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Catalyzing solar and wind technology exports: the «Flywheel Effect» of demand-side factors

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Catalyzing Solar and Wind Technology Exports: The «Flywheel Effect» of Demand-Side Factors

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

Abstract

The paper aims to emphasize the importance of demand-side factors in strengthening countries' efforts to address the climate challenge through the export of solar and wind technologies. While the existing literature has predominantly focused on the supply side, we argue that the demand side has a direct effect and exerts an indirect influence (via the supply side) on the export of these technologies and their widespread adoption. This has implications for the current policy debate. To test our hypotheses, we use a Panel Vector Autoregressive model in first differences for a panel of 20 industrialized countries over a twenty-five-year period. The results reveal mixed support to the hypothesis that demand exerts a positive effect on the export of solar and wind technologies. While the evidence on the role energy intensity is robust across specifications, we observe that other measures of demand - such as the level economic activity and oil prices - positively impacts solar and wind technology exports primarily in the most advanced countries. Additionally, the findings broadly support the hypothesis that all demand factors indirectly influence the export of these technologies by bolstering supply-side effects.

Catalyzing Solar and Wind Technology Exports: The «Flywheel Effect» of Demand-Side Factors

1. Introduction

Governments around the world are working tirelessly to set new climate targets for the coming decades. Recent commitments include Japan's pledge to eliminate all greenhouse gasses, China and South Korea's promise to achieve carbon neutrality, the European Union's net-zero plan to reduce greenhouse gas emissions by 2030 and, finally, the UN Climate Summit in Dubai in December 2023, where the world agreed to move away from non-renewable energy sources and create a "just, orderly and equitable" transition.

Translating these goals into tangible results is proving to be a challenging task. Currently, fossil fuels still dominate the energy mix in many countries and achieving such ambitious targets will require considerable effort. Not only do we need to change the way we produce and consume energy, but we also need to deploy new energy technologies (Eurostat, 2022). According to the International Energy Agency (IEA, 2022a), renewables have the potential to reduce emissions by seven gigatons by 2040. In addition, ongoing technological innovations such as ultra-thin panels and large wind turbines can provide a remarkable boost. These advances could increase renewable electricity generation from the current 25,000 terawatt hours to around 90,000 terawatt hours by 2050 (Energy Transitions Commission, 2021).

Solar and wind power technologies (SWTs) have already played a decisive role and will continue to do so (Jäger-Waldau et al., 2020). They contribute to technological progress and offer practical solutions to the environmental challenge. However, despite the fall in the price of these technologies in recent years, the private sector alone cannot drive their adoption at the required pace and greater public support is essential.

If SWTs are considered critical, it is important to examine what factors may encourage their deployment. The US policy to encourage investment in strategic sectors such as clean technologies is an example of this approach: in 2022, US Treasury Secretary Janet Yellen explained how this policy agenda aligns with the concept of "modern supply-side economics", which focuses on human capital, public infrastructure, research and development (R&D) and investment to spur economic growth and solve long-term

structural problems (Inflation Reduction Act, 2022). Europe is also moving in a similar direction, albeit in a less consistent way, by introducing green subsidies to revitalize "new" manufacturing on the continent.

While most SWTs are technically mature, widespread adoption is essential to reduce costs and improve performance through economies of scale and learning curves (Samant et al., 2020; Muscio et al., 2023). The existing literature has predominantly focused on the supply side and partially neglected the role of the demand side (Costantini and Crespi, 2008; Sung, 2015; Sung and Song, 2014; Marra and Colantonio, 2023). This may have significant implications for the current policy debate.

Our paper aims to emphasize the importance of demand-side factors in strengthening countries' efforts to address the climate challenge through the export of SWTs. We argue that demand has a direct effect on the export of SWTs and their widespread adoption, but also exerts an indirect influence via the supply side. Accordingly, demand-side factors can exert a "flywheel" effect on exports, as improvements in energy intensity can have a positive impact on supply-side factors (Chakraborty and Mazzanti, 2020), and a country's rising economic prosperity can increase its technological capabilities (Jonhstone et al., 2010).

We use a modelling framework based on Verdolini and Galeotti (2011) and we explicitly focus on the demand side. The demand-side factors that are considered relevant include: oil prices, the country's energy demand per unit of GDP, and the level of activity of the economy. The mechanisms linking these factors to the export of SWTs are briefly outlined below. Starting from the first factor, i.e. the oil price, its impact on technological progress is well established in the literature, as the increase in oil prices leads to a decrease in the relative price of SWTs and encourages their adoption (Ley et al., 2016; Lin and Zhu, 2019). However, the impact of oil prices on the export of SWTs is less obvious, as increasing demand for SWTs in international markets can compete with increasing demand domestically. Therefore, we assume that above a certain threshold in SWTs production, a country and its economic system can become a net contributor to renewable energy technology. The same logic applies to the other two factors, energy intensity and country level of economic activity: a more energy-efficient and wealthier country can be expected to invest more in new technologies, including SWTs, and increase the production and domestic deployment of these technologies (Smirnova et al., 2021; Shabir et al., 2023). Although the net impact on exports cannot be determined a priori, the following can be expected: while technologies may be destined for the

domestic market in the initial stages, an increase in exports could follow as the production of SWTs and their competitive advantage increases. The underlying mechanism is as follows: domestic demand boosts production, which can lead to learning-by-doing and lower production costs, which in turn boosts the country's competitiveness and exports. However, the domestic scale of demand-side factors may not be sufficient to catalyse the production and export of SWTs. Under these circumstances, the volatile or "soft" direct effect may be followed by an indirect effect via the supply side. This is our main thesis: in addition to a direct effect, demand can exert an indirect influence on export performance through specific supply-side factors, which include countries' technological capabilities as well as internal (i.e. developed within national borders) and external (i.e. imported from abroad) knowledge (Verdolini and Galeotti, 2011).

In the following section, we provide an overview of the existing literature and propose three research hypotheses. The first concerns the relationship between the supply side and the export of SWTs, which we take for granted as it has been widely discussed in the literature; the second is about the relationship between demand-side factors and exports, which, as mentioned above, has only been partially addressed in the academic debate; the third concerns the interaction between demand and supply on SWTs exports, which finds some evidence in a diversified and rather fragmented empirical analysis. The last two hypotheses are expected to make a contribution to the existing literature.

All hypotheses are tested using a Panel Vector Autoregressive (PVAR) model in first differences for a panel of 20 developed countries over a twenty-five year period, with a subpanel consisting of the ten countries that are most advanced in environmental (or green) technologies. The model allows for an in-depth examination of the impact of individual factors on exports and provides insights into bidirectional dynamic effects and potential path dependencies. The PVAR model is based on a system of multivariate equations and does not require a distinction between endogenous and exogenous variables. By treating all variables as endogenous, the PVAR model effectively captures the dynamic relationships between the variables (Pan et al., 2023; Jawadi and Pondie, 2024; Tzeremes et al., 2024), while static econometric regression models fail to adequately account for potential endogeneity issues (Wang et al., 2022). Moreover, the chosen approach proves to be efficient even with small sample sizes (Zambrano-Monserrate, 2024).

Our contribution to the existing literature is as follows. First, we focus on the export of SWTs, a topic that has received less attention compared to green patents (Liu and Goldstein, 2013; Hille et al., 2019). The export of SWTs serves as a more tangible measure of each country's relative contribution to the climate challenge, as it includes the crucial stages of manufacturing and commercialization, which should not be underestimated (Shakeel et al., 2017). Second, we position our research question within the current debate on industrial and technological dynamics in most modern countries, where energy intensity is expected to change due to the shift from manufacturing to services or to more energy-efficient solutions. These dynamics and their implications for countries' efforts to tackle the climate challenge offer an interesting perspective of analysis (Wurlod and Noailly, 2018; Chakraborty and Mazzanti, 2020). The central role of energy intensity is clear from the results of the model, as it is the only demand-side element that directly boosts exports; in addition, it supports internal and external knowledge and mediates the impact of the oil price on trade. Third, we account for the country's acquisition of external knowledge embedded in imported goods by explicitly including imports of SWTs in the empirical model, as suggested by the trade growth literature (Coe and Helpman, 1995; Groba and Cao, 2015; Ogura, 2020). In particular, higher imports of SWTs strengthen the country's ability to leverage technological opportunities (Verdolini and Galeotti, 2011), thus working as complementary assets. However, it should be noted that SWTs can also be seen as an obstacle to the development of a domestic industry and national exports, as imported technologies are seen as substitutes for domestic production and can actually compete with nationally produced technologies (Kim and Kim, 2015; Tan and Hwang, 2002). In our view, this perspective seems to be weaker than the first one, due to the characteristics of modern supply chains, especially in the renewable energy sector, which consist of multiple production phases providing specialized and sophisticated components subject to rapid technological aging and high obsolescence (Caravella et al., 2024; IEA, 2022b; Carrara et al., 2020). For this reason, we tend to prefer the perspective of complementarity over the perspective of substitutability (Pizer and Popp, 2008).

The article is organized as follows. Section 2 presents the relevant literature and develops the research hypotheses. Section 3 presents an empirical analysis, starting with the results of preliminary tests and then providing an overview and discussion of the main findings. Finally, Section 4 concludes the paper.

2. Literature and research hypotheses

2.1. On the role of the supply side

As far as the supply side is concerned, a milestone is the study by Johnstone et al. (2010), in which the authors emphasize the supply side, although they do not explicitly consider technology push effects. Costantini et al. (2017) investigated selected features of the policy mix to promote innovation in energy efficiency technologies and introduced national innovation capacity as a control variable, using two alternative measures: the stock of knowledge based on gross national expenditure on R&D, and the total number of patents. Costantini and Crespi (2008) provided evidence on the evolution of export flows of environmental technologies across countries for the energy sector and emphasized that innovation systems should be equipped with adequate scientific and technological knowledge. Similarly, Costantini and Mazzanti (2012) found that environmental policies and innovation efforts have a positive impact on export flows.

The effects of R&D spending (Garrone and Grilli, 2010; Álvarez-Herránzet al., 2017; Shen and Lin, 2020) and technology transfer across countries (Pizer and Popp, 2008; Wang et al., 2015; Guan et al., 2023) have been largely investigated in the climate change literature (Samant et al., 2020; Marra and Colantonio, 2023). Garrone and Grilli (2010) examined public research and development in the energy sector and its impact on energy intensity: while government R&D spending alone is not sufficient to drive energy innovation, it has led to improvements in technological progress in energy efficiency. Pizer and Popp (2008) identified two potential ways in which foreign knowledge can affect the domestic economy. The first effect arises from cross-border knowledge flows, where foreign R&D can stimulate domestic R&D and promote innovation. The second effect occurs when foreign technologies are exported, which facilitates the exchange of knowledge and the adoption of new technologies. Verdolini and Galeotti (2011) investigated how changes in technological capabilities affect innovation in the green energy sector, taking into account knowledge spillovers. The authors found that the internal knowledge stock and knowledge spillovers between countries are significant and have a positive impact on innovation. Using trade data as an indicator of knowledge flows, similar results were obtained in the study by Noailly and Shestalova (2017).

2.2. On the role of the demand side

Verdolini and Galeotti (2011) showed that high fossil fuel costs can create incentives for the adoption of renewable energy technologies, as these become relatively more cost-effective compared to fossil fuel technologies. Ley et al. (2016) found a positive correlation between energy prices and green innovations and indicated a significant positive impact on the ratio of green to non-green innovations: a 10% increase in average prices would lead to a 3.4% increase in the number of green innovations and a 4.8% increase in the ratio of green to non-green innovations.

In the current transition phase, we cannot overlook the industrial and technological dynamics that are taking place in all countries, albeit at different speeds. This provides an opportunity to focus on a variable that is at the center of the current scientific debate: energy intensity. In the literature, energy intensity represents the ongoing structural change characterized by a gradual shift from manufacturing to services, as well as the impact of processes to improve energy efficiency (Ma and Stern, 2008; Chen et al., 2016; Fan et al., 2023). As mentioned above, we include energy intensity, which represents the energy demand of the economy, to account for ongoing structural change. This measure has received increasing attention to identify the factors that enable a reduction in energy intensity (Shen and Lin, 2020; Feng et al., 2023; Hu et al., 2023), as well as the impact on climate and carbon dioxide emissions (Cho and Sohn, 2018; Wei et al., 2023). We expect a negative relationship: a decline in energy intensity, primarily due to a shift from manufacturing to services, means that a more energy-efficient country is willing to invest in new technologies, including SWTs, and expand the production and use of these technologies domestically (Chakraborty and Mazzanti, 2020). This may lead to an increase in the export of SWTs. In addition, we use gross value added as a proxy for the the level of activity of the economy, which can be expected to have a positive impact on exports (Verdolini and Galeotti, 2011; Smirnova et al., 2021). Finally, an increase in the price of oil is known to lead to a decrease in the relative price of new energy technologies, which should encourage their adoption domestically and hinder their export (Ley et al., 2016; Lin and Zhu, 2019).

2.3. On the combined role of supply and demand side

Seminal work on the combined impact of supply and demand side factors on energy innovation includes Popp (2002), who estimated the impact of the supply and demand side on energy efficient innovation. The results showed a strong and positive impact of energy prices and the quality of existing knowledge on cost-effective technologies in the long run. Many other papers have recognized the impact of oil and energy prices (Kruse and Wetzel, 2016; Ley et al, 2016; Lin and Zhu, 2019; Hu et al, 2023) and technological knowledge (Costantini and Crespi, 2008; Verdolini and Galeotti, 2011; Sung and Song, 2013, 2014). Kruse and Wetzel (2016) investigated the effects of relative prices and technological knowledge on green energy technologies, taking into account both demand-pull and technology-push effects. The authors came to three main conclusions: the existing stock of knowledge is an important driver; energy prices have a positive effect on certain technologies; and the combined effect of energy prices and technological knowledge increased after the Kyoto Protocol. Much attention has been paid to the causal relationship between technological progress and energy intensity, but less attention has been paid to the inverse relationship through which energy intensity can affect other variables. Chakraborty and Mazzanti (2020) found that there is a short-run and long-run relationship between the two variables, but the magnitude diminishes over time. Moreover, the authors did not find Granger causality between energy intensity and green energy innovation. This finding underscores that further research may be needed.

2.4. Research hypotheses

The above-mentioned literature has guided the selection of relevant variables, the expected directions of the relationships between them and the formulation of the research hypotheses. In brief, the proposed model aims to explain SWTs exports using supply-side factors such as green patents, R&D expenditures and SWTs imports, while demand-side factors include gross value added of the economy, energy intensity and oil price.

First, we argue that an increase in the number of patents in the field of environmental technologies and a higher level of gross domestic expenditure on R&D will lead to an increase in exports of SWTs (Popp, 2002; Johnstone et al., 2010). In line with the findings of Pizer and Popp (2008) and Noailly and Shestalova (2017), we consider the additional source of external knowledge from imports of SWTs. Here, too, we expect a positive

relationship: the greater the stock of knowledge and technology a country imports, the greater its ability to export SWTs.

In line with a consolidated literature (Costantini and Crespi, 2008; Sung and Song, 2013, 2014), we apply the above framework to the export of renewable energy technologies. These arguments allow us to establish our first basic hypothesis on the supply side.

> **Hypothesis #1 (Hp#1)**: On the supply side, an increase in the export of SWTs is stimulated by an increase in the number of green patents, R&D expenditure and the import of SWTs.

Based on these mechanisms, we propose the following research hypothesis, which relates specifically to the demand side.

> **Hypothesis #2 (Hp#2)**: On the demand side, an increase in exports of SWTs is stimulated by an improvement of the level of economic activity, a reduction in the country's energy intensity and a lower oil price.

Our goal is to demonstrate the indirect effects that demand-side factors exert on EXP via the supply side. The literature extensively discusses the expected relationships between demand and supply factors. Such relationships are often presented as one-way links that originate from the supply side and influence demand factors, as in the relationships between patents and energy intensity (Wurlod and Noailly, 2018; Pan et al., 2021; Feng et al., 2023) and R&D and energy intensity (Garrone and Grilli, 2010; Huang et al., 2017; Shen and Lin, 2020; Fan et al., 2023). Less explored are the inverse relationships that originate from the demand side to influence supply-side factors: such as in the case of energy prices and patents (Ley et al., 2016; Hu et al., 2023), energy intensity and patents (Chakraborty and Mazzanti, 2020; Feng et al., 2023). By systematically examining the underlying interactions between several demand-side factors on the supply side, we propose our final hypothesis.

> **Hypothesis #3 (Hp#3)**: Supply and demand are closely intertwined, with the latter boosting supply factors, indirectly and additionally affecting export of SWTs.

3. Empirical Analysis

3.1. Data and research methodology

Based on the relevant literature, we introduce a model based on the following variables: SWTs export (share of GDP, in thousands of current US $, EXP), ‘internal’ knowledge, represented by the number of patents in environmental technologies (% of total, PAT), technological capabilities, represented by R&D expenditure (% of GDP, RAD), ‘external’ knowledge from abroad, defined by the import of SWTs (share of GDP, in thousands of current US $, IMP), the level of economic activity, represented by Gross Value Added (at basic prices, in constant 2015 US $, per worker, GVA), the country’s energy intensity as a proxy for its energy demand indicating ongoing structural change (kWh per US $ of GDP, INT), and the oil price as a proxy for the incentive to abandon fossil fuels and adopt green energy technologies (crude oil import price, US $ per barrel, OIL).

The names of the individual variables, their definition and the corresponding source are listed in Table 1.

Table 1 about here

We emphasize that our choice is to prioritize the rapid evolution of technologies and the knowledge embedded within them over a perspective that favors the accumulation of knowledge over time and years. While it is true that technology lifecycle theory explains how knowledge emerges from other knowledge, in this case the current stage of development in the SWT industry points to a more "fluid" or "turbulent" competitive paradigm between alternative technologies, from which a dominant paradigm has yet to emerge. Such a dominant paradigm could emphasize the phenomenon of increasing returns, which could favor the stock over the flow.

A PVAR approach is applied to investigate the bidirectional interaction between variables, highlight lagged effects and identify possible path dependencies. In addition, variance decomposition analysis provides data to assess the relative importance of shocks in one variable on changes in other variables, and the Impulse Response

Function analysis allows us to observe the temporal evolution of each variable following a shock in another.

The model specification is as follows:

$$X_{it} = \Gamma(L)X_{it} + f_i + g_t + \varepsilon_{it} \quad (1)$$

where X_{it} denotes a vector of stationary variables, $\Gamma(L)$ stands for a matrix polynomial in the lag operator, f_i represents a vector of country fixed effects, g_t is a vector of year fixed effects, and ε_{it} represents a vector of error terms.

The panel includes 20 OECD industrialised countries: Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, Norway, Portugal, the Republic of Korea, Spain, Sweden, the United Kingdom and the United States. These countries were observed over as long a period as possible from 1996 to 2020. The number of countries was determined based on the availability of data. Initially, data for 38 OECD countries were used, but we excluded Australia, New Zealand, Switzerland and Turkey due to incomplete time series data on R&D expenditure. In addition, 15 other countries were excluded because they provided no or incomplete data on crude oil import prices, or because they displayed a low degree of homogeneity in terms of economic wealth, policy goals, and technological levels[1]. In this context, China, which accounts for by far the largest share of exports of SWTs, should not go unmentioned. Specifically, despite its centrality in the global trade of green technologies, we chose to exclude China for three complementary reasons. First, China was excluded because of the considerable difficulties in obtaining consistent and comparable data over the observed time periods. The available series for key variables are limited and fragmented, making it difficult to construct a robust data set for this country. Second, the measures of demand and supply-side factors in China do not always match those used in the OECD database, which clearly makes the cross-country analysis more complex and less reliable. Third, since all countries in our panel were "developed countries" in the reference period (2020), we excluded the countries formally categorised as developing countries by the OECD, a solution that ensures homogeneity within the sample. In addition, and more generally, we did not include China as it is not

[1] Chile, Colombia, Costa Rica, Estonia, Hungary, Iceland, Israel, Latvia, Lithuania, Luxembourg, Mexico, Poland, Slovak Republic, and Slovenia.

a role model for many of the OECD countries analysed (Shubbak, 2019; Hayashi, 2020), a feature that might have increased heterogeneity in the sample. Overall, while the study recognises China's crucial role in global trade in SWTs, the exclusion of China preserves the analytical integrity and comparability of the study.

Of the 20 selected countries, all have a strong performance in terms of SWTs export: 8 of them are among the top 10 countries in the world in terms of SWTs export, and 17 countries are among the top 30 countries. The key descriptive statistics can be found in Table 2.

Table 2 about here

In addition, we form a subpanel consisting of the ten most advanced countries in the field of green technologies that perform well in green patents (above the median value of the distribution in the entire period). These countries include Austria, Canada, the Czech Republic, Denmark, Finland, Germany, Greece, Japan, Norway and Portugal. These countries drive technological progress in the green energy field and SWTs, contributing significantly to the global diffusion and adoption of such technologies. Green patents play a central role in promoting the ongoing energy transition (Feng et al., 2023; Wei et al., 2023). Therefore, the subpanel is an ideal target for investigating the impact of supply-side and demand-side determinants. The most important descriptive statistics for the subpanel are shown in Table 3.

Table 3 about here

The subpanel exhibits a higher average percentage (of the total number) of patents in environment-related technologies. Similarly, higher values are observed for R&D expenditure and imports of SWTs, which represent the country's technological capabilities and external knowledge, respectively. It is likely that these factors have contributed to an increase in the average export of SWTs over the entire period. On the demand side, the subpanel shows poorer scores for all three variables. Countries that score well on PAT have higher INT scores (indicating higher energy intensity), a lower level of economic activity (GVA) and a higher oil price. These factors may serve as an

incentive to reach the technological frontier in SWTs. Interestingly, all variables in the subpanel have higher standard deviation values.

3.2. Preliminary tests

The application of the PVAR approach requires stationary variables to avoid spurious results. In the literature, unit root tests are usually divided into two categories: first-generation and second-generation unit root tests. The former assumes the (strong) cross-sectional independence hypothesis. However, if this assumption is not verified, these tests may incorrectly support the presence of a unit root. Therefore, the latter tests have been introduced to relax the cross-sectional independence hypothesis. A series of standard first-generation (IPS and MW) and second-generation (Pesaran) unit root tests were conducted for all variables, assuming the null hypothesis of stationarity (Maddala and Wu, 1999; Im et al., 2003; Pesaran, 2007). The results, presented in Tables 4 and 5 for the whole panel and the subpanel, respectively, show that the tests generally reject the null hypothesis of a unit root in panel data at a 1% significance level.

Table 4 about here

Table 5 about here

The first difference transformation is commonly used to address this problem (Gyimah et al., 2022; Acheampong, 2021). The previous unit root tests were then performed for the variables in first differences, and the results, presented in Tables 6 and 7, indicate stationarity for both panels (*d* denotes the first difference operator).

Table 6 about here

Table 7 about here

Cointegration among variables was examined to identify potential long-run equilibrium relationships commonly assumed in macroeconomic models. Four cointegration tests

developed by Westerlund (2007) were used to assess potential cross-sectional dependence. The first two tests (G_τ and G_α) examined the null hypothesis of no cointegration for all countries in the panel, while the second two tests (P_τ and P_α) examined the alternative hypothesis of cointegration for the full panel. The results, presented in Tables 8 and 9, show that all tests fail to reject the null hypothesis of no cointegration at the usual significance levels for both panels, based on robust p-values. This further supports the use of first-difference transformations for both panels, as variables in levels are both non-cointegrated and non-stationary.

Table 8 about here

Table 9 about here

Collinearity and multicollinearity were not a problem in our analysis, as indicated by the relatively low values of the correlation coefficients, variance inflation factors (VIF), and mean VIF for both panels (Tables 10 and 11). The VIF analysis was performed by considering EXP (the export value of SWTs) as the dependent variable and regressing it against each of the other indicators.

Table 10 about here

Table 11 about here

The last preliminary step in our analysis was to select the lag order. Specifically, we used the Moment Akaike Information Criterion (MAIC), Moment Bayesian Information Criterion (MBIC), and Moment Hannan-Quinn Information Criterion (MHQIC) to identify the optimal model (Akaike, 1969, 1977; Rissanen, 1978; Schwarz, 1978). Consistent with the econometric literature on the subject, the ideal lag length should minimize the MBIC, MAIC, and MHQIC moment model selection criteria. Based on the results presented in Tables 12 and 13, a first-order PVAR model was chosen for both panels.

Table 12 about here

Table 13 about here

The use of variables in first differences allowed us to remove the country fixed effects in Equation 1. However, it is well known that this transformation can lead to inconsistent and biased coefficients when ordinary least squares (OLS) is used, which is commonly referred to as Nickell bias (Nickell, 1981). To address this problem, we apply the Helmert transformation, which removes the forward mean from each observation, that is the mean of all the future observations available for each unit-period. In this way, orthogonality between transformed variables and lagged regressors is preserved (Love and Zicchino, 2006; Arellano and Bover, 1995). Forward-mean differencing is critical for using lags as instruments in a system GMM estimation. Typically, to eliminate time fixed effects, cross-sectional means are subtracted from each variable in the model. However, applying the Helmert transformation to the data yields the same result as applying the same transformation on demeaned data (Love and Zicchino, 2006; Abrigo and Love, 2016).

3.3. Main results and discussion

Tables 14 and 15 present the estimates of a first-order PVAR model for the entire set of countries and for the subpanel consisting of the best-performing countries in terms of PAT, respectively.

Table 14 about here

Table 15 about here

The Hansen J test (test for overidentifying restrictions) yields a value of 154.69 (p-value = 0.316) for the full panel and 131.06 (p-value = 0.433) for the subpanel. These results confirm that the models are robust, as the joint null hypothesis that the instruments are

not correlated with the error term and the correct exclusion of omitted instruments were verified.

In line with the econometric literature on this topic (Lütkepohl, 2005), the stability of the models was examined by ensuring that the eigenvalues are strictly smaller than 1. Table 16 and Figure 1 show the stability results for the full panel, while Table 17 and Figure 2 show the stability results for the subpanel. The stability of each model is crucial as it ensures its invertibility and thus enables bidirectional interpretations, the estimation of impulse response functions and variance decomposition analyses.

Table 16 about here

Figure 1 about here

Table 17 about here

Figure 2 about here

Finally, Granger causality tests were performed to test the null hypothesis of no causality. The results, which are presented in Tables 18 and 19 for the two panels, show the presence of bidirectional causality and confirm the presence of endogeneity.

Table 18 about here

Table 19 about here

According to the PVAR estimates, the export of SWTs (EXP) exhibits no path dependence; in other words, future SWTs export levels do not seem to be influenced by past export flows (Preston, 2013).

In both panels, supply-side factors promote the export of SWTs. Patents on environmental technologies have a positive effect on the export of SWTs, suggesting

that a percentage growth in green patents leads to an increase in the production, commercialization and export of SWTs. This relationship is supported by the expected positive impact of R&D expenditure on both the export value of SWTs and green patents (Costantini and Crespi, 2008; Marra and Colantonio, 2023). Knowledge spillovers from imports of SWTs (IMP) have a positive effect on both exports of SWTs and patents on environmental technologies, underlining the importance of knowledge in imported goods and technologies as the main source of technological change. This underlines the need for policy makers to promote the transfer and exchange of technical knowledge between countries (Pizer and Popp, 2008; Noailly and Shestalova, 2017). All results related to supply-side factors consistently do not reject Hp#1 and show the expected sign (Sung and Song, 2013, 2014).

As for the demand-side determinants, Hp#2 is only partially supported, with consistent differences observed between the two panels. As expected, a decrease in INT - indicating an improvement in energy intensity - seems to have a positive impact on the export value of SWTs in both groups. The lower energy demand can be attributed to structural shift, along with greater adoption of new energy-efficient technologies, including green energy technologies. This transition is accompanied by a stronger ability to export SWTs (Wurlod and Noailly, 2018; Chakraborty and Mazzanti, 2020).

Instead, Hp#2 regarding the level of economic activity (GVA) is partially rejected. The value added by producers to the goods and services they purchase shows no statistically significant impact on EXP in the full panel. Different trends were observed during the period under review. In the past, the expansion of GVA was generally met with higher demand for energy, which was covered by traditional fossil fuels and related technologies. More recently, rising energy demand has instead been met by cleaner and more energy-efficient technologies, facilitating growth in the manufacture and export of SWTs. Conversely, an increase in GVA in the subpanel stimulates EXP. It appears that in countries that score above average on green patents, attention to the environment prevails given higher technological readiness and industrial capabilities. Furthermore, growth in GVA leads to more green patents in the subpanel, while the reverse relationship is observed in the full panel (Johnstone et al., 2010; Verdolini and Galeotti, 2011).

The crude oil import price (OIL) is not statistically significant in the full panel and has a negative effect on EXP in the subpanel, which leads to a result that is not consistent with the literature (Kruse and Wetzel, 2016; Ley et al., 2016; Hu et al., 2023). As anticipated,

the impact of OIL on the export of SWTs is less straightforward to interpret, as a higher oil price may imply an increasing domestic demand for SWTs, whereby the latter would compete with an increasing demand on international markets.

The evidence for Hp#3 on the extent to which demand influences supply factors is mixed across the full panel. A decrease in energy intensity (INT) leads to an increase in the number of green patents (PAT) and imports of SWTs (IMP), which is consistent with Chakraborty and Mazzanti (2020) and Wurlod and Noailly (2018), while this is not as expected on R&D expenditure (RAD). For the full panel, gross value added is statistically significantly and positively associated with R&D expenditure (Verdolini and Galeotti, 2011). Conversely, Hp#3 is not rejected in the subpanel where demand plays an important role in influencing the supply factors and indirectly the export of SWTs. The results confirm the expected positive relationship between an improvement in the level of activity of the economy and an increase in the number of green patents (PAT). A higher level of technological capacity also has a positive effect on the import of SWTs, which is consistent with Costantini et al. (2017). Similarly, an increase in oil prices affects the supply side, as expected through a positive impact on IMP and PAT (Popp, 2002; Kruse and Wetzel, 2016). The results regarding energy intensity (INT) are in line with the considerations underlying our last hypothesis, as a decrease in INT has a positive impact on all supply factors (Chakraborty and Mazzanti, 2020; Hu et al., 2023; Feng et al., 2023).

To ensure a more comprehensive coverage, we have included in Appendix A the descriptive statistics (see Table A1) and the results of the PVAR analysis (see Table A2) conducted for the group of countries with the worst PAT scores (on average about 2.5 percentage points lower than the best). These countries export less SWT on average, and several of the sub-hypotheses on demand-side factors and the interaction between the demand and supply side are rejected for this group.

The differences in the research hypotheses between the entire panel and the subpanels are summarized in Table 20.

Table 20 about here

3.4. Further evidence

As mentioned above, the method used also allows us to analyse additional relationships beyond the main ones included in the hypotheses and discussed previously.

First, we find that an increase in R&D expenditure (RAD) has a positive effect on green patents (PAT), in line with Popp (2006) and Johnstone et al. (2010). Similarly, knowledge and technology spillovers underlying the import of SWTs appear to positively and directly stimulate green patents. As already mentioned, a decrease in energy intensity has a positive effect on green patents in both panels. This statistically significant relationship may suggest that a virtuous cycle has been initiated, linking lower energy demand to increased R&D in new green technologies. This relationship could be self-reinforcing over time, which is consistent with a path dependency in green patents.

Differences between the two panels are observed with respect to the level of economic activity (GVA) and the crude oil import price (OIL): in the subpanel with the best PAT scores, both growth in value added and the oil price stimulate green patents (Kruse and Wetzel, 2016). The expected relationship between OIL and patents in environmentally related technologies is consistent with the literature (Popp, 2002; Hu et al., 2023), whereas here, too, no comparable effect can be observed across the entire panel. As expected, supply and demand factors are crucial for green patents. In addition, the statistically significant relationship between the oil price and patents in environmentally related technologies has positive and indirect effects on the export of SWTs.

RAD exhibits path dependence in both panels (full and best PAT scores), confirming that earlier R&D strategies and policies strongly influence later R&D outcomes (Jiang and Liu, 2022; Vergne and Durand, 2010). In the entire panel, R&D spending is stimulated by the increase in green patents and the improvement in the level of economic activity. The relationships between the oil price on the one hand and energy intensity and R&D expenditure on the other are more difficult to interpret.

In the full panel and best PAT scores subpanel, the import value of SWTs (IMP) promotes the energy transition as it is associated with lower energy intensity. In the subpanel, countries appear to leverage more on green patents and R&D spending while recognizing the potential contribution of foreign countries. In the full panel, IMP shows path dependence: knowledge spillovers associated with the import of SWTs are a critical source of technological progress (Pizer and Popp, 2008; Noailly and Shestalova, 2017). In both panels, IMP is stimulated by increases in green patents and R&D expenditure. The aspiration to stay at the technological forefront forces these countries not to overlook external sources of knowledge, among other driving factors. In the subpanel, IMP is stimulated by a reduction in energy intensity as well as positive changes in gross value

added and crude oil import prices. However, the latter two factors turn negative in the full panel.

Further differences between the two panels emerge in terms of the level of economic activity. Overall, GVA appears to be positively influenced by both exports and imports of STWs. On the other hand, GVA in the subpanel shows a path dependency (which is not evident in the full panel due to a lack of statistical significance) and appears to be positively influenced by RAD and PAT (although PAT is not statistically significant in the full panel and RAD is negative). Finally, the crude oil import price is an obstacle to GVA in both panels.

A decline in energy intensity (INT) in both panels is driven by positive changes in supply-side factors: rising R&D spending, a higher number of green patents and the growing value of SWTs import all contribute to the decline in energy consumption per unit of GDP. On the demand side, gross value added is negatively associated with rising INT, confirming that the countries observed are modern economies fully committed to the green transition. Furthermore, rising oil prices promote a decrease in INT in the subpanel, while they have no effect in the full panel (Andersson and Karpestam, 2013).

The crude oil import price (OIL) shows a path dependency in both panels. In contrast to the results in the literature, OIL is negatively associated with green patents (PAT) in the full panel. This result can be interpreted as a short-term reaction based on economic convenience, which also increases the adoption of "grey" or "brown" technologies, negatively affecting innovative activities for new energy-efficient solutions and green patents (Acemoglu et al., 2016). However, in the subpanel, OIL is positively associated with PAT and negatively associated with energy intensity, confirming an expected positive response. It is important to emphasise the indirect effect of oil price, mediated by energy intensity, on the export value of SWTs. In the full panel, there is a positive relationship between oil price and energy intensity, with rising oil prices leading to (more energy efficient technologies, but also) higher energy demand. This could indicate a kind of "rebound effect" in which the saving of resources through greater energy efficiency is more than offset by an increase in the consumption of the same resources.

In the subpanel, an increase in the oil price has a negative effect on energy intensity and can indirectly activate SWTs export: the negative relationship between OIL and INT may lead to the conclusion that OIL may indirectly (via INT) have a positive effect on EXP (Andersson and Karpestam, 2013; Hu et al., 2023).

3.5 Variance decomposition and impulse effect

In this section, we present forecast error variance decompositions and impulse–response functions based on the PVAR estimates to better understand the dynamic relationships between our variables of interest.

Tables 21 and 22 show the results of the variance decomposition analyses (after Cholesky decomposition using 1,000 Monte Carlo simulations for 10 periods). For each panel, we assess the relative importance of one variable for changes in other variables over time.

Table 21 about here

Table 22 about here

In general, each variable is mainly influenced by its lag. Interesting differences can be seen in the two panels. In the entire panel, the weight of a change in the export value of SWTs is higher for green patents (27.8%) and SWTs (13.4%). The latter is also relevant for a change in the relative number of patents on environmental technologies (PAT). Similarly, changes in the above-mentioned variables have a different impact on the subpanel: PAT is most important (42.5%). In addition, PAT also has a high weight in terms of energy intensity. It should be noted that a change in crude oil import price has more weight on SWTs import and less on export in the subpanel: this confirms that energy shocks, such as oil price fluctuations, can be absorbed in the short run by technology imports.

Figures 3 and 4 show the results of the analysis of the impulse response function. They illustrate the evolution over time of each indicator after a shock to a different variable, with all other changes equal to zero (in this case we also used the Cholesky decomposition and ran 200 Monte Carlo simulations).

Figure 3 about here

Figure 4 about here

Looking at the full panel of countries, a positive shock to one variable generally leads to weak responses on others and only in the first few periods. In contrast, the same shocks seem to have more pronounced and lasting effects in the subpanel, which is our ideal target. Looking at the plots in the first column of Fig. 14, the results are consistent with the PVAR estimates. EXP shows no path dependency. Moreover, PAT transfers its positive impact to EXP in the early periods, suggesting the need for continuous support over time (especially considering that patents in this area can quickly become obsolete). The impact of R&D expenditure (RAD) on green patents (PAT) occurs with a lag. As for the drivers in the subpanel, a positive shock to GVA stimulates PAT, especially in the first periods, together with a positive change in energy intensity, albeit with a lag. Finally, a positive shock in oil prices lowers the export of SWTs, probably due to a greater internal adoption of new green technologies.

3.6 The role of environment-related taxation

Since we have observed marginal differences in OIL between countries over time, we have included another variable in the theoretical framework mentioned above: the level of environmental-related taxation (TAX, measured as the share of environmental tax revenues in GDP, as provided by the OECD). The TAX variable has a non-negligible direct and indirect impact on energy prices: an increase in the environmental taxation is expected to lower the relative price of green energy technologies, which are then comparatively less taxed, encouraging their adoption domestically and leading to lower exports of SWTs (Popp, 2002; Costantini et al., 2017; Karmaker et al., 2021).

We tested the relevance of TAX in addition to OIL by replicating the PVAR approach. The extended model specification was applied to our original panel. All coefficients resulting from the PVAR analyses for the new specification are shown in Table 23.

Tables 23 about here

The analysis shows that an increase in environment-related taxation, associated with higher crude oil import prices is followed by a decrease in SWTs exports, while the other relationships remain essentially unchanged (see Table 24). This result is consistent with

the existing literature on economic incentives for technological progress (Ley et al., 2016; Lin and Zhu, 2019), which encourages domestic adoption of SWTs while potentially decreasing exports.

Tables 24 about here

4. Conclusion and policy implications

Some energy technologies are still impractical, ineffective or too expensive, so the risk of failure in tacking the climate challenge is very high. For example, carbon dioxide removal technologies are often touted as promising, but the cost (and uncertainty) of removing and safely storing a tonne of carbon dioxide emissions from the air remains prohibitive. On the other hand, SWTs are among the most effective tools available (IEA, 2022a). However, the market is not sufficient to make the expected transition from fossil fuels to renewables, as the private sector does not have the necessary financial resources to manage this endeavour alone. If SWTs are so important, it is crucial to understand how governments can promote their adoption (Nesta et al., 2014).

We have argued that both the supply and the demand side are crucial determinants for the export of SWTs and have focused on the supply-side effects of demand factors. We tested three hypotheses using a panel of 20 developed countries and a subpanel comprising the ten most advanced economies in green patents, covering the period from 1996 to 2020. The results generally confirm the expected results. With respect to Hp#1, which focused on the supply side, our results indicated that higher relative number of green patents (PAT), higher R&D expenditure (RAD) and additional SWTs import (IMP) contribute to the export of SWTs. These results are consistent with the existing literature (Costantini and Crespi, 2008; Sung and Song, 2013, 2014; Noailly and Shestalova, 2017) and suggests that government interventions play an important role not only in promoting PAT and RAD (Nesta et al., 2014), but also in facilitating openness to foreign trade, especially for countries with less strong internal knowledge and technological capabilities.

With regard to Hp# 2, the results and their interpretation were less trivial. Energy intensity has a positive effect on SWTs in both panels, while the effects of oil prices and economic conditions are different in the two panels. In the full panel, the latter has no statistically

significant effect on exports, while in the subpanel an increase in gross value added stimulates exports of SWTs. This suggests that countries that excel in green patents prioritize long-term environmental concerns over short-term economic interests. Governments should be able to separate environmental pressures from economic issues by adopting environmentally friendly positions.

Regarding the interdependence between demand and supply (Hp#3), we found that demand factors have a significant impact on supply, which gives an additional boost to the production and export of SWTs, especially in the subpanel of countries with high patent scores. An interesting finding relates to energy intensity. Improvements in energy intensity are positively related to changes in supply-side factors in both panels: higher PAT, increasing RAD and more IMP are achieved by reducing energy consumption per unit of GDP (Chakraborty and Mazzanti, 2020). Furthermore, the results confirmed the expected relationship between GVA on the one hand and PAT and RAD on the other.

Similarly, an increase in oil prices affects the supply side. Instead, oil price increases do not have a positive direct effect on exports. Only in the subpanel does an increase in crude oil import prices reduce energy intensity and indirectly affect exports of SWTs. In this way, energy intensity plays a key role in mediating the contribution of oil prices. A similar function is played by PAT, which also works as a bridge between OIL and EXP.

As we found marginal differences between countries in terms of OIL over time, we tested the relevance of another variable, namely the level of environment-related taxation (measured as the share of environmental tax revenues on GDP, TAX). TAX has a non-negligible direct and indirect impact on energy prices (Popp, 2002; Costantini et al., 2017; Karmaker et al., 2021). As expected, an increase in environment-related taxes combined with higher oil prices leads to a decrease in SWTs exports, while the other relationships remain essentially unchanged. This result is consistent with the existing literature on economic incentives for technological progress (Ley et al., 2016; Lin and Zhu, 2019). The mechanisms that governments can activate through TAX in the energy transition deserve further investigation and will be the subject of future research efforts.

As expected, the model allows for the investigation of numerous other relationships, such as the substitution relationship between green patents (PAT) and imports of SWTs (IMP). PAT is crucial for SWTs export in countries on the technological frontier (i.e. the subpanel), but less so for others. On the other hand, the function of technological spillovers related to IMP becomes crucial when considering the full panel. IMP plays a role in these countries, albeit not consistently over time. Finally, spillover effects related

to IMP appear to stimulate and promote PAT. As far as the demand-side determinants are concerned, rising oil prices only encourage a decline in INT in the countries of the subpanel.

The next steps of the study will focus on analyzing the relationship between PAT and INT. While this relationship is controversial in the literature, it provides an opportunity for investigation, particularly in terms of its bidirectionality and the mixed contribution of compositional, scale and technical effects. The availability of data on public procurement (PP) at national level could also provide further avenues for research: the "dual" role of public procurement as a demand and supply element is an intriguing topic as it can be interpreted from different analytical perspectives, i.e., as a component of domestic demand and at the same time as an industrial policy instrument.

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Table 1. Description of Variables

Variable	Definition	Source
EXP	Export value of SWTs (per billion GDP)	UN
PAT	Patents on environment technologies (% of total)	OECD
RAD	Research and development expenditure (% of GDP)	World Bank
IMP	Import value of SWTs (per thousand GDP)	UN
GVA	Gross value added at basic prices (constant 2015 US $) / labour force	World Bank
INT	Energy per GDP (kWh per $)	OECD
OIL	Crude oil import price (US $ per barrel)	OECD

Table 2. Descriptive statistics - Entire panel

Variable	Obs.	Mean	Std. Dev.	Min	Max
EXP	495	4.543	3.833	0.419	22.607
PAT	460	10.103	3.623	2.040	25.830
RAD	449	2.047	0.829	0.429	4.528
IMP	495	3.964	2.444	0.590	22.094
GVA	478	68347.05	23429.65	20591.01	143144.60
INT	460	1.528	0.523	0.587	3.621
OIL	496	55.927	30.774	11.660	115.640

Table 3. Descriptive statistics - Subpanel: best performers in PAT

Variable	Obs.	Mean	Std. Dev.	Min	Max
EXP	248	5.684	4.731	0.419	22.607
PAT	230	11.315	3.692	4.910	25.830
RAD	224	2.088	0.867	0.429	3.734
IMP	248	4.378	2.860	0.590	22.094
GVA	238	64839.65	26691.50	20591.01	128099.10
INT	230	1.592	0.604	0.722	3.621
OIL	246	56.563	30.783	11.660	114.750

Table 4. Unit root tests: variables in level - Entire panel

Variable	IPS W-t-bar	MW	Pesaran Z-t-bar
EXP	-0.689	36.342	-0.481
PAT	-0.002	24.727	-1.626*
RAD	3.252	35.111	3.266
IMP	0.791	56.816**	-3.354***
GVA	0.727	52.740*	0.891
INT	-0.766	57.879**	-0.886
OIL	-0.444	5.846	-1.758**

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

Table 5. Unit root tests: variables in level - Subpanel: best performers in PAT

Variable	IPS W-t-bar	MW	Pesaran Z-t-bar
EXP	0.546	8.132	1.488
PAT	-0.866	14.239	-0.484
RAD	2.258	16.378	1.849
IMP	0.639	36.638**	-2.266**
GVA	0.899	29.927*	-1.473**
INT	-1.184	35.038**	-0.593
OIL	-0.404	2.975	-2.280**

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

Table 6. Unit root tests: variables in first differences - Entire panel

Variable	IPS W-t-bar	MW	Pesaran Z-t-bar
dEXP	-13.829***	149.092***	-6.396***
dPAT	-12.467***	112.703***	-6.897***
dRAD	-9.654***	99.499***	-1.396*
dIMP	-13.917***	138.132***	-7.978***
dGVA	-11.536***	170.963***	-2.347***
dINT	-16.408***	218.781***	-6.762***
dOIL	-12.468***	165.026***	-7.641***

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

Table 7. Unit root tests: variables in first differences - Subpanel: best performers in PAT

Variable	IPS W-t-bar	MW	Pesaran Z-t-bar
dEXP	-10.026***	76.311***	-4.115***
dPAT	-9.746***	75.568***	-4.429***
dRAD	-7.121***	50.341***	-1.508***
dIMP	-10.461***	80.430***	-6.933***
dGVA	-8.743***	71.180***	-0.518
dINT	-10.166***	92.127***	-4.150***
dOIL	-8.736***	81.706***	-5.829***

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

Table 8. Cointegration tests - Entire panel

Statistic	Value	p-value
G_τ	-2.211	0.270
G_α	-5.414	0.670
P_τ	-9.450	0.340
P_α	-5.762	0.410

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

Table 9. Cointegration tests - Subpanel: best performers in PAT

Statistic	Value	p-value
G_τ	-2.284	0.300
G_α	-5.691	0.560
P_τ	-6.736	0.350
P_α	-5.367	0.480

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

Table 10. Correlation matrix and variance inflation factor (VIF) statistics - Entire panel

	dRET	dEPO	dAWA	dEDU	dPAT	dTRD	dGDP
dEXP	1.000						
dPAT	0.134	1.000					
dRAD	0.102	0.028	1.000				
dIMP	0.359	-0.002	0.012	1.000			
dGVA	0.118	-0.042	-0.263	0.113	1.000		
dINT	-0.033	-0.017	-0.030	0.031	-0.129	1.000	
dOIL	0.266	0.031	0.074	0.179	0.133	-0.084	1.000
VIF		1.00	1.09	1.05	1.14	1.03	1.07
Mean VIF	1.06						

Table 11. Correlation matrix and variance inflation factor (VIF) statistics – Subpanel: best performers in PAT

	dRET	dEPO	dAWA	dEDU	dPAT	dTRD	dGDP
dEXP	1.000						
dPAT	0.145	1.000					
dRAD	0.096	0.037	1.000				
dIMP	0.296	0.029	-0.033	1.000			
dGVA	0.241	0.005	-0.119	0.131	1.000		
dINT	-0.065	-0.032	-0.044	0.052	-0.226	1.000	
dOIL	0.308	0.041	0.031	0.114	0.353	-0.117	1.000
VIF		1.00	1.03	1.03	1.23	1.07	1.16
Mean VIF	1.09						

Table 12. Lag order selection criteria - Entire panel

Lag	MBIC	MAIC	MHQIC
1	-689.932	-142.565	-361.477
2	-478.121	-113.210	-259.151

Table 13. Lag order selection criteria - Subpanel: best performers in PAT

Lag	MBIC	MAIC	MHQIC
1	-387.781	-87.6469	-209.535
2	-206.446	-56.378	-117.323

Table 14. PVAR results - Entire panel

	Dependent variables						
Independent lagged variables	dEXP	dPAT	dRAD	dIMP	dGVA	dINT	dOIL
dEXP	-0.379***	-1.149***	-0.059***	-0.466***	718.400***	-0.025***	-22.860***
	(0.051)	(0.124)	(0.010)	(0.058)	(187.900)	(0.006)	(2.027)
dPAT	0.107***	0.167**	0.012***	0.198***	-11.910	-0.006***	1.153**
	(0.019)	(0.070)	(0.003)	(0.025)	(51.380)	(0.001)	(0.575)
dRAD	0.989*	7.362***	0.453***	1.345**	-6.545***	-0.165***	-21.350
	(0.524)	(1.846)	(0.079)	(0.629)	(1.424)	(0.036)	(17.350)
dIMP	0.367***	2.043***	-0.020***	0.632***	1.640***	-0.060***	34.470***
	(0.028)	(0.128)	(0.003)	(0.054)	(134.500)	(0.005)	(2.760)
dGVA	0.000	-0.000*	0.000***	-0.000**	0.127	-0.000*	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.097)	(0.000)	(0.001)
dINT	-2.136***	-12.450***	0.266***	-3.698***	-10.941***	0.087	29.280
	(0.701)	(2.075)	(0.099)	(0.795)	(1.872)	(0.070)	(19.910)
dOIL	-0.002	-0.010*	0.001***	-0.007***	-52.860***	0.001***	0.138**
	(0.002)	(0.006)	(0.000)	(0.002)	(6562.000)	(0.000)	(0.056)

Note: Standard errors in parentheses; *p < 0.1; **p < 0.05; ***p < 0.01

Table 15. PVAR results - Subpanel: best performers in PAT

	Dependent variables						
Independent lagged variables	dEXP	dPAT	dRAD	dIMP	dGVA	dINT	dOIL
dEXP	-0.438***	-3.470***	0.0712***	-0.980***	-1.059***	0.0734***	-66.210***
	(0.028)	(0.137)	(0.004)	(0.043)	(60.080)	(0.004)	(2.928)
dPAT	0.145***	0.803***	-0.004***	0.344***	283.200***	-0.026***	7.497***
	(0.008)	(0.050)	(0.001)	(0.018)	(19.920)	(0.001)	(0.491)
dRAD	1.705***	14.410***	0.457***	5.278***	4.902***	-0.141***	83.360***
	(0.445)	(1.379)	(0.070)	(0.492)	(642.600)	(0.050)	(22.140)
dIMP	0.826***	1.184***	0.023***	-0.103***	-317.600***	-0.019***	27.200***
	(0.025)	(0.050)	(0.001)	(0.026)	(27.100)	(0.004)	(1.134)
dGVA	0.000***	0.000***	0.000**	0.000**	0.550***	-0.000***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.060)	(0.000)	(0.001)
dINT	-8.845***	-2.853*	-0.362***	-1.296**	14.733***	-0.348***	19.370
	(0.550)	(1.690)	(0.107)	(0.520)	(1.052)	(0.062)	(26.490)
dOIL	-0.009***	0.025***	-0.001***	0.005**	-9.792***	-0.001***	0.850***
	(0.002)	(0.006)	(0.000)	(0.002)	(2.953)	(0.000)	(0.084)

Note: Standard errors in parentheses; *p < 0.1; **p < 0.05; ***p < 0.01

Table 16. Eigenvalue stability condition - Entire panel

Eigenvalue		
Real	**Imaginary**	**Modulus**
0.956	0.000	0.956
0.688	0.000	0.688
0.104	0.539	0.549
0.104	-0.539	0.549
-0.354	0.157	0.387
-0.354	-0.157	0.387
0.081	0.000	0.081

Table 17. Eigenvalue stability condition - Subpanel: best performers in PAT

Eigenvalue		
Real	**Imaginary**	**Modulus**
0.981	0.000	0.981
0.356	-0.788	0.865
0.356	0.788	0.865
0.503	0.210	0.545
0.503	-0.210	0.545
-0.464	-0.200	0.506
-0.464	0.200	0.506

Table 18. Granger causality tests - Entire panel

Equation Variable	Excluded Variables	Chi2	p-value
dEXP	dPAT	31.336	0.000
	dRAD	3.565	0.059
	dIMP	166.908	0.000
	dGVA	0.2	0.655
	dINT	9.287	0.002
	dOIL	1.84	0.175
	ALL	196.733	0.000
dPAT	dEXP	85.99	0.000
	dRAD	15.898	0.000
	dIMP	254.208	0.000
	dGVA	3.78	0.052
	dINT	36.03	0.000
	dOIL	2.941	0.086
	ALL	336.015	0.000
dRAD	dEXP	36.009	0.000
	dPAT	15.623	0.000
	dIMP	38.754	0.000
	dGVA	13.92	0.000
	dINT	7.266	0.007
	dOIL	28.787	0.000
	ALL	117.962	0.000
dIMP	dEXP	65.596	0.000
	dPAT	64.438	0.000
	dRAD	4.566	0.033
	dGVA	5.526	0.019
	dINT	21.605	0.000
	dOIL	11.724	0.001
	ALL	147.964	0.000
dGVA	dEXP	14.625	0.000
	dPAT	0.054	0.817
	dRAD	21.111	0.000
	dIMP	148.743	0.000
	dINT	34.173	0.000
	dOIL	64.897	0.000
	ALL	225.23	0.000
dINT	dEXP	15.404	0.000
	dPAT	13.692	0.000
	dRAD	20.955	0.000
	dIMP	145.438	0.000
	dGVA	3.373	0.066
	dOIL	13.566	0.000

	ALL	209.68	0.000
dOIL	dEXP	127.236	0.000
	dPAT	4.02	0.045
	dRAD	1.514	0.219
	dIMP	166.657	0.000
	dGVA	1.431	0.232
	dINT	2.164	0.141
	ALL	233.551	0.000

Table 19. Granger causality tests - Subpanel: best performers in PAT

Equation Variable	Excluded Variables	Chi2	p-value
dEXP	dPAT	291.628	0.000
	dRAD	14.690	0.000
	dIMP	1103.508	0.000
	dGVA	8.787	0.003
	dINT	259.000	0.000
	dOIL	24.943	0.000
	ALL	2358.665	0.000
dPAT	dEXP	637.205	0.000
	dRAD	109.175	0.000
	dIMP	554.677	0.000
	dGVA	10.244	0.001
	dINT	2.851	0.091
	dOIL	17.602	0.000
	ALL	924.365	0.000
dRAD	dEXP	371.896	0.000
	dPAT	14.754	0.000
	dIMP	337.106	0.000
	dGVA	4.957	0.026
	dINT	11.450	0.001
	dOIL	8.431	0.004
	ALL	932.237	0.000
dIMP	dEXP	524.793	0.000
	dPAT	354.720	0.000
	dRAD	115.284	0.000
	dGVA	6.136	0.013
	dINT	6.218	0.013
	dOIL	4.104	0.043
	ALL	832.940	0.000
dGVA	dEXP	310.964	0.000
	dPAT	202.132	0.000

	dRAD	58.189	0.000
	dIMP	137.292	0.000
	dINT	196.114	0.000
	dOIL	10.994	0.001
	ALL	789.155	0.000
dINT	dEXP	400.628	0.000
	dPAT	300.202	0.000
	dRAD	8.11	0.004
	dIMP	24.372	0.000
	dGVA	98.973	0.000
	dOIL	24.677	0.000
	ALL	673.696	0.000
dOIL	dEXP	511.246	0.000
	dPAT	232.725	0.000
	dRAD	14.18	0.000
	dIMP	575.238	0.000
	dGVA	14.224	0.000
	dINT	0.535	0.465
	ALL	1174.83	0.000

Table 20. Research hypotheses

Research hypotheses	Entire panel	Sub-panel Best performers in PAT	Sub-panel Worst performers in PAT
Hp#1: On the supply side, an increase in the export of SWTs is stimulated by…			
(a) an increase in the number of green patents	√	√	√
(b) an increase in R&D spending	√	√	√
(c) an increase in the import of SWTs	√	√	√
Hp#2: On the demand side, an increase in the export of SWTs is stimulated by…			
(a) an improvement in the state of the economy	▲	√	√
(b) a decrease in the country's energy intensity	√	√	▲
(c) lower crude oil import prices	▲	√	▲
Hp#3: The demand side influences the supply factors…			
(a) an improvement in the state of the economy stimulates PAT, RAD and IMP	▲ √ ▲	√ √ √	▲ √ ▲
(b) a decrease in the country's energy intensity stimulates PAT, RAD and IMP	√ ▲ √	√ √ √	√ ▲ √
(c) higher oil prices stimulate PAT, RAD and IMP	▲ √ ▲	√ ▲ √	√ √ ▲

Note: √ → not rejected; ▲→ rejected

Table 21. Variance decomposition analysis - Entire panel

	Impulse variable						
Response variable	dEXP	dPAT	dRAD	dIMP	dGVA	dINT	dOIL
dEXP	42.2%	27.8%	3.4%	23.7%	0.3%	1.9%	0.7%
dPAT	3.7%	56.4%	5.4%	31.7%	0.1%	2.5%	0.2%
dRAD	4.4%	12.9%	56.8%	10.1%	7.8%	0.6%	7.4%
dIMP	7.4%	32.3%	5.1%	51.8%	0.6%	1.8%	0.9%
dGVA	9.2%	16.1%	16.0%	17.8%	24.0%	3.2%	13.7%
dINT	9.7%	32.4%	7.0%	28.4%	3.7%	16.9%	2.0%
dOIL	2.4%	26.9%	3.6%	39.3%	4.9%	1.0%	21.9%

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

Table 22. Variance decomposition analysis - Subpanel: best performers in PAT

	Impulse variable						
Response variable	dEXP	dPAT	dRAD	dIMP	dGVA	dINT	dOIL
dEXP	27.1%	42.5%	6.4%	13.4%	1.9%	3.2%	5.5%
dPAT	11.6%	63.2%	5.2%	5.1%	1.2%	1.5%	12.2%
dRAD	21.7%	30.3%	31.9%	7.3%	3.2%	1.6%	4.1%
dIMP	9.1%	42.7%	6.4%	30.2%	1.2%	1.4%	8.9%
dGVA	16.0%	40.0%	5.9%	5.9%	16.7%	4.9%	10.6%
dINT	14.1%	52.5%	5.5%	4.8%	3.1%	11.9%	8.2%
dOIL	18.1%	40.6%	5.2%	7.4%	1.6%	2.6%	24.4%

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

Table 23. PVAR results - Entire panel - TAX in addition to OIL

	Dependent variables							
Independent lagged variables	dEXP	dPAT	dRAD	dIMP	dGVA	dINT	dOIL	dTAX
dEXP	-0.325***	-1.261***	-0.0467***	-0.535***	709.300***	-0.037***	-22.490***	0.018***
	(0.045)	(0.094)	(0.007)	(0.049)	(143.500)	(0.005)	(3.805)	(0.006)
dPAT	0.117***	0.156***	0.015***	0.165***	-85.190*	-0.001	-1.500	-0.014***
	(0.013)	(0.036)	(0.002)	(0.020)	(44.810)	(0.001)	(1.607)	(0.002)
dRAD	0.611*	0.336	0.994***	-1.060***	-24.878***	0.416***	-635.600***	-0.926***
	(0.369)	(0.794)	(0.105)	(0.376)	(2.931)	(0.063)	(78.610)	(0.108)
dIMP	0.304***	1.397***	0.012***	0.431***	659.000***	-0.027***	-6.775***	-0.018***
	(0.024)	(0.072)	(0.003)	(0.035)	(76.710)	(0.002)	(1.936)	(0.003)
dGVA	0.000	-0.000***	0.000***	-0.000***	-0.157	0.000**	-0.012***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.129)	(0.000)	(0.004)	(0.000)
dINT	-2.406***	-9.944***	0.216**	-3.318***	-10.753***	0.0267	80.520	0.057
	(0.470)	(1.222)	(0.107)	(0.573)	(2.376)	(0.065)	(72.020)	(0.104)
dOIL	-0.002*	-0.003	0.001***	-0.003**	-49.030***	0.001***	0.480**	0.000
	(0.001)	(0.003)	(0.000)	(0.002)	(7.562)	(0.000)	(0.196)	(0.000)
dTAX	-0.906***	-8.381***	0.177***	-2.093***	-8.917***	0.276***	-354.400***	0.087
	(0.211)	(0.741)	(0.051)	(0.319)	(1.546)	(0.045)	(51.260)	(0.057)

Note: Standard errors in parentheses; *p < 0.1; **p < 0.05; ***p < 0.01

Table 24. Research hypotheses

Research hypotheses	Entire panel	Entire Panel TAX in addition to OIL
Hp#1: On the supply side, an increase in the export of SWTs is stimulated by…		
(a) an increase in the number of green patents	√	√
(b) an increase in R&D spending	√	√
(c) an increase in the import of SWTs	√	√
Hp#2: On the demand side, an increase in the export of SWTs is stimulated by…		
(a) an improvement in the state of the economy	▲	▲
(b) a decrease in the country's energy intensity	√	√
(c) lower crude oil import prices (and lower environment-related taxation)	▲	√ √
Hp#3: The demand side influences the supply factors…		
(a) an improvement in the state of the economy stimulates PAT, RAD and IMP	▲ √ ▲	▲√ √
(b) a decrease in the country's energy intensity stimulates PAT, RAD and IMP	√ ▲ √	√ ▲ √
(c) higher oil prices stimulate PAT, RAD and IMP	▲ √ ▲	▲√ ▲

Note: √ → not rejected; ▲→ rejected

Appendix A

Table A1. Descriptive statistics - Subpanel: worst performers in PAT

Variable	Obs.	Mean	Std. Dev.	Min	Max
EXP	247	3.398	2.098	0.771	9.455
PAT	230	8.890	3.117	2.040	16.060
RAD	225	2.006	0.789	0.778	4.528
IMP	247	3.549	1.853	1.169	10.193
GVA	240	71825.230	19097.820	27114.390	143144.600
INT	230	1.465	0.419	0.587	2.504
OIL	250	55.301	30.815	11.800	115.640

Table A2. PVAR results - Subpanel: worst performers in PAT

	Dependent variables						
Independent lagged variables	dEXP	dPAT	dRAD	dIMP	dGVA	dINT	dOIL
dEXP	-0.579***	1.718***	-0.213***	0.774***	1.490***	-0.192***	60.220***
	(0.034)	(0.138)	(0.011)	(0.054)	(146.100)	(0.010)	(2.412)
dPAT	0.276***	-1.937***	0.118***	-0.113***	-230.400***	0.124***	15.890***
	(0.019)	(0.093)	(0.005)	(0.017)	(64.500)	(0.006)	(0.994)
dRAD	3.450***	-25.980***	1.234***	-5.621***	7.874***	1.652***	-206.000***
	(0.358)	(1.689)	(0.118)	(0.326)	(1.176)	(0.115)	(14.090)
dIMP	0.305***	-0.625***	0.005	0.217***	3.052***	0.035***	-1.246
	(0.024)	(0.075)	(0.003)	(0.029)	(202.000)	(0.004)	(0.896)
dGVA	0.000***	-0.001***	0.000***	-0.000***	0.327***	0.000***	-0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.063)	(0.000)	(0.001)
dINT	0.916**	-11.590***	1.035***	-0.948**	-12.238***	-0.055	141.400***
	(0.369)	(1.512)	(0.101)	(0.481)	(2.147)	(0.124)	(26.980)
dOIL	-0.001	0.034***	0.001***	-0.007***	-88.380***	-0.001***	-0.270***
	(0.001)	(0.005)	(0.000)	(0.001)	-4.541	(0.000)	(0.048)

Note: Standard errors in parentheses; *p < 0.1; **p < 0.05; ***p < 0.01

Figure Click here to access/download;Figure;figures_resub_nov_24.docx

Fig. 1. Roots of the companion matrix - entire panel

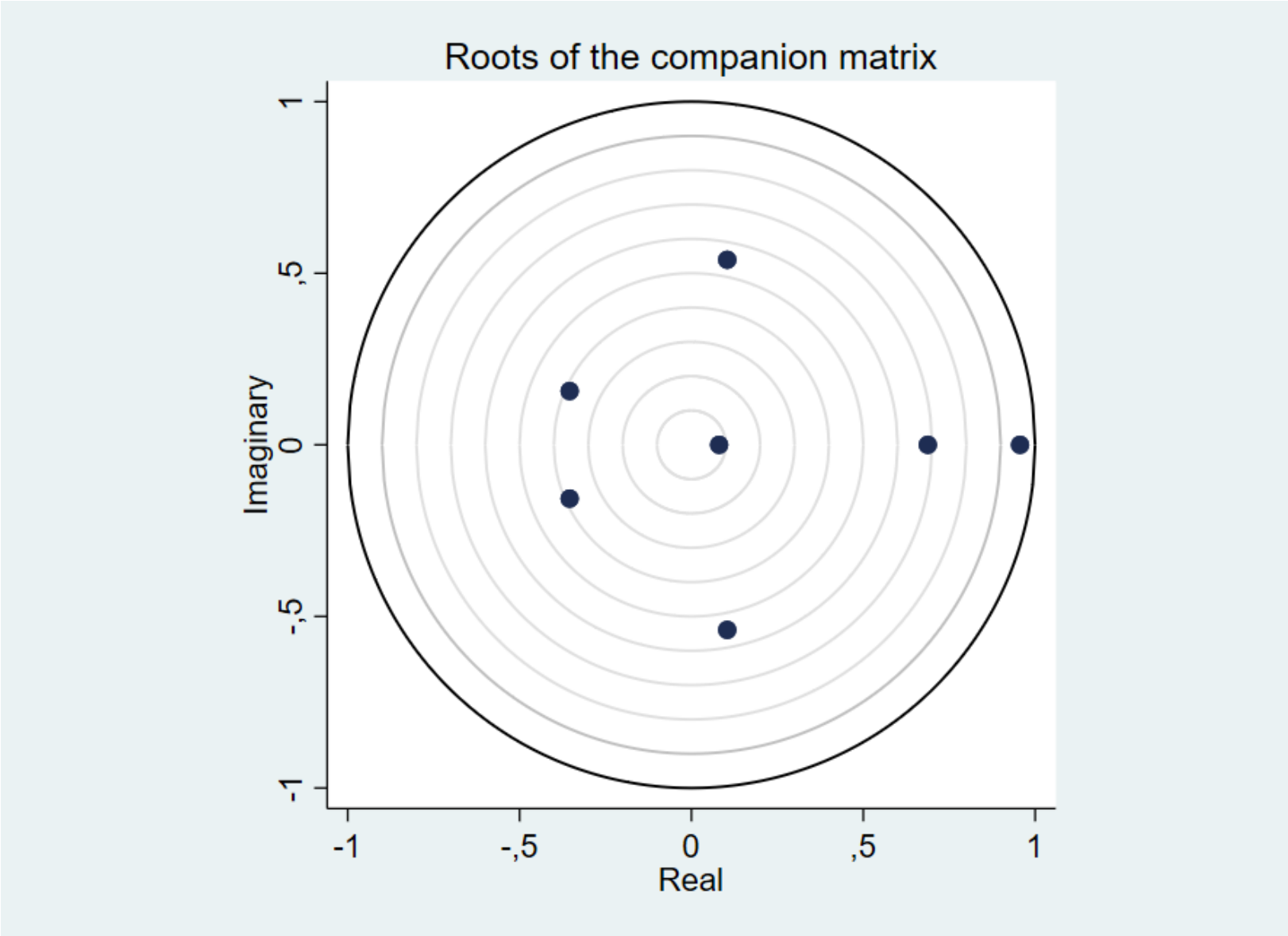


Fig. 2. Roots of the companion matrix - sub-panel - best performers in PAT

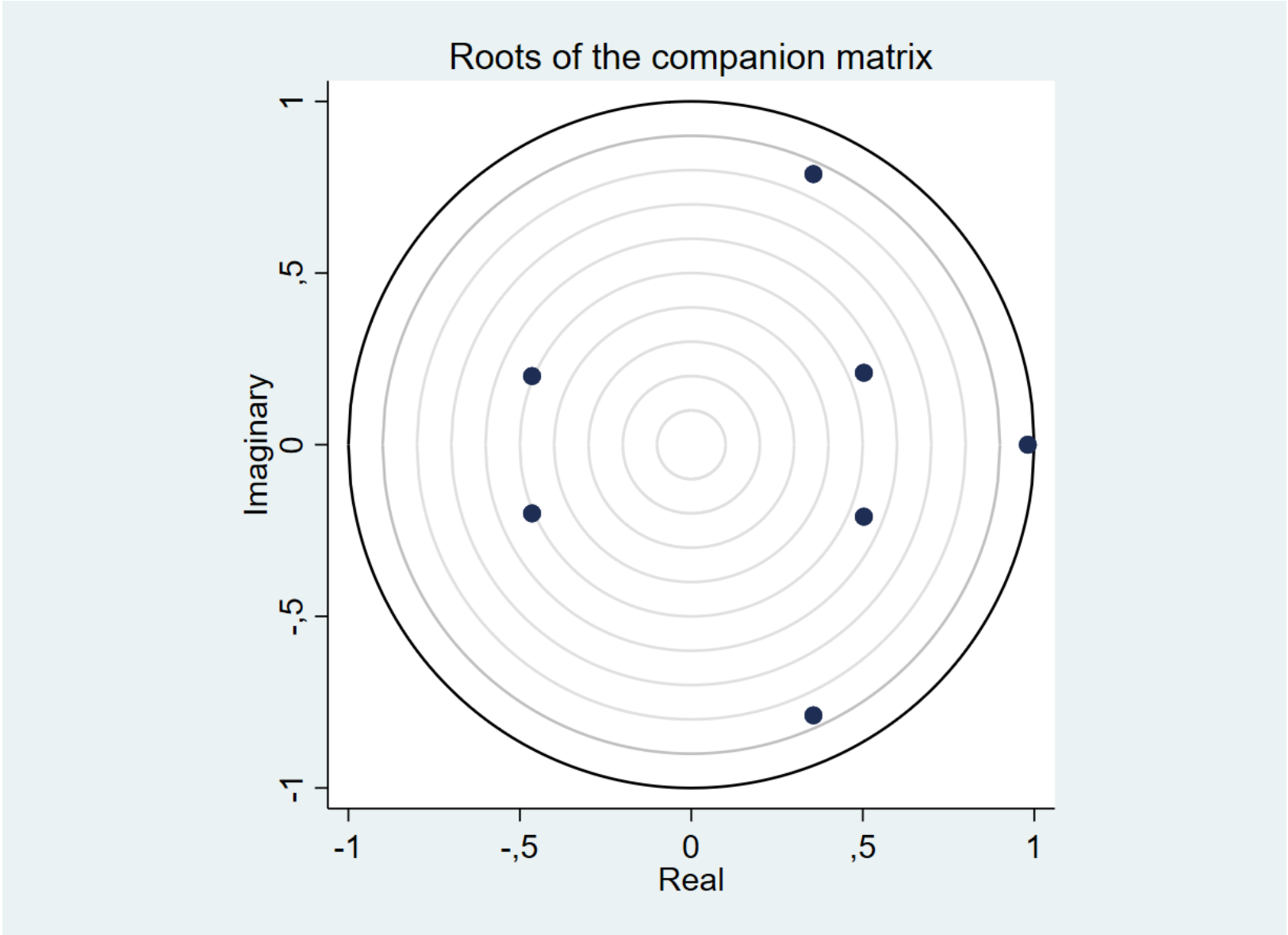


Fig. 3. Impulse response analysis - entire panel

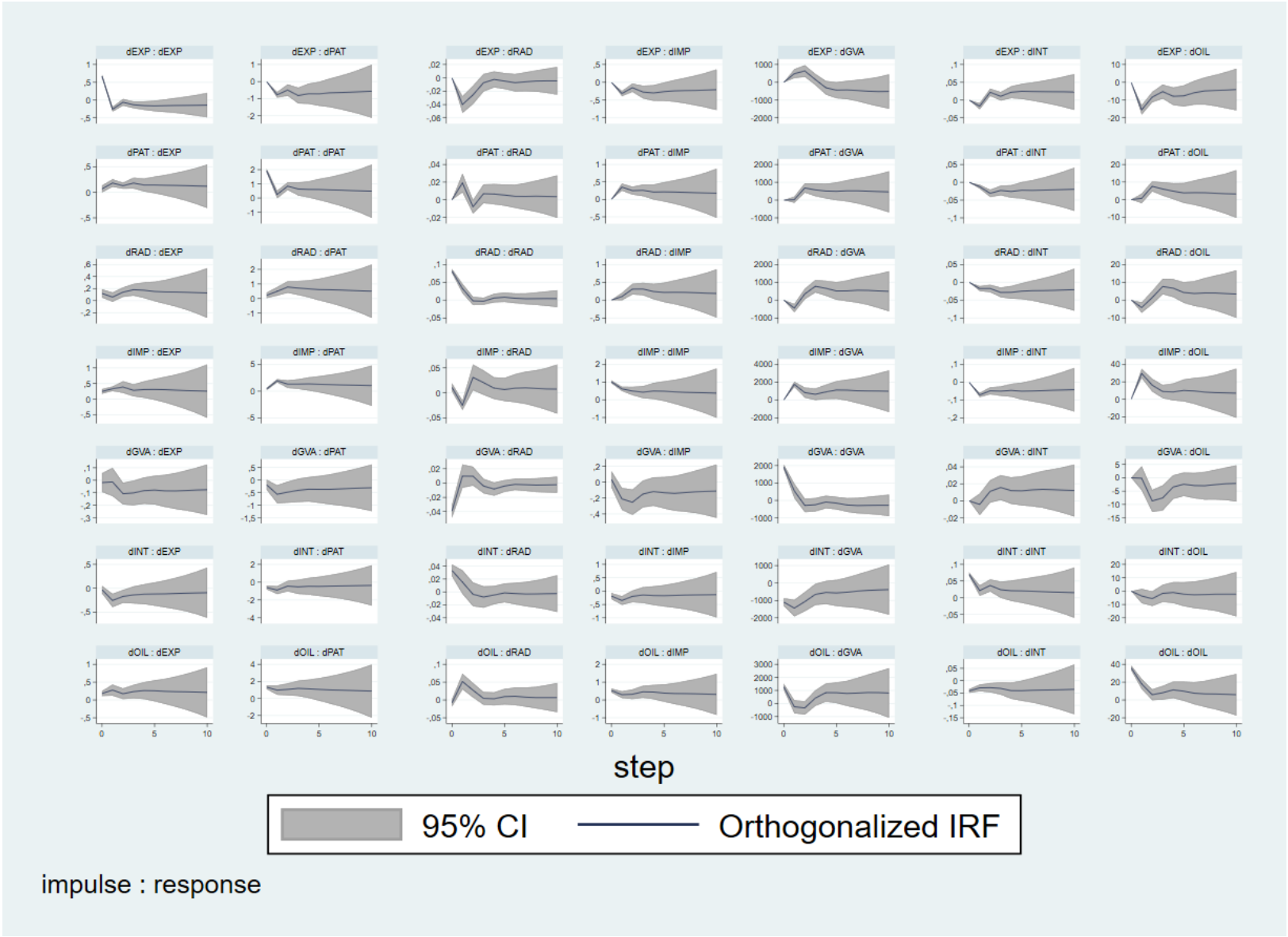
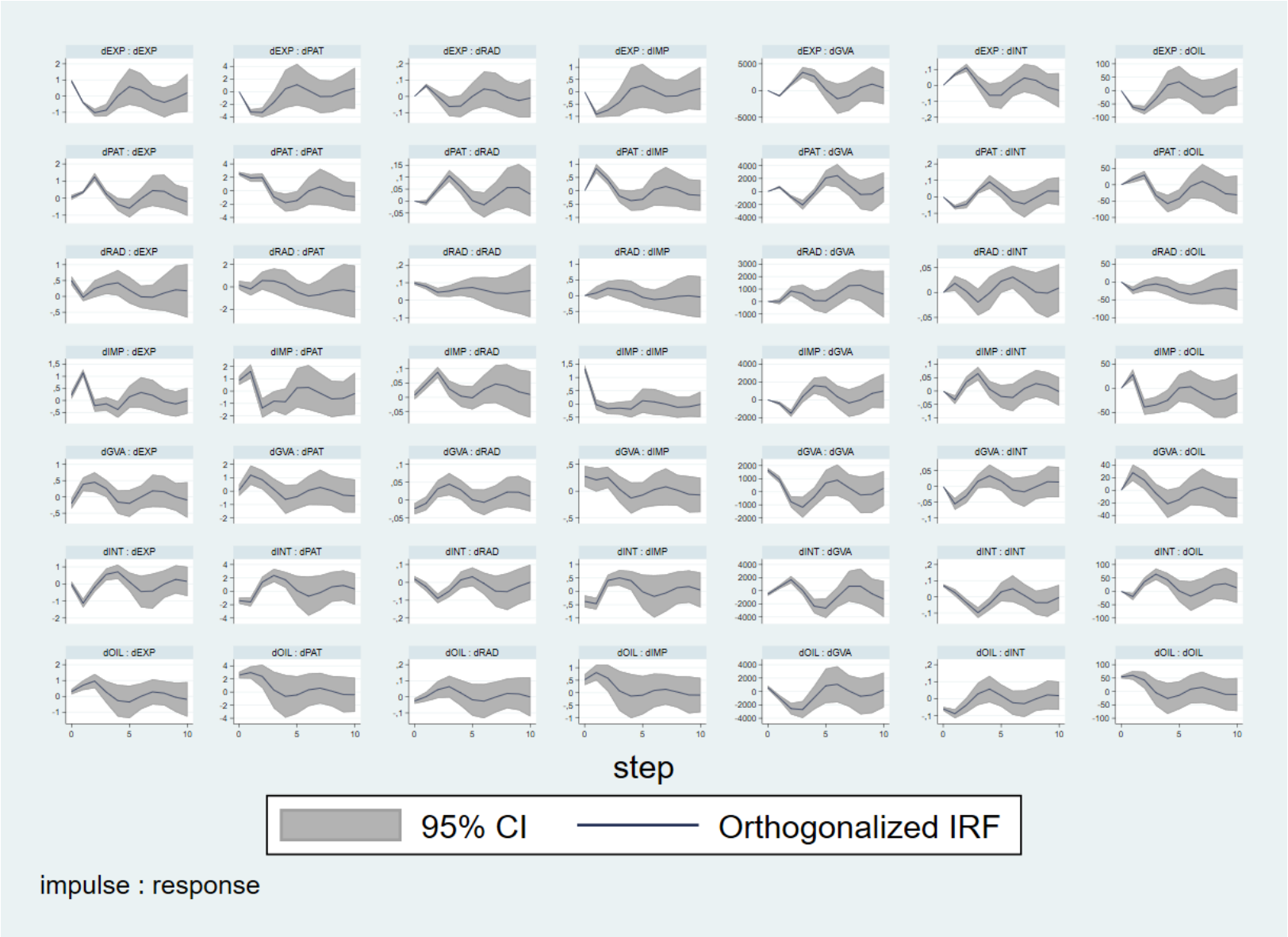


Fig. 4. Impulse response analysis - sub-panel - best performers in PAT



Supplementary Material Click here to access/download;Supplementary Material;title page_resub_nov_24.docx

Catalyzing Solar and Wind Technology Exports: The «Flywheel Effect» of Demand-Side Factors

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

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Abstract

The paper aims to emphasize the importance of demand-side factors in strengthening countries' efforts to address the climate challenge through the export of solar and wind technologies. While the existing literature has predominantly focused on the supply side, we argue that the demand side has a direct effect and exerts an indirect influence (via the supply side) on the export of these technologies and their widespread adoption. This has implications for the current policy debate. To test our hypotheses, we use a Panel Vector Autoregressive model in first differences for a panel of 20 industrialized countries over a twenty-five-year period. The results reveal mixed support to the hypothesis that demand exerts a positive effect on the export of solar and wind technologies. While the evidence on the role energy intensity is robust across specifications, we observe that other measures of demand - such as the level economic activity and oil prices - positively impacts solar and wind technology exports primarily in the most advanced countries. Additionally, the findings broadly support the hypothesis that all demand factors indirectly influence the export of these technologies by bolstering supply-side effects.

Keywords: renewable technologies; export; energy transition; energy intensity; structural change

JEL CODES: O14; Q28; L52

Author's Response to Editor's Comments

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Response to Editor

Ms. Ref. No.: JIBE-D-24-00060

We thank the Editor for the guidance and for the chance to publish on the Journal of Industrial and Business Economics.

Editor's comments

- I would invite you consider an alternative formulation for the "state" of the economy when you refer to GVA. I wonder whether something along the lines of "the level of economic acitivity" would better convey what you refer to and measure. This is just a suggestion, and please feel free to edit in the way that you feel it conveys the concept and measure. This is referred at several points in the paper, so when you change it, please try and be consistent. I have noted a reference to it in the abstract, at page 7, page 9 (economic situation), page 17, 18 and 19.

Thanks for this note. We have changes the word "state" of the economy and adopted "level of economic activity" throughout the paper

- I wonder if the abstract could be slightly modified to better reflect the results in your paper. My understanding is that your Hp2 gets mixed support, depending on the variable you use to measure demand. My suggestion would be to revise the second part of your abstract as follows: "The results reveal mixed support to the hypothesis that demand exterts a positive effect on the export of solar and wind technologies. While the evidence on the role energy intensity is robust across specifications, we observe that other measures of demand - such as the level economic activity levels and oil prices - positively impacts solar and wind technology exports primarily in the most advanced countries. Additionally, the findings broadly support the hypothesis that all demand factors indirectly influence the export of these technologies by bolstering supply-side effects."

Thanks for this indication. The abstract has been revised accordingly

- In Hp1 and Hp2, I think that "under similar/the same cirmustances" can be safely deleted

Deleted

- In Hp3, replace EXP with "export of SWTs"

Replaced

- on p. 11, when you mention 15 countries excluded becuase of incomplete data, please add a footnote with the list of these countries.

Included in a footnote