The long-term effect of renewable electricity on UK employment

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Abstract

Assessment of the employment impact of renewable electricity technologies is generally implemented through either complex and data-intensive methods (such as Computable General Equilibrium models) or simplistic approaches, normally focused on specific technologies, such as employment factors. This article proposes a methodology based on a transparent and easily reproducible econometric analysis using aggregated and widely available data. We apply our approach to the UK, using data from 1990 onwards and provide evidence that the long-term employment impact of renewable technologies is much higher than the impact arising from deploying nuclear or natural gas technologies. We derive the implications of our findings in the context of decarbonisation scenarios for the UK power sector and assess the extent to which decarbonisation pathways based on renewable rather than nuclear technologies contribute to stimulating employment in the generation sector.

Keywords: employment effect, electricity supply, renewable electricity, cointegration, impulse response

JEL: *Q43, J23, L94, C32, C51, C53*

1. Introduction

Renewable energy sources and related technologies are a key component in the mitigation of climate change (IPCC, 2011). In fact, the deployment of renewable energy technologies is sometimes considered a win-win scenario for both the environment and economic welfare, as they reduce carbon emissions and create new work opportunities in various sectors of the economy through direct and indirect employment effects. IRENA (2011) indicates that renewable energy can create a “considerable future potential” for net job creation, a suggestion generally backed up by most studies in the literature (Meyer and Sommer, 2014).

Since 2012, the deployment of renewable energy technologies has substantially increased so that worldwide 10.3 million people are employed in the renewable energy sector in 2017 (IRENA 2018). The rapidly increasing maturity of renewable technologies along with the rising numbers of created jobs make it crucial that we investigate the employment effect of renewable electricity. Although there are several studies that investigates the employment effect of renewable energy, as reviewed below, these studies tend to focus on specific technologies, location and plants and to discard the employment effect of fossil and nuclear generation technologies (Cameron and Zwaan 2015).

The aim of this study is to produce a rigorous but simple approach to the empirical quantification of the employment effects of technologies used in the production of electricity which can be implemented by using relatively aggregated data. In fact, our approach has relatively low data requirements, as it can be estimated on national data for employment and economic activity in the power generation sector (regardless of the technology being used) and the amount of electricity produced by different power generating options. All variables used in our approach are observed at the annual frequency, although our methodology can be used with quarterly or monthly data, in those case where they are available. Ability to use annual data rather more granular observations increases the applicability of our method which uses data which are readily available for at least OECD countries. By quantifying the employment impact of a number of energy technologies, our approach can be applied on the back of the output of energy system models which produce deployment scenarios of electricity generation technologies to achieve a certain level of decarbonisation, as shown below. This implies, as an example, the possibility of computing both the positive and negative impact resulting from the diffusion of renewable technologies on employment in renewable and fossil-fuel based plants, respectively, and the resulting net effect from these two opposite effects. Our approach avoids the data burden typical of Input-Output, CGE and macroeconometrics sectorial model (Cameron and Zwaan 2015), with the additional advantage that the relationships estimated in our model is transparent, contrary to the several elasticity parameters (not always made explicit) used in CGE models. The methodology described below can be easily replicated across countries therefore increasing empirical evidence base while taking into account the context of a particular country, such as industrial and labour policy, technologies being used in the generation of power and labour productivity (Cameron and Zwaan 2015). We implement our approach for the UK although it can be applied to any other countries for which similar data are available.

As far as we are aware, our study is the first cointegration analysis that examines the long-term relationship between employment and renewable electricity while taking also into account the employment effect of energy supplied by conventional thermal, combined cycle gas turbine (CCGT) and nuclear technologies using long-term historical data. By estimating the long-run equilibrium between employment, gross value added (GVA) and electricity supply for the electricity generation sector we investigate a number of key questions related to that. We provide evidence that the increase in employment related to a permanent rise in the generation of renewable electricity is several times higher than the employment effect of an equivalent increase in electricity generated by nuclear or natural gas. More specifically, we find that a permanent 1 GWh increase in the annual electricity supply generated by renewable technologies creates 3.5 jobs in the long-term run. In order to evaluate the policy implications of our results, we apply the estimated employment effect on a set of scenarios for electricity generation in 2030 produced by the UKTM model (Watson et al, 2018). Our results indicate that most of the scenarios in Watson et al (2018) implies increasing employments in the electricity generation sectors, in some cases quite substantial. Our analysis proceeds as follows. We review the recent literature on employment and renewable energy in Section 2 and resent a brief theoretical framework for our analysis and the methodological approach in Section 3. Section 4 analyses the structure of the UK electricity supply market, discusses the historical trends on different types of electricity supply and the observed substitution across technologies, while we provide details on the data used in Section 5. Our empirical results are presented in Section 6 while Section 7 discusses on their policy relevance, based on the findings from Watson et al (2018). Section 8 concludes.

2. Literature review

The existing literature on the employment effect of renewable technologies, part of a wider branch related to the article assessing the employment effect of sustainable development policies (McNeill and Williams 2007), comprises a large number of studies that estimate the employment effect from the deployment of renewables technologies. Cameron and Zwaan (2015) identify 70 publications since the beginning of the last decade, with the publications grouped into 1) studies producing forecast or simulations based on theoretical models, exogenous estimates and adaptations of values from other papers; 2) studies performing some form of literature review studies that analyse historical employment data to empirically estimate gross employment effects, either using input-output analysis models (see for example Lehr et al (2008), Tourkolias and Mirasgedis (2011), Lambert and Silva (2012), Markari et al (2013), Oliveira et al (2013), Simas and Pacca (2014), Baer et al (2015) and Vasconcelos and Carpio (2015)) or using employment factor methods[1] such as Thornley et al (2008), Blanco and Rodriquez (2009), Wei et al (2010), Van der Zwaan et al (2013) and Fanning et al (2014). Input-output models are used to estimate the economic interdependencies between different sectors of the economy and the effects of renewable energy, especially with regard to indirect and induced jobs, while employment factor methods mostly focus on direct employment effects.[2]

Evaluating empirical results found in the literature, Cameron and Zwaan (2015) note that the employment impact varies across renewable technologies. For example, solar panels can create several times more jobs than onshore wind. Studies investigating the employment effect of solar industry development focus especially on Mediterranean countries such as Greece (Tourkolias and Mirasgedis, 2011), Morocco (Ciorba et al 2004), Spain (Moreno and López, 2008; ILO, 2012), Turkey (Çetin and Eğrican, 2011) and Northern Africa (Kost et al, 2012). However, wind energy is expected to significantly affect job creation in the EU (Blanco and

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[1] Employment factors are ratios of a specific type of employment to the level/capacity of electricity supply generated by a specific type of renewable technology (e.g. the direct employment factor for manufacturing and installations for wind energy is measured as job/MW).

[2] Jobs created by renewable technologies can be categorized as (i) direct (ii) indirect and (iii) induced employment (IRENA 2011). Direct jobs are created by the sector's core activities, indirect jobs are those involved in the sector's supply chain and services, e.g. firms providing raw materials, regulatory bodies, banks etc, and induced jobs are generated when wealth created by the renewable sector stimulates demand in the economy. Gross employment comprises the overall number of jobs created by the deployment of renewable energy technologies while net employment takes into account the negative employment effects or the employment impacts which would have been generated in *counterfactuals*, i.e. the employment which would have been generated by the plants which would have been built in the place of renewable technologies.

Rodriquez 2009 and WEA 2012), an argument that is further supported in the case of countries such as Brazil (Simas and Pacca, 2014), Greece (Tourkolias and Mirasgedis, 2011) and Spain (Caldés et al. 2009; Moreno and López, 2008; ILO, 2012). In the case of Texas, however, Hartley et al (2015) found no statistically significant impact of the deployment of wind on employment. Using a panel dataset of 80 countries, Apergis and Salim (2015) finds positive impact of renewable energy consumption on unemployment in European Union and Africa while negative in Asia and Latin American countries. On the other hand, Blazejczak et al (2014), using a macro-economic sectorial model finds that the renewable energy in Germany had positive net employment which are small if labour markets are rigid but considerably high if additional workers can be easily mobilised from the pool of unemployed. The importance of retraining workers in the transition from coal to renewable electricity has been discussed for example in Louie and Pearce (2016). Cost-competitive wind electricity was found to produce initially low but rising benefits in terms of welfare and GDP in the case of US economy (Cohen et al 2018). Doubling the share of renewables in the world production of electricity was found to increase direct and indirect employment in the sector to 24.4 million by 2030, with most renewable energy jobs coming from fuel supply (bioenergy feedstocks), installations and equipment manufacturing. (Ferroukhi et al 2016) With regard to the UK job market, Fanning et al (2014) investigates the potential employment effect in Wales by regional deployment of tidal and wave-based renewable technologies while Thornley et al (2008) evaluates the expected net employment effects resulting from the development of UK bioenergy plants and rising production and use of biomass crops.

From an economic theory perspective, increasing renewable electricity tends to imply higher unemployment rate (Rivers 2013) mainly through increases in the labour tax required to fund renewable electricity schemes. Perriera and Quirion (2018) describes the existence of three economic channels for job creation, so that a shift in investment towards renewable electricity increases employment if it targets sectors with a higher share of labour in value added, lower wages or lower import rates. The authors found positive employment impacts arising from weatherproofing and solar panels, a result that is robust across the models used in the study, with the result due to a higher share of labour and lower wages in these sectors, compared to the “electricity and gas” sector. From an empirical perspective, predictions and estimations of potential or expected employment effects widely vary among studies, as they significantly depend on the approach used, data constraints, type of renewable technology, country being investigated and the extent to which technology is produced locally or imported. Cameron and

Zwaan (2015) argue that the maturity of production techniques, economies of scale and learning-by-doing can lead to reduction of employment in the long run, a point of view supported by a series of studies produced by the German government (O'Sullivan et al, 2008, 2009, 2010, 2011) focusing on the German labour market. A small number of studies quantifying the effect of economies of scale on long-term employment (Heavner and Churchill, 2002; Rutovitz and Atherto, 2009; Liera et al, 2013) indicate high levels of reduction in employment rates, although this subject needs to be investigated further (Cameron and Zwaan 2015). Finally, Cameron and Zwaan (2015) point at the lack of robust empirical analyses comparing the macroeconomic net employment effect of conventional thermal power generation and renewable technologies.

3. Methodological approach

3.1. A theoretical framework

We take as a starting point the consideration, supported by DUKES (2017, p113) that UK electricity system is driven by demand which in other words means that UK electricity supply is completely elastic. A representative firm in the electricity generation market chooses labour inputs at time *t* L_t based on the previous period's expectations about electricity supply in *t* expressed as $E_{t-1}[e_t|I_{t-1}]$:

$$L_t = f(E_{t-1}[e_t|I_{t-1}]) \tag{1}$$

where, as discussed in Section 4, the firm's expectation in relation to electricity supply at time *t* can be further distinguished into four subcategories, namely conventional thermal, CCGT, nuclear and renewables electricity, indicated by con_t, $ccgt_t$, nuc_t and ren_t, respectively so that

$$E_{t-1}[e_t|I_{t-1}] = E_{t-1}[con_t|I_{t-1}] + E_{t-1}[ccgt_t|I_{t-1}] + E_{t-1}[nuc_t|I_{t-1}] + E_{t-1}[ren_t|I_{t-1}]. \tag{2}$$

Based on the theory of adaptive expectations (Nerlove, 1958), the representative firm will form its expectation about time *t* by taking into account demand for electricity observed at time *t-1* and in all past years, with different weights attributed to the years used to form the expectation. Thus, an increase in electricity demand at time *t-1* – and by extent an equal increase in electricity supply – implies an increase in the representative firm's expectations of electricity demand in time *t* with expectation adjusted by a parameter β which takes values between 0 and 1 and works as an "error-adjustment" term that reflects the deviations between expectation in *t-2* of electricity consumption in *t-1, i.e.* $E_{t-2}[e_{t-1}|I_{t-1}]$, and actual consumption of electricity in *t-1*, e_{t-1}:

$$E_{t-1}[e_t|I_{t-1}] = E_{t-2}[e_{t-1}|I_{t-2}] + \beta(e_{t-1} - E_{t-2}[e_{t-1}|I_{t-2}]) \qquad (3)$$

As under the assumption of adaptive expectations, the expectation of a future variable is based on all past observations, equation (3) can iteratively be expressed as follows:

$$E_{t-1}[e_t|I_{t-1}] = \beta(\sum_{j=0}^{\infty}(1-\beta_1)^j\, e_j), \qquad (4)$$

for years *j* in the past. Therefore, it seems quite reasonable to assume that an increase in electricity demand at time *t-1* (or before time *t-1* as well) will result in a positive employment effect in time *t* as the representative firm will prepare for increased demand by increasing its production inputs and thus its workforce. As a positive employment effect in time *t* might not only be the outcome of higher electricity consumption but also of higher economic activity, we also control for gross value added (GVA) in the electricity generation sector. Having established a theoretical framework for our reduced form model that explains how the future number of jobs in the representative firm is determined by the firm's expectation for its future electricity demand, we proceed to the econometric modelling.

3.2. Econometric modelling

We start our empirical analysis by testing the stationarity of our variables using the DF-GLS test (Elliott et al, 1996), a choice motivated by high size-adjusted power in finite samples. If the DF-GLS test cannot reject the null of nonstationary, we implement the Zivot and Andrews (1992) test that allows for series to have a break at an unknown point in time. The choice of the deterministic component used in the test is determined based on the results of Akaike and Bayesian information criteria on two separate specifications, one with intercept only and the other one with intercept and linear trend, and secondly by visual inception of the series (see Figure A1.). The choice of the appropriate lag length is based on modified Akaike information criterion (Ng and Perron, 2001). Since we find evidence of the variables used in the present study being integrated of order 1, and of cointegration among them (see Section 6), we focus on cointegrating VAR as econometric methodology.

In order to estimate the long-run effect of renewable technologies on employment we implement a two-step methodological approach. First of all, we search for evidence of long-run relationships, by implementing a cointegration analysis using a VAR approach (Johansen, 1988; 1991), and estimate a Vector Error Correction (VECM) model of order *p*, where all variables are treated as endogenous.

$$\Delta x_t = \Gamma_0 + \Pi x_{t-1} + \sum_{i=1}^{p} \Gamma_i X_{t-i} \tag{5}$$

where x_t is a 6 x 1 vector containing the logarithms of employment, GVA, and electricity generated by 1) conventional thermal, 2) CCGT, 3) nuclear and 4) renewable technologies, Π and Γ_i are 6 x 6 coefficient matrices and Γ_0 contains the deterministic terms. We explore the appropriate number of cointegrating vectors by performing the trace and the maximum eigenvalue tests. With regard to the deterministic terms in the cointegrating vectors, we choose whether or not to include a linear trend based on estimation of a model with intercept only and one with intercept and trend (following Johansen 1992). Once we have identified the long-term relationship between employment, output and electricity supply, in the second step we use our model to compute the long-term response of employment to a positive shock in the electricity supply of each type of power generation technology using impulse response function (IRF) analysis (Sims 1980). Results from the cointegration testing, discussed below, preclude us from using the bound testing approach of Pesaran et al (2001), as this can be implemented only in the case on one cointegrating vector. In other words, the IRF is used to understand the effect of a positive permanent shock on electricity supply at time *t* on employment from time *t* to *t+n*. We examine the response of employment to a 1 GWh increase, independently taking place in each electricity production technology. As we estimate a reduced form model, we use the generalised impulse response function (Koop et al, 1996) which is invariant to the ordering of the variables in the VAR and "fully takes into account the historical patterns of the correlation observed amongst the different shocks" (Pesaran and Shin, 1998; Pesaran and Smith, 1998).

4. UK electricity supply

The UK electricity market was restructured in 1990 to allow private investors enter the previously nationalised electricity market through a competitive bidding system that ultimately resulted in lower energy prices (DUKES, 2017). Companies generating electricity are classified in two distinct groups, Major Power Producers (MPPs) and Other Generators (OGs), the latter also known as Autogenerators. MPPs are the companies whose "primary purpose is the generation of electricity" (DUKES 2017), a group mainly comprising former nationalized firms responsible for the supply of electricity in the UK before 1990.[3] DUKES (2017) divides electricity supply into four separate subcategories according to the technology used, namely conventional thermal, Combined Cycle Gas Turbine (CCGT), nuclear and renewable electricity supply. Conventional thermal supply includes electricity generated by turbines burning coal and oil, while CCGT is a technology that uses natural gas (or gas oil to a small extent) to produce electricity at higher efficiencies than conventional thermal technologies. Nuclear electricity is generated by nuclear power plants all of which are classified as MPPs while renewable electricity is generated by hydro, wind farms, and solar farms (DUKES, 2017).[4]

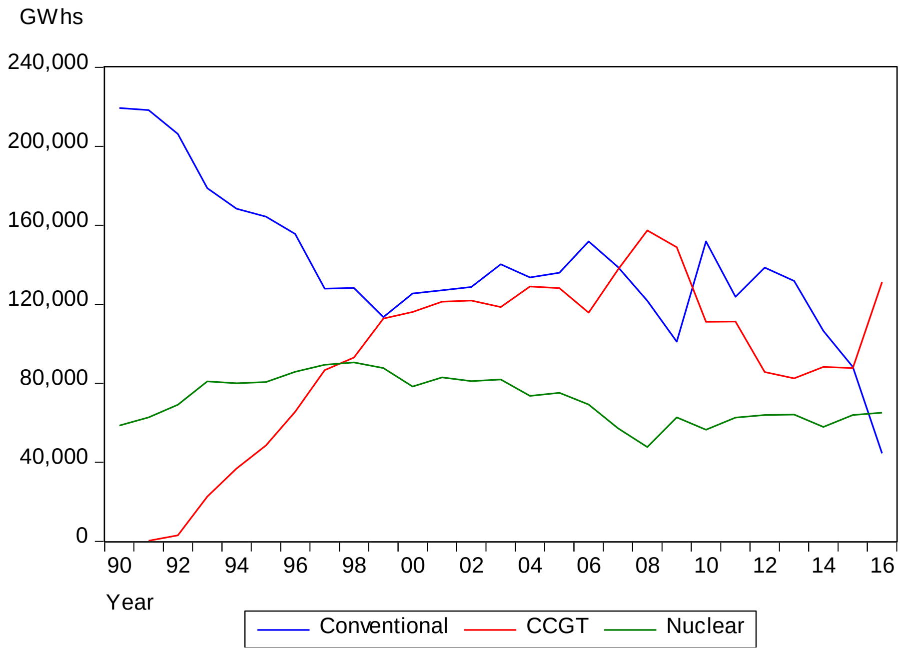
Electricity supply from conventional thermal power stations was responsible for 77% of the total electricity supply in 1990, i.e. the year when the UK electricity market was restructured and CCGT plants introduced in the UK, but by 1999 a 42% reduction took place (see Figure 1) mostly due to coal being replaced by gas burnt in CCGTs, the so-called "dash for gas" (Bocse and Gegenbauer 2017; Panagiotidis and Routledge, 2007) which implied a 113,000 GWh increase in CCGT generation in the same time period - see also the symmetric behaviour of the time series for conventional thermal and CCGT power stations between 1990 and 2000 in Figure 1(a). From 2000 to 2013, conventional thermal and CCGT power stations supplied roughly similar levels of electricity although after the 2008 economic crisis there has been increased instability in the two series. Finally, from 2013 to 2016 electricity from conventional thermal power stations decreased to become responsible only for the 15% of the electricity supply in 2016. This reduction is mainly due to the fact that in 2015 the carbon price floor has doubled from 9£ to 18£ per tonne of CO_2 (DUKES, 2017). Meanwhile, electricity supply from

[3] On the other hand, OGs are companies that "produce electricity as part of the manufacturing or other commercial activities, but whose main business is not electricity generation" (DUKES, 2017). OGs generate electricity mostly to satisfy their industrial energy consumption needs while surplus might be exported to the grid. Although we have also investigated the long-term relationship between electricity supply generated by OGs and employment, we did not find any empirical evidence to support this argument. As a result, the present study focuses solely on MPPs whose "primary purpose is the generation of electricity" (DUKES, 2017).

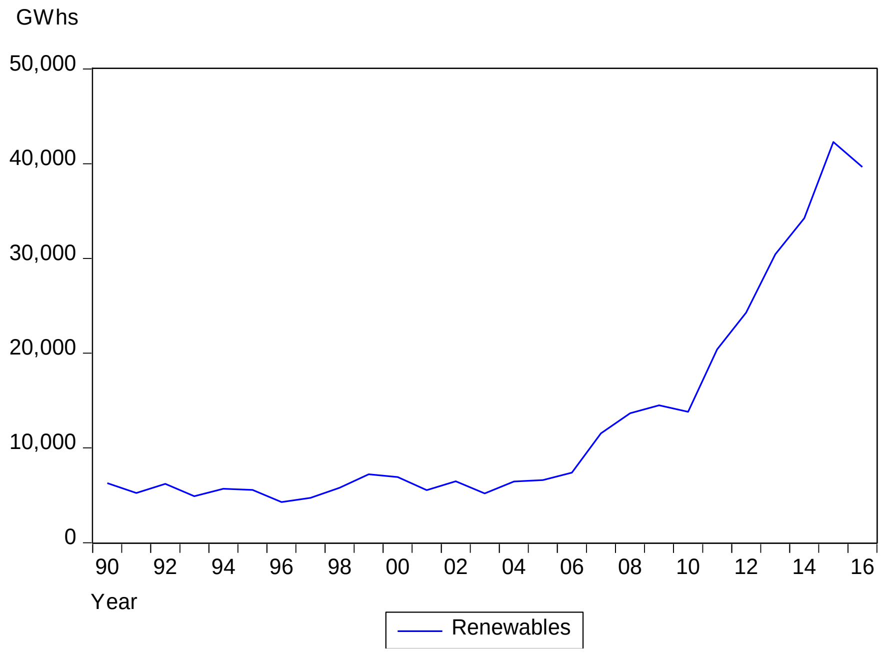
[4] There has been a major amendment in the MPPs definition in 2008 so that major wind farm companies could change classification from OGs to MPPs while the definition was further amended in 2015 to also include large scale solar farm companies which before 2015 were identified as OGs.

CCGT has increased by 20% covering in 2016 almost 50% of the total electricity supply in the UK.

Figure 1. Total annual electricity supplied (in GWhs) by major power producers (MPPs) per type of electricity generation technology used in the power generation process



(a)



(b)

Nuclear power stations have generated on average 23% of the total UK electricity supply since 1991, with the lowest level of electricity supply being 14% in 2008 and the highest being 29%

in 1997 and 1998. The peak in 1997 and 1998 reflects the fact that Sizewell B has been the latest nuclear power plant to enter commercial operation in 1995. Since then several nuclear power plants have been gradually decommissioned so that only eight nuclear plants were left in operation in May 2018 (DUKES 2018) out of the sixteen that were in operation in 1995, explaining the overall reduction in the electricity generated by nuclear since 1998. Decline in electricity from nuclear took place in correspondence of a rebound of electricity from conventional thermal plants up to 2007.

Renewable technologies have generated on average only 2% of UK electricity supply during the 90s but their contribution has steadily increased since the late 2000s, an outcome of national and international incentives. More specifically, in 2007 the EU Renewable Energy Directive (RED) set as target the production of 20% of the total energy by renewable resources by 2020 while in the UK the target was set in 2009 at the level of 15% of the total energy (DUKES, 2017). The highest peak of electricity generated by renewable technologies has occurred in 2015 as one can see in Figure 1(b) while a small reduction in 2016 is attributed to less favourable weather conditions for wind energy in comparison to the previous years (DUKES, 2017). Increase in electricity from renewable plants has occurred in presence of shrinking production from conventional thermal plants from 2010 onwards, as it can be seen in panel b.

To sum up, there have been considerable changes in the composition of technologies used in the production of electricity over the last 30 years. Production from conventional thermal plants has decreased since the restructuring of the power market in the 1990s so that it is reasonable to expect substitution between electricity supply generated by conventional thermal plants and other technologies. More specifically, we expect the existence of substitution between conventional thermal and CCGT, as discussed at length above. Nuclear technologies have played a central role in the UK electricity market with their declining output in the 1990s initially filled by increasing production from conventional thermal plants in a way that we expect substitution to exist between electricity generated by conventional thermal and nuclear technologies. Only nuclear and renewables technologies can be deliver CO_2-free electricity required to meet UK's CO_2 targets. In contrast to nuclear technologies, however, renewable technologies have started to be widely adopted in the UK only in the early 2000s. For that reason, it is reasonable to expect substitution between nuclear and renewable electricity supply, as a certain level CO_2 target can be reached by either increasing electricity from renewable or nuclear, given a certain deployment of electricity from CCGT and conventional thermal plants.

5. Data

Our dataset includes six variables, namely number of jobs, GVA, and electricity supply generated by conventional thermal, CCGT, nuclear and renewable technologies, all observed at an annual frequency between 1990 and 2016. More specifically, employment or to be more precise number of jobs is measured by "workforce jobs", with data sourced from employer surveys like the ONS Labour Force Survey (ONS 2018) on a quarterly basis from which we compute yearly averages. The lowest level of aggregation for which workforce jobs data are available in terms of SIC industrial classification is related to the "D" industrial sector which incorporates all MPPs firms and more generally firms related to "electricity, gas, steam and air conditioning". Data on GVA related to the "D" industrial sector are published in annual figures by the ONS (Lee et al, 2015) and expressed in terms of 2010 prices (measured in million pounds). Finally, electricity supply is equal to the level of electricity supplied to end users in the UK generated by MPPs. We obtain electricity supply data from DUKES that provide the longest time series on UK electricity supply measured in GWhs on an annual basis. All data are converted into logarithms and thus estimated coefficients represent the elasticities of the variables.

6. Results

The results from unit root testing (see Table A2) indicate that all variables are integrated of order 1 - I(1). As the DF-GLS unit root test indicates that only 3 of the 6 variables are I(1) (see Table A2), we assess the remaining variables (conventional thermal, CCGT and nuclear electricity supply) by implementing the ZA test that allows for the existence of an unknown break in the series, a choice validated by the graphical visualization of the series in Figure A1[5]. The results of the ZA test confirm the existence of breaks and the fact that the abovementioned variables are I(1), a result which allows us to proceed with the VECM methodology. As the cointegration tests indicate the existence of four cointegrating vectors in the estimated system (see Table A3)[6], we specify restrictions in the cointegrating vectors based on both economic theory, i.e. the scale effect between output and employment represented in the first

[5] The ZA test indicates the existence of a break in the series of conventional thermal, CCGT and electricity supply at the year 2013, 1995 and 2006, respectively, which can also be confirmed by visual inception of the abovementioned series in Figure A1

[6] We have also performed the cointegration tests without incorporating the trend term and there is no significant difference in the results. More specifically, the trace test indicates the existence of four cointegrating vectors as well while the maximum eigenvalue test indicates the existence of three cointegrating vectors.

cointegrating vector, β_1, and the historical relationships between the four electricity production technologies discussed in Section 3 in the three remaining cointegrating vectors. More specifically, we use β_2 to capture the substitution between conventional thermal and CCGT electricity supply, β_3 the substitution between conventional thermal and nuclear technologies and β_4 to capture the substitution between nuclear and renewable electricity plants.

The resulting long-run component of a VECM with trends included in all cointegrating vectors turn out to be stable and with coefficients having reasonable signs and values - see VECM 1 in Table 1. The cointegrating vector capturing the scale effect indicates the existence of a positive long-term coefficient equal to 0.96 for the relationship between output and employment. When it comes to relationship between different electricity generation technologies, long-term coefficients are all negative as one would expect, with the long-term coefficient of CCGT (β_2 cointegrating vector) taking the value of -0.31, that of nuclear electricity generation (β_3 cointegration vector) -1.36 and the coefficients capturing the substitution between nuclear and renewables being equal to -0.22. The trend in the first cointegrating vector is positive and equal to 0.03 while the trend in the cointegrating vectors capturing the substitution between different electricity generation technologies are negative with values equal to -0.11, -0.89 and -1.01 in β_2, β_3 and β_4 vectors, respectively. The unexpectedly high values (in absolute terms) of the trend in β_3 and β_4 vectors raise some initial concerns on the indication of four cointegrating vectors from the tests.

Table 1. Cointegrating vectors β from the VECM specifications VECM 1 and VECM 2

VECM 1								
	Jobs	**GVA**	**Conventional**	**CCGT**	**Nuclear**	**Renewables**	**Trend**	**Constant**
β_1	1	-0.96					-0.35	2.80
β_2			1	0.31			0.89	-28.27
β_3			1		1.36		-0.12	-25.34
β_4					1	0.22	-1.02	1.58
VECM 2								
	Jobs	**GVA**	**Conventional**	**CCGT**	**Nuclear**	**Renewables**	**Trend**	**Constant**
β_1	1	-1.06					0.06	-2.32
β_2			1	0.46	0.76	0.30	-0.001	-28.25

We assess the statistical significance of the coefficients in the four cointegrating vectors with the use of the LR test (see Table 2). The long-term coefficients are all strongly statistically significant, while the trend coefficient of the first cointegrating vector is statistically significant only at 5% significance level and the coefficient in the fourth cointegrating vector at the 10% significance level. We also check the validity of VECM 1 in see Table 2 by implementing the LM test for serial correlation in the residuals and the white test for heteroskedasticity. As it can be seen in Table 3, the cointegrating VAR has homoscedastic residuals, although the null of no serial autocorrelation is rejected at the 5% significance level. To further test the validity of a model with four cointegrating relationships, we estimate two slightly modified specifications (see VECM 1A and VECM 1B in Table A4) where the trend coefficients in β_2 and β_3 are restricted out of the model, therefore enforcing the results from the LR tests in Table 2. One can see that in both VECM 1A and VECM 1B specifications, the exclusion of only one trend coefficient in each of the models has considerable impact on the value of the long-term coefficients[7]. The remaining trend coefficients in VECM 1A and VECM 1B have in most cases different signs and markedly different values from those in VECM 1[8], although they remain statistically significant (see Table A5). The residuals in the alternative specifications VECM 1A and VECM 1B remain non-heteroskedastic similar to VECM 1, while they become non-serially correlated in VECM 1A (see Table A6). Most importantly, both specifications VECM 1A and VECM 1B are not stable as they have one root out of the unit root circle, a pattern that is further observed for any alternative specification examined except for VECM 1 specification.

Table 2. *P*-values of the Likelihood Ratio tests for the coefficients in the cointegrating vectors presented in Table 1

	GVA	CCGT	NUC	REN	Trend β_1	Trend β_2	Trend β_3	Trend β_4	All trends
VECM 1	0.00	0.00	0.00	0.00	0.04	0.31	0.15	0.07	0.00
VECM 2	0.00	0.00	0.00	0.00	0.00	0.86			0.00

The fact that restricting one coefficient in VECM 1, based on indications from LR tests, implies considerable instability in the values of the other long-term coefficients, changes in their signs

[7] The scale effect takes the values of 0.73 and 1.03 in the VECM 1A and VECM 1B specifications, respectively (see Table A4) in contrast to VECM 1 that is equal to 0.96. The substitution between conventional and CCGT electricity supply changes from -0.31 (VECM 1) to -0.56 and -0.35 in VECM 1A and VECM 1B, respectively. Similarly, the coefficient in β_3 changes from -1.36 (VECM 1) to -1.30 and -.1.15 (VECM 1A and VECM 1B, respectively). Finally, the substitution effect between nuclear and renewables changes from -0.22 (VECM 1) to -0.64 and -0.27 (VECM 1A and VECM 1B, respectively).

[8] The trend coefficient in β_1 cointegrating vector changes from 0.03 in VECM 1 to -0.05 and -0.21 in VECM 1A and VECM 1B, respectively. The trend coefficient in β_2 changes from -0.89 to 0.30 in VECM 1B while that of β_3 changes from -0.11 to -0.03 in VECM 1A. Finally, the trend coefficient in β_4 changes from -1.01 in VECM 1 to 0.02 and -0.37 in VECM 1A and VECM 1B, respectively.

and ultimately explosive behaviour is taken as an indication of four cointegrating vectors in the system being a spurious result from cointegration testing. For this reason, we re-estimate VECM 1 with only two cointegrating vectors, by assuming that the first cointegrating vector β_1 captures the scale effect between employment and GVA, as before, and the second capturing the substitution effect between conventional thermal electricity supply on one side, i.e. historically the main electricity generation technology used in the UK[9], and CCGT, nuclear and renewable technologies on the other side.

Table 3. Diagnostic tests for the residuals of the VECMs cointegrating vectors presented in Table 1

	Lags	Serial correlation	Heteroskedasticity
VECM 1	1	0.04	0.31
VECM 2	1	0.17	0.40

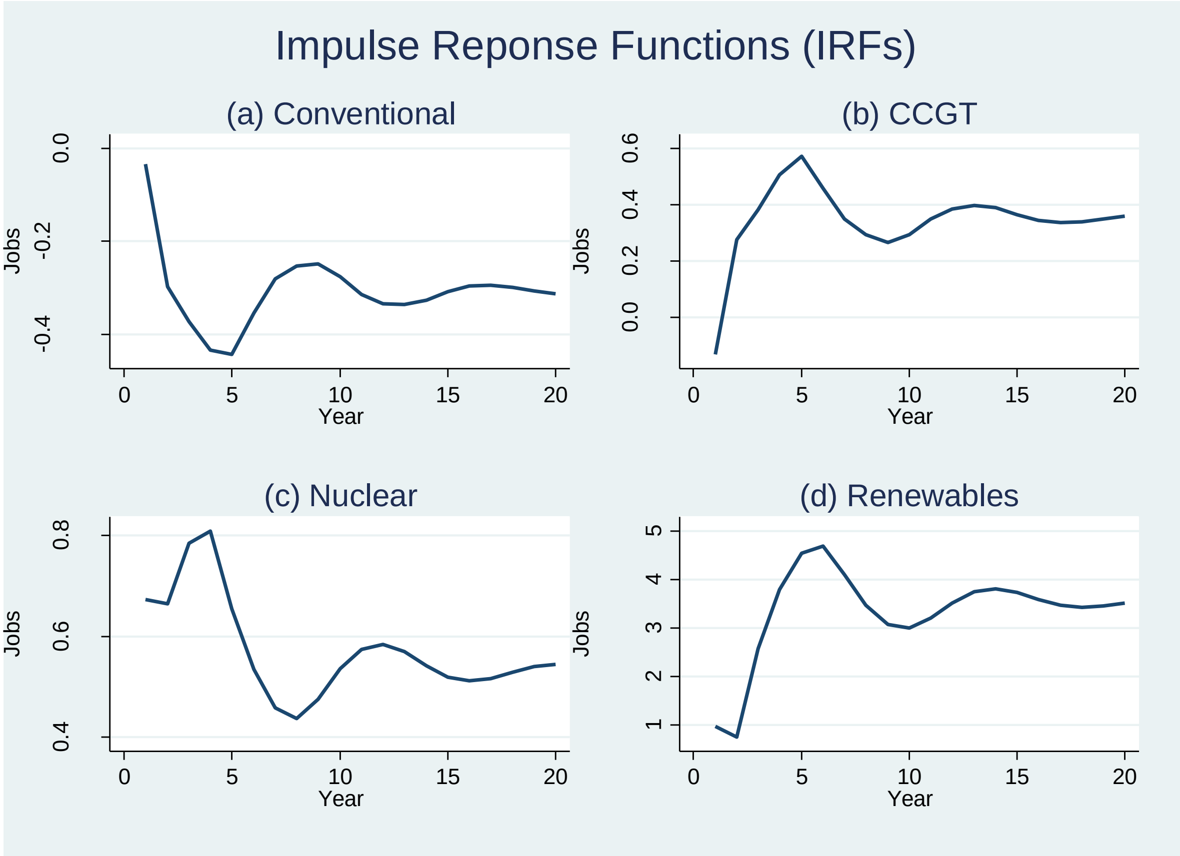
The resulting specification (VECM 2 in Table 3) is stable and has coefficients in the cointegrating vectors of the same sign and value similar to those in the model with four cointegrating vectors (VECM 1). More specifically, the scale effect between employment and GVA remains positive with value equal to 1.06 (see Table 1) which is fairly similar to the 0.96 value in VECM 1. With regard to the substitution effect, the coefficients for the cases of CCGT and renewables (-0.46 and -0.30, respectively) are also close to those in VECM 1. The only exception is the long-term coefficient of nuclear electricity supply which is equal to -0.76, i.e. half the value of the coefficient in VECM 1. The trend coefficient in β_1 is equal to -0.06 while that in β_2 is almost equal to zero (0.001). The coefficient in the two cointegrating vectors are strongly significant – see LR test in see Table 2 - with the only exception of the trend coefficient in β_2. The validity of VECM 2 specification is supported by our failure to detect heteroskedasticity and serial correlation in the residuals (see Table 3). Finally, we examine the validity of our assumption of two cointegrating vectors by assessing its robustness and estimating an alternative specification of VECM 2 where the non-statistically trend term in the β_2 cointegrating vector is restricted out of the model. The results in Table A4 indicate that this change leaves all the long-term coefficients in both cointegrating vectors virtually unaffected so that their values and sign are almost identical to those in VECM 2 (see Table 1). The β coefficients in VECM A2 are strongly statistically significant (see Table A5) while the

[9] As it has already been discussed in Section 4, conventional thermal technologies have generated the largest amount of electricity supply in relation to independently each one of the other electricity generation technologies throughout the whole timespan with the exception of the years 2007, 2008 and 2016 (see Figure 1).

diagnostic tests fail to detect heteroskedasticity and serial correlation in the residuals (see Table A6). The stability of the system is not affected by this restriction, as VECM A2 turns out to be stable with four unit roots.

The last step of our empirical approach involves the implementation of IRF analysis to assess the effect of electricity supply shocks on employment. More specifically, we implement a 1 GWh shock on each type of electricity production technologies, separately, and assess the magnitude and the direction of the response of employment for a time horizon of twenty years starting from year one – which is the year when the shock takes place. Our results indicate that employment responds negatively to a 1 GWh permanent increase in the annual electricity supply generated by conventional thermal technologies in Figure 2(a) reaching the value of -0.3 in the long-term. This is a counterintuitive result which we attribute to the fact that the most recent conventional thermal plant built in the UK predates the start of the sample used in the estimation and that production of electricity from coal plants has largely been decreasing since 1990. In other words, it is unlikely that moderate increases in generation would change expectations of generators on the decreasing share of this electricity production technology. In panel (b), one can observe that the response of employment to a shock in conventional thermal and CCGT electricity supply seem to have roughly symmetrically opposite shapes although the response of employment to a shock in conventional thermal is lower in absolute compared to the impact of a shock to electricity produced from CCGT, a finding which might reflect the considerable pattern of substitution we observe in Figure 1(a). One can also observe that the impact of an increase in CCGT production builds on across time after it takes place and results in an even higher employment effect in the following 4 years where employment reaches its peak value of 0.4 jobs. In the case of a shock in nuclear electricity supply, the response of employment reaches a value of 0.5 jobs in the long-term. Contrary to the impact of CCGT, however, the size of the impact decreases across time from an initial impact of 0.7. Finally, in the case of the response of employment to a shock in renewable electricity generation, we observe in Figure 2(d) that the immediate impact is 1 job to reach the peak of 4.7 jobs after 6 years and eventually stabilises near 3.5 jobs. It is interesting to notice that the impact of an increase in the generation of renewable electricity across time reflects the overall trend in the generation of this technology we observe in Figure 1(b), perhaps incorporating expectation on future increases for this generating technology.

Figure 2. Impulse response function (IRF) of employment to 1 GWh electricity supply permanent shock per type of power generation technology for VECM 2 presented in Table 1



7. Discussion

The results presented in Section 6 allow us to draw a number of insights concerning the long-term relationship between electricity generated by different types of technology and employment, and in particular about the effect of renewable electricity on jobs in the UK electricity generation sector. Starting with the scale effect, Table 1 confirms a positive relationship between GVA and employment in the electricity generation sector, a result supported by Narayan and Smyth (2005) and in general by the extensive literature on the causal relationship between electricity consumption and economic growth – see Payne (2010) for a review. The long-term elasticity of GVA takes the values 0.96 and 1.06 in the case of VECM 1 and VECM 2, respectively, hinting at a positive one-to-one relationship between output and employment. With regard to the relationship between different types of electricity, we find evidence that CCGT, nuclear and renewable electricity plants are all substitutes of conventional thermal electricity. As we found sufficient evidence to conclude that the indication of four cointegrating vectors is likely to be spurious, we focus on the results produced by the second cointegrating VAR specification (VECM 2 in Table 1) where we assume two cointegrating vectors. Electricity generated by CCGT power plants – is a long-term substitute of electricity generated by conventional thermal power plants, with elasticity equal to -0.46, a result supported by the literature related to interfuel substitution in the electric power industry[10]. Our results further indicate that electricity supply generated by nuclear technologies is a substitute of electricity generated by conventional thermal processes with elasticity equal to -0.76. Finally, electricity generated by renewable technologies is also a substitute of electricity from conventional thermal technologies with elasticity equal to -0.30.

As mentioned in Section 2, there is a certain debate on whether jobs created by the deployment of renewable technologies can be sustainable in the long-term period. After examining the historical relationship between employment and electricity supply in the UK, we respond to this question by using our model which allows us to compute the response of employment to a shock in electricity generated by different types of technologies. As one can see in Figure 2, the IRF analysis indicates that a permanent 1 GWh increase in the annual electricity supply generated by renewable technologies creates 4.7 new jobs in the short-term period while the long-term employment effect is 3.5 jobs. Thus, our results indicate that 3/4 of the jobs created by the deployment of renewable technologies are sustainable in the long run. With regard to nuclear electricity supply, a 1 GWh increase creates 0.81 jobs in the short-term period – 6 times lower than those created by an equally sized increase in renewable electricity – while in the long-term period employment stabilises at 0.54 jobs, i.e. 2/3 of the created jobs are sustainable in the long run. As a result, the employment effect of nuclear electricity is not only much smaller in absolute terms than that of renewable electricity but also less sustainable. When it comes to CCGT technologies, the short-term employment effect is 0.57 jobs – 8 times lower to the that created by an equal sized increase in renewable electricity – while the long-term effect is 0.36 jobs.

From a policy perspective, and as a way of testing our methodology, it is interesting to investigate the potential future employment effect from a set of scenarios for electricity generation in 2030, produced by the UKTM model (Watson et al, 2018)[11], which are briefly described in the Appendix, by using the estimated long-run employment effect we showed in Figure 2. We use as a counterfactual the "Energy island" scenario which is the only one to

[10] Gao et al (2013) provides a very helpful overview on the empirical findings related to interfuel substitution in the power generations sector.

[11] For more information on the assumptions of the scenarios produced by Watson et al (2018) please check Appendix A and in particular Table A1.

assume that conventional thermal technologies will be used until 2030. As one can see in Table 4[12] the "Low carbon (no BECCS)" and "Low carbon" are the only scenarios in which there is positive employment effect related to CCGT technologies equal to the creation of about 15,000 and 4,500 jobs, respectively. The only case of nuclear technologies having a positive employment effect equal to about 19,000 jobs is under the counterfactual in which 43% of the total electricity supply is generated by nuclear technologies.[13] When it comes to renewable technologies, we find positive employment effect under all scenarios and in contrast to the counterfactual in which renewable electricity is expected to decrease over time. According to our methodology, renewable technologies are expected to create from a minimum of about 16,000 jobs to a maximum of about 186,000 jobs under the "Low carbon (no BECCS)" and "Low carbon (no CCS)" scenarios, respectively. The former scenario is the most conservative in terms of electricity generated by renewables as only 29% of the electricity is generated by renewable technologies while the latter assumes that 64% of the electricity is generated by renewable technologies and overwhelmingly by wind turbines. The key role of renewable energy in generating a significant number of jobs in the long run is the reason why the employment effect in the "Low carbon" scenario is substantially lower than the impact in the "Low carbon (no CCS)" as in the former negative emissions[14] are delivered through Carbon Capture (CCS) technologies. The scenarios "Low carbon", "Technology optimisation" and "Slow decarbonisation" – where 37%, 56% and 51% of the electricity is generated by renewable technologies – are expected to create about 53,500, 75,000 and 60,000 jobs, respectively.

Table 4. Employment effect for the UKTM energy security scenarios (Watson et al, 2018)

Scenario	CCGT	Nuclear	Renewables	Net employment	Gross employment
1) Energy island	-21,492	19,303	-10,219	-12,408	118,432
2) Slow decarbonisation	-9,278	-19,089	60,034	31,668	162,418
3) Low carbon	4,499	-19,089	53,549	38,960	169,024
4) Low carbon (no CCS)	-32,931	-124	185,594	152,539	283,289
5) Low carbon (no BECCS)	14,956	-19,089	16,124	11,992	142,742
6) Technology optimism	-17,886	-19,089	75,136	38,162	168,912

[12] We do not incorporate conventional thermal in Table 4 as the last coal plant has been commissioned in 1987 and since then UK power generation sector has been significantly reducing its reliance to conventional thermal technologies.

[13] The rest of the scenarios except "Low carbon (no CCS)" assume exactly the same level of electricity generated by nuclear technologies which results in the same negative employment effect as one can observe in Table 4.

[14] The best scenario in terms of CO_2 emissions reduction is the "Low carbon" with negative emissions predicted while the second best is "Low carbon (no CCS)" according to the UKTM model (Watson et al, 2018). The worst performance comes under the counterfactual "Energy island".

In Table 4 gross employment is obtained by adding the net employment effect of electricity generation in each scenario, compared to the generation observed at time *t* that we imposed the shock in our system, to the number of jobs in at time *t*. In contrast to the counterfactual in which there is negative net employment effect, all scenarios generate a positive net employment effect which takes the minimum value of about 12,000 and the maximum of about 152,500 jobs under the "Low carbon (no BECCS)" and "Low carbon (no CCS)" scenarios, respectively. The three remaining scenarios, namely "Low carbon", "Technology Optimism" and "Slow decarbonisation" generate a net employment effect equal to approximately 39,000, 38,000 and 32,000 jobs, respectively. Gross employment under the optimal "Low carbon (no CCS)" scenario is equal to about 283,000 jobs and 1.4 times larger than the estimated gross employment under the counterfactual. The rest of the scenarios indicate that gross employment in the long-term period is expected to vary between about 142,000 to 169,000 jobs which is equal to an increase in gross employment of 20% to 43% in relation to the gross employment estimated under the counterfactual. From a policy perspective, this implies that further support of renewable technologies in the UK results in the creation of a significant number of long term jobs in the power generation sector.

8. Conclusions

This article proposes a transparent and easily replicable methodology to estimate the employment effect of electricity generation technologies by using aggregated data on the economic activity and employment in the power generation sector, and amount of electricity produced by different technologies. For the first time in the literature, we provide empirical evidence on the long-term effect of renewable electricity supply on net employment while taking also into account the employment effect of conventional thermal, natural gas and nuclear electricity supply through standard cointegration analysis. In our article, we analyse the UK electricity generation sector, using annual data from 1990 to 2016, although our approach can be easily applied to other countries. The validity of our long run estimates is assessed through robustness analysis and results of the diagnostic tests. We resorted to generalised impulse response function to compute the response of employment to increases in electricity supply generated by different types of technologies.

Our results indicate there is a positive scale effect between output and employment in the UK electricity generation sector revealing an approximate one-to-one relationship between percentages increases in GVA and jobs. We further find that evidence of substitution between conventional thermal electricity supply on the one side and gas, nuclear and renewables electricity supply on the other side. In terms of the employment implications of electricity generation technologies, we found that the long-term response of employment to an permanent 1 GWh increase in the supply of renewable electricity markedly differ from the employment generated by nuclear and gas generation. More specifically, a 1 GWh permanent increase in renewable electricity supply creates 3.5 jobs in the long-term, i.e. about six times the number of jobs created by an equally sized increase in nuclear generation. We also show that the jobs created by the deployment of renewable technologies are the most sustainable in the long-term period.

Finally, we apply our estimated long-run employment effect to a set of scenarios for electricity generation in 2030 produced by the UKTM model (Watson et al, 2018) so as to analyse the employment implications of those scenarios. We find that several of these scenarios imply an increase in the employment in the electricity production sector, with these changes implied by the six scenarios ranging between a decrease of 12,000 jobs to and an increase of 150,000 jobs. Scenarios where electricity generation is based overwhelmingly on renewable electricity results in up to 1.5 times more jobs than in a scenario where UK power generation sector continues to rely mainly on nuclear and conventional thermal technologies. Bearing in mind recent reduction in the cost of solar generation technology and the fact that the UK has largest global capacity in off-shore wind energy (BEIS, 2018), it becomes evident that renewable electricity supply can have a considerable positive long-term employment effect. Therefore, it is crucial that policy-makers incentivise and support the further deployment of renewable electricity technologies as we find robust evidence of their employment impact in scenarios aimed at progressing the decarbonisation of the UK economy. Nevertheless, it has to be taken into account that our results indicate the future employment effect only in the electricity generation sector and therefore we do not identify potential indirect job employment effects (for example in the manufacturing sector). Future studies should focus on the development of reduced form models that are able to identify the broader employment effect of the deployment of renewables technologies in sectors such as manufacturing, construction or services.

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Appendix

Appendix A. Decarbonisation Scenarios for the UK

Scenarios used in this article were developed by UKERC to assess the energy security implications of different energy futures based om a set of six UK energy scenarios. The scenarios consist of qualitative narratives and quantitative analysis using an energy system model: UK TIMES. UK TIMES is a bottom-up, cost optimisation energy system model that is often used to explore the implications of different energy futures and identify pathways that achieve carbon reduction targets. As not all the parameters used to develop the qualitative narratives could be modelled in UK TIMES, some components of the narratives, such as governance or environmental awareness, are not reflected directly.

The narratives were generated through a morphological analysis. This is a method for developing scenarios that include a number of components and their interrelationships. Each scenario narrative includes a variant of each component, whilst ensuring that it is internally consistent. The components cover national political, economic and societal policy developments, as well as the direction of international policies, and technological innovation. In terms of national context, this included the UK's economic and climate policies, the distribution of governance at different scales, as well as the role of civil society. In terms of the international context, the key parameters include the level of commitment to climate change mitigation and the degree of commitment to international rules-based trading arrangements. Finally, technological progress, and particularly the availability of carbon capture and storage (CCS), was explored as a critical parameter that could affect the future direction of the energy system.

The variants of those key components and the combinations within each scenario narrative are summarised in Table A1 which is taken from Watson et al (2018). The remainder of this section briefly describes the six scenarios. A much more detailed description of the scenarios and a discussion of the findings can be found in Watson et al (2018).

Scenario 1: Energy island

"Energy island" is a scenario based on an "inward-looking tun" in UK. More specifically, UK leaves EU and a new trade agreement is agreed under which there is partial access to European markets on unfavourable terms. Climate policy becomes of second importance while energy independence is emphasized leading to a revival of coal consumption and investment in nuclear power. The effects of climate change such as flooding and increased temperatures become increasingly viable.

Scenario 2: Slow decarbonization

"Slow decarbonization" scenario is a scenario that UK still leaves the European market, albeit, in contrast to the "Energy island" scenario the new trade deal offers access to EU markets but on less favourable conditions. In addition, UK has successfully concluded on alternative bilateral and multilateral trade deals which provide certain benefits. Although policies supporting the deployment of renewable technologies continued to be pursued since the fifth carbon budget has been agreed, there are constant delays and failures in policy implementation. Among else the commercialization of CCS is delayed while investment in biomass CCS is substantially delayed.

Scenario 3: Low carbon

Under the "Low carbon" scenario the UK has still left the UK but negotiations has allowed UK firms to have full access to the European market. UK continues to meet current statutory carbon budgets and targets while there has been government investment towards key infrastructure. Therefore, fossil fuels use is in decline, natural gas continues to remain key component for electricity generation due to the successful commercialization of CCS technologies while biomass CCS (BECCS) plays a gradually increasing role in the electricity generation. This is the only scenario that estimates negative emissions by 2030.

Scenario 4: Low carbon (no CCS)

Under the "Low carbon (no CCS)" the UK leaves the EU but negotiations results to a series of trade deals that provide certain access to the single market, although in less favourable terms. Similarly to the "Low carbon" scenario the UK continues to meet the climate change goals, nevertheless a failure in the commercialization of the CCS technologies affects the decarbonization efforts. Fossil fuels use is in decline while the failure in CCS is offset by significant investment towards specific renewable technologies such as wind and biomass, in particular in wind energy.

Scenario 5: Low carbon (no BECCS)

The "Low Carbon (no BECCS)" scenario is very similar to the "Low carbon" as the UK meets the current carbon budgets and targets. Nevertheless, public opposition to negative emissions technologies results in no deployment of biomass with CCS while decision making responsibilities are shared between central government and local authorities. Therefore, a diverse range of electricity generation technologies such as gas with CCS, nuclear and wind take the place of solar and biomass technologies.

Scenario 6: Technology optimism

The "Technology optimism" is a more decentralized scenario in which more powers are given to devolved administration and local government while a new deal with the EU provides full access to the single market. Under this scenario there are rapid reductions in the cost of renewable technologies, especially solar PV which leads to sustained government support for the deployment of low carbon technologies.

Table A1. Summary of 2017 UKERC scenarios in Watson et al (2018)

Governance level	Government decision-making remains centralized at the UK level ***Scenarios**: 2, 3*	The UK government shares power with the devolved and local administrations ***Scenarios**: 4, 5, 6*	Government decision-making remains centralized but Scotland leaves the UK ***Scenarios**: 1*	Scotland leaves the UK and power is devolved to remaining countries in the UK ***Scenarios**:*	
Economic policy	Dominance of “small State” philosophy, with weak appetite for policy action to change infrastructure sectors or invest in them ***Scenarios**: 1*	Some state intervention to shape markets and selective public investment in infrastructure sectors ***Scenarios**: 2, 4*	Strongly interventionist state: actively shapes markets and co-invests in infrastructure with the private sector ***Scenarios**: 3, 5, 6*		
National Climate policy	Strong long-term commitment to the environment & climate change mitigation, complemented by sustained action. The UK is seen as a global leader ***Scenarios**: 3, 4, 5, 6*	Long-term commitment to decarbonisation remains central for UK policy. However action to meet targets is delayed. Different levels of progress are observed across the UK ***Scenarios**:*	While there is limited interest in decarbonisation, policy commitment is faltering. There is no incentive to achieve & maintain a global leadership position. The forth carbon budget is achieved, but the fifth budget is not ***Scenarios**: 2*	Policy commitment is significantly scaled back in the mid to late 2010s. The UK aims to fulfil a minimum level of commitment due to international agreements. The third carbon budget is achieved but further targets are abandoned ***Scenarios**: 1*	
International climate policy	There is a high level of commitment to climate change mitigation at a global level. Climate policies are implemented in a successful and timely manner ***Scenarios**: 3, 5, 6*	There is a high level of commitment to climate change mitigation at a global level. However obstacles and delays impede policy implementation ***Scenarios**: 2, 4*	There is a fair level of global commitment. However there are significant delays in taking concrete steps and policies are poorly implemented ***Scenarios**: 1*		

International trade	Continuing commitment to liberalisation of global trade ***Scenarios: 3, 4, 5, 6***	Decreased emphasis on global trade; trade barriers increase ***Scenarios: 1, 2***			
Relationship with the EU	The UK stays in the EU ***Scenarios:***	The UK leaves the EU but agrees compromises to ensure full access to the Single European Market ***Scenarios: 3, 5, 6***	The UK leaves the EU. Access to Single European Market on unfavourable terms due to 'red lines' ***Scenarios: 1, 2, 4***		
Fossil fuel prices	High ***Scenarios:*** *1*	Medium ***Scenarios:*** *2*	Low ***Scenarios: 3, 4, 5, 6***		
Environmental awareness	High levels of disposable income have led to continued increases in consumption. There is little interest in sustainability. Environmental awareness and action is low. ***Scenarios:***	Due to economic difficulties, the public is preoccupied with immediate affordability concerns. Environmental awareness is moderate but action is low. ***Scenarios: 1***	There is some public interest in sustainability, but it is a secondary concern. Environmental awareness and action by citizens is moderate. ***Scenarios: 2***	Sustainability issues gain traction. The emphasis is on demand side reduction, social innovation and the adoption of more sustainable lifestyles as well as decentralised low carbon technologies. Environmental awareness and action is high. ***Scenarios: 6***	Sustainability is high on the agenda. The emphasis is on green technology products & 'buying solutions' for climate change, which are seen as a sign of social status. Environmental awareness and action is high. ***Scenarios: 3, 4, 5***
Technological progress, particularly for carbon capture and storage (CCS)	CCS commercialised successfully in the 2020s ***Scenarios: 3***	CCS commercialised successfully in the 2020s, but biomass energy with CCS (BECCS) is not permitted ***Scenarios: 5***	Delays in commercialisation of CCS offset by faster than expected progress in renewables ***Scenarios: 2, 6***	CCS fails to Commercialise ***Scenarios: 1, 4***	

Appendix B

Table A2. Unit root test results for Major Power Producers (MPPs)

	Logs			First differences			Logs		First differences	
	DF-GLS test	lags	Deterministic components	DF-GLS test	lags	Deterministic components	ZA test	lags	ZA test	lags
Jobs	-1.46	1	Trend	-3.91 $^{(*)}$	0	Trend				
GVA	-1.18	2	Trend	-6.43 $^{(**)}$	0	Trend				
Conv. thermal	-1.43	0	Trend	-1.49	2	Trend	-1.86	2	-7.31 $^{(**)}$	0
CCGT	-1.97	1	Trend	-2.81	1	Trend	-3.67	0	-4.59 $^{(*)}$	1
Nuclear	-2.27	0	Trend	-1.85	3	Trend	-3.45	3	-10.19 $^{(**)}$	0
Renewables	-1.57	0	Trend	-6.15 $^{(**)}$	0	Trend				

$^{(+)}$, $^{(*)}$, $^{(**)}$ in the superscripts indicate significance of the test statistics of the unit root tests at 90%, 95% and 99% significance level, respectively. If the DF-GLS test cannot prove sufficient evidence that the series is I(1), we implement the Zivot and Andrews test (ZA) that allows for a break at an unknown point in time.

Table A3. Johansen test cointegration results

	Trace				Max Eigenvalue			
	H0	H1	λ_{trace}	*p*-value	H0	H1	λ_{max}	*p*-value
MPPs	r = 0	r ≥ 1	0.973 $^{(**)}$	(0.00)	r = 0	r = 1	0.973 $^{(**)}$	(0.00)
	r ≤ 1	r ≥ 2	0.897 $^{(**)}$	(0.00)	r = 1	r = 2	0.897 $^{(**)}$	(0.00)
	r ≤ 2	r ≥ 3	0.827 $^{(**)}$	(0.00)	r = 2	r = 3	0.827 $^{(**)}$	(0.00)
	r ≤ 3	r ≥ 4	0.737 $^{(**)}$	(0.00)	r = 3	r = 4	0.737 $^{(**)}$	(0.01)
	r ≤ 4	r ≥ 5	0.507	(0.14)	r = 4	r = 5	0.507	(0.11)

Results from the Trace and max eigenvalue cointegration tests. $^{(+)}$, $^{(*)}$, $^{(**)}$ in the superscripts indicate significance of the test statistics of the unit root tests at 90%, 95% and 99% significance level, respectively.

Table A4. Cointegrating vectors *β* from alternative VECM specifications to those presented in Table 1

	Jobs	GVA	Conv	CCGT	Nuclear	Renewables	Trend	Constant
VECM 1A								
β_1	1	-0.73					0.05	-5.32
β_2			1	0.56				-18.17
β_3			1		1.30		0.03	-26.90
β_4					1	0.64	-0.02	-16.80
VECM 1B								
β_1	1	-1.03					0.21	-4.76
β_2			1	0.35			-0.30	-11.38
β_3			1		1.15			-24.71
β_4					1	0.27	0.37	-19.09
VECM 2A								
β_1	1	-1.06					0.06	-2.27
β_2			1	0.44	0.77	0.28		-28.19

VECM 1A: specification as in VECM 1 in Table 1 with trend in β_2 restricted to zero. VECM 1b: specification as in VECM 1 in Table 1 with trend in of β_3 restricted to zero. 2. VECM 2A: specification as in VECM 2 in Table 1 with trend in β_2 is restricted to zero.

Table A5. *P*-values of the Likelihood Ration tests for the coefficients in the cointegrating vectors *β* presented in Table A4

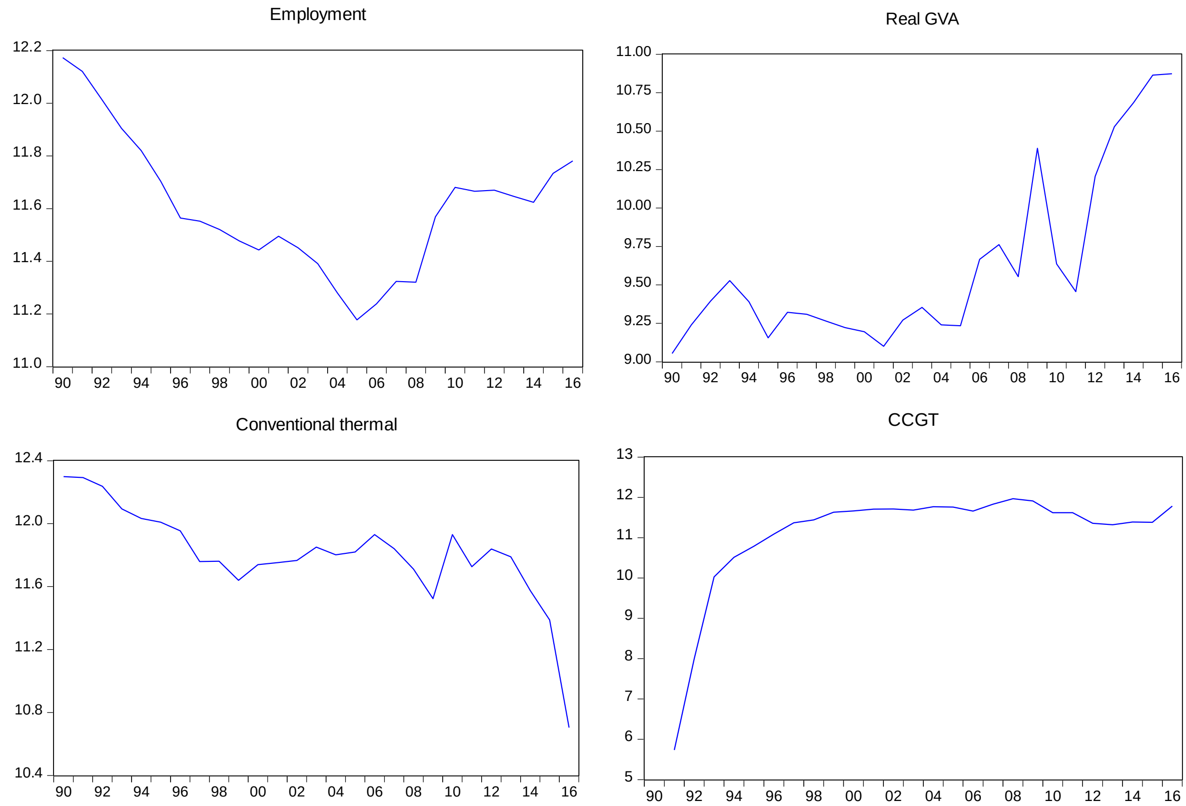
	GVA	CCGT	NUC	REN	Trend β_1	Trend β_2	Trend β_3	Trend β_4	All trends

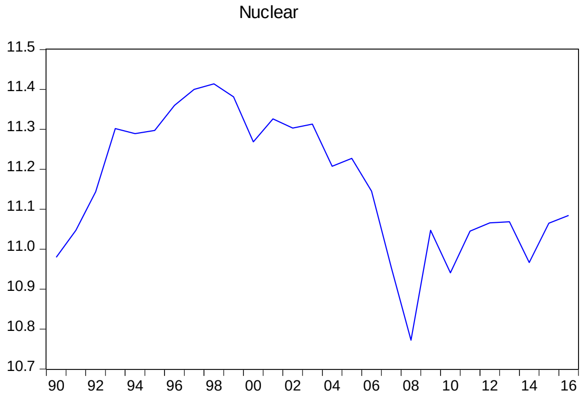
VECM 1A	0.00	0.00	0.00	0.00	0.01		0.00	0.40	0.00
VECM 1B	0.00	0.00	0.00	0.00	0.02	0.00		0.00	0.00
VECM 2A	0.00	0.00	0.00	0.00	0.00				

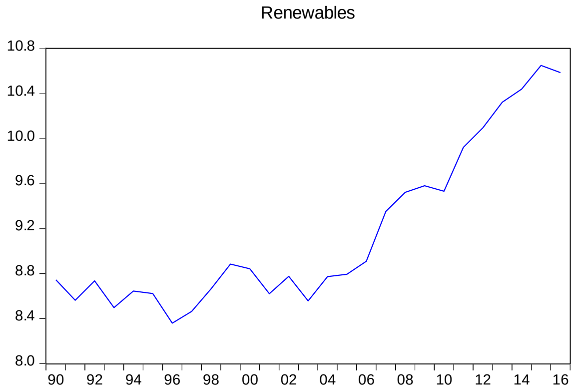
Table A6. Diagnostic tests for the residuals of the VECMs cointegrating vectors presented in Table A4

	Lags	**Serial correlation**	**Heteroskedasticity**
VECM 1A	1	0.37	0.32
VECM 1B	1	0.03	0.32
VECM 2A	1	0.20	0.38

Figure A1. Visual representation of the variables expressed in logarithms




Nuclear
11.5
11.4
11.3
11.2
11.1
11.0
10.9
10.8
10.7
90 92 94 96 98 00 02 04 06 08 10 12 14 16


Renewables
10.8
10.4
10.0
9.6
9.2
8.8
8.4
8.0
90 92 94 96 98 00 02 04 06 08 10 12 14 16