Sustainable Development, Renewable Energy Transformation and Employment Impact in the EU

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Abstract

A successful transition towards renewable energy systems in the European Union is expected to improve growth, reduce greenhouse gas emissions and create employment. Analysing recent data from 28 European Union (EU) countries, we investigate the potential interlinkages in employment, renewable energy and non-renewable energy amongst the EU countries. We further examine assess the contributions of renewable energy and non-renewable energy to the future variation in employment, output and carbon emissions within the EU. Our results suggest that renewable energy has a positive and significant net employment impact for EU. We further find that renewable energy consumption contributes substantially to the future variability in employment both for the short and the medium term. Also, carbon-dioxide emissions negatively impact the employment level in the EU.

1. Introduction

The Sustainable and Clean Energy goal (Sustainable Development Goal (SDG) 7) aims to increase the share of renewables to ensure affordable, reliable and sustainable sources of energy. The transition to renewable energy systems has the potential to affect the entire economy - from food and agriculture, ecosystems and climate, poverty and health, to employment and economic growth etc. The level of impact depends on the available sources of energy, their demand in the various sectors of the economy and the substitution possibilities between the various energy sources. A growing body of research literature is examining the interlinkages of SDG 7 with other SDG indicators (Bali Swain and Karimu, 2020; Hillebrand et al., 2006; Moreno and López, 2008; Neuwahl et al., 2008; Riekkola, Ahlgren and Söderholm, 2011; McCollum et al., 2018). However, only a few studies have examined the interlinkages between employment and renewable energy within the European Union (Manne and Wene, 1992; Neuwahl et al., 2008; Lehr, Lutz and Edler, 2012; Ortega et al., 2015; Mu et al., 2018). In this study our objective is twofold. First, to investigate the potential interlinkages in employment, renewable energy and non-renewable energy amongst the European Union (EU) countries. Second, to assess the potential contributions of renewable energy and non-renewable energy to the variability of future employment, output and carbon emissions in the EU.

Renewable energy is the key to the EU energy system transformation. The share of renewable sources in gross energy use in EU nearly doubled in 2018 as compared to 2005 (EEA, 2019a; EEA, 2019b). This has been possible due to the 2020 targets for renewable energy under the 2009 Renewable Energy Directive (EU, 2009) and the increased competitiveness, following fast technological progress and significant cost reductions (IRENA, 2019). The energy transformation towards renewable resources and technologies is expected to bring about relative improvements of 2.5 per cent in GDP and 0.2 per cent in the whole-economy employment, by 2050 (IRENA, 2019).

To investigate the potential interlinkages in employment, renewable and non-renewable energy and evaluate the impact of renewable energy on future employment variability within the EU, we employ a panel vector autoregressive (PVAR) regression model, which utilizes a system of equations to estimate

interlinkages between various variables and their lags. The analysis is based on the Eurostat database, which cover the EU-28 countries and Norway, during the period from 2000 to 2018. Additional variables are merged from the World Development Indicators (WDI). In this paper we focus on the average employment effect of renewable energy in the EU (plus Norway) and not the individual countries' employment effect. However, we control for the countries' specific effects in order to estimate a reliable average employment effect.

Our results suggest that, renewable energy has a positive but small and significant impact on average employment in EU. We explicitly estimate a net positive employment impact of transitioning from non-renewable energy sources to renewable sources for the EU. According to our estimates, the renewable energy consumption contributes 17.6 per cent (15.1 per cent) to the future variability in employment at 5-year (10-year) horizon. The potential effect of employment on non-renewable energy consumption is relatively lower. Moreover, future renewable energy consumption contributes significantly to variations in non-renewable energy, per capita carbon emissions and GDP per capita in both the short and the medium-term. The contribution of non-renewable energy to the future variability in renewable energy consumption was found to be low.

This paper contributes at several levels. First, acknowledging the interlinkages between the energy sector and various other sustainable development goals, we employ a system of equations via PVAR approach to estimate the impact of both renewable and non-renewable energy on employment, while accommodating the likely interlinkages between the energy sector, economy and the environment. Whilst some of the studies focus on energy nexus with a few SDGs, they seldom use it in assessing the contributions to the variability of future employment outcomes (Bali Swain and Karimu, 2020; McCollum et al., 2018). Some of the literature that considers the various sectors within the economy and their interlinkages, remain limited to a single country (for example, Bulavskaya and Reynes, 2018 on Netherlands; Pereira da Silva, Oliveira & Coelho, 2013 on Portugal; Haerer and Pratson, 2015; Garrett-Peltier, 2017 on USA).

Second, the PVAR approach adopted in this paper provides us with an alternative method to address endogeneity and capture the simultaneous interactive effects of the transition towards renewable energy through the economic mechanisms of price (cost) on the demand of industry and households. A few studies have investigated the employment impact of renewable energy in the EU (Moreno & López, 2008; Lehr et al., 2012) and some that explicitly estimate the net energy employment effect in EU (OECD, 2018; IRENA, 2020, 2019 etc.). However, we go beyond estimating impact of renewable employment to analyze how the unexpected changes in renewable energy may impact the employment in the short and mid-term, while accommodating the potential substitution possibilities of the employment effect of the two energy sources (renewable and non-renewable). According to IRENA (2020), the current global employment in renewable energy is estimated at 11.5 million in 2019, as compared to 11 million in 2018 (32 percent of these jobs are held by women; 38 percent are in China; and about 3.8 million jobs are in the photo-voltaic (PV) industry). Within the EU, 1.3 million renewable energy jobs are estimated in 2019 (EurObserv'ER, 2020). Germany, the United Kingdom, France, Italy, Spain, and Poland are the leading renewable energy

employers. The bioenergy sector is the largest EU renewables employer with 392 400 jobs estimated in the solid biomass (heat and electricity), followed by biofuels (239 000), and biogas (74 900). The International Renewable Energy Agency (IRENA) estimates EU wind power employment at about 292 300 jobs (Wind Europe, 2020) and the employment in the solar PV industry at 127 300 jobs, indicating a significant increase in the European markets (IRENA, 2020).

According to one estimate a transition to renewable energy is expected to lead to 24 million jobs by 2030 and create about 25 million jobs globally by 2050. This new job creation in renewables and energy efficiency is expected to be greater than the job losses in the traditional energy sector, thus leading to a positive net employment (IRENA, 2017b). Finally, we also analyse the impact of carbon-dioxide emissions (CO₂) on employment within the EU, especially employments that are directly dependent on ecosystem services.

The structure of the paper is as follows. The following sections present a brief overview of the existing literature and methods used to investigate the relationship between SDGs, energy sources and employment. Sections 3 and 4 describe the data and methods used in this paper. This is followed by the discussion of results in section 5. The final section presents the discussion and conclusions.

2. Energy Sector And Employment

2.1 Theory, mechanisms and components of renewable energy effect on employment

Recent literature has focused on the consequential effects of clean energy production on economic growth, employment generation, industrial innovation and infrastructural developments (Duscha *et al.*, 2014; Henriques, Coelho and Cassidy, 2016; Manne and Wene, 1992; Messner and Schrattenholzer, 2000; Meyer and Sommer, 2014). Most studies are concerned with the different sources of renewable energy and their contributions in reducing the GHG (greenhouse gas) emissions (Ryan, Convery and Ferreira, 2006) or increasing economic growth and employment generation (Hillebrand *et al.*, 2006; Moreno and López, 2008; Neuwahl *et al.*, 2008; Lambert and Pereira da Silva, 2012; McCollum *et al.*, 2018).

The underlying theoretical explanation of the impact of renewable energy transition on employment is through the economic mechanisms of price and cost effects or the impact of energy prices (costs) on the industry and the households. It is also explained in terms of the structural demand effects or the impact of demand on the industry, the households and trade. Furthermore, the multiplier and accelerator effects of the households and industry behaviour on other economic sectors; and the impact of innovation or productivity on industry and households are other causal factors that lead to changes in employment with transition in the renewable energy sector (OECD, 2018; Walz and Schleich, 2008; Walz, Ragwitz and Schleich, 2008).

The export orientation, technological competitiveness, regulation and market context factors such as demand, prices, market structure etc., leads to quality competition that determines foreign trade successes and creates lead markets or first movers advantage.^[1] The supporting policies for renewable

energy and the resulting first mover advantage, impacts the households, firms and trade as they react to the price, quality and quantity changes. This response is amplified further by the multiplier, accelerator and innovation effects. It leads to an impact on the demand and the prices in the economic sub-sectors such as investment, operation and maintenance and consumption across all sectors in the economy. For a detailed theoretical discussion and conceptual framework, refer to Ragwitz et al. (2009).

The resulting net employment impact of renewable energy policy is disaggregated in the literature into these three components – direct, indirect (substitution and income effect) and trade effect. The direct (gross) effect measures a change in job creation in renewable sectors. However, this does not take into account the substitution and income effects that may be negative for job creation in the non-renewable energy sector. For example, budget re-allocation to renewable sector and increasing extraction cost of exhaustible resources (e.g. crude oil) from a deep well may increase the price of non-renewable energy and may lead to a reduction in the employment opportunities. This type of substitution effect is primarily driven by the re-allocation of investment budget and the changes in energy prices. In the literature (e.g. Lehr et al. 2012; Ortega et al. 2015), this is termed as the indirect effect. The direct effect provides only a positive side of investment in renewables, but the size of indirect effect is a key determinant for estimating the net employment effect. For example, Lehr et al. (2011) suggest that the number of indirect jobs is usually larger than the direct jobs for all renewable energy technologies.

The scope for exports and imports of renewable and non-renewable energy may also influence the size of the net employment effect. The size of trade effect may vary with the gravity of origin and destination countries. For instance, a sharp reduction in consumption of fossil fuels may reduce the employment opportunities in the Organization of the Petroleum Exporting Countries (OPEC) countries, whereas the investment in renewables (e.g. solar or wind energy) may create more jobs in the domestic market.

2.2 Methods for estimating employment impact of renewable energy

An additional challenge in collecting data on green jobs is on how to define and measure them. UNEP et al. (2008) suggest finding universally applicable measures of green employment such as: employment in new technologies, business practices or shifts in employment where it is hard to identify differences between efficiency improvement from regular employment; employment in environment-related technologies or 'green tech'; and employment in newly emerging sectors of the economy such as renewable energy production etc.

The literature on the methodologies estimating the employment generation in the renewable energy literature can be broadly classified into three broad approaches: employment factor approach; supply chain analysis or input-output (I-O) method; and computable general equilibrium (CGE) models. The employment factor approach is the easiest and quickest approach to estimate direct effects, multiplying certain renewable energy capacity by employment factors. The employment factor denotes the number of jobs (in full-time equivalents) created per physical unit (for example, megawatts energy produced or megawatt-hours for electricity generation etc.) (IRENA, 2013). Different employment factors are applied

for different phases of the life cycle. Furthermore, the employment factors also depend on the technology generation, labor productivity and regional characteristics.

Supply chain analysis, or the input-output method are more suited to a project-specific analysis than a macro-economic modeling and employment assessment. Supply chain analysis is a microeconomic approach based on business surveys to map the specific supply hierarchy and relationships among companies of a specific renewable technology. The stages of production and services are identified and based on the data on capacity, project costs, labour and other inputs, turnover and production values at each tier of the supply chain – the labour inputs are related to the output capacity (IRENA, 2013; Llera et al., 2013)

Several studies use a fixed coefficient input-output framework to explore the impact of renewable energy policies on employment and the labour market (Hillebrand et al., 2006; Lehr et al., 2008; Ragwitz et al., 2009). Based in economic theory, the input-output analysis provides in-depth information on the flows of intermediary goods and services among all sectors of the economy and the rest of the world. Thus, the total production of an industry is the sum of all its inputs to the other industries plus final demand and the exports minus imports (IRENA, 2013; Breitschopf et al., 2011). For example, analysing the German renewable support policy, Hillebrand et al. (2006) conclude that the policy is likely to result in positive level of net employment in the short term but a negative level impact in the medium to long-term. Lehr et al. (2008) find a net positive effect of the German renewable support policy, with a lower long-run rate of unemployment. Investigating this for the EU renewable support policies, Ragwitz et al. (2009) confirm a similar net positive impact on employment.

The employment factor approach and the input-output modeling do not capture the economy-wide employment effects in terms of net employment. To estimate these net employment impact, comprehensive economic models (for example CGE or macro-econometric models) are estimated, taking the economy-wide price, income and substitution effects into account. As Breitschopf et al. (2011) argue, these affect the households' consumption and production of intermediate products and services, in addition to impacting the competitiveness of the entire industries due to changed energy prices. CGE models are thus analytical approaches for assessing direct, indirect and induced employment effects (Meyer and Sommer, 2014). For instance, assessing a CGE model in Canada, Böhringer et al. (2012) suggest that the tariff policy is likely to result in a decrease in employment and a rise in unemployment. Implementing a multi-sector, multi-region, recursive dynamic computable general equilibrium model, Kuster et al. (2007) conclude that the impact of renewable energy investment subsidies in EU increase unemployment rates in each of the EU countries.

A body of theoretical literature employs stylized general equilibrium models to investigate the relation between environmental taxation and employment (Bovenberg and de Mooij, 1994; Schneider, 1997; Scholz, 1998; Bovenberg and van der Ploeg, 1996; 1998a; 1998b; Bovenberg, 1995). Employing a three-sector general equilibrium model, Rivers (2013) investigates the impact of renewable electricity support policies on the rate of equilibrium unemployment. Parameterizing the model to represent the US economy,

Rivers concludes that reducing the electricity sector emissions by 10 % by switching to renewable electricity support policies would increase the equilibrium unemployment rate by 0.1 - 0.3 percent.

Previous studies have utilized both a bottom-up (BU) and top-down (TD) models in an interactive fashion to estimate the economic impacts of sustainable energy policy (Böhringer, 1998; Messner and Schrattenholzer, 2000; Chen, 2005; Böhringer and Rutherford, 2008; Neuwahl *et al.*, 2008). The BU models such as MARKAL, APOLLO, MESSAGE[2] etc. provide a technology-detailed description of the energy system, while the TD models, such as MACRO or CGE models describe the broader macroeconomic activities of the country. A synthesis of these BU and TD models allow for interactions between the energy system and the rest of the economy, and are referred to as a soft or hard linked model, depending on the nature of the linkage (Manne and Wene, 1992; Wene, 1996; Böhringer, 1998; Riekkola *et al.*, 2013).

In general, the hybridization of these BU and TD models is considered as a hard-link (Böhringer and Rutherford, 2008), which can ensure the simultaneous equilibrium between the BU energy system models and the TD macroeconomic growth models. The soft-link approach defines a functional form to transmit the estimation outcomes from one to the other model (see Riekkola *et al.* 2013 for details). In the soft-link approach, every single model is treated as an individual entity and allows for explaining the technical details. In doing so, the BU model have a wider space to represent the technical details of energy system, and the TD model can describe macroeconomic activities with a wider scope. In the literature, the hard-link approach has been used extensively in energy policy analysis (Böhringer, 1998; Messner and Schrattenholzer, 2000). With the hard-link it is easier to produce the impact output, as it is embedded in the model system and computes the impact directly. The soft-link approach is more tractable and has been used by the researchers to analyze the impulse response of energy policy on the job market.

2.3 Renewable energy transition and the employment impact

The employment impact of renewable energy sources has largely been found to have a net positive effect (Kabel and Bassim, 2019; Meyer and Sommer, 2014). In a meta-analysis of 23 peer-reviewed impact studies, Meyer and Sommer (2014) analyse the employment impact of renewable technologies and model based scenario assessments from specific renewable policies. They find an overall positive net employment effect, although the results crucially depend on the financing of the renewable energy source support scheme and the global competitiveness of a specific technology.

Several studies also find a positive net employment effect because of new investments in the supply-chains of renewable energy system. Moreno & López (2008) report a large effect on job creation in the construction and installation phase of renewable energy sources, which can possibly drop in the later phase. Lehr *et al.* (2012) find positive effects on labour market with an increased amount of investment in the renewable energy sector. However, the technology effect may lower the employment opportunities. IRENA (2017a) reports that the technological revolution can increase automation in operation and maintenance, e.g. of solar photovoltaics and wind plants, which can lower investment and job creations. IRENA (2017b) finds that low oil prices and oversupply resulted in a loss of about 440 000 jobs in the oil and gas sector.

Analysing an input-output model for US between 2008-2012, Haerer and Pratson (2015) find that renewable energy sources (natural gas, solar and wind industries) create greater employment than the fossil-fuel industry. In fact, Garrett-Peltier (2017) argue that energy efficiency and renewable energy industries in the US created three times as many jobs as the fossil-fuel industry, at the same level of spending. In the US the solar industry alone employs more than the coal industry in Electric Power generation (DOE, 2017).

Overall in the EU, the renewable energy employment has increased, with Germany, UK, France, Spain in the lead (IRENA, 2020). However, other countries are also making successful gains in employment with the transition towards renewable energy. For Netherlands, Bulavskaya and Reynes (2018) find that transition to renewable energy will create about 50 000 new jobs by 2030 and add about 1 percent to the GDP due to higher labour and capital intensity of renewable energy technology, as compared to gas and coal plants. Pereira da Silva, Oliveira & Coelho (2013) also finds significant employment benefit of renewable energy deployment in Portugal. In Ukraine, solar PV deployment capacity tripled in 2019 and created 24 800 jobs (one-third of which are in the labour-intensive rooftop solar segment) (IRENA, 2020).

[1] Lead markets are regional markets with specific attributes that increase the probability that a locally preferred design becomes internationally successful (Beise and Cleff, 2004).

[2] Apollo model, developed by the Sweco Energy Market, is used for simulation of electricity market, as it describes a detail representation of neighboring areas and variable costs of electricity generation (Shafiee, 2014). MESSAGE is a dynamic systems engineering optimization model developed by the International Institute for Applied System Analysis (IIASA) for medium to long-term energy planning and policy analysis (see Messner and Schrattenholzer 2000 for details).

3. Methodology

The focus of this study is to examine the impact of renewable and non renewable energy on employment, taking into account the interlinkages between energy, economy and the environment. Furthermore, we quantify potential contributions of renewable energy and non-renewable energy to the future variation in employment, output and carbon emissions within the EU. To address the various interlinkages between the energy sector, economy and the environment, we use a system of equations modelling approach that underpins the PVAR econometric model. An additional reason for the choice of PVAR is the fact that by design it makes it easy to quantify the potential changes in renewable and non-renewable energy on future changes in employment, output (GDP) and carbon emissions.

The PVAR model for this study is presented compactly as

$$y_{it} = \sum_{t=1}^n \pi_i' y_{it-1} + \mu_{it}$$

where y_{it} is $z \times 1$ vector of z variables for country i in time t , y_{it-1} is a vector of lag variables of the vector y_{it} , Π_i is a $z \times z$ vector of parameters to be estimated, and μ_{it} is a composite term that is made up of time fixed effects (v_t) to account for time variant unobserved factors such as economy policy, unobserved individual effects (γ_i) to capture unobserved country heterogeneity, and a random error term (ϵ_{it}). The variables composed in y_{it} are the logarithmic values of renewable energy, non-renewable energy sources, employment rates, per capita GDP and greenhouse gas emissions. The logarithmic transformation of the employment is used, having the benefit of reducing the effects of outliers.

All the equations stacked in equation (1) are estimated jointly as a system, which makes it possible to trace the feedback effect from each variable on to the other. Thus, we can assess the potential trade-offs or complementarity, for instance, of renewable energy directly on each of the other variables in the model and vice-versa.

Given the lag dependent structure in equation (1), a fixed effect model will suffer from nickel bias if the time dimension is less than 30 years (Bali Swain and Karimu, 2020). The standard procedure to address such a bias is to use instrumental variable (IV) approach if there are valid external instruments or use the generalized method of moment procedure (GMM) when there are no valid external instruments (Arellano and Bover, 1995). In the GMM approach lagged internal variables are used as instruments. We opted for the GMM instrumentation approach due to lack of valid external instruments and applied it to the PVAR model.

The empirical strategy follows two steps. In the first step, the PVAR model is estimated. This step provides estimates for each of the variables in the model for each of the equations that constitute the system. Such a system approach makes it possible to assess the interlinkages and causal impacts of the variables in the model. In the second step, the estimated model results are utilised to quantify the changes in both renewable and non-renewable energy and how these changes contribute to the variation of each of the other variables in the model, particularly employment, output and carbon emissions for a short term (5 years ahead) and medium term (10 years ahead).

It should be noted that our methods have a few limitations. Due to the differences in energy resource endowment across EU countries, trade in these resources is an important issue to consider. Our main result does not explicitly include trade in the analysis but the likely bias that would be created by not explicitly including trade is reduced by the inclusion of the time fixed effects in the model. The time fixed effects capture the trade effect in addition to other factors such as economic policy, which are not explicitly included in the model. Moreover, the development of renewable energy in different countries within the EU is different. A heterogeneous study may have been considered rather than estimating the average effects within the EU, but the available data that we have access to, has a short time dimension and therefore makes it unreasonable to use heterogeneous panel estimators or individual country time series analysis. It is important to note that we included country fixed effects to account for country heterogeneity and therefore limits the likely bias due to country differences.

4. Data

The analysis is based on the Eurostat database for EU-28 countries plus Norway for the period 2000 to 2018. Renewable and non-renewable energy sources are final consumption measured in 1000 tonnes of oil equivalents (TOE). Employment measures the total employment rate. Greenhouse gas emissions (GHG) are CO₂ equivalents measured in tonnes per capita and gross domestic product (GDP) is also measured in per capita terms.

Consumption data is used instead of generation data due to the fact that consumption or demand is the main signal for producing any good or service. In the case of energy production, demand profile determine production profile to a large extent plus renewable energy services. This suggest that relying on production data instead, we will likely lose the potential services aspect of renewable energy technologies (RET) on employment as it only captures the production aspect. In such a case we will not be able to account for RET impact on employment from the services related employment. This is consistent with previous studies such as Apergis and Payne (2014), who used consumption data.

Figure 1 outlines the distribution of the key variables in our study (renewable and non-renewable energy, employment rate and carbon emission). The figure shows significant variability within countries depicted by the size of the boxes (inter-quartile range) and across countries depicted by variation in the median value of the variables of interest (this is depicted by the white inline in the boxes). The top five countries in renewable energy consumption (in volume) over the period under study are Germany, France, Italy, Sweden and Finland, whereas countries such as Malta, Luxemburg and Cyprus have the least renewable energy consumption. Note that these rankings are in absolute values, so naturally the countries with larger economies also have more energy consumption, both from renewable and non-renewable sources. In per-capita terms, the rankings would be somewhat different.

In the case of non-renewable energy, the five top consuming countries in the period are Germany, France, United Kingdom, Italy and Spain. Furthermore, the figure also reveals significant variability both within and between countries. Similarly, we see significant variation between and within countries in the case of employment variable. It appears, however, that the variation is more apparent between countries as the median value of employment between countries range from 63% in Italy (the lowest) to 78% in Sweden (the highest). The variations within and between countries is used in the empirical estimation process in order to answer the key research questions of our study.

5. Results

Before proceeding with the results of the model, we need to verify the model fit and stability. This is required in order to meaningfully interpret the results of the model and asses the causal relationships. We use Hansen's J-test to verify the model fit, and assess the stability of the model by inspecting the modulus of each eigenvalue of the estimated PVAR model.

Hansen's J-test tests whether the model specification is overidentified with the length of lags used for the instruments and can be classified as a model specification test. The model fit is accepted if there is no overidentification. The test statistic is reported in Table 1 and shows that there is no overidentification, justifying the model fit.

The model stability is determined by the modulus of each eigenvalue of the estimated PVAR model. The model is stable only if each modulus is strictly less than 1 (Hamilton, 1994; Lutkepohl, 2005). Results for the stability test are presented in the Appendix (Table A1). All moduli are strictly less than one. The model therefore satisfies both the Hansen's J-test for model fit and the stability test.

Furthermore, in choosing the appropriate lags to use in the PVAR model, Andrew and Lu (2001) Model Moment Selection Criteria (MMSC) was adopted, where the appropriate lag length is based on the minimum value for each of the following lag selection criteria MBIC, MAIC, and MQIC, which are the MMSC versions of the standard BIC, AIC and QIC. The results based on this procedure is reported in the Appendix (Table A2) and all three criteria indicate that the lag length of 1 is appropriate, therefore a lag length of 1 is used for the PVAR model estimation.

Additionally, we check the time series properties of the data, though the time period is short and some of the tests (unit root test) may not be appropriate due to low power in such an instance. In the interest of completeness, we went ahead to perform unit root test on the data. Using the Pesaran's (2007) unit root test, the result suggest all the variables are stationary except GDP and CO₂, which become stationary after first difference. These results are reported in Appendix Table A3. Given the mixed integration, we tested for cointegration based on Pedroni's (1999) panel cointegration approach. The results from the test reported in Appendix Table A4 also suggest that the null hypothesis of no cointegration relationship is rejected at the 5 per cent significance level, implying evidence of long-run relationship among the variables.

5.1 PVAR results

Results from the PVAR are presented in Table 1. The estimated coefficients show that all variables have statistically significant impacts on employment rates at least at the 5% level except in the case of per capita carbon emissions, which is only significant at the 10% level. While the elasticity value of the effect of renewable energy sources on employment is 0.036, that of non-renewable energy sources show a negative effect (-0.031).

Combining the two estimates (0.036 and -0.031), the total net energy impact on employment is positive (0.005) but the magnitude is small. The total net energy impact on employment may be explained in terms of the employment substitution effect from non-renewables via one or both of the mechanism presented in the next paragraph. Relocation of the employment segment of the renewable energy value chain in cost advantage countries such as China can be another possible factor.

There are two potential mechanisms through which energy impacts employment and which explain the above findings. These are the investment impulse mechanism and the price induced mechanism. An increase in investment that favours RET instead of conventional energy technologies (CET) and services, would trigger production in the renewable energy industry and create positive employment outcomes for green jobs. As resources are limited, increased investment in the renewable energy industry will result in a displacement of investment in conventional energy technologies, services and ultimately reduce production in that sector. This will have a negative effect on employment. Furthermore, trade would enhance the employment effect of investing in RET through creating market and increasing demand for renewable energy products and services across the globe (Duscha et al., 2014).

The second mechanism works through prices and how the economy reacts to price changes induced by taxes, levies or direct price changes. Unlike the stimulating effect of the increase in investment, price increases on the contrary have a damping effect on economic activity as it reduces households' budget and hence consumption expenditure. The reduced households' demand will inadvertently reduce production and incomes in the affected industries, which has a multiplier effect and ultimately impact job creation. This suggests that if RET is favoured in terms of lower taxes and levies, it will increase their profit margins and generate more green jobs via the multiplier effect. Conversely, an increase in taxes on CET due to environmental and other concerns would likely affect their profit margins and consequently reduce job creation via the multiplier effect.

The positive net effect of total energy on employment is found to be consistent with previous studies such as Moreno & López (2008) and Lehr et al. (2012). Moreover, these results provide partial evidence in support of a substitution effect between renewable and non-renewable energy impact on employment.

Consistent with our intuition, the results reveal a positive GDP per capita effect on employment. On the other hand, the effect of per capita carbon emissions is negative, but only significant at the 10% significance level. The negative impact of carbon emission is consistent with the finding from ILO (2018), which indicated a net negative effect of CO₂ and broadly climate change on employment. This is driven by the influence of CO₂ on climate change impact on loss of ecosystem services and jobs that rely on such natural processes such as farming; fishing; forestry; food, drink and tobacco; wood and paper; renewable energy; water; textile; chemical and environment-related tourism. A study by Montt et al. (2018) provide further support on the impact of rising levels of CO₂ and climate change on employment. Their study revealed that 16 percent of the total employment in Europe depend directly on ecosystem services, suggesting a significant loss of ecosystem services could potentially result in job losses to a maximum of 16 percent in Europe.

Renewable energy sources are positively impacted by the consumption of renewable energy sources (6.202), and negatively impacted by GDP (-1.934) and carbon emissions (-1.066). The non-renewable energy sources have no significant impact on renewable energy. The reverse causality, how renewable energy affects non-renewable energy, is also positive and non-significant, as shown by the third equation (Non-RES equation).

The consumption of both renewable and non-renewable energy sources is negatively affected by increases in GDP per capita, with elasticity values of -1.934 and -1.876 respectively. This may be explained by the decoupling of GDP from energy in general, driven in part by energy efficiency achievements within the EU. Such a decoupling was also found for Swedish industrial sectors regarding carbon emissions and output for Swedish energy intensive industries by Brännlund et al. (2015).

Table 1
PVAR results

Equation:	Independent var: Employment lag	RES lag	Non-RES lag	GDP lag	GHG emissions lag
Employment	0.498 ^{***} (0.168)	0.036 ^{***} (0.008)	-0.031 ^{**} (0.015)	0.076 ^{***} (0.028)	-0.037 [*] (0.022)
RES	6.202 ^{**} (2.790)	0.490 ^{***} (0.158)	0.181 (0.293)	-1.934 ^{***} (0.564)	-1.066 ^{***} (0.391)
Non-RES	4.214 ^{**} (2.124)	-0.118 (0.114)	0.607 ^{**} (0.257)	-1.876 ^{***} (0.482)	-0.093 (0.311)
GDP	0.033 (0.159)	0.026 ^{***} (0.008)	0.002 (0.014)	0.986 ^{***} (0.025)	-0.058 ^{**} (0.023)
GHG Emission	0.421 (0.324)	-0.001 (0.017)	0.062 ^{**} (0.029)	-0.036 (0.061)	0.916 ^{***} (0.044)
N	489				
Hansen's J	69.549 (p=0.654)				
<p><i>Note: Lags up to a maximum of 5 lags of each of the variables in the model was used as valid instruments in the estimation to resolve potential endogeneity problems based on GMM style of instrumentation. RES denote renewable energy sources and GDP is in per capita terms. Robust standard errors are used to correct for potential heterogeneity. T-statistics are in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$</i></p>					

Furthermore, from the GDP equation, the results indicate that the consumption of renewable energy and previous level of GDP per capita are positive significant causal factors of GDP per capita, whereas carbon emission is a negative significant causal factor. The consumption of non-renewable energy, on the other hand, has a non-significant estimate.

The last equation (carbon emission equation) suggest that greenhouse gas emissions are significantly impacted by non-renewable energy, with an elasticity value of 0.062. The coefficient for renewable energy is negative (-0.001), and significant at the 10% level.

5.2 Forecast Error Variance Decomposition (FEVD)

Forecast Error Variance Decomposition (FEVD) is shown in Figure 2. The focus is to assess the response of each of the variables to the future variability in renewable (Figure 2B) and non-renewable energy consumption (Figure 2A) in the region. The results in Figure 2B indicate that 17.6 and 15.1% of the future variation in employment is explained by renewable energy resources at five year and ten year horizons, respectively. In contrast, non-renewable energy consumption for the five year and ten year horizon explain about 9.8% and 14.3% of the future variations in employment.

Short term and medium term renewable energy consumption contribute significantly to both the future variation in non-renewable energy and per capita carbon emissions (figure 2B). Whereas the short- term response (53.9%) is slightly larger relative to the medium-term (52.8%) in the case of non-renewable energy, the reverse is true in the case of per capita carbon emissions (37% in the short-term against 41.7% for the medium-term). Renewable energy also contributed significantly to the future GDP per capita variability, about 37.6% in the short-term and 30.7% in the medium-term. The future variability in renewable energy is self-contributed by renewable energy (75.2% in the short run and 66% in the medium horizon).

Figure 2A presents the future variability of the other variables in the model in response to non-renewable energy shock. 9.8% (14.3%) of the future variability in employment is in response to non-renewable energy shock in the short (medium) horizon. Non-renewable energy has a low impact on the future variation of GDP per capita and per capita carbon emissions in the short and medium term. Only 0.4% of the future GDP per capita variations in the short-term and 7.1% in the medium-term is explained by non-renewable energy shock. Whereas in the case of per capita carbon emission, 6.1% in the short-term and 4.1% in the medium-term of the future variability is explained by non-renewable energy. Interestingly, non-renewable energy's contribution to the future variability in renewable energy consumption is low, about 2.3% in the short-term and 4.9% in the medium-term.

6. Conclusion

Renewable energy is the key component of the EU energy system transformation with a thrust from the EU Directive 2009 and the energy union strategy of the EU (European Commission, 2015) advocating a move towards using more renewable energy - and supporting research, innovation and competitiveness. The 2030 framework for climate and energy sets the target for achieving a 32 percent share of renewable energy consumption. It is widely accepted that this transformation will have several socio-economic impacts, especially an impact on GDP, greenhouse gas emissions and employment.

Analyzing country level Eurostat data and data from the World Bank's World Development Indicators (WDI) for the period 2000–2018, we estimate the average impact of renewable energy on employment for the European Union (EU) countries. We also analyse the impact of carbon emission on employment in the EU. Furthermore, we examine the contributions of renewable energy and non-renewable energy to the future variation in employment, output and carbon emissions within the EU.

Several interesting results emerge. We find that renewable energy has a positive and significant employment impact for the EU and renewable energy consumption contributes substantially to the future variability in employment both for the short and medium term. We also find that the average total net effect of carbon emission on employment is negative.

Our findings support and extend the earlier research on employment impact of renewable energy (Moreno & López, 2008; Lehr et al., 2012). We further contribute by explicitly estimating the value of the net effect of energy on employment. Furthermore, renewable energy consumption contributes substantially to the future variability in employment, both for the short and medium term. Our results suggest that the transition towards renewable resources and technologies will have a positive employment impact. This employment impact within EU can be further amplified by designing policies that continue to support this transformation and policies that attempt to relocate renewable resource value chain within the European Union.

Declarations

Competing interests: The authors declare no competing interests.

JEL Classification: C61, J23, Q12, Q41

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Appendix

Table A1. Stability test for EU PVAR model

Eigenvalue		
Real	Imaginary	Modulus
0.986	0.156	0.998
0.986	-0.156	0.998
0.779	0.000	0.779
0.571	0.000	0.571
0.255	0.000	0.255

Table A2. Optimal lag selection for EU sample model

lag	CD	J-statistic	J p-value	MBIC	MAIC	MQIC
1	0.999	84.173	0.219	-370.785	-65.827	-186.234
2	0.999	40.597	0.826	-262.708	-59.403	-139.675
3	0.999	13.207	0.974	-138.445	-36.793	-76.928

Table A3. Pesaran (2007) CIPS Unit root Test

Variable	Lag	Test statistic	P-value
Employment	1	-1.580	0.057
RES	1	-4.945	0.000
Non-RES	1	-12.226	0.000
GDP	1	-1.198	0.115
DGDP (first difference)	1	-1.795	0.036
GHG Emission	1	0.070	0.528
D GHG Emission (first difference)	1	-9.298	0.000

Note: The CIPS test accommodate both heterogeneity and cross-sectional dependency in the testing procedure. D denote change which refers to first difference in the time series terminology. The test results reported are without trend the test equation.

Table A4. Panel Cointegration Test

Test	Stats.	Panel	Group
V	-2.811		.
Rho	2.277	4.36	
T	-7.085	-9	
Ad	6.769	8.05	

All test statistics are distributed $N(0, 1)$, under a null of no cointegration, and diverge to negative infinity. It means any of the test value above 2 in absolute terms imply rejection of the null hypothesis.

Figures

Figure 1

Distribution of key variables: Renewable energy sources, non-renewable energy sources, total employment rate and GHG emissions.

Figure 2

Forecast Error Variance Decomposition (FEVD), shown as 5 and 10 year ahead responses to one standard deviation shock to non-renewables (left panel) and renewables (right panel). The measurements show how much shocks in renewables and non-renewables contribute to the future variability of the variables.