# They Took Our Jobs!

The Energy Transition and its Employment Consequences

**Master Thesis**

***MSc Advanced Economics and Finance***

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# Abstract

This study contributes to the existing literature on the potential direct employment effects as a result of the transition from non-renewable energy to renewable energy technologies. Contrary to most existing literature, this study takes a back-looking evaluative approach of understanding the nexus between employment and renewable energy implementation. We utilise the United Kingdom as a case study for the years 1998-2018 by applying an autoregressive distributed lag modelling framework to account for the dynamic nature of the transition, and any persistence in employment. Our findings indicate a positive and statistically significant coefficient of 0.055 for our independent variable of interest. This translates to a contemporaneous 0.055% increase in energy sector employment from a 1% positive shock to the share of renewable energy production. We also found our results to be robust after conducting subsample estimations and when substituting labour for employment in our estimation model.

***Keywords:*** *Renewable energy, employment, autoregressive distributed lag, technology, innovation*

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# 1 Introduction

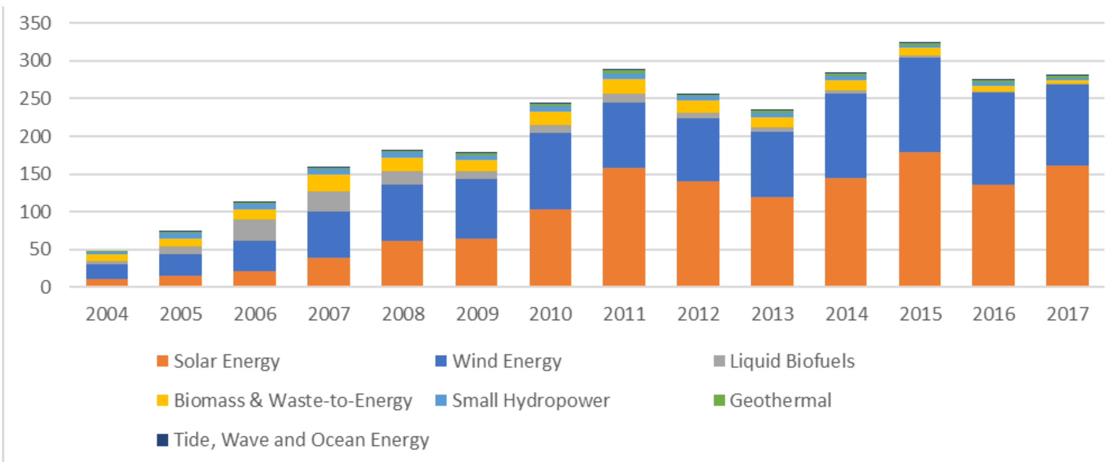
Since the Industrial Revolution, steady energy supply has been essential to development and traditionally, non-renewable fossil fuels such as crude oil, natural gas and coal have dominated the global energy composition. In the recent past, there has been growing concerns about the negative effects associated with the consumption and reliance on non-renewable energy. Scientists have shown that the emissions from fossil fuels are causing climate change that in the long-term can lead to catastrophic consequences such as rising seas levels and the destruction of ecosystems. Additionally, non-renewable energy sources are depletable and the continued exploitation and dependence on these sources will eventually lead to energy shortages. There are also more economic concerns from countries that are overly dependent on the imports of fossil fuels from a few producing states and would prefer moving towards other forms of energy.

Renewable energy as defined by the International Energy Agency includes solar, wind, hydropower, bioenergy, marine and geothermal energy (IEA, 2018). The recent rapid rise in the adoption of renewable energy has been largely driven by the desire for cleaner energy that is less destructive to the environment and to slow down climate change. Society is perhaps facing the biggest challenge in history in the form of climate change. International initiatives such as the Paris Agreement and the annual United Nations Climate Change Conference are leading the global drive for governments and corporations to slow down climate change and environmental damage through investing in and promoting renewable energy sources.

Following the United Nations Framework Convention on Climate Change in 2015 that has adopted the Paris Agreement, member countries are committed to “holding the increase in the global average temperature to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels” (UNFCCC, 2015). Crucially, this drive towards sustainability and decarbonation means that the global energy industries are bound to transition from non-renewable, carbon rich energy sources, into higher reliance on renewable sources.

Renewable energy technology has reached a stage where it is sufficiently developed and is being implemented on a large-scale as a means of replacing non-renewable energy sources. Figure 1 shows the global investment amounts for renewable energy technologies. Significant increases in renewable energy investments only started in 2010 and can be considered a relatively recent 'phenomena'. However, British Petroleum (2019) suggests that by 2040, renewable energy will be the main energy source globally.

***Figure 1: Global Renewable Energy Investment***




*Source: Frankfurt School-UNEP Centre/BNEF (2018) 'Global Trends in Renewable Energy Investment 2018'*

*Legend: Global annual investments in renewable energy by technologies between 2004-2017 in USD billion*

Even though the transition from non-renewable energy sources such as coal and oil to renewable energy has been touted as having large environmental, societal and health benefits, there have been growing concerns about the less apparent drawbacks that the energy transition may bring about. Many renewable energy advocates and governments claim that the introduction of renewable energy will create many new jobs associated with renewable energy but fail to acknowledge the equilibrium effects of adopting renewable energy. Renewable energy production replacing non-renewable energy production means that existing non-renewable operations will cease and associated non-renewable jobs will be lost. As such, it is imperative that the employment effects of renewable energy adoption are not accounted for in isolation but rather the net employment effect of the transition from non-renewable energy to renewable energy technologies that should be focused on.

There is a general consensus among academics that the job creation effect is higher or equal to the job destruction effect. The introduction of renewable energy technologies should not only make up for the lost jobs but may also create more jobs as renewable energy is on average deemed more labour intensive. However, these claims are mostly based on forward-looking forecasts or specific renewable energy projects. There have been many formal forward-looking forecasts but no study that has taken a backward-looking approach to evaluate whether the transition has had a net positive or net negative employment effect.

This study seeks to contribute to the ongoing discussion by empirically estimating the effect that the energy transition has had on net employment. This is done by conducting a historical case-study on a country that has experienced a growth in renewable energy adoption while experiencing a decline in non-renewable energy production. The UK was selected as a suitable case-study candidate and an appropriate estimation model was constructed to formally estimate the net employment effect that the energy transition has had over the last 20 years (1998-2018).

We believe that adopting a case study approach will best help us to understand the energy transitions in a specific environment and then allow us to draw some more generic conclusions.

The paper begins by providing some background information and knowledge about the industry in Section 2. Section 3 covers existing literature about the energy transition and discusses some similar studies. Section 4 discusses the economic theories and foundations that allow us to identify the important factors that should be considered when studying energy sector employment. In Section 5 the formal statistical model is constructed and empirically estimated. Section 6 provides an extension to the findings in Section 5 to provide us with a more rounded understanding of the labour effects of the energy transition. Section 7 discusses the main findings of the study and proposes further studies that build on these findings. Section 8 concludes the paper.

# 2 Background

This section provides background knowledge on the UK energy sector and more specifically, the transitioning of energy generation to renewable sources in the UK.

Firstly, we investigate the academic and non-academic literature to outline the main drivers of renewable energy implementation. Next, we offer a brief overview of the trends within the UK energy sector in order to put theory into context. Lastly, we examine renewable energy as an innovation to gain insight into the potential future direction of the industry.

## 2.1 Drivers of Renewable Energy

Renewable energy is being deployed on a global basis, but this implementation is occurring at varying rates across countries. This section investigates the main determinants of its deployment.

A publication by Hayes & Parker (2018) suggests that historically, renewable energy deployment was driven by the energy sector. In other words, implementation has occurred at the rate that makes economic sense to producers and is as a result based on supply push. Considering the nature of energy as a product, this makes sense as end-users are unable to distinguish between energy from different sources. The literature suggests that there are three main drivers of renewable energy implementation: costs, geographical features and political support.

### 2.1.1 Costs

Various academic sources highlight the increased cost of renewable energy implementation relative to conventional non-renewable energy as the main inhibitor of renewable energy growth. Renewable energy is mainly associated with electricity supply and due to the manner in which electricity markets work, renewable energy may only become feasible once the cost of distributing energy is comparable to conventional non-renewable energy sources (Energy UK, n.d).

Renewable energy deployment is highly capital intensive and historically, most developed nations are locked in on a path dependency in which conventional non-renewable energy sources dominate as a result of existing infrastructure. A shift towards renewable sources requires significant capital investments into adapting existing infrastructure. Despite the low marginal costs of renewable energy generation, one concern with renewable energy generation is that due to high capital costs, it remains relatively costly to distribute compared to conventional non-renewable energy sources.

Alagappan et al. (2011) highlights that due to energy market regulations renewable energy requires revenue streams from the distribution of renewable energy to cover its Levelised Cost of Energy (LCOE) in order to be feasible. Levelised Cost of Energy represents the cost of supplying energy and captures both the discounted capital costs and marginal costs from supplying an additional unit of energy. The LCOE of renewable energy needs to be lowered to a level comparable to conventional non-renewable energy in order for renewable energy to be a competitive option. The LCOE of renewable energy is expected to decrease through economies of scale, allowing for the implementation of more renewable energy production.

Aguirre & Ibikunle (2014) attempts to identify the main drivers of renewable energy share growth across 38 developed and developing countries. They find a statistically significant positive effect of renewable continuity on renewable energy as a share of energy produced. They measure the continuity as a dummy that takes the value of 1 when renewable energy accounts for 20% or more of the electricity supply, and 0 otherwise. They credit this effect to economies of scale and suggest that the LCOE is falling due to previous investments in technologies and infrastructure that benefit renewable energy in the future.

## 2.1.2 Geographical Features

The energy mix of countries hinges on their natural geographical features as renewable energy generation technologies are typically more land intensive compared to non-renewable energy technologies and may rely on specific geographical features to exist. Furthermore, the geographical features that are suitable for specific renewable energy technologies are finite and continued renewable energy deployment may have diminishing the geographical efficiency of a particular renewable energy type. This suggests that countries may initially focus on a single type of renewable energy technology but may diversify into other forms over time.

Aguirre & Ibikunle (2014) uses geographical data to create country-specific wind, solar and biomass potentials. They find the regression coefficients for the energy potential variables to be positive and highly statistically significant in explaining the growth of renewable energy as a fraction of total energy supply. This suggests that the manner in which renewable energy technologies are deployed depends on country-specific geographical factors in the early stages of the energy transition.

### 2.1.3 Political Support

Demand and supply must be equal at all times and price controls ensure that the prices of electricity are limited to the costs of supplying electricity (Ofgem, n.d). Government policies are often introduced to facilitate renewable energy deployment including two popular policy measures; Renewable Portfolio Standards (RPS) and Feed-In-Tariffs (FIT) (Ofgem, n.d).

RPS act as a support scheme for large-scale energy projects by imposing obligations on energy suppliers and utility providers to source a fixed amount of renewable energy on an annual basis.

FIT are mainly used for decentralised smaller scale energy projects. They are long-term contracts obligating energy suppliers to buy a certain amount of energy from small scale generators at a fixed price. FIT are typically considered more aggressive measures and are less politically sustainable in the long term.

Alagappan et al. (2011) found that electricity markets where FIT are in place are more successful in deploying renewable energy supply. However, Aguirre & Ibikunle (2014) find FIT to be statistically insignificant in explaining renewable energy growth. Instead they find that other fiscal support schemes and international institutional commitments, such as the Kyoto protocol of 1997 are highly statistically significant. Interestingly, they find policies such as direct investment, grants & subsidies as well as research, development & deployment statistically insignificant.

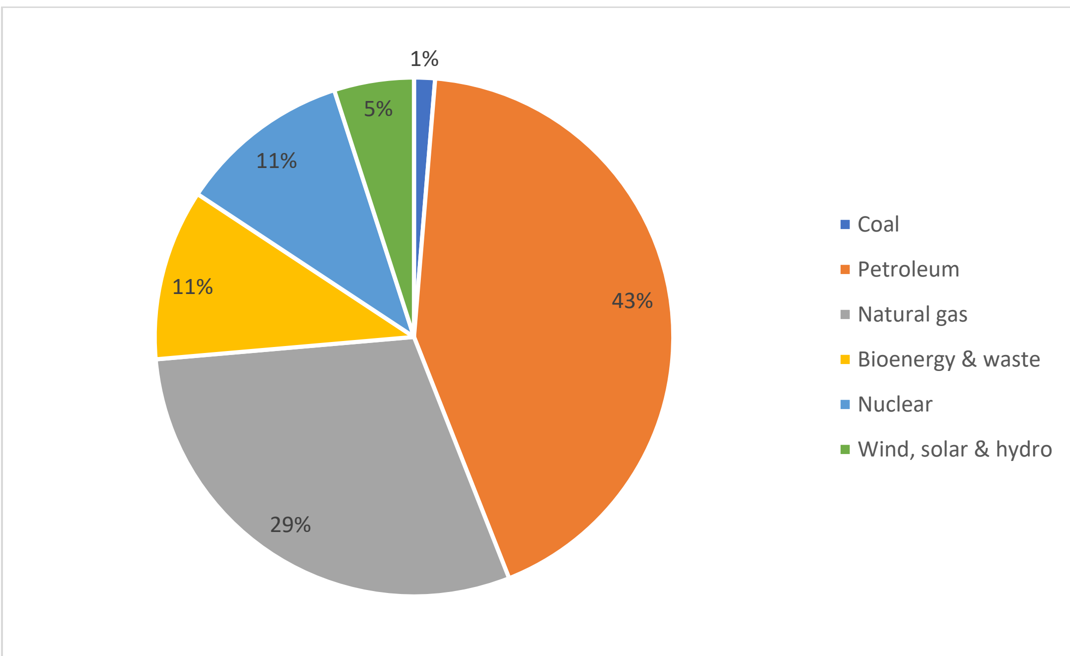
This provides conflicting evidence on the exact policy measures that are successful in supporting renewable energy implementation. Whilst the evidence may be unclear about the effect of FIT, it is suggested that government support and international targets are important in explaining renewable energy growth.

## 2.2 Energy Sector Trends in the UK

This section introduces an overview of the general trends in the UK's energy sector to put the previous section into context. Specifically, it will outline renewable energy implementation in UK.

The UK currently has a diverse energy composition in which non-renewable energy sources dominate. Figure 2 shows the UK's energy mix in 2018. It can be observed that petroleum and natural gas account for 72% of total energy production. Coal accounts for only 1% of the energy supply while nuclear energy produces 11% of the supply. Renewable energy sources account for 16% through bioenergy & waste and wind, solar & hydro energy.

***Figure 2 - UK Energy Production Mix, 2018***



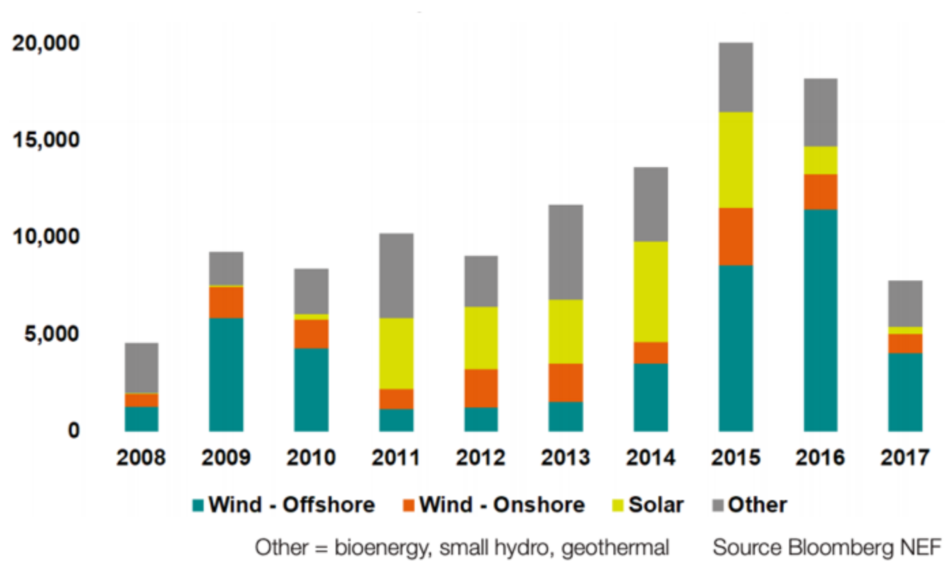

*Source: Department for Business, Energy & Industrial Strategy (2018) 'Indigenous Production of Primary Fuels'*

*Legend: Energy production composition of the UK by source in 2018*

The UK has introduced both RPS and FIT schemes to support renewable energy growth. RPS was introduced in 2002 and have been steadily increasing whilst FIT was introduced in 2010.

Section 2.1 has mentioned that renewable energy growth is determined by the supply push which requires large investments. Since the Climate Change Act was implemented in 2008, the UK has experienced an upward trend in investments in renewable energy as seen in Figure 3. The figure reveals that offshore wind power and solar power have been the main targets of renewable energy investment and have almost double between 2008 and 2009 from approximately £5 billion to almost £10 billion. The increase continues until its peak of £20 billion in 2015 which coincides with the Paris Agreement. Following 2015, we observe a decline in investments. This is partly due to policy changes lowering FIT that has made new investments in onshore wind power and solar power less attractive (UK Energy, 2018). Lowering FIT means that energy suppliers are obliged to buy a lower quantity of green energy from generators. The reason for its removal however is that green energy in many cases now can compete with non-renewable energy

***Figure 3: UK Renewable energy investment***

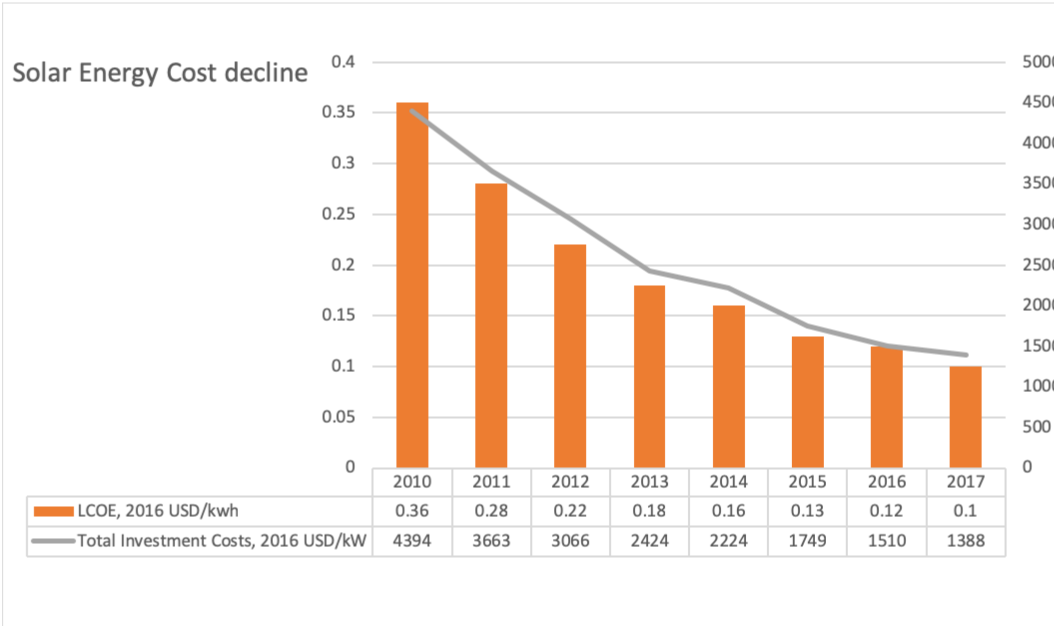



*Source: Energy UK (2018) 'Energy in the UK'*

*Legend: Investment in renewable energy by technology in UK between 2008-2017 in £ million*

In World Energy Investments, The International Energy Agency (2018) suggests that globally, a third of the fall in investment spending is a result of the decline in the cost of renewable energy implementation. Figure 4 highlights this by presenting the LCOE and Investment costs of solar Photovoltaics between 2010 and 2017.

***Figure 4: Solar Energy LCOE and Investment Costs***




*Source: IRENA (2018) 'Renewable Power Generation Costs in 2017'*

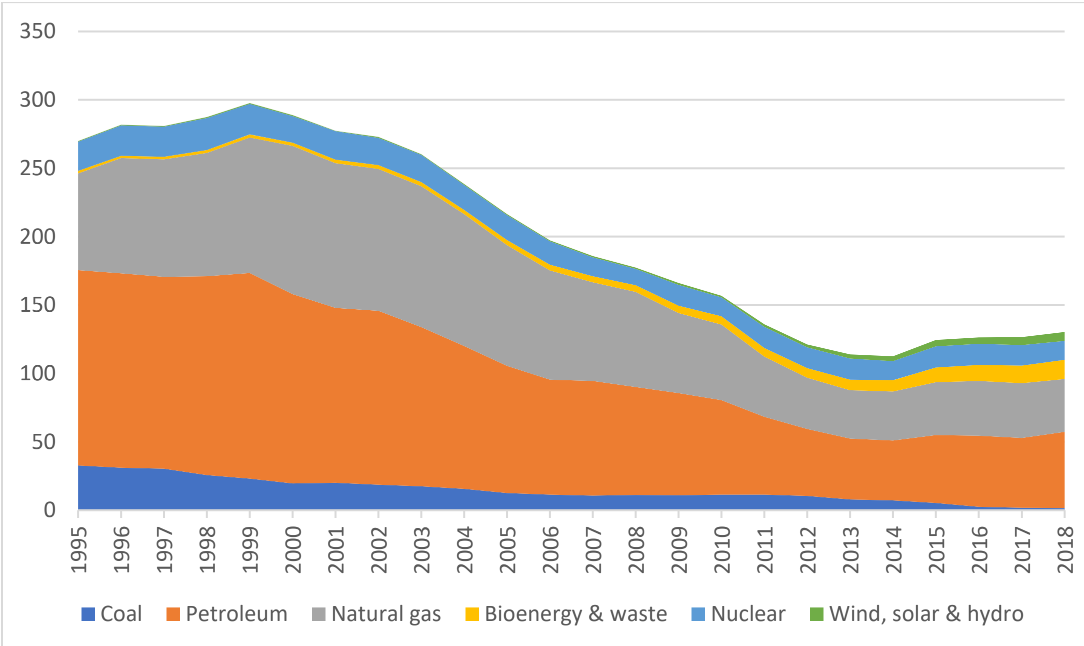
*Legend: Levelised Cost of Energy and Investment Cost of solar photovoltaics between 2010 and 2017 in 2016 $/kW*

Figure 4 shows that both LCOE and total investment costs have been steadily declining since 2010. Between 2010 and 2017, both items have declined to around a quarter of their 2010 levels. The fall in LCOE indicates that it has become cheaper to supply solar power and is more likely to be able to compete with non-renewable energy sources. This decrease in LCOE and increase in competitiveness results in lower investment risks. This fall in risk leads to a lower required return of capital and by extension a decline in investment costs observed in the figure. This has also led to the increase in solar energy within the UK's energy composition.

Additionally, the large amounts of investments in wind power may be explained by the geographical feature of the UK. As an island kingdom, its coastlines offer large potentials for wind energy generation.

Political agreements such as the Paris Agreement and the Climate Change Act in combinations with the declining costs of renewable energy and the geographical features of the UK have increased the attractiveness of investing in renewable energy. Despite the drive towards renewable energy implementation, its share in the total energy mix has remained relatively small.

***Figure 5: Total Indigenous Production of Primary Fuels in Million Tonnes of Oil Equivalent, UK***




*Source: Department for Business, Energy & Industrial Strategy (2018) 'UK Energy in Brief 2018: Dataset'*

*Legend: Total production of primary fuels in UK by technologies in million tonnes of oil equivalent*

Figure 5 shows the total indigenous production of primary fuels in million tonnes of oil equivalent by production type. It is interesting to observe that energy production has been continuously decreasing in the past 20 years and that between 1998 and 2017, energy production almost halved. Production has particularly declined for petroleum, natural gas and coal, with coal constantly declining to almost being eliminated from the energy composition. This trend has been continuous since coal mines began to close across the UK in the 1970s. Only bioenergy & waste and wind, solar & hydro energy have experienced significant increases over the past 20 years.

In conclusion, an increase in investment attractiveness through political initiatives, attractive geographical features and declining costs is driving the elevating share of renewable energy in the UK's energy composition.

## 2.3 Process Innovation & Creative Destruction

This section draws on the academic literature on innovation to examine renewable energy as an innovation and categorise renewable energy based on various factors. This provides insights into the potential implications for the energy industry and provide an indication on how to measure this transition towards further adoption of the innovation.

### 2.3.1 Types of Innovation

Innovations are normally categorised to be either a product or process innovation (Shilling, 2017). Product innovations refer to the change in the product of a firm or industry while process innovations are new techniques of production for the firm or industry. Renewable energy being a different product than non-renewable energy indicates a product innovation but should be considered a process innovation as they only differ in their inputs. Hence, whether the inputs are coal, petroleum, solar or wind, the output remains energy, meaning the product consumed by end-users remains the same.

Process innovation typically introduces increased efficiency by means of a new and improved process. Despite increased financial costs, it can be argued that renewable energy is more efficient when it internalises a key externality, emissions. As such, it may be argued that renewable energy is more efficient through a decrease in economic cost to society and this increased efficiency allows us to consider the introduction of renewable energy to be a process innovation.

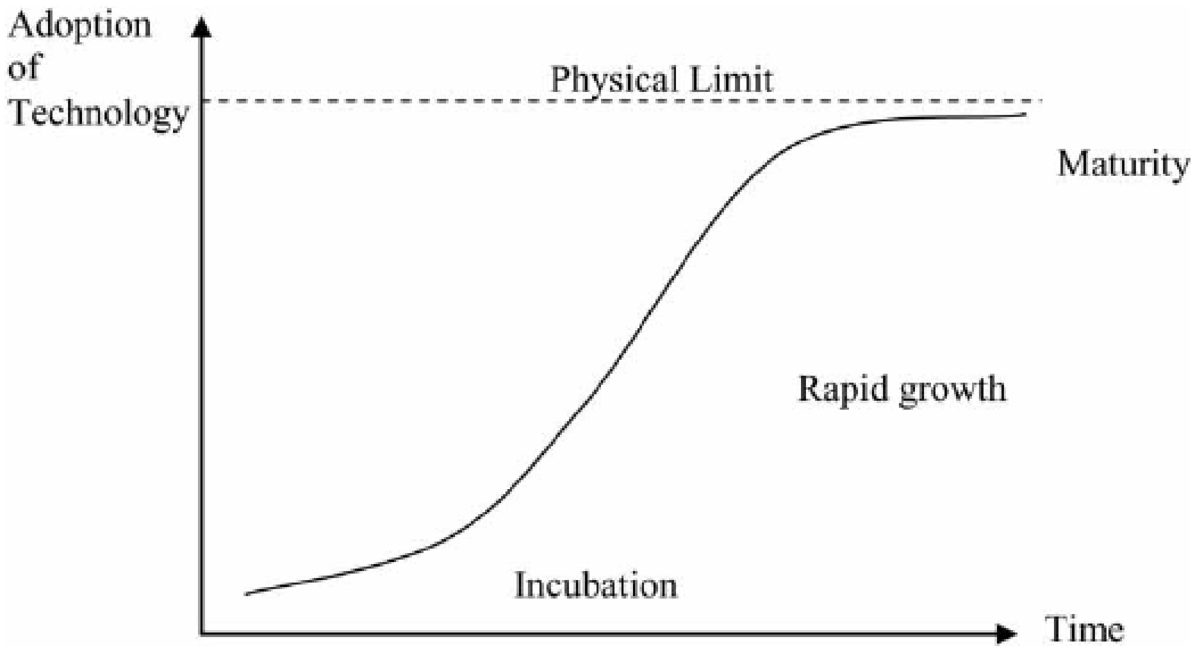
Innovations can also be categorised as competence-enhancing or competence-destroying. An innovation that is competence-destroying does not build on existing competencies but instead renders existing competencies obsolete (Shilling, 2017). As such, under the assumption that renewable energy is a process innovation that makes the industry more efficient, it can be considered a competence-destroying innovation.

### 2.3.2 Technology Change and Diffusion

Schumpeter (1943) discusses the dynamics of capitalism and socialism and refers to capitalism as being a constant economic change. Moreover, he suggests that capitalism is built upon the idea that "the capitalist engine" is kept running by the need to adapt in a dynamic social and natural environment to make economic sense. This includes innovating to remain efficient on an industry level and introduces the concept of creative destruction. With increasing social and political pressure forcing the energy industry to adapt, the emergence of renewable energy is destroying the need for and competencies of traditional non-renewable technologies. The introduction of renewable energy is likely to result in a systematic replacement effect in which non-renewable energy sources are made redundant.

Considering the notion of renewable energy as a process innovation that is characterised by being competence-destroying, we can apply an S-curve of technological diffusion to interpret its continued emergence (Shilling, 2017). This shows the adoption of the technology through a population, and hence by extension the degree to which it may make non-renewable energy types redundant. The S-Curve is shown in Figure 6, with time on the horizontal axis and adoption of technology on the vertical axis. It shows that technologies initially go through an incubation stage in which the technology is developed and optimised and the level of adoption remains relatively constant. A phase of rapid growth follows until the technology reaches maturity at which it slowly inches towards the physical limit.

***Figure 6: S-Curve of technological diffusion***

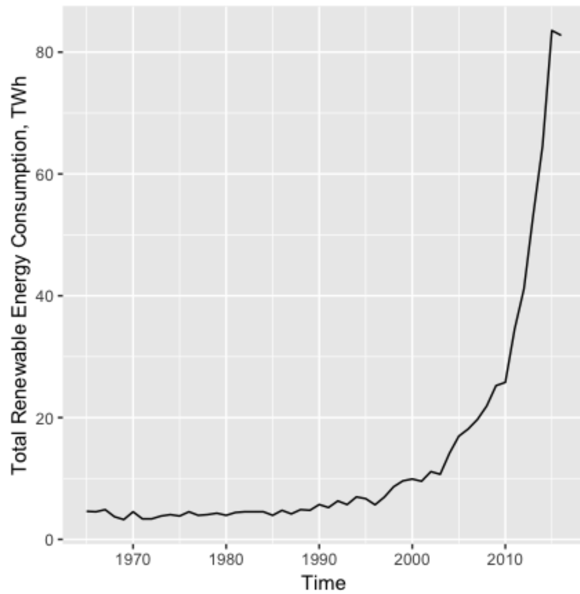



*Source: Wong et al. (2016) 'Technology Diffusion in the Telecommunications Services Industry in Malaysia'*
*Legend: The S-curve of technological diffusion of an innovation. The curve shows the consumption path of an innovation over time through three distinct stages*

Applying this framework to renewable energy, we plot the consumption of renewable energy in the UK over time. Figure 7 shows renewable energy consumption between 1965 and 2016. Figure 7 suggests that renewable energy went through a long incubation period until approximately 1995 after which the phase of rapid growth began as consumption increases exponentially. As renewable and non-renewable energy are substitutable, this period marks the beginning of the decline of non-renewable energy in the energy sector.

The S-curve predicts that the rapid growth period will continue until the technology reaches maturity and converges to its physical limit. Considering that energy is supplied in line with end-user demands and disregarding energy imports and exports, the physical limit can be assumed to be the total energy consumption level within the UK. The rapid growth phase of renewable energy consumption is associated with the decreasing consumption of other energy sources and creative destruction in the energy sector appears to be in the process of making non-renewable energy obsolete.

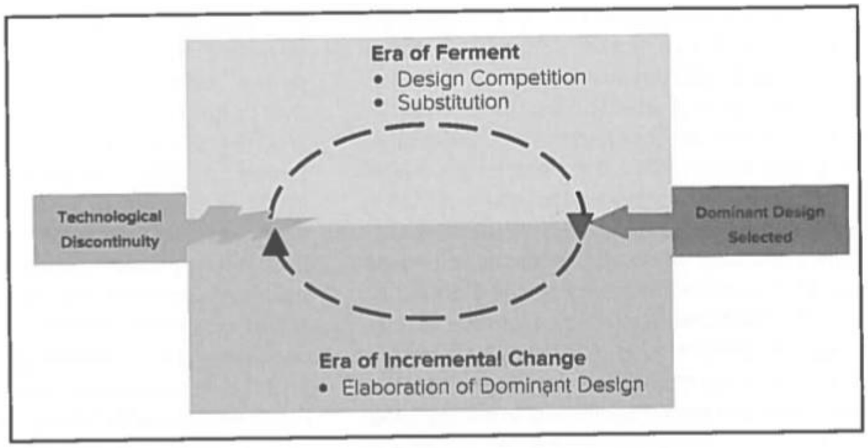
***Figure 7: Renewable Energy Consumption, UK***




*Source: British Petroleum (2018) 'British Petroleum Statistical Review of World Energy'*
*Legend: Renewable energy consumption in UK between 1975-2018 in TWh. Indicates the incubation and early stages of rapid growth*

Under the assumption that renewable energy is a process innovation in the phase of rapid growth, the energy industry may follow a technology cycle as proposed by Utterback & Abernathy (1975). In this model, non-renewable energy sources are referred to as the dominant design. Since the Industrial Revolution, which marks the beginning of commercial energy production, energy production technologies have become increasingly efficient. This is in line with the *era of incremental change* in which the technology is improved in terms of efficiency and penetration. Coal, as the historically most significant non-renewable energy source may be characterised as the dominant design while the emergence of renewables can be termed as a technological discontinuity resulting in an *era of ferment*. This is characterised by turbulence and uncertainty, as the sources of energy are shifting (Anderson & Tushman, 1990). This is apparent by the many variations of renewable energy sources of which *the best* is yet to be determined. Assuming that a single superior technology of renewable energy generation can be found, this will then displace coal as the dominant design after which it will enter the *era of incremental change*. As such, the energy industry may be assumed to follow similar technology cycles as other industries, albeit far slower and long term than most. The technology cycle is illustrated in Figure 8.

***Figure 8: Technology Cycle***




*Source: Shilling (2017) 'Strategic Management of Technological Innovation'*

*Legend: The technology cycle stages (Utterback & Abernathy, 1975). Dominant design of a technology enters the era of incremental change in which it is gradually improved to become more efficient. A technological discontinuity disrupts the industry as it enters the era of ferment. Here different types of technologies compete, and a degree of substitution away from the dominant design occurs, until a new dominant design is selected.*

In conclusion, renewable energy is characterised as a process innovation with competence-destroying features. By entering the period of rapid growth in the S-curve, renewable energy appears to be making non-renewable technologies obsolete. Based on theory, we would expect a complete substitution effect towards the new technology in the domestic energy industry.

# 3 Literature Review

The previous section looked at how renewable energy is introduced into the energy mix while the following section reviews the literature to understand how renewable energy introduction may affect employment. Firstly, we examine the literature covering labour intensity differences, followed by assessing the channels through which the energy transition is creating and destroying jobs. The third part assesses the type of jobs required for different energy generation technologies followed by a brief overview of the studies conducted on renewable energy and its employment effects. This further justifies our empirical study and provides an indication of past results.

## 3.1 Labour Intensity Differences

The previous section outlined how the introduction of renewable energy is creating new jobs whilst reducing the demand for other energy technologies and their associated jobs. The job intensities of the different technologies directly affect the magnitude of job creation and destruction. Classic economic theory suggests that innovation is associated with labour- or capital-saving processes to improve productivity but it was previously argued that this is not necessarily true in the context of renewable energy. Academic literature mostly suggest that renewable energy generation is more labour intensive as compared to non-renewable energy types (del Rio & Burguillo, 2008; Wei et al., 2010).

Del Rio & Burguillo (2008) note that non-renewable energy benefits from economies of scale and keeping labour constant, non-renewable energy sources may generate higher units of energy compared to renewable energy sources due to increased efficiency. This is supported by the findings of Wei et al. (2010) that suggest that renewable energy create more jobs per unit of energy than fossil fuels-based jobs in the US. They find that solar PV on average create 0.87 total job-years per GWh whereas coal only creates 0.11 total job-years per GWh over the lifetime of their facilities.

On the flip side, Bowen (2012) notes that the increased labour intensity occurs only in the installation phase and following the installation phase, renewable energy may become more labour efficient than conventional non-renewable energy. Hughes (2011) argues that ‘green jobs’ are an illusion and suggests that although labour intensity is currently higher for renewable energy technologies than non-renewable energy technologies, this relationship is unlikely to hold in the future. As the central objective of renewable energy implementation is not to create jobs but to limit CO2 emissions, the industry targets cost minimisation including labour costs and over time, the renewable energy industry may aim to limit employment. Therefore, he suggests that the UK cannot gain a long-term net gain in jobs regardless of ‘green job’ promotion policies.

## 3.2 Renewable Energy Job creation and Job Destruction

Existing literature suggests renewable energy to be more labour intensive as compared to non-renewable energy. However, the relative youth of the industry and the long lifetime of energy capital instalments means that there is no widely accepted way of measuring the potential for job creation.

The channels through which jobs are created and lost may be broken into three categories and are summarized in Table 1 (IRENA, 2011; Lambert & Silva, 2012).

The effects do not necessarily occur over the same time horizon and do not need to be of the same sign. Hillebrand et al. (2006) suggests that the timing and direction of the effects differ and argues that increased investments into the accumulation of capital results in immediate positive direct and indirect effects. However, the high capital costs of renewable energy will transfer into high LCOE and thereby causing increased electricity prices. This burden will be shifted to consumers which in turn lowers consumption and investment and ultimately resulting in negative induced effects. Moreover, they argue that the negative induced effects may offset the positive direct and indirect effects over time.

***Table 1: Energy job effects***

| Effect | Mechanism |
|---|---|
| **Direct Effect** | The jobs related to the core activities of the renewable and non-renewable energy. This includes manufacturing, construction, project development and operation & maintenance. |
| **Indirect Effect** | These are the jobs involved in supplying to the energy sector. This includes extraction of raw materials for construction, positions in governmental bodies, consultancy firms and research agencies. |
| **Induced Effect** | These are the effects that occur as a result of the implementation of renewables. For example, how the wealth generated by the renewable industry is spent, or how the potential change in energy prices affect inputs for other businesses or sectors, and by extension, how this affects their employment capabilities. |

*Source: IRENA (2011) 'Renewable Energy Jobs: Status, Prospects & Policies'*

*Legend: Channels of employment effects through renewable energy deployment.*

Similarly, Frondel et al. (2011) suggests that renewable energy will create green jobs but that these jobs will be offset by broader economic implications. This is largely driven by the assumption that renewable energy implementation will result in the increase in energy prices, reducing the private consumers' purchasing power and slowing down the economy. This will subsequently limit job growth and it is therefore suggested that many predictions with regards to green jobs are overly optimistic.

Nevertheless, contrary to these findings, Bowen (2012) highlights the necessity to focus on renewable energy production. It is suggested that any growing economy without focus on renewable energy production will be affected by environmental degradation and will lead to lower societal welfare and productivity. Therefore, he argues that the alternative to renewable energy will be worse in terms of employment as well as other macroeconomic factors. UNEP (2011) supports this argument by noting that the employment effects will have increasing returns over time. An economy that has “green policies” in place will experience higher positive employment effects compared to economies that do not. They do however note that this hinges on the assumption of a “green economy” being able to effectively re-skill and re-educate workers.

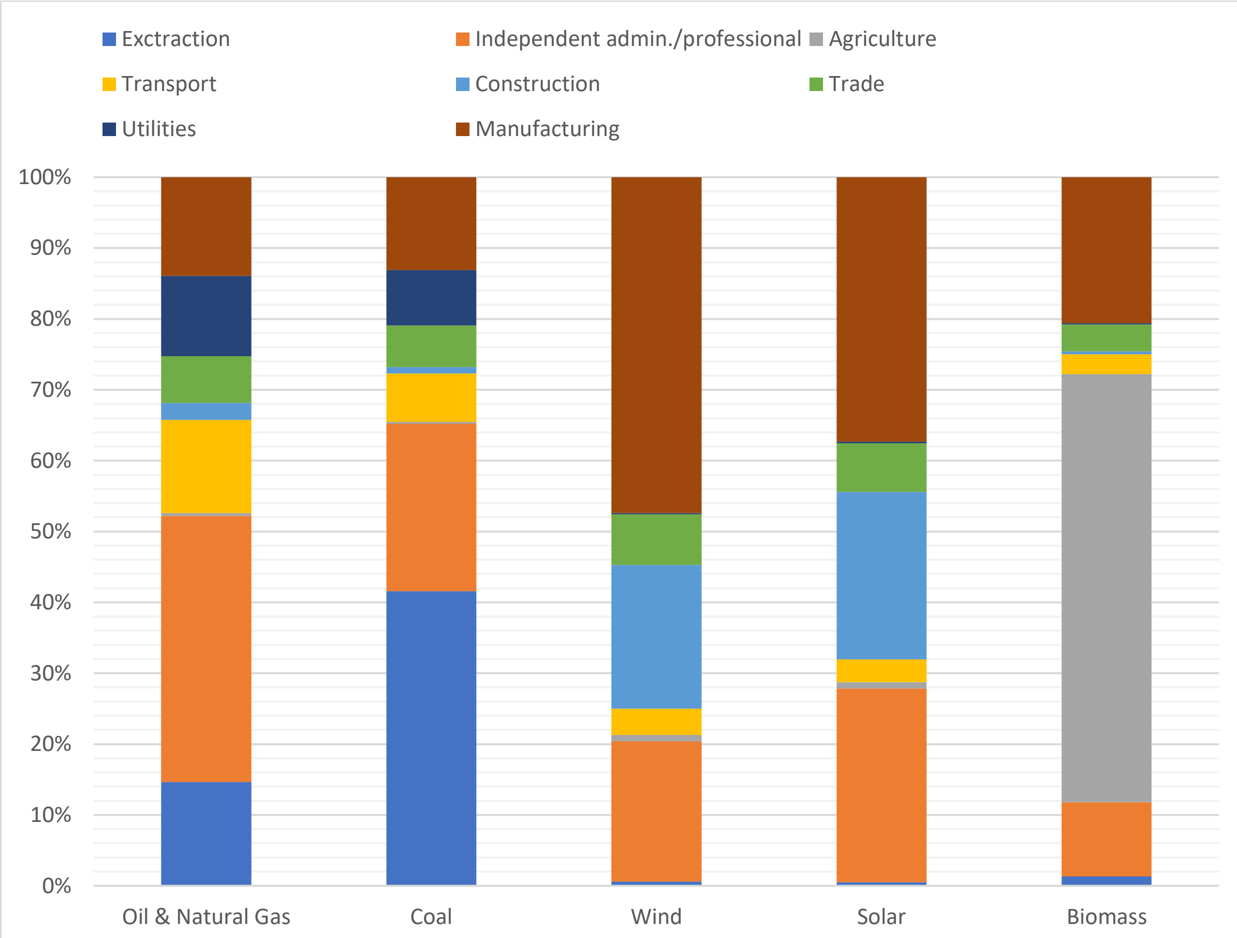
## 3.3 Job Types

Increased labour intensity resulting in positive direct and indirect effects may indicate that renewable technology innovations affect employment through labour productivity. However, renewable energy may have employment implications beyond productivity through a different mix of job types and skill requirements. Job types affect whether jobs are temporary or permanent, and skill requirements relate to the quality and wage levels associated with the jobs. Figure 9 shows the job types by energy technology as found by Pollin et al. (2009).

Fossil fuel jobs are mainly found in extraction with coal having 41.6% of the jobs involved in extraction. By contrast, renewable energy jobs are mainly found in manufacturing with 47.4%, 37.4% and 20.6% respectively for wind, solar and biomass. Manufacturing refers to the creation and servicing of spare parts. Construction is also a main job creator for renewable energy, with 20.3% and 23.7% of jobs for wind and solar found in this category.

All five technologies employ a significant portion of employees in the independent admin./professional category. Renewable energy jobs tend to have higher skill requirements (IRENA, 2011) and may be an indicator of higher quality jobs. A study in Germany found that 40% of the renewable workforce have a university degree, compared to only 10% for the non-renewable workforce (Lehr et al., 2011). The difference in job types and skill requirements may be an indicator of the renewable energy sector creating entirely different jobs as compared to non-renewable energy. As such, renewable energy does not only affect employment through labour productivity but also through the creation of entirely different jobs.

***Figure 9: Job types by energy technology***




*Source: Pollin et al. (2009)'The Economic Benefits of Investing in Clean Energy'*

*Legend: Job compositions of energy technologies by job types.*

## 3.4 Past Research

This section discusses previous research approaches used to analyse the energy employment dynamics. It highlights different methods used and their main potential drawbacks. Moreover, it notes the drawbacks of forecasts and justify the need to do an evaluating study.

In spite of differing scope and approaches to understanding the relationship between renewable energy and employment, much of the previous work has been aimed at forecasting. With regards to forecasting, Lambert & Silva (2011) argues that two main approaches exist.

Firstly, input-output models can be used. Such models allow for the analysis of a shock to one sector on all other sectors and can determine the combined direct, indirect or induced effects. A significant drawback from these models is that they rely on static input coefficients, making them less applicable for dynamics over time. Therefore, they cannot account for economies of scale or real wage changes. Additionally, it assumes homogeneity across and within all sectors which complicates any interpretation made by the model, and the data requirements for input-output models are usually outdated. A good exemplification of this is the study by Caldes et al. (2009), which estimate various economic effects on the Spanish economy from solar energy implementation where only data up to the year 2000 was available.

The second approach are analytical models that examines annual shifts in the data or more sophisticated timeseries modelling. They are more transparent than input-output models and simpler to understand. However, the biggest drawback of such models is that they can usually only be applied to analyse direct effects. Additionally, since the amount of data available is limited, these models often use extensive surveys which may be inherently biased.

Forecasts commonly rely heavily on their assumptions. On top of that, different forecasts have very different assumptions and by extension, there are large variations in employment estimates. Diaz et al. (2008) and Management Information Services (2009) both estimate the direct employment effect of renewable energy deployment in USA up to 2030 under different assumptions and produced vastly different forecasts. Diaz et al. (2008) estimates a direct gross employment effect of 802,000 jobs. This may be compared to Management Information Services that find a net direct effect of 1.15 million jobs in the same time period. Diaz et al. (2008) made the key assumption that 40% of electricity will be renewable by 2038 and that its growth will be linear. By contrast, Management Information Services assume a more aggressive growth in renewable energy which ultimately causes the inflated effect

Although the forecasts vary greatly, the effects in most instances are estimated to be net positive or not statistically significant, depending on the time horizon. However, forecast studies are by definition forward-looking estimates and to our best knowledge, no study has taken a backward-looking stance to estimate the employment effect. The lack of backward-looking studies means that forecasts are difficult to validate and we argue that evaluative studies are required in order to gain better insights into the job creation potential of renewable energy implementation.

# 4 Economic Theory

We examine economic frameworks in order to understand what factors affect employment that will assist us in our empirical approach, by allowing us to isolate the employment effects from our variable of interest. Economic theory tends to focus on labour rather than employment. Even though they are not necessarily equivalent, they are fundamentally similar. Therefore, by examining labour theory we are able to draw similar conclusions with regards to the theoretical drivers of employment.

Firstly, we assess the employment effects through the demand and supply of labour. Thereafter, we examine the Cobb-Douglas production function to understand the important determinants of labour and by extension employment. In light of this relationship, we examine how this can be relevant for innovation changes. Finally, this section establishes the important factors that should be considered when constructing our statistical model.

## 4.1 Labour Demand and Supply

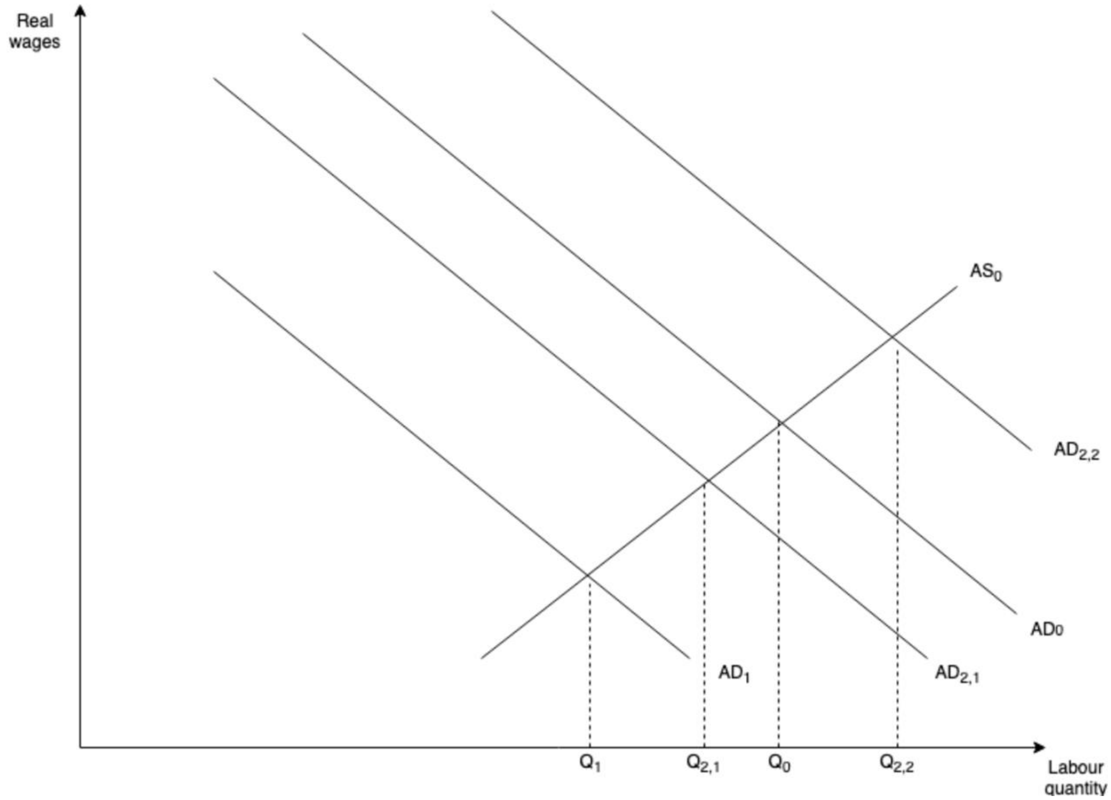
The direct labour market effects may be illustrated by modifying the argument put forward by Bowen (2012). He analyses the effects that emissions limiting policies may have on “green jobs”. To demonstrate the potential effects that these policies may have, he uses a simple neoclassical model of labour demand and supply that can be seen in Figure 10. The Aggregate Demand (AD) curve for labour is a downward sloping function of real wages, and the Aggregate Supply (AS) curve of labour is an upward sloping function of real wages. The AD curve represents how firms decide on the optimal labour demand based on profit maximisation while the AS curve represents the willingness of individuals to participate in the workforce based on real wages.

In Bowen (2012), the labour market is initially in an equilibrium and production is dominated by non-renewable energy sources. Bowen argues that as an economy targets to limit emissions, policies are introduced that affect the profitability of non-renewable energy generation and will cause a downward shift of $AD_0$ to $AD_1$ while the AS curve remains fixed. This results in a lower aggregate labour quantity equilibrium, $Q_1 < Q_0$. However, as renewable energies gain a relative advantage, it will become more profitable which increases the demand for labour and causes a shift from $AD_1$ to $AD_{2,2}$. The magnitude of the shift is partially driven by the labour intensity of the respective technologies. As suggested in Section 3.1, renewable energy may be more labour intensive than conventional non-renewable energy. Conversely, lower relative labour intensity of renewable energy technologies will cause a shift from $AD_1$ to $AD_{2,1}$. Holding total output constant, the relative labour intensity of renewable energy technologies as compared to non-renewable energy will affect whether we observe a net positive or negative employment effect from the shift in the AD curve.

Regardless, Section 3.3 found that different technologies demand different job types and skill requirements that affects the supply of labour. Depending on the industry structure, endowments and labour market institutions of the country, the AS may respond differently and hence affect the net employment effect (Bowen, 2012).

As AD and AS are functions of real wages, real wages is an important factor in determining the level of labour input in the energy sector, on top of relative labour intensities.

***Figure 10: Neoclassical labour market effects***




*Source: Self-made based on Bowen (2012)*

*Legend: Neoclassical labour market diagram to visualise the theoretical effects of the substituting non-renewable energy for renewable energy. Shows dynamics of aggregate demand and aggregate supply of labour based on regulatory changes.*

## 4.2 Cobb-Douglas Production

The Cobb-Douglas production function establishes a link between output, labour, technology and capital stock and may be represented as:

***Equation 1: Cobb-Douglas Production Function***

$$log(Y) \ = log(A) + \propto log(L) + \ \beta log(C)$$

where Y is output, A is a total productivity factor, L is labour, and C is capital stock, and are all non-negative (Cobb & Douglas, 1928). $\propto$ and $\beta$ are returns to scale parameters and are between 0 and 1. Typically, A is associated with technology, aimed at making production more efficient. This may often be done through labour-saving technology development. Considering that we are investigating employment changes, it is the labour-saving technologies that affect employment through improved labour productivity and the lower relative need for labour inputs.

Rearranging to represent labour on the left-hand side:

***Equation 2: Rearranged Cobb-Douglas function***

$$log(L) = \frac{1}{\propto}(\ log(Y) - log(A) - \beta log(C))$$

The Cobb-Douglas production function is a generic production function that can be applied to different industry and products. In the context of the energy sector, labour employed is determined by the amount of energy produced, the capital assets of the sector and the labour-saving technology aimed at making production more efficient. However, given that the introduction of renewable energy is not aimed to be labour-saving, the energy transition effect may not be captured in the Cobb-Douglas production function.

Van Reenen (1997) attempts to identify the effect of a technical change on job creation by utilising the Cobb-Douglas production function to empirically test the relationship. He tests this by using employment instead of labour across 598 firms. The innovation variables are created as counts of the number of innovations introduced per firm and per industry respectively. Additionally, he argues that for employment studies involving the UK, it is conventional to introduce two lags of employment due to adjustment costs in net employment changes.

In Section 2.3.1, we identified renewable energy to be considered a process innovation. Van Reenen (1997) argues that the type of innovation plays a role in determining the subsequent employment effect. Product innovations are thought to typically have a positive effect on employment as a new product will generate new demand, which requires additional labour and employment. In contrast, process innovations are characteristic by their ambiguity. They may aim to make production more efficient, which can be through labour-saving improvements that will lead to a negative effect on labour. However, if production is more efficient through a process innovation, total output is likely to increase and hence have a positive effect on labour. As such, these findings further justify the need to investigate the employment effects of renewable energy deployment.

Based on the economic theories discussed in this section, factors such as output, capital, labour-saving technology and real wages should be considered when studying labour, and by extension employment. As such, these factors will be included in our empirical study when constructing our statistical model in Section 5.1.

# 5 Methodology

In this section, the previously discussed economic framework is transformed into a sound statistical approach for empirically investigating the effect that the energy transition has on energy sector employment. We first introduce the statistical model and the variables necessary to conduct a formal empirical study and then tackle various issues relating to time-series model estimation such as autoregressive processes, stationarity, cointegration and seasonality. Finally, estimation results of the selected model are presented, and additional robustness checks are conducted.

## 5.1 Statistical Model

From Section 4 we know that employment depends on output, capital, labour-saving technology (labour productivity) and real wages. Moreover, it was proposed that in the energy sector, the transition from non-renewable energy to renewable energy sources causes an additional effect as new jobs are introduced. As such, our statistical model adopts each of these factors and may be represented as:

***Equation 3: Statistical Model***

$$\begin{aligned} Employment = {} & Measure\ of\ the\ Energy\ Transition + Output \\ & + Labour\ Saving\ Technology + Real\ Wages + Capital \end{aligned}$$

To estimate this statistical model, our chosen variables are discussed in the following section.

## 5.2 Data

This subsection describes the variables and the corresponding data that will be used in our statistical model including variable selection, data sources and data transformation. Table 2 provides an overview of all variables incorporated in the empirical approach including their description and units of measurements.

### 5.2.1 Dependent Variable: Energy sector employment

This study seeks to investigate the net direct effect of the renewable energy transition on renewable jobs. Therefore, the main dependent variables that we are interested in is the total energy sector employment in the UK. Total energy sector employment includes both jobs created and jobs destroyed through the transition and is as such a good measure of the overall net effect. The jobs created are mainly involved in the installation and manufacturing of renewable energy production while jobs removed are mainly associated with the extraction of non-renewable fossil fuels. For this measure, quarterly data from the Eurostat database has been used. The Eurostat database groups industry NACE codes into Main Industrial Groupings (MIGs) based on their end-use categories. For energy sector employment, the “MIG – Energy” employment statistics have been used for energy sector employment. The “MIG – Energy” category contains:

- B05: Mining of coal and lignite;
- B06: Extraction of crude petroleum and natural gas;
- C19: Manufacture of coke and refined petroleum products;
- D35: Electricity, gas, steam and air conditioning supply;
- E36: Water collection, treatment and supply.

This includes the main aspects we are trying to capture for our dependent variable and thus constitutes a sound variable. Energy sector employment is recorded as an index based on the base-year of 2015. Energy sector employment is defined as the number of persons employed in the energy sector.

To normalise our variable, the logarithm of energy sector employment was computed and named ENERGY_EMP.

### 5.2.2 Independent Variable: Share of renewable energy production

The transition of energy from non-renewable technologies to renewable energy technologies imply that renewable energy production has increased compared to non-renewable energy production. As previously discussed, this results in a replacement effect rather than a complementary production effect. In order to estimate our statistical model, an appropriate measure of the energy transition needs to be identified. A number of potential measures were considered but renewable energy production as a share of total energy production was ultimately chosen.

Renewable energy production as a share of total energy production was selected over raw renewable energy production volumes as it is a good indicator of the energy transition rather than the absolute production level of renewable energy.

Share of renewable energy production has been chosen as the measure of renewable energy intensity over other potential variables such as share of renewable energy consumption and share of renewable energy investment. Firstly, energy production data is readily available and directly associated with energy sector employment. Renewable energy consumption has been used in other studies of the nexus between employment and renewable energy such as Apergis & Salim (2015) but we argue that renewable energy consumption is not a good indicator when considering energy sector employment as it is affected by the international energy trade. Using share of renewable energy consumption would not account for energy sold to and consumed outside the UK and may lead to overestimation of the employment effect. As such, share of renewable energy consumption is not appropriate for our model.

Share of renewable energy investment is an alternative indicator for quantifying the renewable energy transition. It would allow for interesting interpretations from a policy perspective and indicate whether investing in renewable energy would result in a net gain of energy jobs. However, using share of renewable energy investment as an indicator of the energy transition does have its drawbacks. Investments are rarely made with the intention of immediate returns and some renewable energy projects such as hydroelectric dams face long durations between initial investment and final project commissioning. In an evaluative time-series study of renewable energy, which has only become significant in the last 20 years, taking into account such a gap between investment and completion would result in very few reliable observations which would reduce the power of the study. On top of that, renewable energy investment data for the UK is only accessible annually and from 2004 onwards.

Quarterly energy production data has been retrieved from the UK's Department of Business, Energy & Industrial Strategy (BEIS) statistical publication: Indigenous production of primary fuels (ET 1.1). BEIS's energy production data is classified by energy type and we have composed renewable energy production as the sum of 'Bioenergy & waste' and 'Wind, solar & hydro' while non-renewable energy production is composed of 'Coal', 'Petroleum', 'Natural Gas' and 'Nuclear'. Our independent variable RE_SHARE is then constructed as:

***Equation 4***

$$RE\_SHARE = log\left(\frac{Renewable\ energy}{Renewable\ energy\ +\ Non-renewable\ energy}\right)$$

## 5.2.3 Control Variables

Based on the discussions in Section 4 and the statistical model constructed in Section 5.1, indicators for output, capital, labour saving technology and real wages should be used as control variables to isolate the transitionary effect and thereby improve the quality of our model.

### 5.2.3.1 Total energy production

The total amount of energy produced in the UK is used as an indicator of output and is expected to have a positive relationship with energy sector employment as labour is positively correlated with the production of energy. Quarterly energy production data has been retrieved from the UK's Department of Business, Energy & Industrial Strategy (BEIS) statistical publication: Indigenous production of primary fuels (ET 1.1). BEIS's energy production data is classified by energy type and our total energy production variable is the sum of all energy types.

To normalise our variable, the logarithm of total energy production was computed and named TOTAL_PROD.

### 5.2.3.2 Labour productivity

As discussed previously, technology plays a part in the Cobb-Douglas production function and more specifically labour-saving technology is what affects labour inputs. In our estimation model, labour productivity has been chosen as the indicator for labour-saving technology. Technological changes that increase labour productivity will allow the same amount of output to be delivered by lower amounts of labour. As such, increased labour productivity in the energy sector could potentially lead to a decrease in energy sector employment.

To include labour productivity as a control in our model, we have retrieved quarterly labour productivity data for the UK from the Office for National Statistics (ONS)'s dataset: Labour productivity time series. The dataset consists of industry specific estimates of output per hour based on UK Standard Industrial Classification (SIC) 2007 codes. Due to EU legislation, SIC 2007 codes and NACE codes are identical. Labour productivity is defined as output per hour (£ per hour) at current prices.

For the labour productivity control variable to be consistent with our dependent variable, we want to retrieve and use labour productivity data based on the same NACE codes used to construct our dependent variable. We were able to retrieve labour productivity data for the following codes:

- B06: Extraction of crude petroleum and natural gas;
- C19: Manufacture of coke and refined petroleum products;
- D35: Electricity, gas, steam and air conditioning supply.

Unfortunately, data for the other two codes are not available. Nevertheless, we believe that including these productivity indicators in our model will still allow us to control for labour productivity effectively and is the best we can do with the data available.

As labour productivity is mainly a control variable in our study and not a variable of interest, we are not interested in interpreting its coefficient post-regression. As such, we have decided against constructing a labour productivity composite of the three codes that we could retrieve as this would introduce unnecessary complications. Instead we will include all three labour productivity indicators as individual variables in our model.

To normalise our variable, the logarithm of the three labour productivity measures were computed and named PRODUCTIVITY_1, PRODUCTIVITY_2 and PRODUCTIVITY_3 respectively.

#### 5.2.3.3 Real wages

Another factor that can influence employment are real wages. A higher real wage can entice individuals to enter the labour market where they otherwise may not. Being a subset of general employment, energy sector employment may be positively impacted by an increase in real wages.

National wage data was used instead of energy sector specific wages. Industry specific wage data was only available at the 'alphabet' level (SIC 2007) and not the 2-digit level that we require for the variable to be consistent with our dependent variable.

Quarterly wage data for the UK has been retrieved from the ONS' database: Gross weekly earnings of full-time employees (EARN04). The database provides 'median weekly wage of full-time employees' which is a measure of nominal wages and has to be converted to real-terms.

To convert nominal wages to real wages, we adopt the 'Consumer Price Inflation including Owner-Occupiers' Housing Costs' (CPIH) index. The CPIH index is based on the standard 'Consumer Price Index' (CPI) but adjusted to reflect changes in average residential rents. CPIH data for the UK is retrieved from the ONS' database: Consumer price inflation time series (MM23).

The real wage is then calculated as an index by normalising the median weekly wage with the CPIH index as shown in Equation 5.

***Equation 5***

$$WAGES = log\left(\frac{Median\ weekly\ wage}{CPIH}\right)$$

#### 5.2.3.4 Interest rates

As previously discussed, capital is also an important factor in the study of labour. The relative cost at which capital can be employed in the production of energy can directly influence the amount of capital employed in production and due to the substitutability of capital and labour, indirectly influence the amount of labour needed. As such, the cost of capital should be controlled for when investigating energy sector employment and is used as the indicator for capital in our statistical model.

Specifically, interest rates has been chosen as the indicator for the cost of capital as quarterly data is readily available. Quarterly average yields for 10-year UK Government bonds was retrieved from the Bank of England's database (IUQAMNPY). To normalise our variable, the logarithm of the interest rate was computed and named INTEREST.

***Table 2: Data Summary***

| Type | Name | Description | Unit of Measurement |
|---|---|---|---|
| Dependent variable (y) | *ENERGY_EMP* | Energy sector employment | Number of employees (2015 Index) |
| Independent variable (x) | *RE_SHARE* | Share of renewable energy production | Percentage of total production |
| Control variable 1 (z1) | *TOTAL_PROD* | Total energy production | Million tonnes of oil equivalent |
| Control variable 2 (z2) | *PRODUCTIVITY_1* | Labour productivity (B06) | £ per hour of labour |
| Control variable 3 (z3) | *PRODUCTIVITY_2* | Labour productivity (C19) | £ per hour of labour |
| Control variable 4 (z4) | *PRODUCTIVITY_3* | Labour productivity (D35) | £ per hour of labour |
| Control variable 5 (z5) | *WAGES* | Real wages | Mean weekly earnings (price adjusted) |
| Control variable 6 (z6) | *INTEREST* | Interest rates | Percentage (quarterly average) |

## 5.3 Descriptive Statistics

***Table 3: Descriptive Statistics***

| | ENERGY SECTOR EMPLOYMENT | RE SHARE | TOTAL ENERGY PRODUCTION | LABOUR PRODUCTIVITY 1 | LABOUR PRODUCTIVITY 2 | LABOUR PRODUCTIVITY 3 | REAL WAGES | INTEREST RATES |
|---|---|---|---|---|---|---|---|---|
| **Units** | *Number of employees (2015 Index)* | *Percentage of total production* | *Million tonnes of oil equivalent* | *£ per hour of labour* | *£ per hour of labour* | *£ per hour of labour* | *Mean weekly earnings (price adjusted)* | *Percentage (quarterly average)* |
| **Mean** | 87.60 | 0.052 | 48.37 | 694.08 | 129.74 | 81.86 | 4.78 | 3.74 |
| **Standard error** | 1.25 | 0.005 | 1.90 | 27.86 | 7.16 | 2.07 | 0.03 | 0.16 |
| **Median** | 89.80 | 0.030 | 45.42 | 641.71 | 117.46 | 78.59 | 4.84 | 4.28 |
| **Standard deviation** | 11.24 | 0.047 | 17.06 | 250.76 | 64.47 | 18.66 | 0.25 | 1.43 |
| **Sample variance** | 126.25 | 0.002 | 291.04 | 62879.69 | 4155.84 | 348.20 | 0.06 | 2.05 |
| **Kurtosis** | -0.62 | -0.208 | -1.22 | -0.41 | 2.22 | -0.73 | 0.32 | -1.13 |
| **Range** | 41.40 | 0.166 | 56.57 | 1055.03 | 323.98 | 74.84 | 0.98 | 5.21 |
| **Minimum** | 65.10 | 0.008 | 24.40 | 272.72 | 39.91 | 49.40 | 4.17 | 0.84 |
| **Maximum** | 106.50 | 0.174 | 80.98 | 1327.75 | 363.90 | 124.25 | 5.16 | 6.04 |
| **Count** | 81.00 | 81.000 | 81.00 | 81.00 | 81.00 | 81.00 | 81.00 | 81.00 |

*Legend: Summary table of descriptive statistics of all variables used in the main estimation model. Data used is for the period Q1 1998 to Q1 2018.*

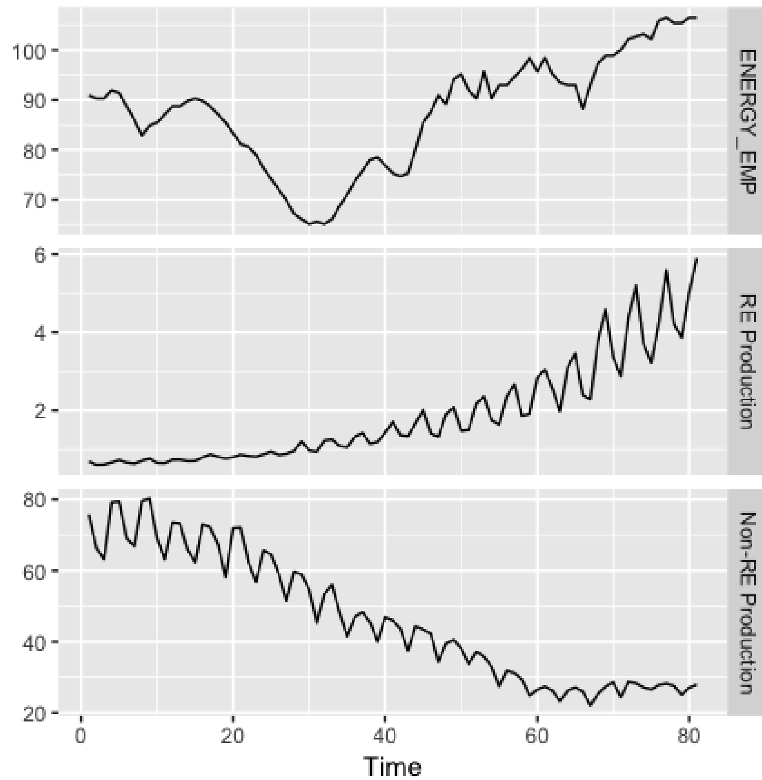
### 5.3.1 Dependent Variable: Energy sector employment

Figure 11 shows a plot of energy sector employment as well as the output from renewable and non-renewable sources over the time-period of this study. The top panel shows energy sector employment, from which it can be seen that energy sector employment experiences a large amount of variation over the total sample period. Initially, we observe a relatively large decrease between 1998 - 2005 that bottoms out at 65.1 in Q2 of 2005. The decrease in energy sector employment from 1998 to 2005 can be attributed to the decreasing trend in total energy production in the UK, in particular non-renewable energy. Coal and gas production peaked in 1999 and 2000, as the UK benefitted from the largest offshore drilling region in the world in the North Sea (Planete Energies, 2015).

Following this period, there has been a general upward trend, with the exceptions of the 2008 financial crisis and a period in 2014. The 2008 dip due to the financial crisis is unsurprising due to a general increase in unemployment in this period across the entire economy. It is this general increase in employment following 2005 that serves as a further motivation for our study. The second panel in Figure 11 shows energy production from renewable sources. It can be observed that from 2005, renewable energy production starts gaining traction. Intriguingly, this increase in the production of renewable energy from 2005 coincide with the turnaround in energy sector employment.

Energy sector employment peaks in our two final observations, with a 2015 index value of 106.5. As renewable energy production continues to increase, it is reasonable to expect energy sector employment to continue increasing.

***Figure 11: Dependent variable & energy production***



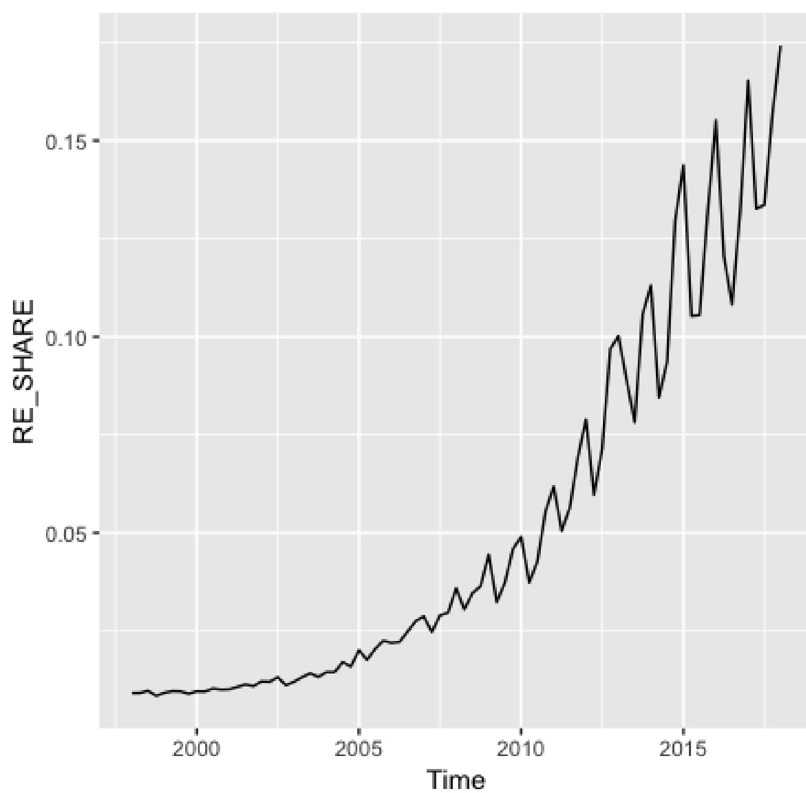

*Legend: Plots of the Energy Employment, Total Renewable Energy Production and Total Non-Renewable Energy Production series for the periods Q1 1998 to Q1 2018.*

## 5.3.2 Independent Variable: Share of renewable energy production

As seen in Figure 11, the relative youth of renewable energy in the UK energy mix means that we can observe a small share of renewable energy production in the initial years of our study. The share of renewable energy production ranges between 0.91% and 17.43% within the sample period. Figure 12 shows the share over time which is generally an upward trend with the lowest share (0.91%) observed in the first time-period and the highest share (17.43%) at the last observation.

As previously argued, it can be seen that the share is relatively constant in the initial years. From around 2005 onwards, when renewable energy share passes the 2% mark, more variation is introduced. A clear point at which the share of renewable energy production picks up is following the introduction of the Climate Change Act in 2008. The beginning of 2009 introduces a period in which the share of renewable energy production grows exponentially. On top of that, the data begins to exhibit clear seasonality. The inherent quarterly seasonality of renewable energy sources, and general energy demand means that variation increases. Wind turbines generate larger amounts of energy during autumn and winter months when it is windier and solar PV generates more energy during summer when there are more hours of sunlight. The shift towards renewable energy alternatives means that seasonality will become more apparent.

***Figure 12: Renewable energy share of total energy production***




*Legend: 81 observations over the periods Q1 1998 to Q1 2018*

### 5.3.3 Control Variables

Table 3 displays the key descriptive statistics for all the variables in our study. Starting with the first control variable, total energy production is shown to have a mean and median of 48.37 and 45.42 respectively. It ranges from a minimum of 24.4 to a maximum of 80.98 million tonnes of oil equivalent, indicating a relatively high standard deviation and sample variance of 17.06 and 291.04.

The following three labour productivity measures show large differences in their descriptive statistics. The first productivity measure (extraction of crude petroleum and natural gas) exhibits the largest mean and median compared to the other productivity measures, with values of 694.08 and 641.71. Along with the second productivity measure (manufacturing of coke, and refined petroleum products), they exhibit large variation, with standard deviations relatively close to their mean and median values. The last productivity measure (electricity, gas, steam and air conditioning supply) is far more constant, with a lower standard deviation relative to the mean and median. It is also far lower in its range, between 49.4 and 124.25.

Real wages possess a relatively small standard deviation of 0.25 compared to its mean of 4.78. This suggests that it has not changed much over our sample period. This is also evident as it only ranges between 4.17 and 5.16.

The final control variable, 10-year government bond yields, holds a mean and median of 3.74 and 4.28 respectively. This variable shows large variation with a standard deviation of 1.43 with values ranging between 0.84 and 6.04.

In general, we observe negative kurtosis for all variables other than real wages and labour productivity 2. This suggests that we are unlikely to encounter many outliers which would skew our results.

The standard errors of our variables indicate that our sample observations are close to the true population observations. RE share has the largest standard error compared to its mean, which is unsurprising given its nature as a ratio.

## 5.4 Model Specification

After specifying the statistical model and identifying the appropriate indicators to be used in the model, we would like to address any relevant model specification issues. Firstly, it is unlikely that our dependent variable, energy sector employment, is static and a dynamic model specification may be necessary to accurately model it. Additionally, this section addresses common issues with time-series data such as stationarity, cointegration and seasonality to ensure that our estimation model is well-specified.

### 5.4.1 Autoregressive Distributed Lag (ARDL) Approach

Van Reelen (1997) has argued that there is a dynamic relationship between innovations and employment. In our case, the move from non-renewable energy to renewable energy technologies may have a dynamic effect on employment. It is not unreasonable to assume that our independent variable of interest, RE_SHARE, may therefore hold a dynamic relationship with our dependent variable, ENERGY_EMP. Changes in RE_SHARE is likely to affect employment contemporaneously as well as in future periods due to employment contracts. Furthermore, due to rigidities in employment markets, it is also reasonable to assume that ENERGY_EMP is affected by its own past, as also suggested by Van Reelen (1997). Hence, the ARDL approach offers an appropriate single equation solution to model this relationship.

The general ARDL model takes the following form:

***Equation 6***

$$y_t = a_0 + A(L)y_{t-1} + C(L)x_t + \varepsilon_t$$

A(L) and C(L) are polynomials in the lag operator for our dependent and independent variables respectively. Therefore, the main aim is to estimate the parameters A(L) and C(L), in a parsimonious manner. The polynomial C(L) is of particular interest to us, as it represents how a change in $x_t$ affects the time path of $y_t$. In other words, how many periods, a change in $x_t$ affects $y_t$ directly. Conversely, the A(L) polynomial represents the decay in changes to our dependent variable.

To estimate an ARDL, two central assumptions should be satisfied. Firstly, it is crucial that all variables included are stationary processes with white noise errors. This is dealt with in Section 5.4.2 and is satisfied. Secondly, it is assumed that $x_t$ is exogenous to $y_t$ in order to be an appropriate explanatory variable. This means that the innovations of $y_t$ do not affect $x_t$, as they are not simultaneously determined. Additionally, the $\varepsilon_t$ error term of the model should be normally distributed and not serially correlated for the ARDL model to be considered well-specified.

### 5.4.1.1 Exogeneity of Independent Variable

We argue that our independent variable, RE_SHARE is exogenous to the dependent variable, ENERGY_EMP. Endogeneity exists if RE_SHARE is determined by ENERGY_EMP but we argue that the share of renewable energy production is not determined by number of people working in the sector. The share of renewable energy production in the UK is mainly determined by the factors discussed in Section 2.1 and not the availability of its inputs.

As such, we can conclude that our dependent variable, RE_SHARE, at least is weakly exogenous and the ARDL assumptions are satisfied.

## 5.4.2 Stationarity

To satisfy the first assumption of the ARDL approach, we need to ensure stationarity across all variables. A stationary process is a stochastic process whose distribution does not change over time. Not only does using non-stationarity series not satisfy the assumptions of the ARDL modelling approach but can also lead to cointegration relationships across variables (discussed further in Section 5.4.5).

As we are conducting a time-series study, it is likely that the variables in our study are originally non-stationary (dependent on time). Therefore, the following section tests and conducts the necessary transformations to ensure stationarity of our variables. To test for stationarity, both a Kwiatkowski–Phillips–Schmidt–Shin (KPSS) and an Augmented Dickey Fuller (ADF) test have been employed. The KPSS test is a Lagrange-multiplier (LM) test of stationarity for time series with a null hypothesis of stationarity and an alternative hypothesis of non-stationarity (Kwiatkowski et al., 1992). The ADF test is a unit-root test for stationarity with a null hypothesis that a unit-root is present and as such the time series is non-stationary (Said & Dickey, 1984).

By using two distinct tests, we can reasonably conclude on the stationarity of the variables. An overview of the respective test statistics and methods of dealing with non-stationarity are summarised in Table 4.

#### 5.4.2.1 Energy sector employment

The KPSS test on ENERGY_EMP produced a test-statistic of 0.9375 which is higher than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can reject the null hypothesis of stationarity at the 1% significance level.

After observing the data, we initially conducted the ADF test with the inclusion of a drift and trend term and found that neither of them was significant. We removed the drift and trend terms and conducted the ADF test again. The ADF test produced a test-statistic of 0.5184 which is lower in absolute magnitudes than the critical values at all the standard significance levels (10%: -3.15, 5%: -3.45, 1%: -4.04). As such, we fail to reject the null hypothesis of non-stationarity at all standard significance level. As both the KPSS and ADF test suggest non-stationarity, we take the necessary steps to make ENERGY_EMP stationary.

As the drift and trend terms of the initial ADF test were not significant, is it unlikely that ENERGY_EMP is trend stationary and the detrending approach cannot be used to address non-stationarity. The alternative approach to stationarising a time series is through first-differencing provided the series is integrated of order 1 and higher orders of differencing if the series is integrated of higher orders.

Upon first differencing, we tested the transformed ENERGY_EMP for stationarity by applying the KPSS test and ADF test again. The KPSS test produced a test-statistic of 0.3006 which is lower than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739), and we therefore fail to reject the null hypothesis of stationarity. The ADF test produced a test-statistic of -4.3397 which is lower than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels and conclude that the first differenced variable is stationary after conducting both tests.

#### 5.4.2.2 Share of renewable energy production

When applying the KPSS test on RE_SHARE, the produced test-statistic of 2.12 is higher than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can reject the null hypothesis of stationarity at the 1% significance level.

We conducted the ADF test with the inclusion of a drift and trend term and found that the test-statistics for the drift and trend terms were highly significant even at the 1% significance level. On top of that, the test-statistic of the lagged RE_SHARE term was -5.2279 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -3.15, 5%: -3.45, 1%: -4.04). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels when we include the drift and trend terms. The combination of non-stationarity indicated by KPSS, and stationarity when including drift and trend terms in ADF, indicates that RE_SHARE is trend stationary (i.e. a stationary process when its linear trend is removed).

After establishing that RE_SHARE is a trend stationary process, the appropriate way to transform and stationarise RE_SHARE is to detrend it. We detrended RE_SHARE and then once again tested it for stationarity by conducting the KPSS and ADF test. The KPSS test produced a test-statistic of 0.2868 which is lower than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we cannot reject the null hypothesis of stationarity. The ADF test without the drift and trend term produced a test-statistic of -5.2426 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels and conclude that RE_SHARE is now a stationary process.

Even though RE_SHARE is stationary after detrending, we would like to further transform RE_SHARE so that its coefficient can be better interpreted post-regressions. We transform RE_SHARE by first-differencing it so that it is consistent with our dependent variable, ENERGY_EMP, and we can interpret their coefficients 'one-for-one'. As the process was already stationary prior to taking first difference, it can be assumed to remain stationary.

#### 5.4.2.3 Control variable: Total energy production

The KPSS test when applied to total energy production produced a test-statistic of 2.01412 which is higher than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can reject the null hypothesis of stationarity at the 1% significance level.

Similar to before, ADF test was initially conducted with the inclusion of a drift and trend term. Again, we found the test-statistics for the drift and trend terms to be highly significant at the 1% significance level which points towards TOTAL_PROD being trend stationary. On top of that, the test-statistic of the lagged TOTAL_PROD term was -4.3466 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -3.15, 5%: -3.45, 1%: -4.04). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels when we include the drift and trend.

We detrended TOTAL_PROD and tested it for stationarity by conducting the KPSS and ADF tests again. The KPSS test produced a test-statistic of 0.2317 which is lower than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we cannot reject the null hypothesis of stationarity and conclude that TOTAL_PROD is now stationary. The ADF test without the drift and trend term produced a test-statistic of -4.4255 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels and conclude that the transformed TOTAL_PROD variable is now stationary.

### 5.4.2.4 Control variable: Labour productivity 1

The KPSS test produced a test-statistic of 0.3973 which is higher than the critical values at the 10% significance level but lower than the critical values at the 5% and 1% significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can only reject the null hypothesis at the 10% significance level. We argue that the result of this test is inconclusive and justifies the need for another stationarity test.

Similar to before, we initially conducted the ADF test with the inclusion of a drift and trend term and found that neither of them was significant. We removed the drift and trend terms and conducted the ADF test again. The ADF test produced a test-statistic of 0.4249 which is lower in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we cannot reject the null hypothesis of non-stationarity at all standard significance levels. We therefore conclude the variable is non-stationary.

Given the lack of significance in the drift and trend term in the ADF test, the appropriate method of making PRODUCTIVITY_1 stationary is to take the first difference. The transformed PRODUCTIVITY_1 is tested for stationarity by conducting the KPSS and ADF tests again. The KPSS test produced a test-statistic of 0.0848 which is lower than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we cannot reject the null hypothesis of stationarity. The ADF test produced a test-statistic of -6.2201 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels and conclude that PRODUCTIVITY_1 is now stationary.

#### 5.4.2.5 Control variable: Labour productivity 2

The KPSS test produced a test-statistic of 0.8719 which is higher than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can reject the null hypothesis of stationarity at the 1% significance level.

Again, we initially conducted the ADF test with the inclusion of a drift and trend term and found that neither of them was significant. We removed the drift and trend terms and conducted the ADF test again. The ADF test produced a test-statistic of -0.0073 which is lower in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we cannot reject the null hypothesis of non-stationarity at all standard significance levels and conclude that PRODUCTIVITY_2 non-stationarity.

To make PRODUCTIVITY_2 stationary, PRODUCTIVITY_2 was first differenced. The transformed PRODUCTIVITY_2 is tested for stationarity by conducting the KPSS and ADF tests again. The KPSS test produced a test-statistic of 0.0408 which is lower than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we cannot reject the null hypothesis of stationarity and conclude that PRODUCTIVITY_2 is now stationary. The ADF test produced a test-statistic of -5.3221 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels and conclude that PRODUCTIVITY_2 is now stationary.

### 5.4.2.6 Control variable: Labour productivity 3

The KPSS test produced a test-statistic of 1.1557 which is higher than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can reject the null hypothesis of stationarity at the 1% significance level and conclude that the PRODUCTIVITY_3 variable is non-stationary.

Similar to before, we initially conducted the ADF test with the inclusion of a drift and trend term and found that neither of them was significant. We removed the drift and trend terms and conducted the ADF test again. The ADF test produced a test-statistic of 0.7128 which is lower in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we cannot reject the null hypothesis of non-stationarity at all standard significance levels and conclude that it is non-stationary.

To make PRODUCTIVITY_3 stationary, PRODUCTIVITY_3 was first differenced. The KPSS test produced a test-statistic of 0.0404 which is lower than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we cannot reject the null hypothesis of stationarity. The ADF test produced a test-statistic of -4.9089 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels and conclude that PRODUCTIVITY_3 is now stationary.

### 5.4.2.7 Control variable: Real wages

The KPSS test produced a test-statistic of 1.1091 which is higher than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can reject the null hypothesis of stationarity at the 1% significance level and conclude that the WAGES variable is non-stationary.

Similar to before, we initially conducted the ADF test with the inclusion of a drift and trend term and found that neither of them was significant. We removed the drift and trend terms and conducted the ADF test again. The ADF test produced a test-statistic of 1.7885 which is higher in absolute magnitude than the critical values at the 10% significance levels but lower than the critical values at the 5% and 1% significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can only reject the null hypothesis at the 10% significance level. We argue that the result of this test is inconclusive but as the KPSS test above has indicated that WAGES is non-stationary, transformation of WAGES is necessary to make it stationary.

To make WAGES stationary, WAGES was first differenced. The transformed WAGES is tested for stationarity by conducting the KPSS and ADF tests again. The KPSS test produced a test-statistic of 0.6533 which is lower than the critical value at the 1% significance level but higher than the critical values at the 10% and 5% significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can reject the null hypothesis of stationarity at the 5% significance level but not the 1% significance level. We argue that the result of this test is inconclusive and justifies the need for another stationarity test. The ADF test produced a test-statistic of -7.1877 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels. Given that KPSS test concluded that WAGES was stationary at the 5% significance level and the ADF test indicated stationarity, we can conlude that WAGES is now stationary.

#### 5.4.2.8 Control variable: Interest rates

The KPSS test produced a test-statistic of 1.7632 which is higher than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we can reject the null hypothesis of stationarity at the 1% significance level and conclude that the INTEREST variable is non-stationary.

Similar to before, we initially conducted the ADF test with the inclusion of a drift and trend term and found that neither of them was significant. We removed the drift and trend terms and conducted the ADF test again. The ADF test produced a test-statistic of -1.4449 which is lower in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we cannot reject the null hypothesis of non-stationarity at all standard significance levels.

To make INTEREST stationary, INTEREST was first differenced. The transformed INTEREST is then test for stationarity by conducting the KPSS and ADF tests again. The KPSS test produced a test-statistic of 0.0642 which is lower than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we cannot reject the null hypothesis of stationarity. The ADF test produced a test-statistic of -6.5503 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels and conclude that INTEREST is now stationary.

***Table 4: Stationarity Overview***

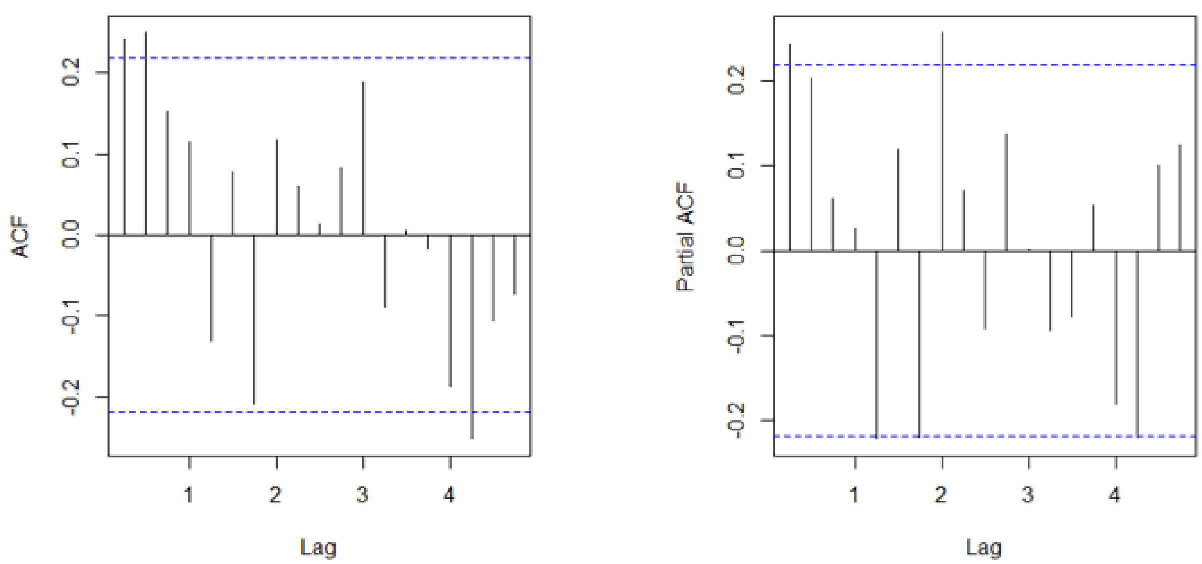
| Variable | Transformation | Pre-transformation KPSS (Null of stationarity) | Pre-transformation ADF (Null of non-stationarity) | Post-transformation KPSS (Null of stationarity) | Post-transformation ADF (Null of non-stationarity) |
|---|---|---|---|---|---|
| *ENERGY_EMP* | First Difference | 0.9375*** | 0.5184 | 0.3006 | -4.3397*** |
| *RE_SHARE* | Detrend | 2.12*** | -5.2279*** | 0.2868 | -5.2426*** |
| *TOTAL_PROD* | Detrend | 2.01412*** | -4.3466*** | 0.2317 | -4.4255*** |
| *PRODUCTIVITY_1* | First Difference | 0.3973* | 0.4249 | 0.0848 | -6.2201*** |
| *PRODUCTIVITY_2* | First Difference | 0.8719*** | -0.0073 | 0.0408 | -5.3221*** |
| *PRODUCTIVITY_3* | First Difference | 1.1557*** | 0.7128 | 0.0404 | -4.9089*** |
| *WAGES* | First Difference | 1.1091*** | 1.7885 | 0.6533** | -7.1877*** |
| *INTEREST* | First Difference | 1.7632*** | -1.4449 | 0.0642 | -6.5503*** |

*Null rejected at significant levels: *10% level, **5% level, ***1% level*

### 5.4.3 Autoregressive (AR) Process

To estimate the order of the A(L) polynomial in Equation 6, we need to establish the order of the AR(p) process that ENERGY_EMP follows. To evaluate ENERGY_EMP, plots of the ACF and PACF were observed.

***Figure 13: ACF and PACF - ENERGY_EMP***




*Blue lines: 5% significance-level*

Figure 13 shows the ACF and PACF of the stationary dependent variable. When a variable is an AR(p) process, its ACF plot will show an exponential decay while the PACF plot will show p significant spikes. The number of significant spikes in the PACF provides an indication of the order of the AR(p) process that ENERGY_EMP follows and the order of the A(L) polynomial to be included in the ARDL model. Based on Figure 13, no clear pattern may be observed. Therefore, we cannot determine the order of its AR(p) through visual inspection.

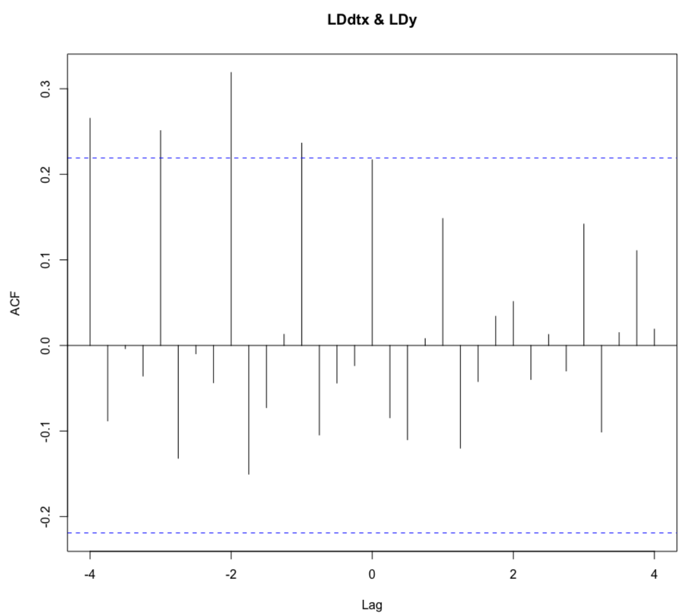
An alternative approach to determining the optimal order of the AR process of ENERGY_EMP is to compare across different options, using AIC and BIC. We therefore estimated six alternative AR processes, including lags between zero and five. When comparing for AIC, an AR(2) process performs the best. By contrast, when comparing using BIC, an AR(0) appears optimal by a narrow margin.

As these techniques give us inconsistent results, we will implement a model that allows us to account for the persistent nature of ENERGY_EMP. Further, we will check for the appropriate lag length of ENERGY_EMP to include based on the information criterions.

### 5.4.4 Cross-correlogram

In order to investigate the correlation between the stationary dependent and independent variables, a cross-correlogram can be applied, as depicted in Figure 14. The cross-correlogram displays the cross-correlations between our dependent variable, and the lags and leads of the independent variable. In doing so, we are able to observe the potential candidates for the C(L) function in the ARDL. From Figure 14, we can interpret that every forth lag of RE_SHARE is correlated with ENERGY_EMP.

***Figure 14: Cross-correlogram of lagged and lead RE_SHARE on ENERGY_EMP***




*Blue lines: 5% significance-level*

A potential explanation for why we only observe a single spike per year may be due to the difference in seasonality between our dependent and independent variable. As previously seen, our independent variable exhibits a seasonal process. As such, the significant lags of RE_SHARE (t-4, t-8, t-12, etc.) are affecting ENERGY_EMP through the seasonal AR process of the independent variable RE_SHARE. This implies that including more than four lags of RE_SHARE would be overinclusion and will make the contemporaneous RE_SHARE estimator downward biased. As such, we should not include lags of more than four periods for RE_SHARE.

## 5.4.5 Cointegration

Both of our variables of interest are initially non-stationary but after testing, we concluded that ENERGY_EMP and RE_SHARE are both stationary processes post transformation.

Cointegration exists when the residual of regressing a non-stationary variable on another non-stationary variable is stationary (Engle & Granger, 1987). This indicates that the two variables move together over time and there may be a long-run relationship between the two variables. It is possible that a cointegrating relationship may exist between two initially non-stationary processes, ENERGY_EMP and RE_SHARE. If so, regressing our initial ENERGY_EMP on our initial RE_SHARE will lead to stationary residuals. If variables are cointegrated and this is not accounted for through an error correction model, the resulting estimates may be biased (Engle & Granger, 1987).

### 5.4.5.1 Engle-Granger two-step procedure

To test for a cointegrating relationship between ENERGY_EMP and RE_SHARE, the Engle-Granger two-step procedure can be applied (Engle & Granger, 1987). In the first step, we regress our initial non-stationary ENERGY_EMP against our initial non-stationary RE_SHARE and save the residuals. Next, we conduct an ADF test for stationarity on the saved residuals. If the residuals are stationary, we can conclude that there is a cointegrating relationship between ENERGY_EMP and RE_SHARE. The ADF test gives us a test-statistic of -1.6729 which is lower in absolute magnitude than the critical values at the 5% significance level (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, at the 5% significance level, we are unable to reject the null hypothesis of non-stationarity of the residuals. Therefore, we may conclude that residuals are not stationary and that ENERGY_EMP and RE_SHARE are not cointegrated.

#### 5.4.5.2 ARDL Bounds testing approach

By using the Engle-Granger test we found the lack of a cointegrating relationship between our dependent and independent variable of interest. Nevertheless, a cointegrating relationship may exist across all the variables we would like to include in our model (dependent variable, independent variable and control variables).

To test for cointegration across all our variables, we have used the ARDL bounds testing approach (Pesaran et al., 2001). The bounds test is testing for the absence of a long-run equilibrium relationship between the variables by conducting a joint F-test on Equation 7 with a null hypothesis of $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta_7 = \theta_8 = 0$. Rejection of the null hypothesis implies the potential existence of a long-run cointegrating relationship. The critical values for the bounds test are taken from Pesaran et al. (2001) where the lower bound values assume that the variables are purely I(0) while the upper bound values assume that the variables are purely I(1). If the F-statistic falls outside the bounds, we are able to conclude on the cointegrating relationship and if the F-statistic falls within the bounds, inference would be inconclusive.

We have chosen the ARDL bounds testing approach over the Johansen cointegration testing approach (Johansen, 1988) as it is more flexible. The ARDL bounds testing approach allows variables to be stationary at different levels (I (0) or I (1)) while the Johansen test requires the variables to all have the same order of integration. In Section 5.4.2 we found that RE_SHARE and TOTAL_PROD are trend stationary which means that they are integrated at order 0, whilst the remaining variables are integrated at order 1. Therefore, the ARDL bounds test is more suited for our modelling approach. On top of that, the Johansen test suffers from low power when the sample size is not large.

To perform the bounds test, we first run the following model:

***Equation 7***

$$\begin{aligned}\Delta y_t = \ & \beta_0 + \beta_1 \Delta y_{t-1} + \beta_1 \Delta y_{t-2} + \beta_2 \Delta x_{t-1} + \beta_3 \Delta z1_{t-1} + \beta_4 \Delta z2_{t-1} + \beta_5 \Delta z3_{t-1} + \beta_6 \Delta z4_{t-1} \\ & + \beta_7 \Delta z5_{t-1} + \beta_8 \Delta z6_{t-1} + \theta_1 y_{t-1} + \theta_2 x_{t-1} + \theta_3 z1_{t-1} + \theta_4 z2_{t-1} + \theta_5 z3_{t-1} \\ & + \theta_6 z4_{t-1} + \theta_7 z5_{t-1} + \theta_8 z6_{t-1} + \epsilon_t\end{aligned}$$

$y = ENERGY\_EMP$ (Pre-transformation)

$x = RE\_SHARE$ (Pre-transformation)

$z1 = TOTAL\_PROD$ (Pre-transformation)

$z2 = PRODUCTIVITY_1$ (Pre-transformation)

$z3 = PRODUCTIVITY_2$ (Pre-transformation)

$z4 = PRODUCTIVITY_3$ (Pre-transformation)

$z5 = WAGES$ (Pre-transformation)

$z6 = INTEREST$ (Pre-transformation)

When we run the model in Equation 7 and conduct an F-test on the coefficients of the lagged-level variables, we obtain a F-statistic of 1.939. Figure 15 reflects the critical values based on Table CI(iii) in Pesaran et al. (2001). The critical values for the lower bound when using eight variables are 1.95 at the 10% significance level, 2.22 at the 5% significant level and 2.48 at the 1% significance level. The critical values for the upper bound are 3.06 at the 10% level, 3.39 at the 5% significance level and 4.10 at the 1% significance level. With a F-statistic of 1.939 which is lower than all the lower bound critical values, we can conclude that there is no significant cointegrating relationship across our variables.

***Figure 15: Bounds test critical values***

| | 0.100 | | 0.050 | | 0.025 | | 0.010 | | Mean | | Variance | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $k$ | $I(0)$ | $I(1)$ | $I(0)$ | $I(1)$ | $I(0)$ | $I(1)$ | $I(0)$ | $I(1)$ | $I(0)$ | $I(1)$ | $I(0)$ | $I(1)$ |
| 0 | 6.58 | 6.58 | 8.21 | 8.21 | 9.80 | 9.80 | 11.79 | 11.79 | 3.05 | 3.05 | 7.07 | 7.07 |
| 1 | 4.04 | 4.78 | 4.94 | 5.73 | 5.77 | 6.68 | 6.84 | 7.84 | 2.03 | 2.52 | 2.28 | 2.89 |
| 2 | 3.17 | 4.14 | 3.79 | 4.85 | 4.41 | 5.52 | 5.15 | 6.36 | 1.69 | 2.35 | 1.23 | 1.77 |
| 3 | 2.72 | 3.77 | 3.23 | 4.35 | 3.69 | 4.89 | 4.29 | 5.61 | 1.51 | 2.26 | 0.82 | 1.27 |
| 4 | 2.45 | 3.52 | 2.86 | 4.01 | 3.25 | 4.49 | 3.74 | 5.06 | 1.41 | 2.21 | 0.60 | 0.98 |
| 5 | 2.26 | 3.35 | 2.62 | 3.79 | 2.96 | 4.18 | 3.41 | 4.68 | 1.34 | 2.17 | 0.48 | 0.79 |
| 6 | 2.12 | 3.23 | 2.45 | 3.61 | 2.75 | 3.99 | 3.15 | 4.43 | 1.29 | 2.14 | 0.39 | 0.66 |
| 7 | 2.03 | 3.13 | 2.32 | 3.50 | 2.60 | 3.84 | 2.96 | 4.26 | 1.26 | 2.13 | 0.33 | 0.58 |
| 8 | 1.95 | 3.06 | 2.22 | 3.39 | 2.48 | 3.70 | 2.79 | 4.10 | 1.23 | 2.12 | 0.29 | 0.51 |
| 9 | 1.88 | 2.99 | 2.14 | 3.30 | 2.37 | 3.60 | 2.65 | 3.97 | 1.21 | 2.10 | 0.25 | 0.45 |
| 10 | 1.83 | 2.94 | 2.06 | 3.24 | 2.28 | 3.50 | 2.54 | 3.86 | 1.19 | 2.09 | 0.23 | 0.41 |

*Source: Pesaran et al. (2001) 'Bounds testing approaches to the analysis of level relationships'*

## 5.4.6 Seasonality

As previously observed, it is possible that there exists seasonality in our data due to quarterly data being used. Considering that our area of study involves energy production, and especially renewable energy production that may be affected by weather patterns, it is necessary to account for such seasonal patterns in our model. We apply two different techniques for controlling for seasonality.

#### 5.4.6.1 Seasonal lag term

The first method to control for seasonality in our model is to include a seasonal lag term of $y_{t-4}$ to the right-hand side of the equation. The coefficient for $y_{t-4}$ will capture any annual persistence of the dependent variable. The benefits of this method for accounting for seasonality is that it only adds one additional term into our model rather than three additional terms by using seasonal dummies and as such results in a more parsimonious model. However, inclusion of such a seasonal lag term may complicate interpretations for our other lagged independent variables.

#### 5.4.6.2 Seasonal dummies

The more conventional approach to controlling for seasonality is the inclusion of seasonal dummies; one dummy for each quarter except the baseline Q1. The seasonal dummies will be added to our model and tested for joint-significance to test for seasonality in our model. This method is relatively straightforward and easy to implement. However, it will require three additional dummy variables to be added to the model and may lead to the model being less parsimonious. Nevertheless, we apply both techniques separately to check and control for seasonality in our model.

## 5.5 Initial Regressions

### 5.5.1 Accounting for Possible Seasonality

As explained in Section 5.4.6, we will try to account for seasonality using two distinct approaches. We will start out by including $y_{t-4}$ into a simple regression of $y_t$ on $x_t$ to investigate the potential presence of seasonality in our dependent variable. Subsequently, we use the seasonal dummies approach.

***Equation 8***

$$y_t = \beta_0 + \beta_1 y_{t-4} + \beta_2 x_t$$

By implementing the model above, we found $\mathrm{y}_{\mathrm{t}-4}$ to be not statistically significant at all standard significance levels (1%, 5% and 10%) with a P-value of 0.4782. This suggests it is unlikely that our dependent variable, energy sector employment, possesses seasonal properties.

***Equation 9***

$$y_t = \beta_0 + \beta_1 x_t + Seasonal\ Dummies$$

We then included seasonal dummies instead of the $y_{t-4}$ term and found them to be neither individually, nor jointly-significant with an F-statistic of 0.5342 and P-value of 0.6602. This suggests that there is no significant seasonality in the dependent variable that we can identify in our model and we may not need to be overly concerned about it. Nevertheless, we will continue to include the seasonal dummies in the model and conduct further tests when our dynamic specification and control variables have been included.

## 5.5.2 Dynamic Specification: Determining Number of Lags

As previously stated, the aim of the ARDL model specification is to estimate the optimal A(L) and C(L) polynomials. The findings in Section 5.4.3 suggested an A(L) polynomial up to order two, and in Section 5.4.4, the cross-correlogram suggests that lags of up to four periods should be considered for the C(L) polynomial. As such, a good starting point for determining the dynamic specification of our model is to include two lags of the dependent and four lags of the independent variable as shown in Equation 10.

***Equation 10***

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 x_t + \beta_4 x_{t-1} + \beta_5 x_{t-2} + \beta_6 x_{t-3} + \beta_7 x_{t-4} + Seasonal\ Dummies$$

The model was estimated, and a step-wise elimination method was adopted. The stepwise elimination method was conducted by removing statistically insignificant lagged *x* variables and comparing the BIC of the models. Thus, we started by removing $x_{t-4}$. If the coefficient of a lagged *x* term is not significant and removing it improves the BIC of the model, we deem including that term unnecessary and remove it permanently. We continue this step-wise elimination for all our lagged *x* terms and find that all the lagged *x* terms are not significant and that including them makes our model perform worst. As such, we have excluded the lagged *x* terms and will only keep contemporaneous x in our model.

After deciding to only keep contemporaneous $x$ in our model, we performed the same stepwise elimination to lagged $y$ variables. We find that when two lags of $y$ are included ($\mathrm{y}_{\mathrm{t-1}}$ and $\mathrm{y}_{\mathrm{t-2}}$), both of the lagged terms are statistically significant at the 10% significance level. To ensure that this model is statistically sound, the residuals of the estimates were tested for serial correlation using the Breusch-Godfrey test for serial correlation. The test-statistic of 12.327 and p-value of 0.2638 does not allow us to reject the null hypothesis of no serial correlation. Equation 11 shows the model that we have arrived at.

***Equation 11***

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 x_t + Seasonal\ Dummies$$

The correlogram in Section 5.4.4 suggested statistically significant correlation between our dependent variable and every fourth lag of our independent variable. As such, we test whether introducing only the fourth lag of RE_SHARE ($x_{t-4}$) on top of contemporaneous RE_SHARE might affect $y_t$ by estimating the following model:

***Equation 12***

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 x_t + \beta_4 x_{t-4} + Seasonal\ Dummies$$

We found that by estimating this model, both the coefficients of $x_t$ and $x_{t-4}$ are insignificant. Moreover, the BIC of our model increases from -322.3805 to -309.6956, which indicates that adding $x_{t-4}$ makes the model worse. This suggests that $x_{t-4}$ does not directly affect our dependent variable but may affect contemporaneous $x_t$ which in turn affects our dependent variable. As such, we will not include $x_{t-4}$ in the further model specifications.

As such, we find that Equation 11 best represents the dynamic specification and ARDL polynomial for the relationship between ENERGY_EMP and RE_SHARE.

## 5.6 Full Model Estimation

In our efforts to estimate an ARDL model, we specified our A(L) and C(L) polynomial to be of order two and zero respectively. Additionally, we then include our six control variables presented earlier. As such, our model is now represented by Equation 13.

***Equation 13***

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 x_t + \beta_4 z1_t + \beta_5 z2_t + \beta_6 z3_t + \beta_7 z4_t + \beta_8 z5_t + \beta_9 z6_t + Seasonal\ Dummies$$

***Table 5: Regression Overview***

| | **Model 1** *Seasonality 1* | **Model 2** *Seasonality 2* | **Model 3** *Dynamic specification* | **Model 4** *Full Model w/ seasonality* | **Model 5** *Final model* |
|---|---|---|---|---|---|
| *ENERGY_EMP* ($y_{t-1}$) | | | ✓ | ✓ | ✓ |
| *ENERGY_EMP* ($y_{t-2}$) | | | ✓ | ✓ | ✓ |
| *RE_SHARE* ($x_t$) | ✓ | ✓ | ✓ | ✓ | ✓ |
| *ENERGY_EMP* ($y_{t-4}$) | ✓ | | | | |
| *Seasonal Dummies* | | ✓ | ✓ | ✓ | |
| *Control Variables* | | | | ✓ | ✓ |
| $R^2$ | *0.05901* | *0.067* | *0.1794* | *0.3977* | *0.3868* |
| *No. of Observations* | *80* | *80* | *80* | *80* | *80* |

The model was estimated, and the seasonal dummies were once again tested for joint-significance. The joint F-test gave a F-statistic of 0.3929 and a P-value of 0.7585 which is once again not statistically significant. For the final model, seasonal dummies were removed as it is deemed to improve our model specification. When the seasonal dummies were removed, the BIC improved from -320.3656 to -332.0339. The final model was estimated as represented by Equation 14. Table 5 provides an overview of all the key models estimated.

***Equation 14***

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 x_t + \beta_4 z1_t + \beta_5 z2_t + \beta_6 z3_t + \beta_7 z4_t + \beta_8 z5_t + \beta_9 z6_t$$

## 5.6.1 Results

***Table 6: Results Overview***

| | ***Model 1*** *Seasonality 1* | ***Model 2*** *Seasonality 2* | ***Model 3*** *Dynamic specification* | ***Model 4*** *Full model w/ seasonality* | ***Model 5*** *Final model* |
|---|---|---|---|---|---|
| *Intercept* | 0.001926 (0.003113) | 0.008532 (0.006176) | 0.007342 (0.005994) | 0.0060341 (0.0063109) | 0.002368 (0.002651) |
| *ENERGY_EMP* ($y_{t-1}$) | | | 0.225701* (0.115973) | 0.1506061 (0.1106818) | 0.175003* (0.101834) |
| *ENERGY_EMP* ($y_{t-2}$) | | | 0.204784* (0.117810) | 0.2868785** (0.1097921) | 0.271385*** (0.101396) |
| *RE_SHARE* ($x_t$) | 0.039075* (0.020701) | 0.029988 (0.025759) | 0.036664 (0.025516) | 0.0514694** (0.0242439) | 0.055072*** (0.017628) |
| *ENERGY_EMP* ($y_{t-4}$) | 0.81756 (0.114691) | | | | |
| *Seasonal Dummies* | | ✓ | ✓ | ✓ | |
| *Control Variables* | | | | ✓ | ✓ |
| *AIC* | *-328.0964* | *-346.0428* | *-341.2342* | *-353.3595* | *-357.9577* |
| *BIC* | *-318.7735* | *-331-7506* | *-322.3805* | *-320.3656* | *-332.0339* |

*Significance levels: *10% level, **5% level, ***1% level.*

The results of the five variations of our model are presented in Table 6. Models 1 and 2 were used to check for seasonality in our dependent variable while Model 3 adopts our estimated A(L) and C(L) polynomials for a dynamic specification. Model 4 adds the previously specified control variables to our dynamic specification model and Model 5 is our final model.

Other than the models used for specification testing (models 1-3), the coefficient of the independent variable remains statistically significant and of similar magnitude in Models 4 and 5. In our final model (Model 5), the coefficient of RE_SHARE is 0.055072 and is highly significant (1% significance level). The coefficient is higher in our final model than when controls are not included (Model 3) which signals the presence of a downward omitted variable bias when we do not include the control variables

When comparing the information criterion across the six models, we can observe that the AIC and BIC are the lowest in our final model. This suggests that the final model is better specified compared to the other models. As such, based on the information criteria, we can conclude that our final model is statistically the best specified model as compared to the other models.

The full results of Model 5 are presented in Table 7.

***Table 7: Final Model Results***

| | *Estimate* | *Standard Error* | *t-value* | *P-value* | *Significance* |
|---|---|---|---|---|---|
| *Intercept* | *0.002368* | *0.002651* | *0.893* | *0.37475* | |
| *ENERGY_EMP* ($\boldsymbol{y_{t-1}}$) | *0.175003* | *0.101834* | *1.719* | *0.09025* | * |
| *ENERGY_EMP* ($\boldsymbol{y_{t-2}}$) | *0.271385* | *0.101396* | *2.676* | *0.00932* | *** |
| *RE_SHARE* ($\boldsymbol{x_t}$) | *0.055072* | *0.017628* | *3.124* | *0.00262* | *** |
| *TOTAL_PROD* ($\boldsymbol{z1_t}$) | *0.011161* | *0.23463* | *0.476* | *0.63584* | |
| *PRODUCTIVITY_1* ($\boldsymbol{z2_t}$) | *-0.59723* | *0.014432* | *-4.138* | *0.0000985* | *** |
| *PRODUCTIVITY_2* ($\boldsymbol{z3_t}$) | *0.030076* | *0.013525* | *2.224* | *0.02949* | ** |
| *PRODUCTIVITY_3* ($\boldsymbol{z4_t}$) | *-0.019913* | *0.033544* | *-0.594* | *0.55473* | |
| *WAGES* ($\boldsymbol{z5_t}$) | *-0.040496* | *0.208055* | *-0.195* | *0.84626* | |
| *INTEREST* ($\boldsymbol{z6_t}$) | *0.010444* | *0.022227* | *0.470* | *0.63995* | |

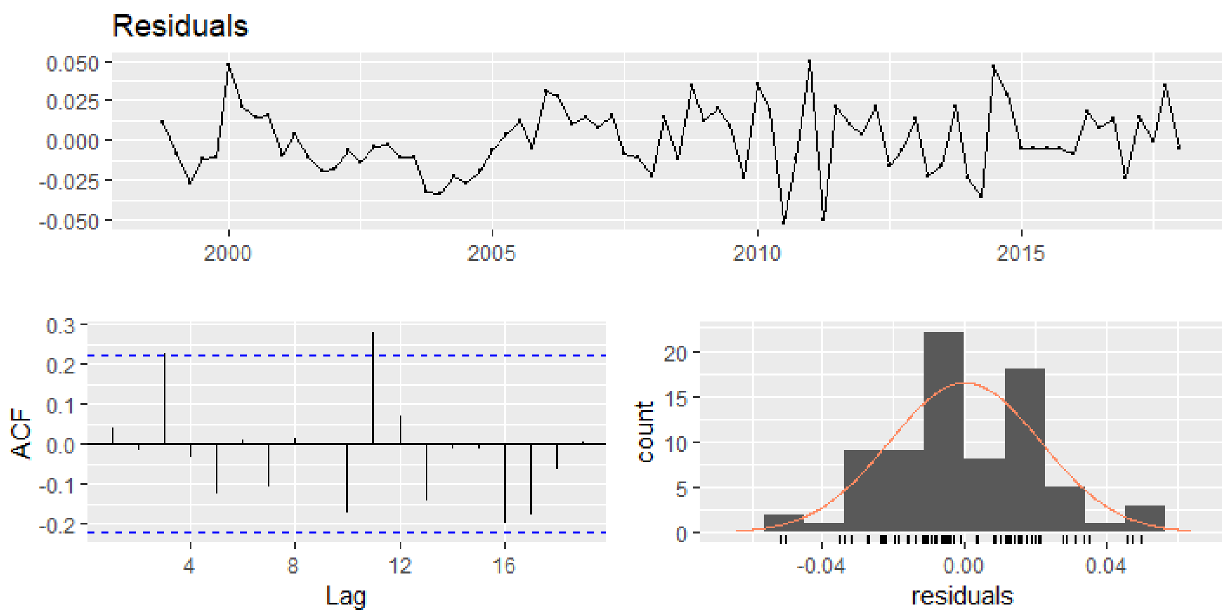
*Significance levels: *10% level, **5% level, ***1% level.*

We have found the following variables to be statistically significant in our analysis:

- Lagged energy sector employment ($y_{t-1}$)
- Lagged energy sector employment ($y_{t-2}$)
- Share of renewable energy production ($x_t$)
- Labour productivity (B06) ($z2_t$)
- Labour productivity (C19) ($z3_t$)

Despite statistical insignificance of the remaining control variables, we opted against their removal. Section 4 highlighted the theoretical need for them to be included and if excluded would result in a possible omitted variable bias.

***Figure 16: Residuals Diagnostics***




*Legend: Residual plot, ACF of residuals and distribution of residuals*

To further ensure that our final model is correctly specified, diagnostics on the residuals of the final model were conducted. As previously discussed in Section 5.4.1, the $\varepsilon_t$ error term of the ARDL should be normally distributed and not serially correlated for the ARDL model to be considered well-specified. Residuals that are serially-correlated or have a non-normal distribution may indicate that the estimates are inconsistent, and that some information is still contained in the residuals. This would indicate the existence of a better-specified model. In the bottom right of Figure 16 we can see that the residuals are generally normally distributed and are not significantly skewed. The ACF of the residuals only displays one significant spike at the 5% significance level. At a 5% significance level, there is a one in twenty chance of error in the ACF and the one significant spike may be ignored.

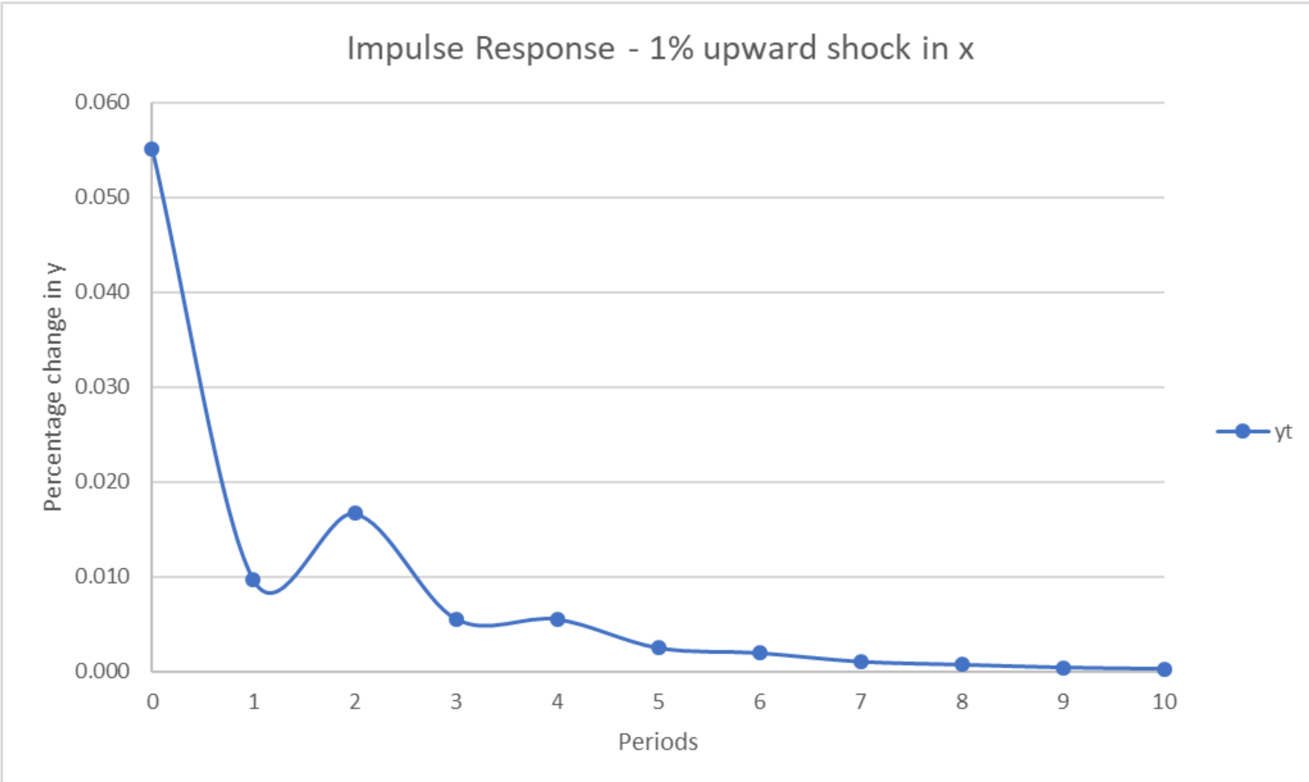
The plot of the residuals does not show any particular trend or persistence and are indicative of a white noise process. A formal Breusch-Godfrey serial correlation test was conducted which produced a test-statistic of 6.2623 with a P-value of 0.1804. Under the null hypothesis of no serial correlation, this may not be rejected at a 10% level of significance.

Additionally, a formal heteroskedasticity test was conducted to ensure that the residuals are homoscedastic. Heteroskedasticity in our model will cause the estimated variance in our model to be biased and affect our inferences (Breusch & Pagan, 1979). A Breusch-Pagan test for heteroskedasticity produced a test-statistic of 5.3124 with a P-value of 0.8063 which does not allow us to reject the null hypothesis of homoskedasticity. As such, we can conclude that there is no heteroskedasticity present in our final model and there is no indication of the estimated variances to be biased.

The residual diagnostics confirm our assumption of well-behaved residuals in the ARDL approach and indicates that the model is correctly specified.

The results from the final model (Table 7) produces a statistically significant coefficient of 0.055072 for our main variable of interest, share of renewable energy production. This implies that there is a positive contemporaneous relationship between change in share of renewable energy production in the UK and change in the amount of energy sector employment over the time-period of the study. Our model suggests that on average, a 1% increase in the share of renewable energy production in the UK leads to an approximate 0.055% contemporaneous increase in the number of people employed in the energy sector. This is in line with previous research suggesting a small positive direct net gain in employment from the increased reliance on renewable energy.

***Figure 17: Impulse Response***




*Legend: Impulse response of energy sector employment as a result of a 1% upward shock in the share of renewable energy production*

The two lagged dependent variable terms added into the ARDL model both remain statistically significant in our final model even after the control variables were added. The coefficients for $y_{t-1}$ and $y_{t-2}$ were 0.175003 and 0.271385 respectively. As both the right and left-hand side of the equation are first-differenced, the coefficients are interpreted as the rate of decay of the change in RE_SHARE (Enders, 2014). Figure 17 shows the impulse response of our dependent variable from a 1% positive shock to our independent variable. It may be observed that a 1% shock to the share of renewable energy production can have a decaying persistent effect on energy sector employment that almost converges to zero after around five quarters.

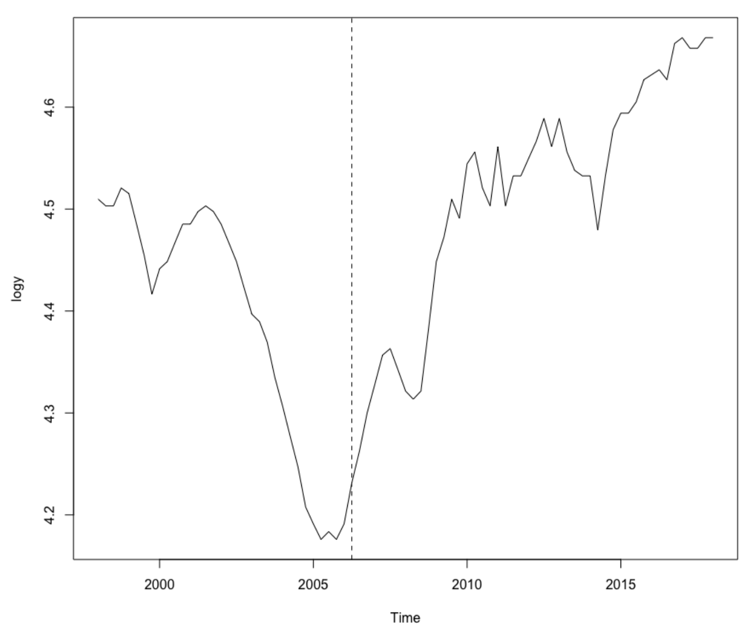
## 5.7 Structural Breaks

As discussed in Section 5.3.1, ENERGY_EMP had been decreasing from 1998 to 2005 and then experienced a turnaround and has been increasing from 2006 to 2018. This is indicative of a structural break within our time-period and should formally be evaluated.

### 5.7.1 Identifying Structural Breaks

To formally identify the presence of a structural break in the data, the algorithm developed by Bai & Perron (2003) was used. This algorithm simultaneously estimates the regressions of our independent variable against our dependent variable at multiple potential breakpoints, such that the residual sum of squares is minimised. This procedure established a breakpoint, as shown in Figure 18. Specifically, the procedure suggests a possible structural break in Q2 of 2006 which is in line with our initial impressions.

***Figure 18: Possible Structural Breakpoint***




*Legend: Suggested breakpoint in data based on algorithm by Bai & Perron (2003)*

## 5.7.2 Subsample Estimation

As a structural break has been identified in Section 5.7.1 above, we would like to conduct subsample estimations as a means of checking the robustness of the results produced in Section 5.6. Subsample estimates that are similar to the results in Section 5.6 would be indicative that the identified structural break is not of a large concern and that our full-sample results are robust.

Considering the nature of the data for our independent variable, only the post-break estimation was deemed to be statistically appropriate. Prior to the breakpoint, our independent variable exhibits limited variation as shown in Section 5.3.2 and consists of only 33 observation. Therefore, any inference testing on the coefficients risk being inefficient and not meaningful.

We then conducted a subsample estimation with the 47 observations for the time-period 2006Q2 to 2018Q1 using the same model specification as in Equation 14. The results are shown in Table 8.

We acknowledge that estimating the same model using only 47 observations compared to our initial 80 observations may make the estimates less efficient. It may however serve as a robustness check for the validity of our model and the significance of our independent variable, share of renewable energy production.

The estimate produces a coefficient of 0.055298 for RE_SHARE which is similar to the coefficient of 0.055072 that was produced by the full sample estimation. RE_SHARE loses some significance, but it is still statistically significant at the 5% significance level. Interestingly, the two control variables that were initially statistically significant (PRODUCTIVITY_1 and PRODUCTIVITY_2) remain significant with similar coefficients. Meanwhile, the two lagged terms of the dependent variable ($y_{t-1}$ and $y_{t-2}$) lose their statistical significance even at a 10% level of significance. This indicates that ENERGY_EMP in the subsample may possess a different AR process as compared to the full sample but will not be investigated further in this study.

***Table 8: Subsample Estimation Results (2006Q2 – 2018Q1)***

| | **Subsample estimation** | | | **Full sample estimation** | | |
|---|---|---|---|---|---|---|
| | *Estimate* | *Standard Error* | *Significance* | *Estimate* | *Standard Error* | *Significance* |
| *Intercept* | *0.007250* | *0.004204* | * | *0.002368* | *0.002651* | |
| *ENERGY_EMP* ($\boldsymbol{y_{t-1}}$) | *-0.029262* | *0.136438* | | *0.175003* | *0.101834* | * |
| *ENERGY_EMP* ($\boldsymbol{y_{t-2}}$) | *0.169246* | *0.132706* | | *0.271385* | *0.101396* | *** |
| *RE_SHARE* ($\boldsymbol{x_t}$) | *0.055298* | *0.022210* | ** | *0.055072* | *0.017628* | *** |
| *TOTAL_PROD* ($\boldsymbol{z1_t}$) | *0.012606* | *0.033265* | | *0.011161* | *0.23463* | |
| *PRODUCTIVITY_1* ($\boldsymbol{z2_t}$) | *-0.048579* | *0.017771* | *** | *-0.59723* | *0.014432* | *** |
| *PRODUCTIVITY_2* ($\boldsymbol{z3_t}$) | *0.053986* | *0.019203* | *** | *0.030076* | *0.013525* | ** |
| *PRODUCTIVITY_3* ($\boldsymbol{z4_t}$) | *-0.18281* | *0.041759* | | *-0.019913* | *0.033544* | |
| *WAGES* ($\boldsymbol{z5_t}$) | *0.025229* | *0.288071* | | *-0.040496* | *0.208055* | |
| *INTEREST* ($\boldsymbol{z6_t}$) | *0.003825* | *0.025201* | | *0.010444* | *0.022227* | |
| *Observations* | | *47* | | | *80* | |

*Significance levels: *10% level, **5% level, ***1% level.*

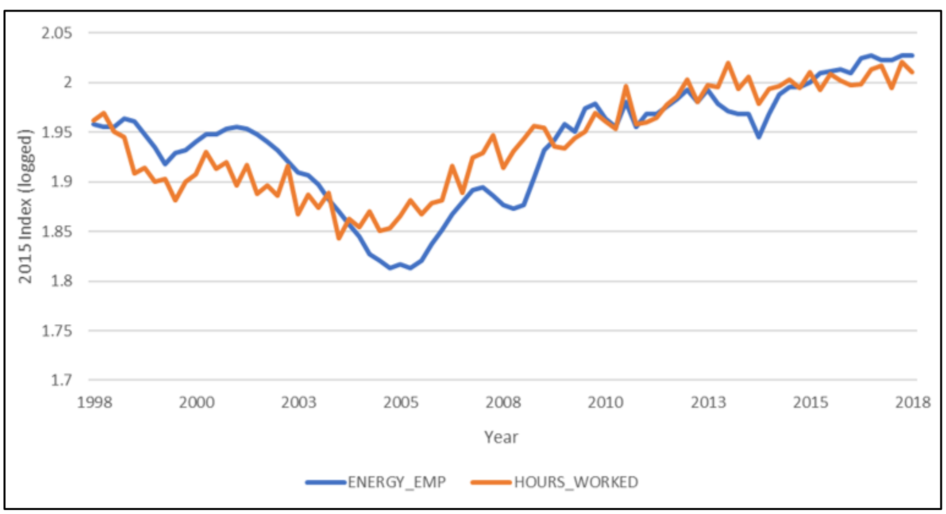
# 6 Extension

Our dependent variable, energy sector employment, is a measure of employment that accounts for the number of people employed by the energy sector. However, it does not take into account the number of hours worked by each individual or the total volume of labour being used in the production of energy in the UK. Even though we have found a positive relationship between the share of renewable energy production and energy sector employment, it is possible that employees are now working less as compared to before. As such, the energy transition towards renewable energy may lead to higher employment but not necessarily higher labour input. This would indicate that the labour is simply split across more employees, and therefore the labour efficiency of renewable energy would not be significantly less than non-renewable energy.

The following extension will simultaneously act as a robustness check to ensure that our previously attained results are not invalid by introducing labour (hours of work) instead of employment as our dependent variable in a similar ARDL model.

## 6.1 Hours of Work

***Figure 19: Employment vs Labour***




*Legend: Plot comparing the movement of energy sector employment and energy sector labour between the periods Q1 1998 to Q1 2018*

Hours of work is defined as the total number of hours worked in the energy sector and is measured as an index based on the base-year of 2015 similar to our initial dependent variable. Likewise, quarterly data was retrieved from the Eurostat database groups for the "MIG – Energy" industry classification. To normalise our variable, the logarithm of hours of work was computed and saved as HOURS_WORKED.

Figure 19 shows that HOURS_WORKED and ENERGY_EMP generally followed a similar pattern between 1998 and 2018 with HOURS_WORKED showing signs of seasonality as compared to a relatively smooth ENERGY_EMP.

## 6.2 Model Estimation

We conducted the ADF stationarity test on HOURS_WORKED and found it to be trend stationary. We detrended HOURS_WORKED and tested it for stationarity by conducting the KPSS and ADF test again. The KPSS test produced a test-statistic of 0.3437 which is lower than the critical values at all the standard significance levels (10%: 0.347, 5%: 0.463, 1%: 0.739). As such, we cannot reject the null hypothesis of stationarity. The ADF test produced a test-statistic of -3.0825 which is higher in absolute magnitude than the critical values at all the standard significance levels (10%: -1.61, 5%: -1.95, 1%: -2.6). As such, we can reject the null hypothesis of non-stationarity at all standard significance levels and conclude that HOURS_WORKED is now a stationary process.

Similar to what was done to RE_SHARE, we would like to further transform HOURS_WORKED so that its coefficient can be better interpreted post-regressions. We transform HOURS_WORKED by first-differencing it and as the process was already stationary prior to taking first difference, it can be assumed to remain stationary.

To ensure that the ARDL model is not misspecified as a result of using a different right-hand side variable, A(L) and C(L) polynomials should be reestimated. The stepwise elimination approach previously used in Section 5.5.2 was conducted on the new dependent variable.

As a result of stepwise elimination, including only the contemporaneous effect and the first lags of both *y* and *x* returned the best performing model according to the information criteria (AIC and BIC) and statistical significance of coefficients. Equation 15 best represents the dynamic specification when using HOURS_WORKED as our dependent variable instead of ENERGY_EMP.

***Equation 15***

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_3 x_t + \beta_4 x_{t-1} + Seasonal\ Dummies$$

***Equation 16***

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 x_t + \beta_3 x_{t-1} + \beta_4 z1_t + \beta_5 z2_t + \beta_6 z3_t + \beta_7 z4_t + \beta_8 z5_t + \beta_9 z6_t + Seasonal\ Dummies$$

The same six control variables were added to the ARDL model as shown in Equation 16. The seasonal dummies were tested for joint significance using a joint F-test. The resulting F-statistic of 5.6771 and a P-value of 0.001605 indicates that the seasonal dummies are jointly statistically significant at a 1% level of significance. This suggests that contrary to our initial dependent variable, our new dependent variable, hours of work, possesses seasonal properties. As such, the seasonal dummies were not removed as they are necessary to control for seasonality in our data.

## 6.3 Results

***Table 9: Extension Model Results***

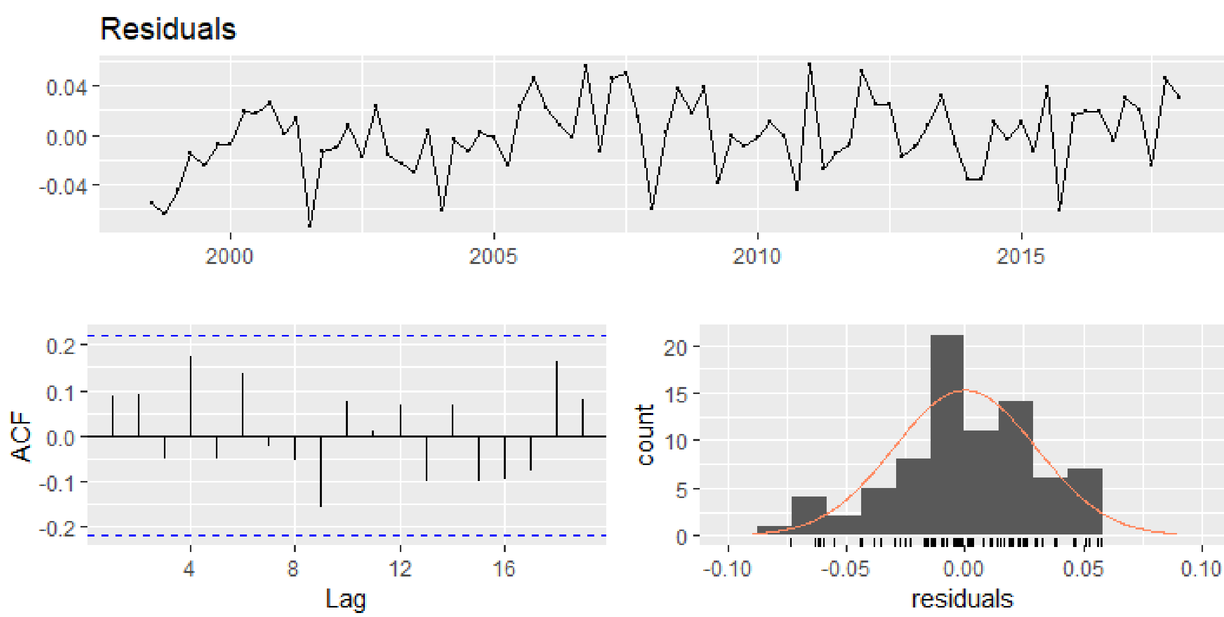
| | Estimate | Standard Error | t-value | P-value | Significance |
|---|---|---|---|---|---|
| *Intercept* | -0.025786 | 0.009416 | -2.739 | 0.007924 | *** |
| *ENERGY_EMP* ($y_{t-1}$) | -0.439640 | 0.090640 | -4.850 | 0.000008 | *** |
| *RE_SHARE* ($x_t$) | -0.004513 | 0.033600 | -0.134 | 0.893574 | |
| *RE_SHARE* ($x_{t-1}$) | 0.1151174 | 0.032809 | 3.510 | 0.000812 | *** |
| *TOTAL_PROD* ($z1_t$) | -0.012252 | 0.042842 | -0.286 | 0.775787 | |
| *PRODUCTIVITY_1* ($z2_t$) | -0.073518 | 0.022556 | -3.259 | 0.001767 | *** |
| *PRODUCTIVITY_2* ($z3_t$) | -0.004939 | 0.019684 | -0.251 | 0.802660 | |
| *PRODUCTIVITY_3* ($z4_t$) | -0.147954 | 0.049099 | -3.013 | 0.003662 | *** |
| *WAGES* ($z5_t$) | 0.123408 | 0.305998 | 0.403 | 0.688035 | |
| *INTEREST* ($z6_t$) | 0.016309 | 0.031347 | 0.520 | 0.604612 | |
| *Seasonal Dummies* | | F-statistic: 5.6771 | | 0.001605 | *** |
| $R^2$ | | | 0.5504 | | |
| *Observations* | | | 80 | | |

*Significance levels: *10% level, **5% level, ***1% level.*

The results from the model does not produce a statistically significant contemporaneous coefficient for our main variable of interest $x_t$, but a highly statistically significant coefficient of 0.1151174 for its lagged value $x_{t-1}$. This suggests the existence of a positive relationship between the change in share of renewable energy production in the UK and the change in the number of hours worked one period after, but not contemporaneously. This is interesting as it differs from the results that we obtained when using energy sector employment as the dependent variable.

On average, a 1% increase in the share of renewable energy production in the UK leads to an approximate 0.115% increase in the total number of hours worked in the energy sector in the next quarter.

***Figure 20: Residual Diagnostics***




*Legend: Residual plot, ACF of residuals and distribution of residuals*

As before, residual diagnostics were conducted to verify that the residuals are well-behaved and that the model is well specified.

The residual diagnostics confirm our assumption of well-behaved residuals in the ARDL approach and indicates that the model is correctly specified.

In the bottom right of Figure 20 we can see that the residuals are generally normally distributed and are not significantly skewed. The ACF of the residuals shows no significant spikes at the 5% significance level and this suggests no serial correlations between residuals. The plot of the residuals does not show any particular trend or persistence and are indicative of a white noise process. A formal Breusch-Godfrey serial correlation test was conducted which produced a test-statistic of 4.5852 with a P-value of 0.3326. Under the null hypothesis of no serial correlation, this may not be rejected at a 10% level of significance and we can conclude that there is no significant serial correlation in the residuals.

Additionally, a formal heteroskedasticity test was conducted to ensure that the residuals are homoscedastic. A Breusch-Pagan test for heteroskedasticity produced a test-statistic of 9.6507 with a P-value of 0.6466 which does not allow us to reject the null hypothesis of homoskedasticity. As such, we can conclude that there is no heteroskedasticity present in our final model and that the estimated variances are not biased.

The residual diagnostics confirm our assumption of well-behaved residuals in the ARDL approach and indicates that the model is correctly specified.

## 6.3.1 Employment vs Labour

***Table 10: Employment vs Labour Results***

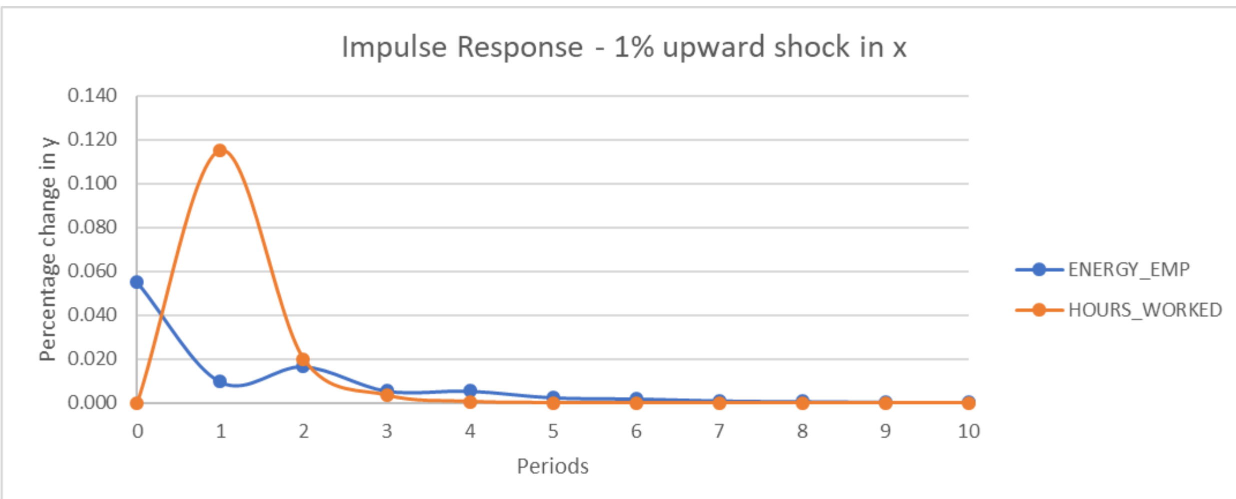
| | ***Employment as Dependent Variable*** | | | ***Labour as Dependent Variable*** | | |
|---|---|---|---|---|---|---|
| | *Estimate* | *Standard Error* | *Significance* | *Estimate* | *Standard Error* | *Significance* |
| *Intercept* | *0.002368* | *0.002651* | | *-0.025786* | *0.009416* | *** |
| *ENERGY_EMP* ($y_{t-1}$) | *0.175003* | *0.101834* | * | *-0.439640* | *0.090640* | *** |
| *ENERGY_EMP* ($y_{t-2}$) | *0.271385* | *0.101396* | *** | - | - | - |
| *RE_SHARE* ($x_t$) | *0.055072* | *0.017628* | *** | *-0.004513* | *0.033600* | |
| *RE_SHARE* ($x_{t-1}$) | - | - | - | *0.1151174* | *0.032809* | *** |
| *TOTAL_PROD* ($z1_t$) | *0.011161* | *0.23463* | | *-0.012252* | *0.042842* | |
| *PRODUCTIVITY_1* ($z2_t$) | *-0.59723* | *0.014432* | *** | *-0.073518* | *0.022556* | *** |
| *PRODUCTIVITY_2* ($z3_t$) | *0.030076* | *0.013525* | ** | *-0.004939* | *0.019684* | |
| *PRODUCTIVITY_3* ($z4_t$) | *-0.019913* | *0.033544* | | *-0.147954* | *0.049099* | *** |
| *WAGES* ($z5_t$) | *-0.040496* | *0.208055* | | *0.123408* | *0.305998* | |
| *INTEREST* ($z6_t$) | *0.010444* | *0.022227* | | *0.016309* | *0.031347* | |
| *Seasonal Dummies* | | - | | *F-statistic: 5.6771* | | *** |
| *Observations* | | *80* | | | *80* | |

*Significance levels: *10% level, **5% level, ***1% level.*

Table 10 shows the results from using employment and labour as dependent variables. As previously mentioned, our independent variable, share of renewable energy production, affects employment and labour at different periods. When there is a shock in the share of renewable energy production, employment is contemporaneously affected while labour is only affected one period later. The magnitudes of the effects also defer with the lagged effect on labour being more than twice as large as the contemporaneous effect on employment.

Another interesting difference when modelling employment and labour is that employment is estimated as an AR(2) process while labour is estimated to be an AR(1) process. This suggests that there is more persistence in employment than labour and that the rate of decay of a change in RE_SHARE might be less rapid in employment than labour.

***Figure 21: Impulse Response***




*Legend: Impulse response of energy sector employment and energy sector hours worked as a result of a 1% upward shock in the share of renewable energy production*

Figure 21 shows the impulse response of a 1% upward shock in RE_SHARE on ENERGY_EMP and HOURS_WORKED. We can see that the delayed jump in HOURS_WORKED is of a much larger amplitude compared to ENERGY_EMP. However, we also observe a rapid decay such that HOURS_WORKED is lower than ENERGY_EMP after two periods. Visually we can observe that the area under the HOUR_WORKED curve is significantly larger than the ENERGY_EMP curve. This suggests that the total effect of an increase in the share of renewable energy production is larger on labour compared to employment. As the total increase in number of hours worked is larger than the total increase in employment, not only are more people being employed as a result of the energy transition, but the average number of hours worked by employees in the energy sector have increased. A possible reason why employment is affected contemporaneous and before labour is that firms have to first hire new employees and train them before putting them to work.

# 7 Discussion

This section presents and highlights key findings of the study and any implications that these findings may have. We also acknowledge the potential weaknesses that our study might have and propose certain topics that future researchers can look into that will shine more light onto our area of study.

## 7.1 Implications

The main objective set out at the beginning of the study is to understand the employment effect of the transition from non-renewable to renewable energies. This study finds that the share of renewable energy production has a positive and statistically significant effect on the number of people employed in the energy sector. As such, it is suggested that the energy transition results in a direct net positive employment effect in the energy sector.

The findings suggest that despite jobs being lost, the job creation effect from renewable energy implementation outweighs the jobs lost. As such, policy-makers should expect an expansion in energy sector jobs by transitioning to renewable energy technologies. Nevertheless, as highlighted in Section 3.3, the job types vary significantly between energy technologies. Despite a net employment gain, the jobs lost may still leave parts of the workforce vulnerable because of their lack of appropriate skills to find a new job. Policy-makers may want to shift focus from preserving redundant non-renewable jobs to retraining and re-educating workers to satisfy the requirements of renewable energy jobs. Considering the generally higher level of skill requirement for renewable energy jobs as discussed in Section 3.3, retraining would not only improve the quantity of jobs, but may also improve the quality for jobs.

Nonetheless, it is important to note the delimitations of this study. Specifically, it takes the approach of understanding the energy transition by focusing on a single country and conducting a case study on the UK for the period between 1998 and 2018. As such, the estimated effects of the energy transition on energy sector employment may vary depending on underlying country-specific factors or the composition of renewable energy technologies adopted.

Other than the positive effect of the energy transition on job creation, it also highlights the relative labour inefficiency of renewable energy production. In line with the arguments of Hughes (2011), there is an incentive for profit maximising renewable energy producers to reduce the cost of producing renewable energy. They will want to improve labour efficiency and reduce labour costs associated with production. On top of that, renewable energy technologies are still relatively new and renewable energy production has the potential to become more efficient as the sector matures. Moving forward, the increase in labour efficiency of renewable energy technologies will affect the positive relationship between energy sector employment and the share of renewable energy production that has been observed in this study. Countries that are later adopters of renewable energy may not be able to gain any positive net employment effect from switching away from non-renewable energies.

However, we argue that the findings of this study still provide a good indication that there has been and can still be a positive employment effect by moving from non-renewable to renewable energy production.

## 7.2 Challenges & Weaknesses

Even though we have constructed our empirical model based on sound theoretical and statistical foundations, no model is perfect and less so when studying a relatively new field. In this section, we highlight potential challenges and weaknesses that our approach may possess and should be considered when drawing conclusions from the results.

### 7.2.1 Omitted Variable Bias

When designing a study, the risk of misspecification is always present, and we acknowledge that model misspecification may be present in our final model. Our model runs the risk of omitted variable bias as energy sector employment may be affected by many observable and unobservable variables that we have not included in our final model. Omitted variables can make our estimates biased and invalidate them. We have leveraged existing literature and economic theory to determine the appropriate variables to include when modelling energy sector employment. We therefore believe that significant omitted variable bias is unlikely. Nevertheless, we acknowledge that the literature on the energy transition is still in its youth and there may be some relationships and factors that have not yet been identified and as result have not been incorporated in our study.

### 7.2.2 Measurement Error

Previous studies on energy employment that did not employ the input-output framework have opted for survey level data to analyse the regional effects over time (Blanco & Rodrigues, 2009; Sastresa et al., 2010). On a national level it may be difficult to accurately measure energy sector employment as data may capture jobs that are not directly involved in energy production. Such an example is employees of energy producing companies such as kitchen and janitorial staff that are not involved in energy production but may have been classified otherwise. As such, there may be measurement error in our study.

### 7.2.3 Data Availability

The potential for model misspecification is directly linked to challenges with regards to data availability. IRENA (2011) highlights the deficiencies in renewable energy employment data by referring to it as being weak and notes that reliable data will be expensive to obtain. Renewable energy is in its youth and due to this immaturity of the industry, data is only available for a limited number of years. Due to this restriction, we have opted to utilise quarterly data. Even when using quarterly data, we only have 80 observations (20 years) which may not be considered high. We acknowledge that this is not ideal and if available, a longer period of data should be used to get more efficient estimators. The problem related to a low number of observations was also highlighted in Section 5.7 where we did not proceed with the estimation of the pre-breakpoint subsample that only had 33 observations.

The lack of data availability also poses challenges in the identification of controls. The controls added for real wages and cost of capital (interest rates) are national-level data rather than industry specific. It is possible that there exist significant differences between national and industry-specific values that may affect the quality of the estimation results. Nevertheless, national-level data was used as they were deemed to be appropriate proxies for industry-specific data.

### 7.2.4 Varying Labour Intensities of Different Technology Types

As discussed in Section 3.1, the labour intensity of energy production not only varies between the renewable energy and non-renewable energy segments but also between different technology types within the segments. Our study focuses on the independent variable, share of renewable energy production, which implicitly assumes that all renewable energy technologies employed in the UK possess the same or similar labour intensities. This is highly unlikely to be true in the case of the UK which adopts various types of renewable energy technologies and has a changing composition in the total energy mix over the period of our study. As such, it is likely that the results of this study would be different if the energy mix in the UK was significantly different over the period of our study. We argue that the estimation results are still relevant as the goal of this study is to conduct a backward-looking analysis of the overall employment impact of the energy transition in the UK.

## 7.3 Further research

This study established a positive relationship between the share of renewable energy production and energy sector employment. However, to the best of our knowledge, there have been no directly comparable studies. Forecasts have suggested a positive relationship as discussed in Section 3.4, but the lack of evaluating studies makes comparisons complicated. Hence, to gain deeper insights into the nexus between employment and energy technology, further research should be conducted. Firstly, future studies should attempt to apply a similar framework as ours on other countries. In the event that similar effects are found for other countries, it will point towards a generalised positive net employment effect of shifting towards renewable energy technologies. Such findings would support local policy implementation aimed at increasing energy employment through renewable energy deployment.

Future research should also attempt to establish a general relationship across countries. It was suggested in Section 3.1 that labour intensity may only be greater for renewable energy technologies in the early stages of implementation. Assuming different levels of renewable energy dependence across countries, such research would indicate whether the level of renewable energy share affects employment by using a wider range of values in the independent variable.

Combining cross-sectional and time-series observations through the likes of panel data may also produce interesting findings. A panel data study would allow for the use of annual data due to the increased number of observations and thus avoid problems of seasonality in the independent variable. Additionally, panel data would ignore any country-specific differences in the findings. As such, the findings may be more accurate by isolating the employment effects. Therefore, such findings would provide stronger policy implications for countries that are just starting to implement renewable energy technologies.

Considering the multitude of energy technology types that produce the same product, more focus should also be placed in investigating the empirical differences in employment effects of the various technologies. Such research would provide policy makes with a better insight when deciding upon policies to promote particular renewable energy types.

Lastly, assuming that the relationship established in this study holds, research should investigate the implications of our findings. Specifically, research should critically assess the positive relationship between energy sector employment and the energy transition. This can be done by assessing the quality of the jobs created in the renewable energy subsector as compared to the jobs destroyed in the non-renewable energy subsector. Our findings only point towards higher employment, but previous findings suggest that these additional jobs may be associated with higher skill requirement. As such, understanding the dynamics of the energy transition’s impact on the quality of jobs could shine some light on the development among employees in the energy sector. If job quality is not improved, it is possible to argue that the increased labour requirements is a disadvantage of renewable energy adoption due to lower labour efficiency.

# 8 Conclusion

This study sets out to investigate the net direct energy employment effect resulting from the transition from non-renewable energy to renewable energy technologies in the UK. This was done by taking an alternative approach as compared to existing academic literature through a backward-looking evaluative study rather than a forward-looking approach. This approach allows us to attain a more accurate understanding of the interaction between a shift in energy sources and employment. The UK was selected as the suitable case-study candidate and a statistical model was constructed based on factors identified through established theoretical frameworks such as labour demand and supply theory, as well as the Cobb-Douglas production function.

The estimates of our ARDL model found a statistically significant relationship between share of renewable energy production and energy sector employment with a contemporaneous 0.055% increase in energy sector employment from a 1% positive shock to the share of renewable energy production. The magnitude and sign of our findings are in line with most previous forward-looking studies that find a slight net positive employment effect. Subsample estimation accounting for the structural break in our data produces similar results and signifies that our estimates are robust. Labour was also used in place of employment as our dependent variable and similarly a positive effect was found. The higher magnitude of the effect on labour as compared to employment also points towards energy sector employees working more as a result of the energy transition.

In conclusion, this study provides a thorough understanding of the potential employment benefits that a shift from non-renewable to renewable energy technologies has on the energy sector, both empirically and theoretically. This provides intriguing further insights into one of the most relevant topics of discussion in today’s world. Although further research is necessary to better understand the role that the energy transition plays, these findings can be of great importance to policy-makers as we can expect to experience a continuous journey toward a greener future.

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# 10 Appendix

## Appendix A – Regression using lagged dependent variable for seasonality

| | Estimate | Standard Error | t-value | P-value | Significance |
|---|---|---|---|---|---|
| Intercept | 0.0003254 | 0.0032054 | 0.102 | 0.9194 | |
| ENERGY_EMP ($y_{t-4}$) | 0.0817563 | 0.1146907 | 0.713 | 0.4782 | |
| RE_SHARE ($x_t$) | 0.030754 | 0.0207013 | 1.888 | 0.0631 | * |
| $R^2$ | | | 0.05901 | | |
| Observations | | | 80 | | |

*Significance levels: *10% level, **5% level, ***1% level.*

## Appendix B – Regression using seasonal dummies

| | Estimate | Standard Error | t-value | P-value | Significance |
|---|---|---|---|---|---|
| Intercept | 0.007303 | 0.006531 | 1.118 | 0.267 | |
| RE_SHARE ($x_t$) | 0.02988 | 0.025759 | 1.164 | 0.248 | |
| Seasonal Dummies | | F-statistic: 0.5342 | | 0.6602 | |
| $R^2$ | | | 0.067 | | |
| Observations | | | 80 | | |

*Significance levels: *10% level, **5% level, ***1% level.*

# Appendix C – Dynamic Specification

| | Estimate | Standard Error | t-value | P-value | Significance |
|---|---|---|---|---|---|
| *Intercept* | *0.003684* | *0.010614* | *0.347* | *0.7297* | |
| *ENERGY_EMP* ($y_{t-1}$) | *0.238168* | *0.121480* | *1.961* | *0.0542* | * |
| *ENERGY_EMP* ($y_{t-2}$) | *0.196909* | *0.121259* | *1.624* | *0.1092* | |
| *RE_SHARE* ($x_t$) | *0.034057* | *0.041463* | *0.821* | *0.4144* | |
| *RE_SHARE* ($x_{t-1}$) | *0.011759* | *0.043938* | *0.268* | *0.7898* | |
| *RE_SHARE* ($x_{t-2}$) | *0.021489* | *0.046198* | *0.465* | *0.6434* | |
| *RE_SHARE* ($x_{t-3}$) | *0.025474* | *0.042066* | *0.606* | *0.5469* | |
| *RE_SHARE* ($x_{t-4}$) | *0.037729* | *0.039725* | *0.950* | *0.3458* | |
| *Seasonal Dummies* | | *F-statistic: 0.3795* | | *0.7681* | |
| $R^2$ | | | *0.2087* | | |
| *Observations* | | | *80* | | |

*Significance levels: *10% level, **5% level, ***1% level.*