with the relevant literature (Costantini and Crespi, 2008; Hille and Möbius, 2018; Awijen et al., 2022). Nonetheless, a possible interpretation builds on the thesis that the driving force exerted by PAT is weaker and does not have the strength to trigger a robust industrial transition process.

Hp#3, according to which socio-technical drivers may interact and also amplify the stimulus of public policies, works only partially with regard to the entire panel: EPO can be facilitated by more PAT (Costantini and Crespi, 2008; Hille and Möbius, 2018) and AWA (Menegaki, 2011; Marra and Colantonio, 2021). In addition, EDU and PAT have a positive effect on AWA, boosting public concern and awareness, and PAT increases EDU. Moreover, as expected, the following increase in RET can originate a virtuous circle in relation to PAT, while the same does not apply to EDU.

Additional evidence merits some reflection. The effect of GDP on RET is statistically not significant. This result seems to be in contrast with the literature (Sung, 2015). On the other hand, an increase in GDP can hinder the use of more stringent policies (Salim and Rafiq, 2012): increments in income would stimulate a short-term strategy intended to prioritise energy production that – especially in the past – has been satisfied by traditional sources (Marra and Colantonio, 2022). On the contrary, increasing AWA raises GDP and lowers EPO: this is evidence that economic interests may well prevail in relation to environmental protection. As expected, surges in EDU are positively associated with GDP, while more EPO does not represent an obstacle to economic growth (GDP).

The interplay between AWA and GDP, and between GDP and EPO, has been addressed by Sadorsky (2009) and Menegaki (2011), inter alia, who emphasise that a growth in carbon dioxide emissions enhances the concern about environmental protection and renewable deployment. In the entire panel, an increase in TRD has a negative impact on RET and PAT, despite the fact that greater openness to foreign trade should favour the exchange of knowledge and the export of RTs (Groba, 2014; Groba and Cao, 2015). Only RET and EDU show path dependence. Surprisingly, EPO and AWA demonstrate unstable variations over time: this might be explained by the fact that the virtuous circle for reducing carbon dioxide emissions has still not been established (Grasso, 2019).

Table 13 shows the variance decomposition (following the Cholesky decomposition using 1000 Monte Carlo simulations for 10 periods), which evaluates the relative importance of shocks in one variable on variations in other variables over time.

Table 13 about here

As expected, Table 13 highlights that each variable is mainly influenced by its lag. Furthermore, and specifically, RET is mainly determined by TRD (10.40%), AWA (6.75%), GDP (4.78%), and PAT (4.45%) on average during a 10-year period, while PAT is mainly influenced by shocks in RET (23.74%). This demonstrates that EPO can influence RET at an early stage, while an increase in RET can be seen as a good signal and stimulate the R&D activities in the field of environment-related technologies.

Figure 3 depicts the impulse response functions, which illustrate the evolution of each variable over time after a shock in another indicator, with all other variations being equal to zero (in this case, the Cholesky decomposition has been followed and 200 Monte Carlo simulations have been performed). The impulse response analysis highlights that when a positive shock is exerted on one indicator in the present, the response variable usually shows a prominent variation in the early periods, followed by minor fluctuations.

Figure 3 about here

Policymakers should support the energy transition through constant effort over time, to have a greater chance of success on the road to more sustainable development. Specifically, the effect of a shock in EPO on RET is slightly positive after some periods, settling around zero after five years. In other words, the impact of environmental policies on RT exports still appears to be weak and needs more effectiveness and consistency. The results also show that the effects on RET of shock in AWA are positive in the short term, before fluctuating around zero in subsequent periods. Interestingly, the response of EPO to a shock in TRD appears strongly positive and destined to last for some periods: there could be some indication that environmental policies would be affected by a greater openness to trade with foreign countries, with an indirect positive effect on RET.

3.3. Analysis on the best performers

Some unexpected results highlighted by the previous analysis may derive from the heterogeneity across countries. For example, in the last five years an average value of 20.85 has been reported for RET in Slovakia (first in this special ranking), compared to 0.08 recorded by Cyprus (which occupies the last position). Table 14 shows the PVAR estimates for the panel of countries that have performed better than others in terms of export of RTs during the last five years.

Table 14 about here

By observing the first column, it is possible to notice that Hp#1 and Hp#2 are also confirmed for the best-performing countries. Specifically, increases in EPO (Hp#1) and AWA (Hp#2a) positively affect the export of RTs. Such results are not surprising, given the previous evidence.

In these countries, however, RET is also stimulated by increases in PAT (Hp#2b) and EDU (Hp#2c). In other words, a larger number of green patents are followed by a more intense production and commercialisation of green technologies, in part destined to satisfy foreign demand (Sung, 2015; Sung and Wen, 2018). PAT also shows path dependence, starting and strengthening a flywheel absent in the entire panel. Furthermore, with regard to the best-performing countries, an increase in the average educational attainment seems to stimulate RET, contributing to achieve higher performance (Xie et al., 2017; Neves et al., 2020; Shahbaz et al., 2020a).

Focusing on Hp#3, and specifically the interplay between supporting dimensions, we can appreciate the positive interplay between EDU and AWA, and PAT and EDU. This confirms the increasingly close relationship between the different socio-technical aspects in more climate-sensitive countries, which are also in an advanced position with respect to educational attainment and the ability to patent green technologies. In addition, AWA and EDU have a positive impact on PAT. In the best-performing countries, these factors represent a strong stimulus for R&D activities and an indirect boost for the energy transition (Huang et al., 2007; Kardooni et al., 2018; Makki and Mosly, 2020, Shahbaz et al., 2020a).

Some consideration should be given to further relationships. GDP is confirmed to have a statistically not significant impact on RET. This may be due to the economic growth striving between two contrasting forces: industrial lobbies may act against renewables because of the risk of higher energy prices and less stability in supply, while higher attention to the environment may emerge in modern and wealthy societies (Sung and Wen, 2018; Marra and Colantonio, 2021). In addition, TRD is positively associated with EPO: this means there may be an indirect positive effect on RET. Interestingly, the association between TRD, EPO and RET suggests some link with Costantini et al. (2017), in which the authors register the effects from foreign policies on eco-innovation. Although they stress that such a relationship should be considered ‘exploratory’, they underline how there could be some indication that domestic innovation in the energy efficient field is influenced by the public policies adopted abroad (Dechezleprêtre and Glachant, 2014). In our case, the channel between EPO and RET would be affected by a higher technology/exchange transfer (TRD), instead of foreign environmental policies. At the same time, openness to trade with foreign countries, which favours the acquisition of new knowledge from the outside, has a negative influence on RET. It is worth noting that an explorative analysis of the worst-performing countries in terms of RET (that is, countries with levels of RET in the last five years on average below the median) highlights a positive effect of TRD on RET, as well as a negative one of PAT and EDU on RET.

To summarise, in the best-performing countries, in addition to EPO, their better export performance seems to derive from more PAT, as well as from the stimulus (both direct and indirect) exerted by AWA and EDU. On the other hand, the worst-performing countries benefit from the knowledge imported from abroad, while internal R&D activities and the socio-technical regime seem to play a secondary role.

The variance decomposition analysis is reported in Table 15. Interesting differences emerge between the two panels. Specifically, it is important to underline that in the subset of best-performing countries, more stringent environmental policies (EPO), as well as positive variations in AWA and EDU, have a greater impact on RET over time, when compared with what has been observed in the whole group of member states. In other words, in the panel of the 14 best performers, the weight of EPO on RET is emphasised by the socio-technical regime (AWA and EDU). Similarly, the shock in the three variables acts with respect to PAT.

Table 15 about here

The impulse response function analysis highlights that a shock exerted on one variable usually produces its effects in the early period, and this impact gradually decreases as time goes on (see Figure 4).

Figure 4 about here

In greater detail, the results show that the effect of a shock in EPO on RET is more pronounced and long-lasting than in the whole panel, a sign that more stringent policies on average allow for achieving better results in terms of RT exports. While the response of RET to a shock in AWA is analogous to those recorded with respect to the entire group of countries, a fundamental difference in the sub-panel emerges with reference to the effect of a shock in EDU on RET. The impact, at least initially, is positive, then decreases towards zero after some periods. In the best-performing countries, education is a relevant driver in the energy transition.

4. Conclusion and policy implications

The export of RTs is strategic for countries and crucial to solving the environmental challenge at the global level. There is an extensive body of literature that corroborates the need for public policies for RTs. Nonetheless, public policies cannot be isolated from the socio-technical issues underlying the energy transition.

Our work is complementary to the extant literature in its attempt to provide a broad and comprehensive perspective within which to investigate the roles of public policies and socio-technical issues. We maintained three research hypotheses: first, renewable energy policies influence positively the export of RTs; second, socio-technical issues are relevant drivers of the export of RTs, together with renewable energy policies; third, an increase in the export of RTs is generated (additionally and indirectly) by the interplay of socio-technical variables.

The research hypotheses have been tested using a PVAR model in first differences for a panel of 28 EU member states and a sub-panel of the 14 best-performing countries with respect to RTs, from 1996 to 2020. The analysis provided interesting results that can be followed up by important policy recommendations.

As commonly accepted, a more focused policy approach to renewables boosts the exports of RTs. Based on the results of our analysis, the countries with the highest level of RET are also those that have adopted, on average, the most stringent policies. Although EPO has a positive effect on RET across the entire panel, among the best-performing countries the variance decomposition analysis showed a greater weight of EPO on RET, and the impulse response function highlighted a better response of RT exports to a policy shock. As anticipated, this result is deep-rooted in the literature (Costantini and Mazzanti, 2012; Sung, 2015; Kuik et al., 2019).

As is well known, the EU has adopted strict ‘green’ regulations and is leading the promotion of policies and technologies to reduce carbon dioxide emissions at the global level. These actions are expected to reduce emissions by 80%–90% compared to 1990 levels (Eurostat, 2019). The increasing overlap between energy and environmental policies, as confirmed by the recent European Green Deal, will favour a holistic approach to address the climate challenge, all within a continued focus on technological progress and economic growth.

The rising level of carbon dioxide emissions means greater concern for the environment (Sadorsky, 2009; Menegaki, 2011; Salim and Rafiq, 2012). This induces a strong demand for new environment-related solutions, including the R&D, manufacturing, and export of RTs, especially in the best-performing countries (Sung and Wen, 2018; Kardooni et al., 2018; Makki and Mosly, 2020). This is in line with the proactive policy approach pursued in the last decade by the EU, which has successfully integrated a growing number of RTs within the national energy systems. Counterintuitively, at least in the short term, EDU is negatively associated with some dimensions (specifically, RET and EPO). This does not mean that education is an obstacle in the energy transition. An increase in EDU guarantees a return in terms of environmental sustainability: this thesis would seem to be confirmed by the positive and statistically significant influence on AWA. Such counterintuitive results are limited to the entire panel and can be explained by the heterogeneity of the European countries observed. The estimates on the panel of the best-performing countries have shown that better results in terms of RET are directly due to AWA and EDU, in line with the literature (Salim and Rafiq, 2012; Sung and Wen, 2018; Marra and Colantonio, 2021). It goes without saying that policymakers should pay increasing attention to the socio-cultural dimension by implementing specific programmes (at schools and universities) on climate change to adequately inform and train students and citizens on the role that they can play in the energy transition.

In addition, green patents play a major role. When considering the entire panel, we found some unexpected results: PAT does not stimulate RET directly, at least in the short period. Indirectly, more PAT would allow for more stringent policies, with positive effects on RET. In the best-performing countries, an increase in patents on environment technologies directly stimulates RT exports and, contrary to the whole set of countries, also shows path dependence. Policymakers should insist on stimulating R&D activities through specific support actions (public investments, subsidies, etc.). Moreover, it is important to underline that more EPO, as well as positive variations in AWA and EDU, have a greater impact on RET over time, if compared with the whole panel. Where PAT is not relevant, TRD can take over, allowing (low-performing in particular) countries to benefit from the trade in terms of knowledge and technology exchange.

The interaction between socio-technical variables seems to support the export of RTs. Specifically, in line with the literature (Huang et al., 2007), an increase in the level of education positively affects public awareness. However, in the sub-panel, a more favourable social framework (higher levels of public concern regarding climate change and educational attainment) can stimulate PAT. In other words, in the best-performing countries, the socio-technical context directly and indirectly (through PAT) favours the export of RTs. Accordingly, policymakers need to prioritise the climate challenge, increasing public concern and awareness as well as countries' technological capability, while consciously assessing the positive returns from green growth.

In addition to the socio-technical variables mentioned above, the model included foreign trade to account for external sources of technological progress (Groba, 2014) and GDP per capita to control for countries' wealth and industrial modernity (Groba and Cao, 2015). Concerning TRD, we found that the openness to foreign trade is positively associated with EPO, with an indirect positive effect on RET. Openness to trade means a higher chance of obtaining new and innovative technologies from abroad, with a green paradigm cutting across countless sectors and markets: through more responsive policies, TRD can indirectly impact on RET.

There is a good chance that growing economic systems will consume greater amounts of energy, including that from renewable and non-renewable sources for the time being. For this reason, the overall impact of rising income per capita is ambiguous on RET. There are two contrasting forces working on GDP, including, on the one side, industrial lobbies acting against renewables because of the risk of higher prices and less stability in supply, and on the other, the increasing attention paid by citizens to the environment. With the worrying implications from the environmental challenge, a gradual shift towards the second direction is expected.

In the best-performing countries, the increase in countries' wealth and industrial modernity boosts more stringent green policies, using income to support the regulatory costs associated with the adoption of renewables, and indirectly stimulating RET. Therefore, policymakers should provide continuous support and incentives to increase the internal supply for renewable energy.

The main shortcoming of this investigation may be the exclusion of potential sources of heterogeneity among the countries. Thus, a possible extension of this study could focus on segmenting the panel into multiple different sub-panels, depending on the determinants of RTs. Another limitation may include the lack of a comparison between European and non-European countries. Hence, a possible extension may focus on this benchmark, without neglecting the heterogeneity across countries. In future, further works could employ the same model for different regions (i.e., African states, Middle East region, Asian region, South Asian region, etc.) and/or groups of countries (i.e., high-, middle-, and low-income economies). Lastly, scholars could incorporate other socio-technical variables and adopt different econometric techniques in order to attain further reliable findings.

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Fig. 1. Roots of the companion matrix

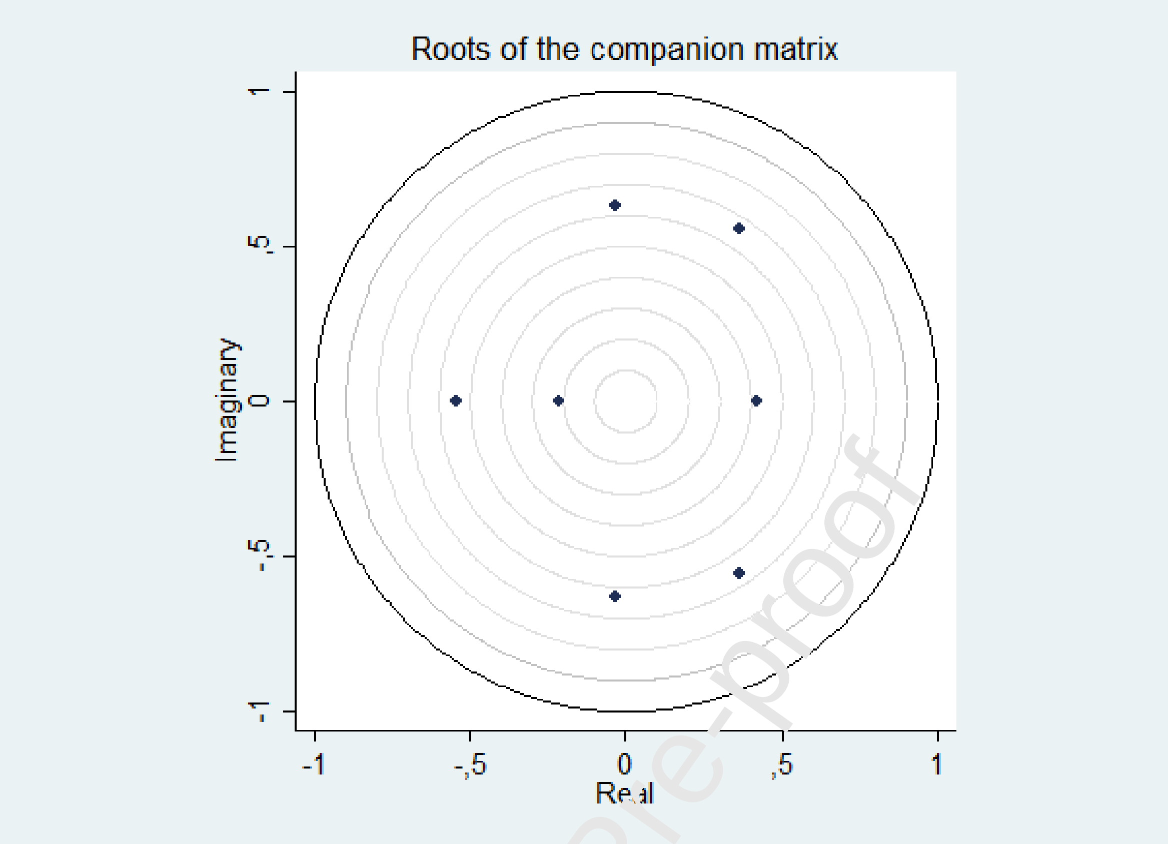

Fig. 2. Roots of the companion matrix (best-performing countries only)

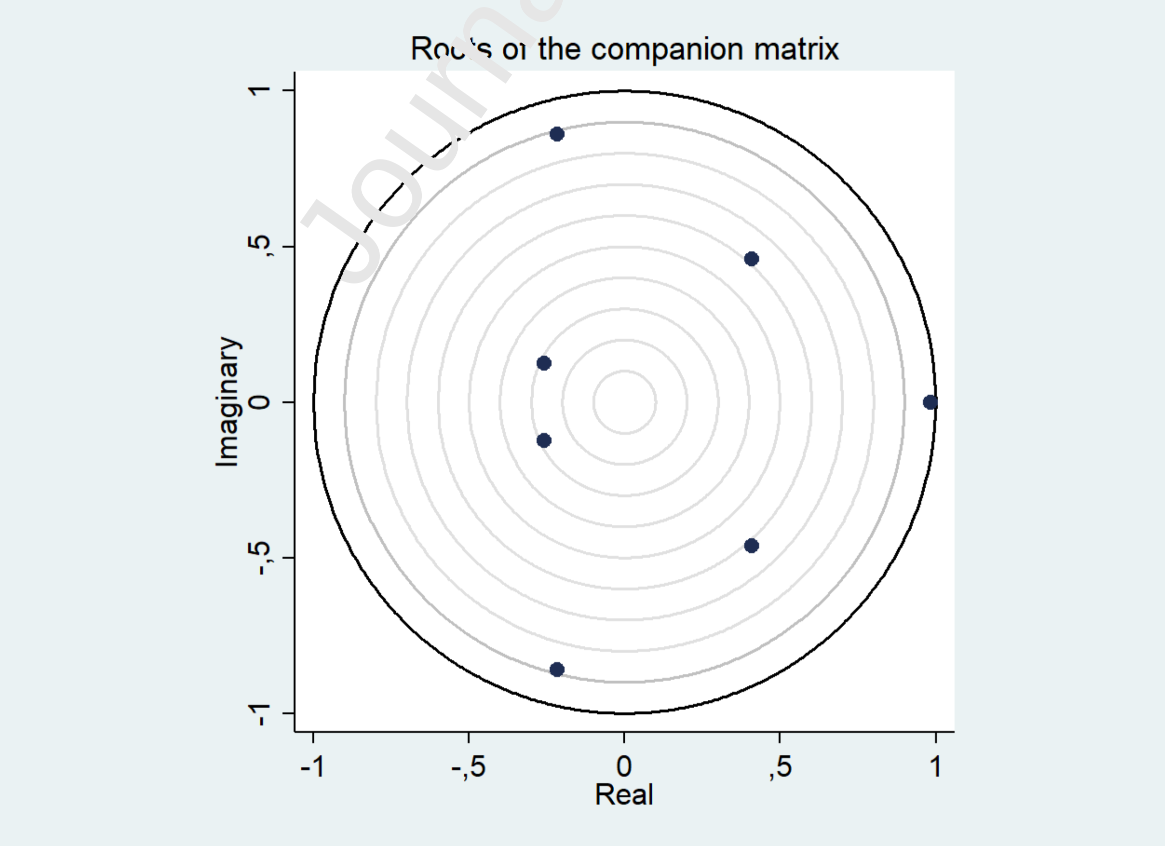

Fig. 3. Impulse response analysis

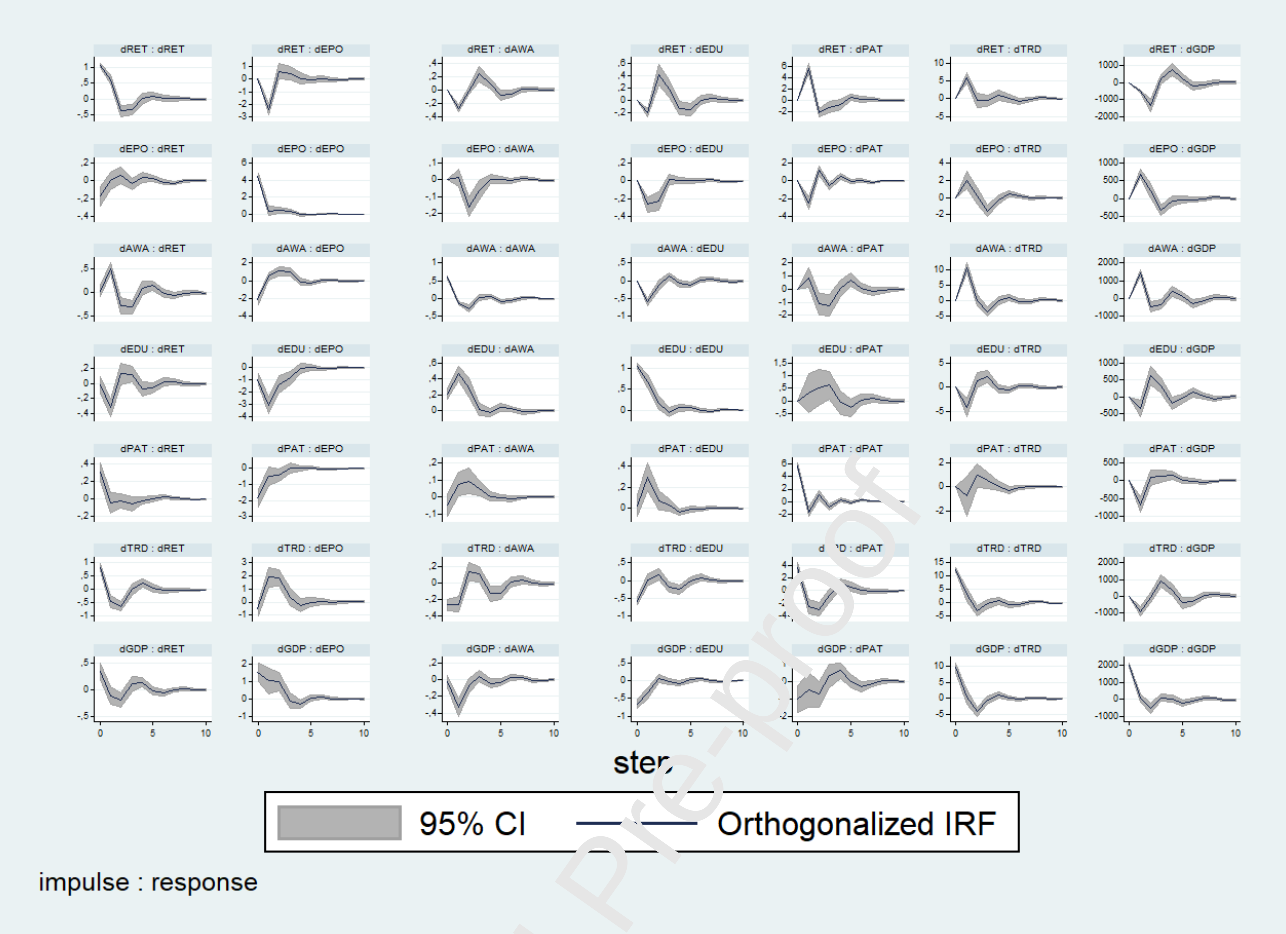

Fig. 4. Impulse response analysis (best-performing countries only)

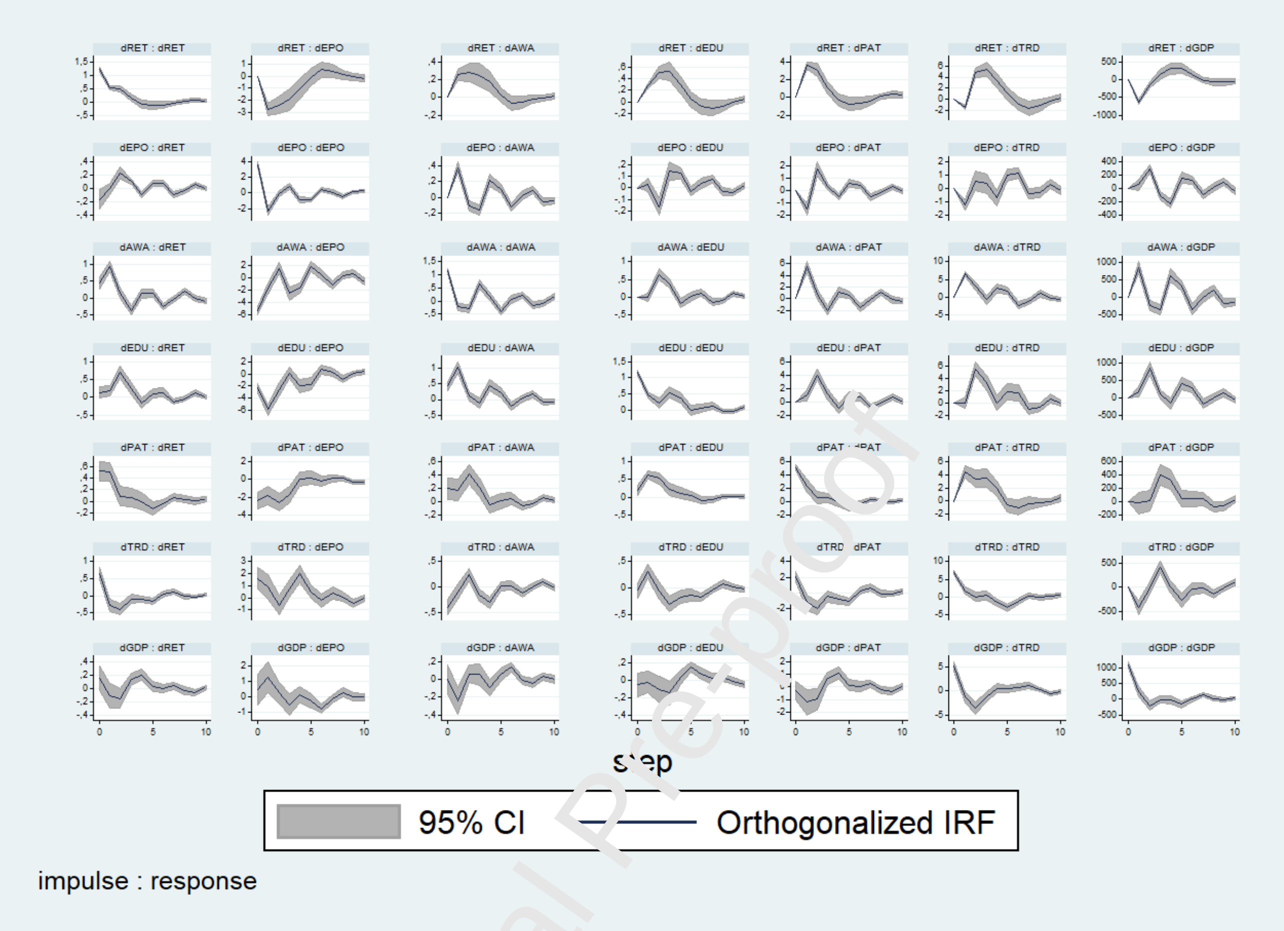

Table 1. Description of Variables

Variable	Definition	Source
RET	Export value of RTs (share of GDP, in thousands of current US $)	UN
EPO	Renewable electricity output (% of total electricity output)	World Bank
AWA	CO_2 emissions (metric tons per capita)	World Bank
EDU	Upper secondary, post-secondary non-tertiary and tertiary education (levels 3-8)	Eurostat
PAT	Patents on environment technologies (% of total)	OECD
TRD	Trade (% of GDP)	World Bank
GDP	GDP per capita, PPP (constant 2017 international $)	World Bank

Table 2. Descriptive statistics

Entire panel

Variable	Obs.	Mean	Std. Dev.	Min	Max	Median
RET	687	5.68	4.75	0.04	22.82	4.26
EPO	700	24.17	21.33	0.00	81.62	17.47
AWA	644	7.79	3.50	2.93	25.67	7.31
EDU	661	69.26	13.89	19.30	89.20	73.10
PAT	655	10.68	5.04	0.84	48.89	10.31
TRD	700	112.70	60.98	37.50	380.10	95.20
GDP	700	37345.73	18490.12	9960.89	120647.80	34625.39

Best-performing countries only

Variable	Obs.	Mean	Std. Dev.	Min	Max	Median
RET	345	8.65	4.88	1.29	22.82	7.82
EPO	350	24.57	21.58	0.00	81.62	17.21
AWA	322	8.06	2.64	3.37	14.81	7.89
EDU	326	76.00	6.45	59.50	87.90	76.80
PAT	332	11.04	4.91	0.92	26.41	10.55
TRD	350	106.14	33.62	45.01	190.70	100.45
GDP	350	32897.85	13264.87	9993.45	57161.69	30063.03

Table 3. Unit root tests: variables in level

Entire panel

Variable	IPS W-t-bar	MW	Pesaran Z-t-bar
RET	0.038	73.49*	1.106
EPO	10.383	73.096*	-2.511***
AWA	2.421	63.812	-1.406*
EDU	1.699	164.712***	-0.887
PAT	-5.996	67.785	-3.954***
TRD	-0.926	109.313***	1.711
GDP	-1.043	58.695	-0.635

Best-performing countries only

Variable	IPS W-t-bar	MW	Pesaran Z-t-bar
RET	1.384	28.779	1.669
EPO	7.439	26.075	-0.728
AWA	-0.827	32.976	-1.199
EDU	-1.489*	44.094**	-0.255
PAT	-3.833***	25.842	-1.864**
TRD	-1.001	42.660**	-0.550
GDP	0.503	33.653	-0.944

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 4. Unit root tests: variables in in first differences

Entire panel

Variable	IPS W-t-bar	MW	Pesaran Z-t-bar
ΔRET	-17.7355***	224.887***	-5.46***
ΔEPO	-16.23***	328.074***	-8.639***

ΔAWA	-17.242***	210.283***	-6.999***
ΔEDU	-18.8157***	394.671***	-7.696***
ΔPAT	-21.3056***	274.014***	-10.088***
ΔTRD	-16.3724***	231.904***	-2.404***
ΔGDP	-8.1309***	130.528***	-1.674**

Best-performing countries only

Variable	**IPS W-t-bar**	**MW**	**Pesaran Z-t-bar**
ΔRET	-13.695***	126.475***	-3.417***
ΔEPO	-10.759***	165.744***	-5.653***
ΔAWA	-14.651***	137.969***	-6.779***
ΔEDU	-14.477***	234.397***	-7.055***
ΔPAT	-14.663***	162.301***	-7.364***
ΔTRD	-11.860***	124.138***	-1.981**
ΔGDP	-6.596***	66.952***	-0.427

Table 5. Cointegration tests

Entire panel

Statistic	**Value**	**p-value**
G_τ	-1.472	0.72
G_α	-1.433	0.86
P_τ	-11.882	0.80
P_α	-5.806	0.79

Best-performing countries only

Statistic	**Value**	**p-value**
G_τ	-1.766	0.49
G_α	-1.940	0.36
P_τ	-9.062	0.45
P_α	-6.039	0.47

Note: p-value are robust critical values obtained through bootstrapping with 100 replications

Table 6. Correlation matrices and variance inflation factor (VIF) statistics

Entire panel

	ΔRET	ΔEPO	ΔAWA	ΔEDU	ΔPAT	ΔTRD	ΔGDP
ΔRET	1.00						
ΔEPO	-0.11	1.00					
ΔAWA	0.15	-0.37	1.00				
ΔEDU	-0.05	0.02	0.00	1.00			
ΔPAT	0.05	-0.02	0.00	-0.04	1.00		
ΔTRD	0.27	0.02	0.19	-0.07	-0.05	1.00	
ΔGDP	0.12	-0.02	0.27	-0.08	-0.04	0.32	1.00
VIF		1.17	1.28	1.01	1.01	1.14	1.19
Mean VIF	1.13						

Best-performing countries only

	ΔRET	ΔEPO	ΔAWA	ΔEDU	ΔPAT	ΔTRD	ΔGDP
ΔRET	1.00						
ΔEPO	-0.16	1.00					
ΔAWA	0.16	-0.38	1.00				
ΔEDU	-0.01	-0.08	0.07	1.00			
ΔPAT	0.07	-0.16	0.01	-0.09	1.00		
ΔTRD	0.40	-0.07	0.24	0.04	-0.02	1.00	

ΔGDP	0.23	-0.10	0.31	0.00	-0.02	0.46	1.00
VIF		1.22	1.31	1.02	1.04	1.28	1.34
Mean VIF	1.20						

Table 7. Lag order selection criteria

Entire panel

Lag	MBIC	MAIC	MHQIC
1	-716.315	-131.791	-363.407
2	-487.003	-97.320	-251.731

Best-performing countries only

Lag	MBIC	MAIC	MHQIC
1	-625.1758	-138.8604	-335.6245
2	-424.1413	-99.9311	-231.1071

Table 8. Eigenvalue stability condition - Entire panel

Eigenvalue		
Real	Imaginary	Modulus
0.361	0.554	0.661
0.361	-0.554	0.661
-0.036	-0.627	0.628
-0.036	0.627	0.628
-0.547	0.000	0.547
0.420	0.000	0.420
-0.212	0.000	0.212

Table 9. Eigenvalue stability condition - Best-performing countries only

Eigenvalue		
Real	Imaginary	Modulus
0.984	0.000	0.984
-0.215	-0.861	0.887
-0.215	0.861	0.887
0.409	0.461	0.616
0.409	-0.461	0.616
-0.257	-0.124	0.285
-0.257	0.124	0.285

Table 10. Granger causality tests - Entire panel

Equation Variable	Excluded Variables	Chi2	p-value
ΔRET	ΔEPO	7.281	0.007
	ΔPAT	10.487	0.001

	ΔAWA	133.574	0.000
	ΔEDU	130.469	0.000
	ΔGDP	0.068	0.794
	ΔTRD	103.208	0.000
	ALL	239.404	0.000
ΔEPO	ΔRET	113.518	0.000
	ΔPAT	3.249	0.071
	ΔAWA	18.84	0.000
	ΔEDU	104.787	0.000
	ΔGDP	57.377	0.000
	ΔTRD	56.607	0.000
	ALL	233.07	0.000
ΔAWA	ΔRET	118.548	0.000
	ΔEPO	2.016	0.156
	ΔPAT	24.075	0.000
	ΔEDU	142.158	0.000
	ΔGDP	0.373	0.541
	ΔTRD	7.152	0.007
	ALL	331.702	0.000
ΔEDU	ΔRET	39.175	0.000
	ΔEPO	39.266	0.000
	ΔPAT	12.118	0.000
	ΔAWA	299.26	0.000
	ΔGDP	14.906	0.000
	ΔTRD	9.73	0.002
	ALL	433.26	0.000
ΔPAT	ΔRET	162.683	0.000
	ΔEPO	48.865	0.000
	ΔAWA	0.095	0.758
	ΔEDU	0.174	0.676
	ΔGDP	10.07	0.002
	ΔTRD	105.501	0.000
	ALL	330.649	0.000
ΔTRD	ΔRET	80.596	0.000
	ΔEPO	49.698	0.000
	ΔPAT	0.04	0.842
	ΔAWA	298.494	0.000
	ΔEDU	94.869	0.000
	ΔGDP	72.601	0.000
	ALL	401.578	0.000
ΔGDP	ΔRET	105.124	0.000
	ΔEPO	107.267	0.000
	ΔPAT	2.651	0.103
	ΔAWA	329.398	0.000
	ΔEDU	68.459	0.000
	ΔTRD	0.915	0.339
	ALL	396.992	0.000

Table 11. Granger causality tests - Best-performing countries only

Equation Variable	Excluded Variables	Chi2	p-value
ΔRET	ΔEPO	30.257	0.000
	ΔPAT	44.344	0.000
	ΔAWA	47.285	0.000
	ΔEDU	9.265	0.002
	ΔGDP	0.354	0.552
	ΔTRD	62.384	0.000
	ALL	130.633	0.000
ΔEPO	ΔRET	42.331	0.000
	ΔPAT	1.673	0.196
	ΔAWA	40.540	0.000

	ΔEDU	179.307	0.000
	ΔGDP	6.619	0.010
	ΔTRD	54.019	0.000
	ALL	246.360	0.000
ΔAWA	ΔRET	2.749	0.097
	ΔEPO	7.300	0.007
	ΔPAT	2.597	0.107
	ΔEDU	103.530	0.000
	ΔGDP	6.559	0.010
	ΔTRD	35.358	0.000
	ALL	189.787	0.000
ΔEDU	ΔRET	55.001	0.000
	ΔEPO	0.387	0.534
	ΔPAT	19.356	0.000
	ΔAWA	4.321	0.038
	ΔGDP	0.337	0.562
	ΔTRD	18.542	0.000
	ALL	87.964	0.000
ΔPAT	ΔRET	177.163	0.000
	ΔEPO	2.929	0.087
	ΔAWA	72.328	0.000
	ΔEDU	107.223	0.000
	ΔGDP	0.269	0.604
	ΔTRD	162.928	0.000
	ALL	405.999	0.000
ΔTRD	ΔRET	10.683	0.001
	ΔEPO	3.961	0.047
	ΔPAT	116.875	0.000
	ΔAWA	187.644	0.000
	ΔEDU	119.358	0.000
	ΔGDP	173.172	0.000
	ALL	400.282	0.000
ΔGDP	ΔRET	196.907	0.000
	ΔEPO	19.387	0.000
	ΔPAT	1.622	0.203
	ΔAWA	90.095	0.000
	ΔEDU	176.661	0.000
	ΔTRD	129.615	0.000
	ALL	483.638	0.000

Table 12. PVAR results - Entire panel

	Dependent variables						
Independent variables	ΔRET	ΔEPO	ΔAWA	ΔEDU	ΔPAT	ΔTRD	ΔGDP
ΔRET	0.578***	-2.252***	-0.260***	-0.183***	5.320***	5.501***	-492.251***
ΔEPO	0.022***	0.003	-0.007	-0.066***	-0.342***	0.659***	136.100***
ΔAWA	0.900***	1.031***	-0.238***	-1.218***	-0.104	19.435***	2906.217***
ΔEDU	-0.462***	-3.211***	0.482***	0.835***	0.084	-7.312***	-789.211***
ΔPAT	-0.022***	0.058*	0.020***	0.026***	-0.682***	-0.015	-18.725
ΔTRD	-0.069***	0.159***	0.008***	0.017***	-0.367***	-0.013	-7.564
ΔGDP	0.000	-0.001***	0.000	0.000***	0.001***	-0.003***	-0.171***

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 13. Variance decomposition analysis - Entire panel

	Impulse variable						
Response variable	ΔRET	ΔEPO	ΔAWA	ΔEDU	ΔPAT	ΔTRD	ΔGDP
ΔRET	70.73%	0.34%	6.75%	2.56%	4.45%	10.40%	4.78%
ΔEPO	5.91%	56.43%	2.01%	28.65%	1.80%	3.67%	1.54%

ΔAWA	20.15%	9.53%	35.31%	24.29%	6.73%	2.29%	1.70%
ΔEDU	14.59%	7.97%	9.44%	60.39%	3.81%	1.70%	2.10%
ΔPAT	23.74%	5.53%	1.16%	3.91%	53.69%	9.70%	2.28%
ΔTRD	30.34%	2.68%	15.15%	17.52%	2.34%	17.98%	13.99%
ΔGDP	26.07%	4.57%	16.81%	12.20%	7.76%	4.99%	27.59%

Note: Variation in Response Variable explained bythe Impulse Variables in the columns (10 periods ahead)

Table 14. PVAR results - Best-performing countries only

	Dependent variables						
Independent variables	ΔRET	ΔEPO	ΔAWA	ΔEDU	ΔPAT	ΔTRD	ΔGDP
ΔRET	0.229***	-0.804***	0.055*	0.242***	2.350***	0.687***	-521.842***
ΔEPO	0.102***	-0.309***	0.021***	-0.007	-0.089*	-0.099**	-38.704***
ΔAWA	1.063***	-2.195***	-0.211***	-0.221**	3.430***	4.167***	670.413***
ΔEDU	0.715***	-5.444***	1.230***	0.616***	2.217***	-3.859***	-1117.075***
ΔPAT	0.094***	-0.050	-0.017	0.081***	0.205***	0.660***	-13.522
ΔTRD	-0.080***	0.169***	-0.028***	-0.020***	-0.354***	0.453***	86.522***
ΔGDP	0.000	0.000***	0.000***	0.000	0.000	-0.004***	-0.124**

Note: *p < 0.1; **p < 0.05; ***p < 0.01

Table 15. Variance decomposition analysis - Best-performing countries only

	Impulse variable						
Response variable	ΔRET	ΔEPO	ΔAWA	ΔEDU	ΔPAT	ΔTRD	ΔGDP
ΔRET	44.55%	12.13%	7.54%	23.97%	3.63%	6.66%	1.52%
ΔEPO	23.07%	31.17%	5.37%	28.96%	4.83%	5.48%	1.11%
ΔAWA	19.34%	22.39%	14.81%	32.03%	5.49%	4.27%	1.66%
ΔEDU	23.96%	15.00%	4.33%	42.03%	7.75%	6.29%	0.64%
ΔPAT	24.85%	17.51%	5.71%	26.00%	17.46%	6.88%	1.58%
ΔTRD	23.82%	16.50%	4.29%	22.94%	5.40%	15.83%	11.22%
ΔGDP	9.55%	13.93%	4.40%	20.72%	3.33%	8.56%	39.51%

Note: Variation in Response Variable explained bythe Impulse Variables in the columns (10 periods ahead)

Highlights

Public policies play a key role in stimulating the export of renewable technologies

Public policies need a supportive socio-technical regime in the current energy transition

Socio-technical drivers include social, technical, political, and cultural aspects

Socio-technical drivers, if operating together, amplify the stimulus of public policies