The environmental and socioeconomic impact of energy demand and supply in the UK industry

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Statement of Originality

"I, Theodoros Arvanitopoulos confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis."

Publications

Peer-reviewed publications based on this thesis

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Abstract

The UK government has identified Clean Growth as one of the four grand challenges for the UK industry, with goal to improve industrial energy efficiency by at least 20% by 2030. This thesis tackles three aspects of the challenges faced by the industrial sector and the impacts of delivering Clean Growth. I develop a new econometric approach based on linear state space modelling to explore the role of economic growth and energy price on historical trend in energy efficiency. Findings indicate that price signal has been an important driver of energy efficiency to the extent that it has largely offset the surge in consumption induced by economic growth. The remaining component of energy efficiency is imputable to exogenous processes, not directly induced by energy prices.

Although increasing energy efficiency can stimulate Clean Growth by reducing emissions, it is equally important to identify the determinants directly responsible for reducing emissions. I employ a panel time series methodology that accounts for cross sectional dependence to assess the long-term relationship between industrial processes and emissions. Findings indicate emissions can be reliably reduced by decreasing energy consumption, encouraging fuel substitution and market competition to counteract the increase in emissions related to higher capital investment. I observe considerable similarities in the relationship between market concentration on one side and emissions and innovation on the other.

The transition to renewables posits the issue of net job creation as outdated carbon intensive technologies become obsolete leading to job losses. I develop an econometric framework, based on Vector Error Correction model, that estimates the employment impact for the power sector and finds that a 1 GWh increase in annual renewable electricity results in 3.5 jobs in the long-term. By applying results to decarbonisation scenarios, I find renewable technologies can lead to the creation of on average 55,000 jobs by 2030.

Impact statement

This thesis contributes substantially, both from an academic and a policy perspective, to the challenges faced by industrial subsectors in relation to the decarbonisation targets set by the UK government. In terms of my contribution to the academic literature, the work presented in chapter 4, assessing the environmental impact of industrial energy demand, has been published in the journal Energy Economics, while the work presented in chapter 5, investigating the socioeconomic impact of energy supply, have been published in the journal Renewable and Sustainable Energy Reviews. In addition, this thesis further advances the academic discussion on the econometric methodology employed to model industrial energy demand while it highlights the importance for future academic research to identify industrial policies that promote Clean Growth by stimulating innovation dynamics and improving competition within the UK industrial subsectors.

From a policy perspective, this thesis has informed the UK government officials and public policymakers and helped in the shaping of the UK industrial policy. By employing my expertise in energy economics and applied econometrics, I have contributed in the redevelopment of the UK Department for Business Energy and Industrial Strategy (BEIS) Energy Demand Module used by the UK government to produce the energy and emissions projections for the industrial sector. This contribution has been acknowledged in the preamble of the "Updated Energy and Emissions Projections 2016". This thesis has allowed me to contribute to the UK Clean Growth policy debate by providing valuable insights on the determinants of emission intensity on the subsectoral level of the UK industry. The policy implications of the research findings presented in chapter 4 have been employed by the UK Climate Change Committee (CCC) in the redevelopment of their industrial indicators on energy efficiency, carbon intensity and emissions reduction. This contribution has been acknowledged in the preamble of the "Reducing UK emissions – 2018 Progress Report to Parliament".

Finally, the empirical findings presented in chapter 5, such as the employment impact of renewable electricity, can be applied on the back of the output energy system models which produce deployment

scenarios of electricity generation technologies to achieve a certain level of decarbonisation and, by extension, inform policymakers on the expected employment gains or losses of decarbonisation scenarios. From an international perspective, the econometric approaches developed in this thesis can be employed in the context of OECD countries with similar characteristics to the UK economy for policy design purposes regarding energy prices, industrial emissions, and employment impact from the diffusion of renewable technologies.

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1 Introduction

1.1 Overview and research objectives

The UK government has identified Clean Growth as one of the four grand challenges of the UK industry for the future (BEIS, 2018)[1]. According to the UK industrial Strategy, Clean Growth translates into delivering increased economic growth while reducing the overall level of emissions (BEIS, 2018). With the introduction of Clean Growth Strategy, the UK government sets the policy framework for the UK industry so that the country meets the fourth and fifth carbon budgets[2]. However, achieving Clean Growth in the long-term period is not a straightforward process as it requires combination of the appropriate policy measures and incentives. This thesis sheds light into this challenge by analysing the dynamics that underpin Clean Growth for the UK industry and assessing the enabling factors that can minimize the environmental and socioeconomic externalities. More specifically, this thesis responds to this challenge by investigating the following overarching research question:

What are the long-term drivers of Clean Growth in the UK industry?

Minimizing environmental externalities - i.e., industrial emissions - while delivering increased economic growth requires both increasing industrial energy efficiency[3] while as well improving distinct industrial processes directly or indirectly responsible for industrial emissions. For that reason, it is important to identify the underlying factors that can enable the long-term Clean Growth in the UK industry. To be able to identify those enabling factors that can drive Clean Growth in the long-term period in the UK industrial sector, I examine a) the factors responsible for *long-term energy efficiency gains* in the industrial sector and b) the role of *distinct industrial characteristic*, not directly related to

[1] The other three grand challenges set by the UK industrial Strategy (BEIS, 2018) are i) growing artificial intelligence and data driven economy, ii) future of mobility and iii) ageing society.
[2] The fourth and fifth carbon budget were introduced under the 2008 Climate Change Act and set the cost-effective pathways for the periods 2023-2027 and 2028-2032, respectively, so that the UK government meets its emission reduction commitments (BEIS, 2017).
[3] Energy efficiency improvement (or energy efficiency gains) corresponds to the process of reducing the amount of energy required for a specific industrial activity compared to the amount of energy consumed for the same activity in a different point in time.

energy use, responsible for long-term reduction of industrial emissions. Nonetheless, the development and adoption of novel industrial technologies able to stimulate Clean Growth dynamics in the UK industrial sector raises concerns over long-term negative socioeconomic externalities, such as job loses, due to the gradual phase out of emission intensive technologies. For that reason, I finally assess in this thesis c) the *employment impact of low-carbon technologies* and estimate future net job creation for the UK economy based on decarbonisation scenarios.

Improving industrial energy efficiency is one the key policy targets set by the UK government in the UK Clean Growth Strategy as it can assist in reducing emissions while delivering increased economic growth (BEIS, 2018). This essentially means that improving industrial energy efficiency would result in producing same level of output while using a lower level of energy and by extension lower level of emissions. More specifically, the UK government has set the ambitious target to improve industrial energy efficiency by at least 20% by 2030 (BEIS, 2018; CCC, 2018) compared to 2018 industrial energy consumption levels, in order to address the negative environmental externalities of energy use, i.e. to reduce the overall level of industrial emissions. Nonetheless, the UK government has not clearly outlined the exact details of the associated policies that can stimulate long-term energy efficiency gains in the industrial sector (CCC, 2018; CCC, 2019). This lack of a detailed policy pathway towards achieving the policy goal of improving long-term industrial energy efficiency highlights the difficulty in identifying and targeting the enabling factors that can effectively deliver long-term Clean Growth dynamics within UK industrial sector. This lack of consensus over the exact nature of the enabling factors that can deliver long-term energy efficiency gains can be also found in the related energy economics literature. Thus, this thesis contributes to the energy economics literature by providing robust empirical evidence on the long-term drivers of industrial energy efficiency and by extension on the ways through which the UK government can stimulate long-term Clean Growth dynamics in the UK industrial sector. More specifically, this thesis contributes to the associated policy debate by identifying the long-term drivers of energy efficiency in the UK industry that have historically led to the adoption of energy saving technical change, by introducing a novel systematic methodological

approach that uses the Kalman filter to estimate state space models representing energy consumption.

Improving industrial energy efficiency is a necessary condition to minimise the negative environmental externalities of industrial activity in the UK and stimulate Clean Growth dynamics. As already mentioned, higher energy efficiency essentially means that lower energy use is required to produce the same level of industrial output, and by extension a lower level of industrial emissions is generated. Although increasing energy efficiency can facilitate the reduction of environmental externalities associated with industrial production, there are also *distinct industrial characteristics in the production process that are also directly responsible for industrial emissions*. This is especially relevant if the government wants to develop and deliver efficient Clean Growth industrial policies at the disaggregated level of the UK industrial sector, as certain industrial subsectors such as "non-metallic minerals" (SIC 23), "coke and refined petroleum" (SIC19), "chemical and chemical products" (SIC 20) are characterised by increased levels of emission intensity. Thus, it is crucial to identify the characteristics of the production process that have been directly responsible for reducing the overall level of emission intensity in the UK industry. This thesis contributes to the UK Clean Growth policy debate by providing valuable insights on the determinants of emission intensity on the subsectoral level of the UK industry.

The deployment of renewable energy sources and the related low-carbon technologies is a key component in the efforts towards achieving the goals set by the UK Clean Growth Strategy. The deployment of renewable energy technologies is considered a win-win scenario for both the environmental and socioeconomic welfare, as renewable energy technologies reduce carbon emissions and create new job opportunities in various sectors of the economy through direct and indirect employment effects. However, the closure of conventional thermal power plants is expected to create redundancies in the labour market given that a key governmental policy in the Clean Growth Strategy is the phase out of unabated coal in the power generation sector by 2025 (CCC, 2018). Thus,

the transition to renewable technologies, facilitated by UK government policies, posits the question of its *impact on net job creation in the UK economy as carbon intensive technologies are gradually being abandoned* with consequent reduction in employment. This thesis provides helpful policy insights on this research topic by developing a novel econometric framework that can be used to estimate the long-term employment impact of renewable electricity for the UK power generation sector and apply these estimates to UK decarbonisation scenarios for 2030.

Delivering Clean Growth in the long-term period requires a combination of policy measures and incentives. For that reason, I explore in section 1.1.1 the role of energy demand determinants on historical energy efficiency gains in the industrial sector. Secondly, I identify in section 1.1.2 the industrial characteristics of production process that have been directly responsible for reducing industrial emissions. Finally, I assess in section 1.1.3 the socioeconomic impact of renewable electricity supply on the power sector. By addressing the above-mentioned key issues, I provide credible policy recommendations on delivering Clean Growth and respond to the key overarching research question of what needs to be done to enable long-term Clean Growth dynamics and by extension effectively meet the decarbonisation targets set by the UK government for the industrial sector.

1.1.1 Energy price and industrial energy efficiency

Improving industrial energy efficiency is one of the key policy objectives in the UK Industrial Strategy. The idea that technological change affects energy efficiency in a complex and apparently random manner is typically captured by including a stochastic trend component in a standard energy demand equation. Such common feature in empirical energy economics is normally justified by appealing on the existence of nonlinear effects characterizing technological progress. Part of this technological progress is indeed the result of incentives created by the historical dynamics in energy prices and by exogenous factors such as regulation or institutional changes, and part is instead related to structural features of the economy, such as consumer preferences and the sectorial composition of the

economy. It is important to understand the relative importance of different drivers in the reduction of industrial energy consumption. In other words, one needs to identify whether this reduction in industrial energy consumption has been historically induced by improvements in energy efficiency – i.e. induced by price signals and exogenous factors – or rather by structural changes within the industrial sector.

By decomposing manufacturing energy use in International Energy Agency (IEA) countries from 1973 to 1998, Unander (2007) finds that the aggregate energy use per real manufacturing value added in the UK fell by 2% to 3% on average per year. This reduction in energy use can be explained almost to its entirety by changes in the energy intensity. On the other hand, structural changes have historically accounted only for a negligible proportion of this effect. This argument is also supported by Norman (2017) that decomposes the UK industrial energy consumption from 1997 to 2011. This study finds that energy consumption before 2007 has mainly been driven by the energy intensity effect while structural effects become more evident only during the 2009 crisis with crisis-driven structural changes stabilising and becoming permanent in the post-crisis period. The above-mentioned studies indicate that historical reduction in UK industrial energy consumption has mainly been induced by improvements in industrial energy efficiency while structural changes within the sectorial composition of the UK industry have become partly influential only in the post-crisis period. Hence, this thesis focuses on identifying the long-term drivers of energy efficiency in the UK industrial sector.

Different empirical methodologies were employed in the literature to identify the drivers of energy efficiency. Gately and Huntington (2002) model price asymmetry in the energy demand function to capture energy efficiency improvements as a response to past price increases. However, the chosen methodology essentially underlines the a priori assumption that energy saving technical change is solely induced by changes in energy prices. On the other hand, Griffin and Schulman (2005) argue that price asymmetry employed in Gately and Huntington (2002) acts as a proxy of an omitted variable that captures energy saving technical change. Since technical change can be induced both by price signals

and exogenous factors, such as regulation or institutional changes, price asymmetry cannot fully capture all the underlying dynamics. Secondly, it is true that energy demand might behave asymmetrically to increases in energy prices in the short-term period. Nonetheless, the Neoclassical economic theory posits that long-run energy demand should respond symmetrically to changes in energy prices, ceteris paribus constant technical change. For that reason, Hunt et al. (2003) introduced a stochastic linear trend term in the industrial energy demand function which accounts for nonlinear unobserved factors in order to capture the elusive effect of exogenously induced energy saving technical change on energy demand. However, the coefficient of energy price is modelled as a constant parameter in Hunt et al. (2003) which means that if energy saving technical changes are price induced then the stochastic trend would act as a proxy for price induced energy saving technical changes and by extension mispecifying the model. If indeed this hypothesis is true, then one would expect that the introduction of time-varying coefficient of industrial energy price in the state space model will severely affect the stochastic nature of the long-term energy consumption trend.

This thesis contributes to the current understanding of relevance of price-induced against exogenous technological change by proposing a systematic econometric approach, as well as overcoming the standard restrictive assumption that the coefficient of energy price elasticity is constant. Chapter 3 considers the UK economy over the longest time period ever studied of almost 50 years and explores the extent to which the observed long-run trend in the industrial energy demand is endogenous to changes in market energy prices. As this relationship may have been subject to important shifts over time, this thesis also investigates whether there is significant time-variation in the energy price elasticity, and how relevant it is to capture this time variation in order to explain the influence of energy price on technological change. To this aim, I develop a novel approach that makes use the Kalman filter to estimate state space models representing energy consumption in section 3.3. Using this novel procedure, I am able, first, to characterise the nature of the trend in the UK industrial energy demand, second, to assess how much of the observed shape in the long-run trend is due economic

activity and price effects, and third, to determine how much of this relationship with price has changed over time.

Improving energy efficiency is necessary for reducing emissions in the industrial process and by extension achieving Clean Growth targets set by the UK government. However, apart from energy efficiency, there are also distinct industrial characteristics, not directly related to energy consumption in the industrial process that are responsible for industrial emissions. Thus, I move on to section 1.1.2 in which I examine distinct characteristics of industrial process and assess their long-term role in achieving Clean Growth.

1.1.2 Industrial emission determinants

There is a shortage of studies that assess the relationship between industrial activity and air pollution outside of the United States. Cole et al. (2005) – from now onwards CES (2005) – were the first to empirically investigate the nature of this relationship for the UK manufacturing[4] sector using data from 1990 to 1998. Although the manufacturing sector is one of the major air polluters in Europe (ONS, 2016a; EEA, 2015), not many studies have responded to the task highlighted by CES (2005) so that this apparent lack of investigative effort is preventing a rigorous understanding of the historical determinants of emissions from the manufacturing sector, at least in Europe. In fact, many contributions focus only on national or regional CO_2 emissions rather than from the industrial sector, e.g. Li et al. (2017), Mussini and Gross (2015), Omri (2014), Qi et al. (2016), Tajudeen et al (2018). When focusing on the industrial sector, analysis has been often implemented by using decomposition analysis rather than econometric modelling, e.g. Dachraoui and Harchaoui (2006), Kim and Kim (2012), Liaskas et al. (2000), Tan and Lin (2018), Wang et al. (2018), with Floros and Vlachou (2005) being a

[4] Despite the difference between the two sectors based on the international SIC taxonomy, I use the term "manufacturing" and "industrial" interchangeably. The list of the industrial subsectors covered by this study can be seen in Table 2-3.

notable exception but only focusing on CO_2 rather than set of air emissions discussed in this thesis. However, the existence of unobserved common factors, such as technological progress and regulatory pressure that can materialise either through the impact of spillovers or common shocks, can significantly affect industrial subsectors simultaneously and result in biased estimates (Chudik et al., 2011). Given the abovementioned studies employing decomposition methodologies do not control for the existence of these latent common factors, it is not clear whether their empirical finding would hold once one controls for the existence of those unobserved common factors.

Research findings in CES (2005) indicate that emission intensity is positively related to energy use, physical capital intensity and human capital intensity and negatively related to sector's average firm size and productivity. Research and development (R&D) expenditures were reported to have a mixed impact on emission intensities, with the direction of the impact depending on the pollutants being assessed. Impact of capital expenditure was positive but non-statistically significant. Emissions were also negatively influenced by regional population density, prosecution activity and regional age of population and positively by unemployment. This thesis responds to the task highlighted by CES (2005) on establishing an empirically grounded understanding of the relationship between emissions and industrial activity, with a focus on the UK manufacturing subsectors. Lacking an established and generally accepted theoretical framework, the best way to analyse the extent to which emissions from the manufacturing sector are related to the characteristics of the production process is to assess the robustness of established findings in the literature such as those in CES (2005).

This thesis investigates the long-term determinants of emissions from the industrial sector in chapter 4 by assessing the robustness of the results in CES (2005) in three ways. First, I adopt a specification as close as possible to the one CES (2005) estimated on a 1990-1998 sample, which I re-estimate on a sample that covers the time period from 1997 to 2014. If results from CES (2005) are reflective of long-term determinants of emissions, one would expect results to be fairly similar to those in CES (2005), with some changes in the value of the coefficients maybe due to the possibility of time-varying

parameters in the data generation process or missing variables. Secondly, I estimate a model augmented by two factors, namely fuel substitution and market concentration, which might have an impact on emissions from the manufacturing sector. Fuel substitution seems an obvious candidate as an explanatory factor as emission intensities vary across different fuels. Building on the results in Aghion et al. (2005), I also introduce market concentration in the estimation process as it might help to consider the impact of innovation on emissions and therefore tackling the lack of R&D data at the subsectoral level. Again, if results from CES (2005) are reflective of long-term determinants of emissions, one would expect changes from introducing two explanatory variables to be limited, especially in cases where correlation between the explanatory variables is low. Thirdly, as the requirements for long-term determinants of emissions are not met by most of the variables in CES (2005), this thesis assesses the extent to which unobserved common factors affect results through the existence of cross section dependence (CSD) within the sample (Chudik et al., 2011). The choice of focusing on CSD is motivated by the fact that industrial subsectors in the same country are likely to be affected, to some extent, by a common set of unobserved factors such as technological progress and regulatory pressure, either through the impact of spillovers or common shocks as confirmed by the statistical tests performed in this thesis. Not taking CSD into account is a serious shortcoming, as it may impact both the statistical significance of explanatory variables and the values of the estimated coefficients, as discussed in section 4.3.

Introduction of clean technologies and improvement of existing industrial practices can effectively enable the reduction of emissions generated during the industrial process and by extension assist the efforts towards meeting Clean Growth targets set by the UK government. However, the adoption of novel technologies raises concerns about job loses as the gradual phasing out of outdated, emission intensive technologies, increases the risk of negative socioeconomics externalities, such as redundancies and job losses. These concerns could significantly hinder the efforts to develop and adopt energy saving technical change and thus slow down Clean Growth dynamics within the UK

industrial sector. Thus, section 1.1.3 explores the employment impact from the deployment of renewable power generation technologies.

1.1.3 Renewable electricity and employment impact

Since 2012, the deployment of renewable technologies has substantially increased, leading to the renewable energy sector globally employing 11 million people in 2018 (IRENA, 2019). The rapidly increasing maturity of renewable technologies along with the rising numbers of created jobs make it crucial that one investigates the employment effect of renewable electricity. IRENA (2011) indicates that renewable energy can create a “considerable future potential” for net job creation, a suggestion generally backed up by most studies in the literature (Meyer and Sommer, 2014). Although there is a large number of studies that investigate the employment effect of renewable energy, these studies tend to focus on specific technologies, location and plants and to discard the employment effect of fossil and nuclear generation technologies with no clear consensus over the long-term sustainability of renewable jobs (Cameron and Zwaan, 2015).

This thesis helps fill this gap by developing a novel methodology to assess the long-term employment effect of different types of power generation technologies, including conventional thermal, from a macroeconomic perspective so that an estimate of the potential future net job creation can be obtained by using the results presented in chapter 5 in combination with national decarbonisation scenarios for 2030. The approach of this study is a rigorous but simple and can be implemented by using relatively aggregated data. Employment in the UK power generation sector is modelled as a function of a) economic activity and b) the level of electricity generated by conventional thermal (oil and coal), combined cycle gas turbine (CCGT), nuclear and renewable technologies. The proposed econometric methodology has relatively low data requirements based on a Vector Error Correction (VECM) model. This means that it can be estimated on national data for employment and economic activity in the power sector (regardless of the technology being used) and the amount of electricity

produced by different power generating options. Therefore, the main advantage of this approach is that it avoids the data burden typical of Input-Output (IO), Computable General Equilibrium (CGE) and macroeconometrics sectorial models (Cameron and Zwaan, 2015), with the additional advantage that the relationships estimated in this model are transparent, contrary to other approaches, such as CGE models, using several elasticity parameters, not always made explicit in the studies. I implement the proposed methodology to the UK electricity generation market as it is highly competitive (Ofgem, 2018) with diverse energy mix, a significant proportion of which has been increasingly being generated by renewable technologies.

By quantifying the employment impact of a number of energy technologies, the proposed methodology can be applied on the back of the output of energy system models which produce deployment scenarios of electricity generation technologies to achieve a certain level of decarbonisation. This implies the possibility of computing the net effect from the deployment of renewable technologies on employment in renewable and fossil-fuel based plants, respectively. In addition, the proposed methodology can be easily replicated across countries therefore increasing empirical evidence base while taking into account the context of a particular country, such as industrial and labour policy, technologies being used in power generation and labour productivity. All variables used are observed at the annual frequency, although one could use quarterly or monthly data, in those cases where they are available. The ability to use annual observations instead of more granular ones increases the applicability of the method which uses data which are readily available for the member countries of the Organisation for Economic Co-Operation and Development (OECD). Thus, this dissertation is of interest to both UK policymakers and government officials while replication of this study in other countries would be of similar interest to policymakers in the country of interest.

1.2 Research questions and key findings

This thesis focuses on Clean Growth, one of the four Grand Challenges as identified by the UK government. In order to deliver economic growth while reducing emissions produced in the industrial process, it is crucial to identify the factors enabling the long-term transition towards Clean Growth. Hence the **key overarching research question** of this thesis is the following:

What are the long-term drivers of Clean Growth in the UK industry?

The research findings produced by this dissertation can contribute substantially to the redevelopment of the UK industrial policy and help meet the decarbonisation goals set by the UK government. More specifically, this thesis provides robust empirical evidence that long-term Clean Growth can be reliably delivered by improving industrial energy efficiency that can be enabled by the development and adoption of innovative, clean technologies within the industrial sector. Although in the short-term period energy price dynamics and fuel switching from dirtier to cleaner fuels can reduce energy consumption to a certain extent, they are not sufficient to support the efforts towards achieving long-term Clean Growth. In the long-term period the UK government should actively incentivise and support the development and adoption of technologies able to improve energy efficiency and minimise emissions so as to counteract increases brought about by increased economic activity. The introduction of low carbon technologies within industrial sector can generate positive employment effects and thus policymakers should clearly address this message to the wider public, so that they generate wider support for the related technologies within the UK industrial sector. More specifically, and in an effort to comprehensibly respond to all underlying dynamics behind the enabling factors of Clean Growth in the UK industry – i.e. improving industrial energy efficiency and adopting clean industrial processes along with renewable technologies – I examine in depth the following three **sub-research questions**:

1. What is the importance of energy prices on long-term industrial energy efficiency?

2. What are the long-term industrial determinants of emission intensity?

3. What is the long-term employment effect of renewable electricity?

Figure 1-1. Thesis outline and the relationship between overarching research question and sub-research questions

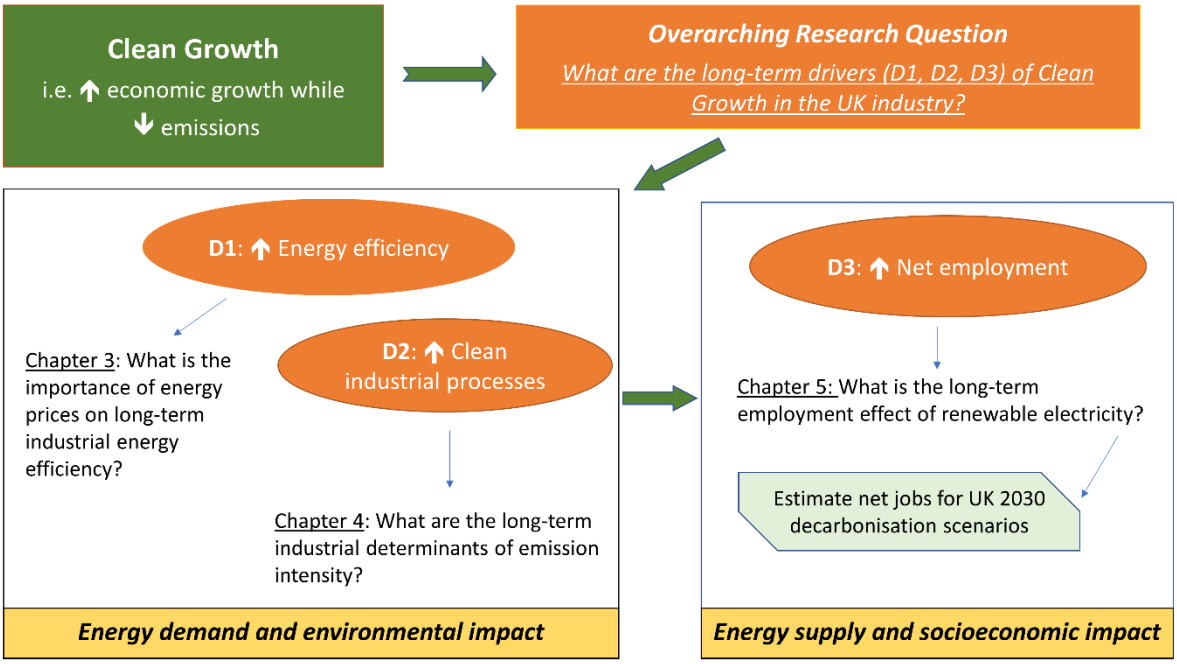


Figure 1 reveals the relationship between the key overarching research question and the three sub-research questions. Each one of the three sub-research questions is associated with one of the three long-term drivers (D1, D2, D3) of Clean Growth in the UK industry as allocated accordingly in Chapter 3, 4 and 5. Starting with the *sub-research question 1*, energy efficiency gains can be successfully stimulated, although to a different extent, both by higher energy prices and exogenous factors such as for example changes in the regulatory framework. Results indicate that long-term energy demand trend is stochastic in nature and retains comparable variance size across a number of alternative specifications confirming absence of changes in its stochasticity. The stochastic nature of the energy demand trend does not change when I control for the effect of economic activity and energy price on energy consumption. This indicates that exogenous factors leading to the adoption of energy saving

technical changes within the industrial sector are the main drivers of energy efficiency that can effectively enable Clean Growth dynamics within the UK industrial sector. Higher prices have stimulated energy efficiency to the extent that they have largely offset a surge in energy consumption induced by an increase economic activity, while the remaining component of energy efficiency is induced by gradual and irregular institutional changes, unrelated to energy prices. This is an important outcome for policymakers as it reveals that policies employing price signals can counteract for the negative effect of economic activity on energy efficiency. Finally, I proceed in several robustness tests that support the robustness of the proposed employed methodological approach and the validity of my results. As a matter of fact, results indicate that the coefficient of energy price has negligible time variation and when modelled as constant it increases the fit of the model.

Responding to *sub-research question 2*, results indicate that reducing energy consumption and encouraging substitution of dirty fuels to cleaner ones can counteract for an increase in emissions due to higher capital investment. In addition, improving competition within industrial subsectors can stimulate Clean Growth as findings indicate that higher market competition incentivises innovation processes towards clean technologies. Application of the Common Correlated Pooled Group estimator (Pesaran, 2006) that tackles CSD enables me to point at energy intensity, fuel substitution, and capital expenditure intensity as robust determinants of industrial emissions across the pollutants assessed in this thesis. Reflecting on the results from Aghion et al. (2005) on the relationship between market concentration and innovation, my findings point at a robust U-shaped relationship between market concentration and emission intensities and therefore contributing to an area of environmental economics which appears surprisingly under-researched. This thesis also concludes that factors such as production inputs i.e. labour and capital, total factor productivity and size of typical firm are not robust determinants of emissions from industrial sector, at least for the timespan assessed in this study, based on the chosen definition of the variables and the level of aggregation at which analysis in chapter 4 is conducted.

Finally, responding to *sub-research question 3*, results indicate that the deployment of renewable technologies, a key governmental policy in the Clean Growth Strategy, can generate substantial employment gains in the UK power sector leading to potential for significant net job creation by 2030. I provide evidence that the increase in employment related to a permanent rise in the generation of renewable electricity is several times higher than the employment effect of an equivalent increase in electricity generated by nuclear or natural gas. More specifically, findings indicate that a permanent 1 GWh increase in the annual electricity supply generated by renewable technologies creates 3.5 jobs in the long-term run while the deployment of renewable technologies can generate up to 150,000 net jobs by 2030 in the UK power sector depending on the types of energy mix that is delivering decarbonisation. In section 1.3, I present the outline of this thesis along with the structure of each one of the following chapters in this thesis.

1.3 Structure of the thesis

Chapter 2 presents and discusses on the historical trends in industrial energy consumption, industrial emissions, electricity supply and employment while it also provides an extensive literature review on the studies assessing the socioeconomic and environmental impact of industrial energy demand and supply in the UK industrial sector. More specifically, section 2.2 assesses the historical energy trends in the UK industry and analyses studies assessing energy efficiency. Section 2.2 further reviews in depth studies employing various econometric methods to estimate energy demand and finally focuses on studies estimating energy demand for the UK industry. Section 2.3 assesses the historical trends in UK industrial emissions and reviews the literature that focuses on the characteristics of the manufacturing process that are expected to be responsible for the historical reduction in industrial emission intensities. Section 2.4 assesses the historical trends in electricity supply generated by various power generation technologies along with the employment trends in the power generation

sector and it thoroughly reviews a large number of studies that assess the employment impact of renewable technologies.

Chapter 3 focuses on industrial energy demand and assesses the importance of energy prices and exogenous factors on industrial energy efficiency. This chapter starts with an overview in section 3.1 while section 3.2 presents the variables employed in the empirical analysis. Section 3.3 outlines the chosen econometric methodology and introduces a systematic econometric approach used to characterise the nature of the trend in industrial energy consumption. Section 3.4 presents the empirical results for the univariate and multivariate model, respectively, and performs relevant robustness checks while section 3.5 discusses on the policy relevance of the findings. Section 3.6 presents concluding remarks and responds to the key overarching research question.

Chapter 4 identifies the industrial determinants responsible for the historical reduction in industrial emission intensity. Section 4.1 presents an overview of the chapter and section 4.2 discusses on the variables employed in the analysis. Section 4.3 outlines the econometric methodology which builds on CES (2005) and further expands by incorporating additional factors along with accounting for cross sectional dependence. Results are presented in section 4.4 and section 4.5 discusses on their policy relevance. Section 4.6 presents concluding remarks and responds to the overarching research question.

Chapter 5 assesses the employment effect of renewable electricity on the UK power sector. This chapter starts with an overview in Section 5.1 and section 5.2 presents all relevant details on the variables used in the empirical analysis. Section 5.3 outlines the methodological approach employed to model electricity demand as a function of economic activity and the level of electricity generated by conventional thermal, combined cycle gas turbine (CCGT), nuclear and renewable technologies, respectively. Section 5.4 presents the empirical findings while section 5.5 discusses on their policy relevance. Finally, Section 5.6 applies the estimated results presented in section 5.4 on a set of decarbonisation scenarios for the UK in 2030 to assess the potential future employment impact of

renewable electricity. Section 5.7 presents concluding remarks and responds to the overarching research question.

Finally, Chapter 6 summarises the key research findings of this thesis, concludes on their policy relevance for the UK industry and discusses on existing limitations and potential opportunities for future research.

2 Energy demand and supply

2.1 Overview

To identify the long-term drivers of Clean Growth, one should first understand the underlying dynamics that underpin the factors responsible for minimizing energy use and by extension industrial emissions. This chapter starts by reviewing the historical trends of energy consumption in the UK industry in subsection 2.2.1. Then it moves to review the studies that examine the dynamics underpinning industrial energy demand to gain deeper understanding of the long-term relationship between energy consumption and energy efficiency. Hence, I first review the literature on energy efficiency in subsection 2.2.2 and the literature on econometric methodologies employed to model industrial energy demand and identify the determinants of long-term industrial energy efficiency in subsection 2.2.3. Apart from energy consumption and energy efficiency, it is also important to identify the distinct characteristics of industrial production process that have been historically responsible for reducing industrial emissions. For that reason, I review in section 2.3 the related environmental and energy economics literature to identity the most widely discussed and empirically tested industrial emission determinants. The deployment of renewable electricity generation technologies can further assist the efforts to meet the decarbonisation targets set by the UK government under the Clean Growth Strategy. However, the gradual replacement of fossil intensive power generation technologies by low carbon and renewable energy generation technologies raises concerns about potential negative socioeconomic impacts. To this aim, I assess the related literature in section 2.4 so that I gain deeper understanding of the underlying dynamics in the labour market from the deployment of renewable technologies.

2.2 Energy demand

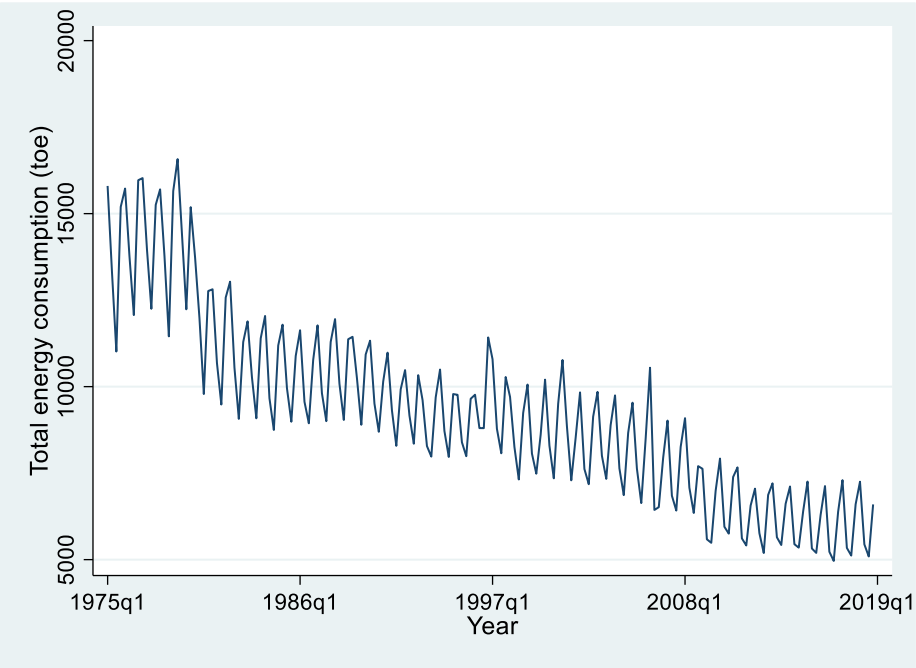
2.2.1 Energy trends in the industrial sector

Energy consumption in the UK industrial sector has significantly reduced over the course of the last half century in the UK industry as it can be seen in Figure 2-1 that indicates a clear downward trend. Industrial energy consumption is characterised by significant seasonal fluctuations. This seasonal pattern indicates that energy consumption peaks occur during the winter months while the lowest level of industrial energy consumption take place during the summer months. Initially, from 1975 to 1980, one can observe that the overall level of industrial energy consumption remained at the same levels when considering the annual average energy consumption for the specified years. However, in 1980 a significant drop in total energy consumption has taken place, followed by a clear downward trend till 1997. To fight back the rising inflation in 1980, the UK government introduced strong deflationary fiscal policies and combined them with monetary policies that resulted in the appreciation of the national currency (£). These polices made UK exports of industrial products significantly more expensive, which by extension made them less attractive to the international markets, accelerating in this way the decline of the UK industrial sector. This drop in exports and the subsequent economic decline have affected more severely energy intensive industrial subsectors such as iron and steel. The 1990 economic crisis further deteriorated the decline in the UK industrial sector and by extension further accelerated the rate of reduction in industrial energy consumption.

In 1997, the UK economy started to bounce back resulting in higher levels of economic activity. This economic boom in combination with the lowest level of energy price since the OPEC crisis can explain the above-than-average winter peaks in industrial energy consumption from 1997 till 2007. However, neither this economic boom, nor the observed reduction in fuel prices have been sufficient to reverse the long-term downward trend in industrial energy consumption. This can be considered as an indication that although economic activity and energy price seem to affect to a certain extent the level of energy use in the industrial sector, there is a remaining component of this downward trend that is

mostly imputable to exogenous factors. Finally, the 2008 great recession in combination with increasing fuel prices from 2006 and onwards, can explain the lower-than-average drop in energy consumption during the winter months of 2008. From 2012 to 2019, annual industrial energy consumption seems to be virtually constant.

Figure 2-1. Total energy consumption in the UK industrial sector at the aggregate level



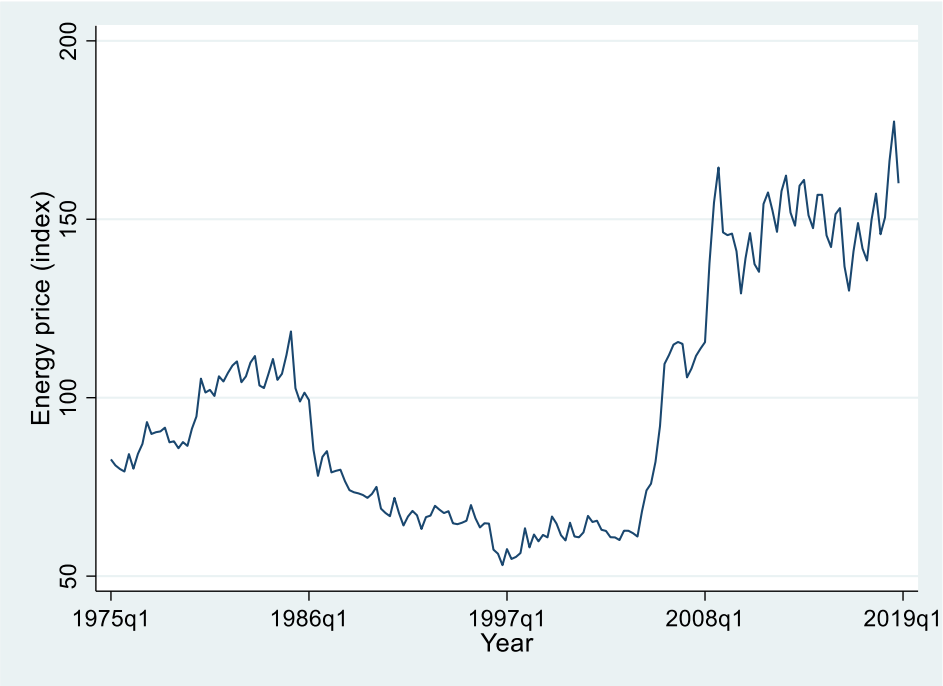
Notes: Energy consumption, including autogeneration[5], is obtained by summing consumption of coal, manufactured fuel, petroleum products, natural gas and electricity, all measured in tonnes of oil equivalent (toe). Data for industrial energy consumption are sourced from UK Energy Trends.

Analysing the historical trends in industrial energy price in Figure 2-2 can help us understand better the dynamics that underpin the observed long-term reduction in industrial energy consumption. From 1975 (the first data point in Figure 2-2) till 1985, one can observe that energy price is trending upwards. This gradual increase in energy price can be explained, first by the 1973 OPEC crisis when global oil supply dropped due to the oil embargo by Saudi Arabia, and second by the 1979 oil shock caused by drop in global oil supply due to the revolution in Iran. The highest peak in energy price occurred in 1985. From 1985 and onwards there has been a significant reduction in fuel prices, known

[5] Autogeneration of energy by final users is included in final energy consumption while any fuel used for autogeneration by final users is reported within the transformation section (DUKES, 2018).

as the oil glut. This has been induced by slowed economic activity in the industrial sector that reduced demand for oil combined with surplus of oil in the international market. Industrial energy price has remained at low levels till 2004. However, from 2004 and onwards, a combination of political factors, turmoil in Middle East and increasing energy demand in China has resulted in substantial increase in fuel prices, which has been halted at the wake of the great recession in 2008. Since then, one can observe increased volatility in industrial energy price, mainly driven by seasonal variations in the type of energy used in the industrial sector. More specifically, over the past ten years, the share of electricity consumption has increased over the summer months while it has dropped during the winter months. In contrast, industrial consumption of fossil fuels, such as natural gas (and to a lower extend fuel oil) has increased during the winter period. This indicates that industrial facilities consume more electricity during the summer period when electricity price is at lower levels and increase consumption of fossil fuels during the winter months given electricity price is significantly higher at that period. Having analysed the historical trends in industrial energy consumption and energy price, the next step involves analysing the role of energy saving technical change in the long-term reduction of industrial energy consumption through energy efficiency gains.

Figure 2-2. Energy price in UK industrial sector



Notes: Energy price is an index of real fuel prices of coal, heavy fuel oil, gas and electricity weighted by the share of each fuel in the total energy consumption, as defined above. All seasonally unadjusted quarterly fuel prices are compiled by the UK Department for Business, Energy and Industrial Strategy (BEIS) and include the Climate Change Levy within their prices. Nominal prices are deflated using the GDP deflator

2.2.2 Energy efficiency

Energy saving technical change that improves energy efficiency can be either endogenously induced by changes in energy prices, or exogenously induced by changes in the corresponding regulatory framework, or more generally by institutional changes within the economy. However, the elusive nature of energy efficiency makes it very difficult to quantify and explicitly control for these factors. To this effort, historically there have been two main methodological approaches employed in the energy economics literature to account for the endogenous effect of changes in energy price on stimulating energy efficiency dynamics. The first methodological approach captures energy saving technical change through the introduction of asymmetric prices in the energy demand function (Gately and Huntington 2002; Dargay 1992; Dargay and Gately 1994, 1995). In contrast, the second methodological approach introduces simple time-effect coefficients (or else time dummies) in a panel regression analysis (Griffin and Schulman 2005). The main criticism on the former approach lies on the fact that asymmetric prices might be working as a proxy for exogenously induced energy-saving technical changes that are not controlled for in the methodological approach. Therefore, asymmetric prices might not only be controlling, as initially expected, for endogenously induced energy saving technical change due to changes in energy prices (Griffin and Schulman 2005). Although the second methodological approach is in general much simpler than the first one in terms of modelling requirements, it has been equally criticised on the basis that year dummies could potentially capture price-induced technological change. As a result, time dummies could function as a rough proxy for both endogenous and exogenous factors affected energy-saving technical change (Huntington, 2006). Hence, there has been extended criticism in the energy economics literature over the effectiveness of proxies such as time dummies in capturing the effect of factors for which they have been originally designed to account for. Most of subsequent chronologically studies such as Agnolucci (2010) and

Adeyemi and Hunt (2014) have mainly incorporated asymmetric energy prices within the structural time series models (STSM – discussed at length in subsection 2.2.3) to examine the underlying factors driving energy saving technical change.

Although there is no consensus in the literature over which is the most effective empirical index for capturing energy efficiency (Zarinkau 1999), energy intensity is the most common proxy employed to measure changes in energy efficiency. According to IEA (2020), energy intensity captures energy use per unit of economic output while energy efficiency changes are often captured by measuring the rate of change of energy intensity ratio specifically for energy intensive technologies. It is common practice in the energy economics literature to decompose energy intensity to efficiency and structural effect to examine the dynamics of energy-saving technical change and energy prices. Haas and Kempa (2018) develop a theoretical model and calibrate it by using 15 years of data for over 40 OECD countries. Simulation results indicate that economies with energy intensive sector have dominant the efficiency effect while economies with labour intensive effects have dominant the structural effect. This essentially means that for energy intensive sector – such as the industrial sector – energy saving technical change mainly drives the reduction in energy intensity. Simulation results also indicate that temporal positive shocks in energy price can have permanent effect on innovation dynamics stimulating endogenous energy saving technical change. However, this model does not explicitly control for the effect of exogenous factors on energy saving technical change as it implicitly assumes that all factors in relation to the adoption of energy saving technical change are endogenous. Therefore. it is not clear whether the observed long-term effect of energy price shocks on energy saving technical change would remain once one specifically controls for those exogenous factors. Similar decomposition analyses have been implemented in Mulder and de Groot (2012), Voigt et al (2014) and Cao (2017) differentiating mainly on the time length of the dataset and the number of countries employed to estimate results in each study. An alternative methodological approach employed in the literature to measure the relative energy efficiency between countries or sectors involve the data envelopment analysis (DEA) method employed in Makridou et al (2014). Similarly, the

stochastic frontier approach can also be employed to measure the distance between the optimal energy efficiency frontier (Filippini and Hunt 2011; Zhang and Adom 2018). However, these empirical strategies face similar modelling constraints with the above-mentioned decomposition studies as they fail to explicitly control for the effect of exogenous (and/or latent) factors on the development and adoption of energy saving technical change.

There is an ongoing discussion in the related literature on whether energy savings due to increase in energy efficiency could be offset by an associated increase in energy consumption, a phenomenon known in the literature as the rebound effect (Greening et al 2000). However, a number of studies (Gillingham et al. 2013, Gillingham et al. 2015 and Sorrel et al 2009) argue that the energy rebound effect is overplayed in the literature as there is little evidence towards this "back-fire hypothesis". In addition, supporters of the energy rebound hypothesis tend to marginalise the positive effect of productivity and innovation dynamics in this process.

Although energy saving technical change can help reduce environmental externalities associated with energy use, the literature indicates that the adoption of these technologies by businesses is limited, a phenomenon also known in the related literature as the energy efficiency gap (Jaffe and Stavins, 1994; Gerarden et al 2017). There are multiple potential causes for this phenomenon, involving market failures often observed as entry barriers within subsectors of the economy, behavioural failures of economic actors that result to deviation from cost minimisation objectives, and modelling flaws in economic models whose research findings are employed to inform policymakers on their decisions on over policies aiming to stimulate energy efficiency dynamics within the economy (Gerarden et al 2017; Gillingham et al 2009). One proposed policy approach to effectively tackle the energy efficiency gap is combining investment in energy-saving technologies with appropriate energy management practices (Backlund et al 2012). This can be of particular use to the manufacturing industries and the commercial sector given they have increased needs for energy use in comparison to other economic sectors such as services (Backlund et al 2012). Nonetheless, existing national and international policy pathways are

often not sufficiently effective in incentivising economic actors within the economy to actively pursue technologies and management practices that can lead to significant energy efficiency improvements. Malinauskaite et al (2020) discuss over the effectiveness of the proposed EU energy efficiency directives as part of the integrated national energy and climate actions plans set specifically for the industrial sector given it is one of the largest consumers of energy within the EU. Interestingly, Bertoldi and Mosconi (2020) argue that energy efficiency policies in the EU had counterintuitive outcome, at least as far as it concerns EU energy consumption levels in 2013. Focusing on the UK, policymakers should specifically target the industrial sector and actively promote the adoption of more energy efficient industrial processes through the development of a corresponding regulatory framework (Malinauskaite et al 2019).

Having extensively reviewed the related literature on energy efficiency, I choose to focus on the branch of energy economics literature modelling the energy demand function by employing the structural time series model. The advantage of this methodological approach is that allows me to keep an agnostic approach over the nature of the drivers of energy efficiency. In addition, I can explicitly model and control on the one hand, for the endogenous effect of energy price on energy saving technical change and on the other hand, independently control for the effect of exogenous factors on energy efficiency gains.

2.2.3 Modelling energy demand

Energy demand is traditionally modelled as a function of economic activity and energy prices in which energy consumption is postulated to have a positive relationship to economic activity and a negative relationship to energy prices. The energy demand function has been deployed to account for the drivers of energy consumption for various economic sectors such as industry, transport, residential and also for the aggregate level of energy consumption within national borders. Various econometric methodologies have been employed in the literature to estimate energy demand including:

1. time series cointegration studies with constant or time-varying parameters such as Polemis (2007) and Chang et al. (2014), respectively,
2. panel cointegration studies such as Bjørner and Jensen (2002) and El-Shazly (2013),
3. input factor and fuel substitution models such as Christopoulos (2000), Frondel and Schmidt (2002), Kim and Heo (2013) and Urga and Walters (2003),
4. studies assessing the asymmetric effect of energy price such as Adeyemi and Hunt (2007), Adeyemi and Hunt, (2014), Dargay and Gately (1995) and Sharimakin (2021),
5. studies employing the Structural Time Series Model (STSM) (Adeyemi and Hunt, 2014; Hunt et al., 2003; Dilaver and Hunt, 2011), which is the main focus of this thesis and, in particular, of chapter 3. In this thesis, I employ the STSM model as it has the advantage that it allows me to explicitly control for both endogenously and exogenously induced energy saving technical change.

Although price and income elasticities of demand are mostly modelled as constant parameters in the studies employing the Structural Time Series Model (STSM), there has been increasing discussion in the related literature on whether these two drivers remain constant over time or vary instead. Before being able to respond to this question, it is crucial to understand the dynamics between energy demand on the one hand, and a set of underlying nonlinear effects not captured by gross value added (GVA) and energy price on the other hand. Section 0 reviews studies modelling energy demand with a stochastic trend to capture these unobserved non-linear determinants and section 2.2.3.2 reviews studies modelling economic activity and energy price as time-varying parameters. Finally, section 2.2.3.3 focuses specifically on studies modelling energy demand in the UK industry.

2.2.3.1 Energy efficiency and stochastic trend

Apart from the traditionally modelled drivers of energy demand, Hunt et al. (2003) argue that energy consumption is also determined by a set of non-linear unobservable factors. These exogenous factors,

often non-measurable, involve technological improvements in the industrial process leading to higher energy efficiency. Therefore, given the assumption that these unobservable factors are likely to affect energy demand in the long run, Hunt et al. (2003) and Hunt and Ninomiya (2003) model the trend term as a stochastic component so that it captures this time variation. This stochastic trend model is also known as the Underlying Energy Demand Trend (UEDT) model. The conventional linear trend term model, which is a restricted version of the UEDT, is not able to capture these nonlinear unobserved factors (Hunt and Ninomiya, 2003). The UEDT model, that is based on the STSM (Harvey, 1989; Harvey et al., 1986), has been adopted by a number of studies in the energy economics literature in order to estimate the energy demand elasticities for various countries and sectors – see for example Adeyemi and Hunt (2014), Amarawickrama and Hunt (2008), Broadstock and Hunt (2010), Broadstock and Papathanasopoulou (2015), Dimitropoulos et al. (2005), Dilaver and Hunt (2011), Doornat et al. (2008) and Javid and Qayyum (2014).

State space models are a popular econometric technique in modelling energy demand as they can capture any non-linear effects and estimate time-varying parameters both in terms of parameter accuracy and in terms of the overall fit of the model. The UEDT is a restricted form of a standard state space model, as economic activity and energy price are modelled as constant parameters. By performing Monte-Carlo simulations, Alptekin et al. (2018) find that state space models are more efficient than econometric methods such as rolling regressions and flexible least squares in estimating accurately energy demand elasticities. In addition, Alptekin et al. (2018) find that generalised state space models are expected to be superior in terms of estimation accuracy than restricted forms of state space models such as the UEDT. Although state space models are 90% 'accurate'[6] in larger samples, Alptekin et al. (2018) argue that they are only 60% 'accurate' in small samples.

[6] Alptekin et al. (2018) employ a Monte-Carlo simulation to compare the performance of estimators and to obtain 'accurate' (as they name it) estimates of time-varying parameters.

2.2.3.2 Time-varying coefficient of energy price

There is a small number of studies (reported in Table 2-1) that employs the Kalman filter methodology to model industrial, residential or aggregate energy demand. These studies model the impact of economic activity and energy price as time-varying parameters in the long run period. Instead of assessing the nature of the trend of energy consumption or that of the drivers of energy efficiency, the goal of these studies is to rather simply report the observed time variation in the elasticities of energy demand determinants. More specifically, Ingletzi-Lotz (2011) assess electricity consumption in South Africa from 1980 to 2005 while Arisoy and Ozturk (2014) estimate income and price elasticities of industrial and residential energy demand in Turkey from 1960 to 2008. Tiwari and Menegaki (2019) apply the Kalman filter in conjunction to linear and nonlinear unit root tests to assess the long-run electricity price elasticity for India. All three studies find that first, price and income elasticities vary over time in the first subperiod of their sample, i.e. roughly before 1990 and second, elasticities become virtually constant in the second sub-period of their sample. However, the limited time span of the sample used in these studies (for example Ingletzi-Lotz (2011) use only 25 observations) raises doubts about the accuracy of their empirical estimates as, according to Alptekin et al. (2018), a standard state space model is only 60% 'accurate' in small samples.

Table 2-1. Studies estimating energy demand with time-varying coefficient of energy price

Study	Method	Electricity type	Country/ies	Estimation period	Frequency
Arisoy and Ozturk (2014)	Kalman filter	Residential, industrial	Turkey	1960-2008	Annual
Chang et al. (2014)	Time-varying coefficient cointegration	Residential, commercial, industrial	South Korea	1985-2012	Quarterly
Ingletzi-Lotz (2011)	Kalman filter	Residential	South Africa	1980-2005	Annual
Liddle et al. (2020)	Non-parametric panel data	Aggregate	Non-OECD	1966-2014	Annual
Mousavi and Ghavidel (2019)	Kalman filter	Transport	Iran	1980-2016	Annual
Tiwari and Menegaki (2019)	Kalman filter	Aggregate	India	1975-2013	Annual
Wang and Mogi (2017)	Kalman filter	Industrial, residential	Japan	1989-2014	Annual

Wang and Mogi (2017) estimate energy price elasticity by employing a Kalman filter approach for Japan using annual data for the industrial and residential sector spanning from 1989 to 2014. Findings indicate that the coefficient of energy price varies across time while the coefficient of income elasticity remains virtually constant both for the industrial and residential sector. According to Wang and Mogi (2017), the time-variation in price elasticity can be explained by the process of deregulation that took place in Japan during the 1990s while this variation is roughly in accordance to certain important events such as the 2008 financial crisis and the Fukushima nuclear incident. Nonetheless, the trend term is not modelled as stochastic and therefore it is not clear whether energy price acts as a proxy for exogenous factors affecting long-term energy consumption. In addition, there are certain concerns about the accuracy of the estimates as the study uses a limited time sample of only 25 observations. Mousavi and Ghavidel (2019) estimate the energy demand determinants for Iran's transport sector using a state space model with stochastic trend term and find sizable time variation in the trend term both for diesel and gasoline fuels.

Chang et al. (2014) employ a time-varying coefficient cointegration approach to estimate the elasticities of energy demand in South Korea using quarterly observations from 1995 to 2012 for the residential, commercial[7] and industrial sectors. By comparing time-varying coefficients to fixed coefficients, Chang et al. (2014) find that fixed coefficients overestimate income elasticities. Finally, Liddle et al. (2020) use a non-parametric panel approach to estimate time-varying elasticity across a set of non-OECD countries and find non-statistically significant price elasticity for energy demand in the long-term period.

[7] By "commercial", Chang et al (2014) define the "public and service" sector after subtracting out power used by utilities.

2.2.3.3 Modelling energy demand in the UK industrial sector

Focusing on the UK industrial sector, there are studies estimating the long-term income and price elasticities for energy demand using various econometric techniques. The majority of the studies reported in Table 2-2 – i.e. Adeyemi and Hunt (2014), Agnolucci (2010), Dimitropoulos et al. (2005) and Hunt et al. (2003) – base their methodological framework on the STSM (Harvey, 1989) while allowing for various methodological additions/alterations where relevant. For example, Agnolucci (2010) further expands the STSM framework by introducing asymmetric energy prices in the energy demand function. On the other hand, Agnolucci (2009) uses a panel time series econometric framework that takes into account the existing cross-sectional dependence in the dataset to estimate elasticities. Finally, Agnolucci et al. (2017) that employs a time series cointegration approach, is the first study to estimate industrial energy demand at a disaggregated industrial level.[8] Concerning the values of the elasticities, income elasticity varies from 0.45 (Agnolucci, 2010)[9] to 0.71 (Hunt et al., 2003) while price elasticity takes values from -0.16 (Dimitropoulos et al., 2003) to -0.65 (Agnolucci, 2010)[10]. It is evident that there is significant variation across the estimated values for the income and price elasticities in the abovementioned studies, which is especially true for the case of price elasticity. In fact, one could argue that this variation in price elasticity might be a sign of potential model misspecification and therefore it would be interesting to compare the estimates reported in Table 2-2 to the empirical findings of this thesis.

[8] Agnolucci et al. (2017) estimate price and income elasticities for the following industrial subsectors: 1) Food, Beverages and Tobacco, 2) Textiles, Clothing, Leather and Footwear, 3) Pulp, Paper, Printing and Publishing, 4) Chemicals, 5) Non-Metallic Mineral products, 6) Engineering and Vehicles, 7) Non-Ferrous Metals and 8) Other industries.

[9] Agnolucci (2010) estimates two separate specifications, one with symmetric and the other with asymmetric prices. This result corresponds to the specification with symmetric prices.

[10] This result corresponds to the specification with asymmetric prices in Agnolucci (2010) and is the elasticity for the price maximum.

Table 2-2. Studies estimating energy demand for the UK industrial sector

Study	Method	Estimation period	Frequency	Income elasticity	Price elasticity
Adeyemi and Hunt (2014)	STSM with symmetric price	1962-2010	Annual	0.47	-0.71
Agnolucci (2009)	Average from various panel estimators	1978-2004	Annual	0.52	-0.64
Agnolucci (2010)	STSM with symmetric price	1973-2005	Annual	0.45	-0.59
Agnolucci (2010)	STSM with asymmetric price	1973-2005	Annual	0.48	-0.65/-0.47/-0.37
Agnolucci et al. (2017)	Average from sub-sector analysis	1990-2014	Annual	0.57	-0.41
Dimitropoulos et al. (2005)	STSM with symmetric price	1967-1999	Annual	0.70	-0.16
Hunt et al. (2003)	STSM with symmetric price	1971-1995	Quarterly	0.71	-0.19

2.3 Environmental impact

Energy use is an obvious determinant of industrial emissions. An increase in energy efficiency essentially means that, ceteris paribus, the same level of output can be produced with a lower level of energy consumption, and by extension a lower level of emissions. Nonetheless, beyond energy consumption and energy efficiency, industrial emissions are also related to distinct characteristics of the manufacturing process and potentially to the status of the sector's economic structure. Hence, it is important to understand the underlying dynamics behind industrial emissions and emissions intensity to be able to set up a reliable policy pathway towards delivering Clean Growth in the UK industry. In order to identify the relevant industrial determinants, first I assess in section 2.3.1 the historical trends for a set of industrial air pollutants both on the subsectoral and on the aggregate level for the UK industry and second, I review in section 2.3.2 existing studies that investigate the underlying dynamics between manufacturing processes, economic structure and air emissions.

2.3.1 Industrial emission trends

The UK has experienced a significant reduction in the overall level of atmospheric emissions from the manufacturing sector since 1990. More specifically, between 1990 and 2014 carbon dioxide (CO_2) emissions have fallen by 32%, nitrogen monoxide (N_2O) emissions by 96%, nitrogen oxides (NO_X) by 64% and sulphur dioxide (SO_2) emissions by 84% (Brown et al., 2016, p.108-111), with the great majority of the reductions additional to those assessed in CES (2005) which are related only to the 1990-1998 time period (see Figure 2-3). As one can see in Table 2-3, there is considerable variation in the average emission intensity across manufacturing subsectors in the sample (1997-2014) so that one can notice a handful of emission intensive sectors, such as "wood and products of wood and cork" (SIC 16), "paper and paper products" (SIC 17), "coke and refined products" (SIC 19), "chemical and chemical product's" (SIC 20), "non-metallic minerals" (SIC 23) and "basic metals" (SIC 24). Although the overall emissions have significantly decreased since 1990, industrial subsectors have continued to experience disparate trends in regards to emission intensities as one can see in Figure 2-5 for CO_2[11]. Indeed, Agnolucci et al. (2017) further verifies the existence of considerable heterogeneity across UK industrial subsectors when it comes to the long-run impact of economic activity on energy consumption. Therefore, it seems sensible to implement an investigation focused on industry-specific determinants, like the one pursued in CES (2005).

This thesis centres on emission intensities rather than the level of emissions, a choice motivated by the aim of identifying long-term industrial characteristics related to industrial emissions by assessing the robustness of results in CES (2005), but also by the fact that the time pattern of emissions is driven by intensive factors rather than the level of production, as one can appreciate from comparing the time pattern of emissions (Figure 2-3) and emission intensity (Figure 2-4). Following CES (2005), I focus on a set of air pollutants i.e. carbon dioxide (CO_2), nitrogen oxides (NO_x), sulphur dioxide (SO_2), total

[11] Figure 2-5 shows the emission intensity for CO_2 per SIC07 manufacturing sector, given that CO_2 is the most widely researched air pollutant in related the literature.

acid precursor emissions[12] (TAC), particular matter (PM_{10}) and carbon monoxide (CO). I also add another greenhouse gas to the set in CES (2005), i.e. Nitrogen Monoxide (N_2O), data for which is available in ONS (2016a).

Table 2-3. Average emission intensities per UK manufacturing subsector for 1997-2014

SIC07	Manufacturing Industry	SO_2	NO_x	Tot. Acid	CO	PM_{10}	CO_2	N_2O
10	Food Products	2.88E-04	9.56E-04	1.34E-03	1.21E-03	1.01E-04	4.25E-01	4.52E-03
11-12	Beverages and Tobacco products	2.27E-04	5.81E-04	8.19E-04	8.28E-04	4.25E-05	2.84E-01	1.49E-03
13	Textiles	6.24E-04	1.10E-03	1.73E-03	2.66E-03	1.78E-04	6.03E-01	3.19E-03
14	Wearing apparel	1.36E-04	3.35E-04	4.67E-04	8.32E-04	3.76E-05	1.92E-01	7.44E-04
15	Leather and related products	2.95E-05	2.17E-04	2.61E-04	3.57E-04	3.58E-05	1.26E-01	4.32E-04
16	Wood and products of wood and cork*	3.88E-04	**2.24E-03**	**2.95E-03**	**2.79E-02**	**1.14E-03**	**1.05E+00**	**9.08E-03**
17	Paper and paper products	**1.08E-03**	1.60E-03	2.69E-03	2.44E-03	2.09E-04	1.01E+00	5.59E-03
18	Printing and reproduction of recorded material	5.78E-05	3.36E-04	4.01E-04	6.70E-04	2.32E-05	2.12E-01	1.11E-03
19	Coke and refined petroleum	**4.10E-02**	**1.15E-02**	**5.27E-02**	**2.21E-02**	**1.44E-03**	**9.80E+00**	**1.86E-02**
20	Chemical and chemical products	**2.63E-03**	**2.54E-03**	**5.90E-03**	**7.96E-03**	**3.51E-04**	**1.90E+00**	**4.04E-01**
21	Pharmaceutical products	1.17E-04	1.90E-04	3.09E-04	4.90E-04	1.47E-05	1.52E-01	4.92E-04
22	Rubber and Plastic	8.76E-04	9.84E-04	1.87E-03	2.05E-03	2.03E-04	4.17E-01	3.46E-03
23	Non-metallic minerals	**6.70E-03**	**6.50E-03**	**1.35E-02**	**9.65E-03**	**1.24E-03**	**3.32E+00**	**1.45E-02**
24	Basic metals	**1.89E-02**	**7.22E-03**	**2.61E-02**	**1.17E-01**	**2.48E-03**	**8.18E+00**	**1.90E-02**
25	Fabricated products**	1.06E-04	5.07E-04	6.19E-04	1.07E-03	1.45E-04	2.61E-01	1.54E-03
26	Computer, electronic and optical products	4.07E-05	2.09E-04	2.57E-04	4.47E-04	3.12E-05	8.21E-02	1.21E-03
27	Electrical equipment	4.36E-05	3.75E-04	4.26E-04	8.35E-04	7.72E-05	1.61E-01	1.61E-03
28	Machinery and equipment	4.62E-05	4.37E-04	4.89E-04	9.99E-04	9.64E-05	1.69E-01	1.23E-03
29	Motor vehicles, trailer and semi-trailers	1.88E-04	3.20E-04	5.11E-04	6.91E-04	1.67E-04	1.81E-01	1.07E-03
30	Transport equipment	1.06E-04	2.96E-04	4.09E-04	3.97E-04	7.21E-05	1.36E-01	5.86E-04

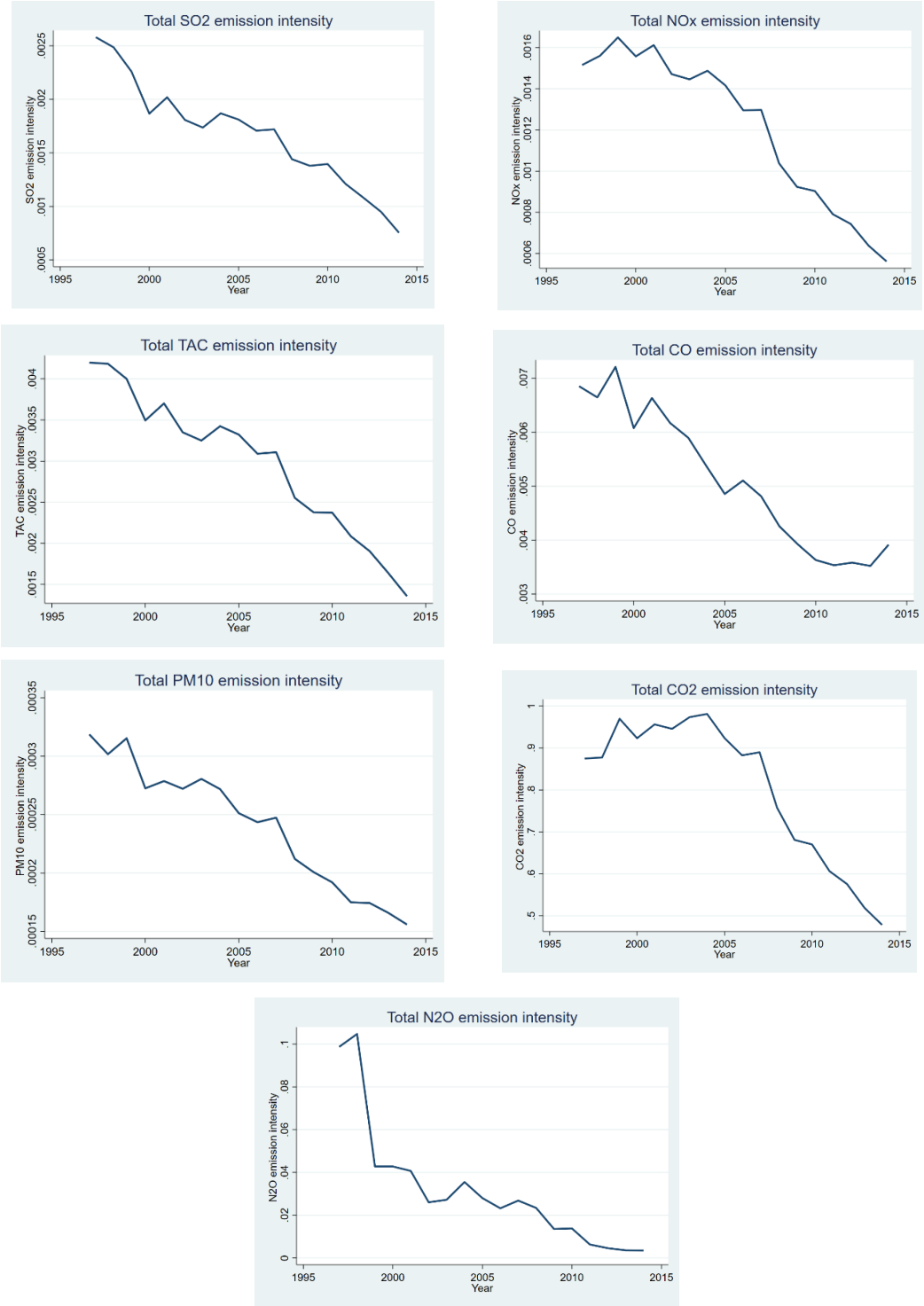
Notes: Emission intensities are measured as thousand tonnes per million pounds sterling of real GVA. For each column, the five highest emitting industries are highlighted in bold. I use the SIC07 industrial classification.
*Except furniture. **Except machinery and equipment.

[12]Total acid precursor emissions (TAC) are the weighted sum of SO_2, NO_x and NH_3 (ammonia) produced by industrial processes and direct fuel use at the point of release.

Figure 2-3. Total emissions for all industrial sectors expressed in thousand tonnes - variable scaling across sectors

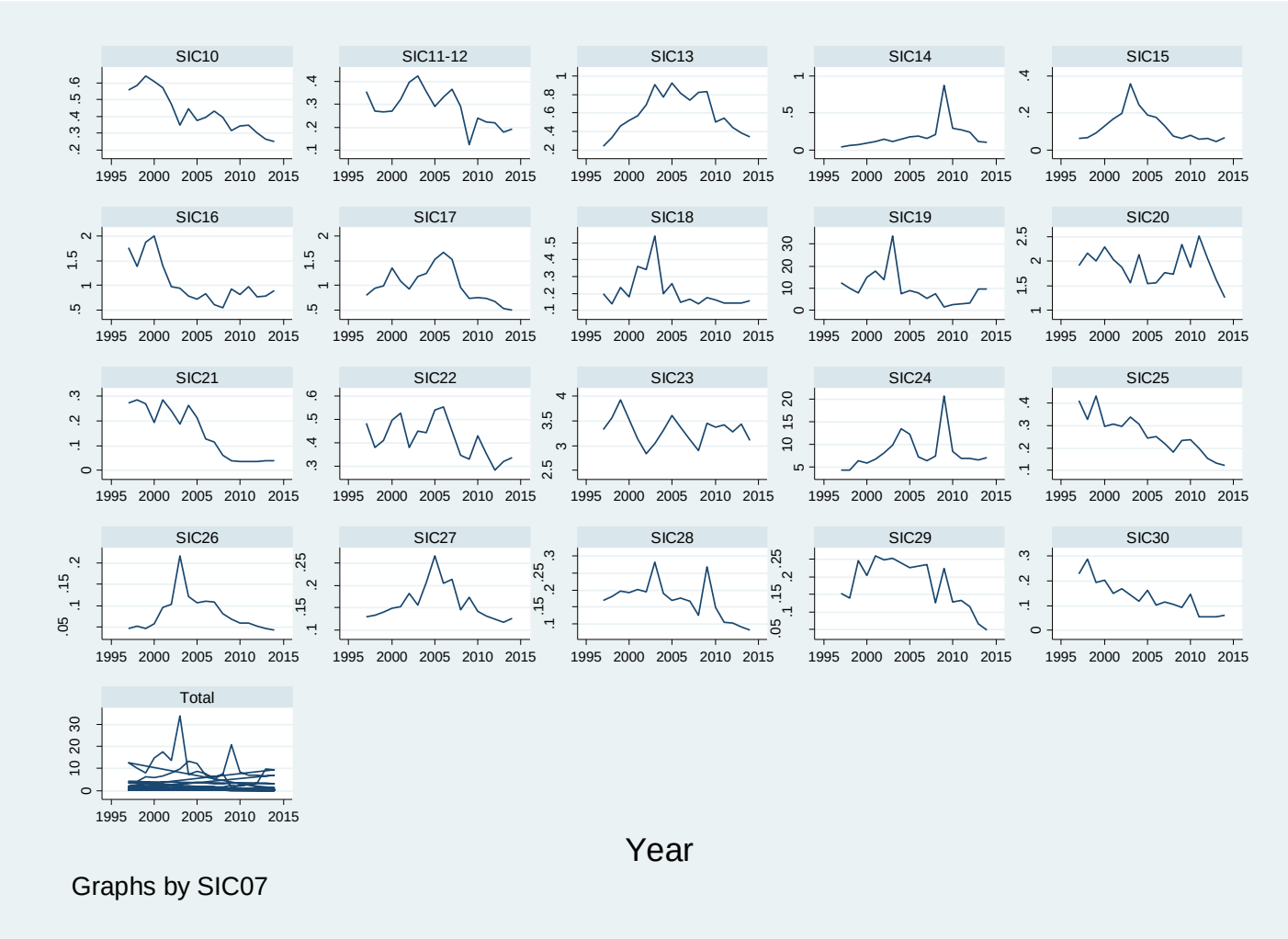
Notes: Emissions data are derived from the National Atmospheric Emissions Inventory (NAEI) and are available from 1990 onwards for each pollutant, respectively.

Figure 2-4. Total emission intensities for all industrial sectors - variable scaling across sectors



Notes: Emission intensity is derived by dividing emissions to the level of economic activity. Given that economic activity data are available at the same level of industrial classification to emissions from 1997 onwards (ONS Input-Output Supply and Use tables), emission intensities figures cover the same time period.

Figure 2-5. CO_2 emission intensity per industrial sector - variable scaling across sectors



2.3.2 Industrial determinants in emissions

Emission intensities in the manufacturing sector can be influenced by various industrial determinants depending on distinct characteristics of the production process and the status of the economic structure within industrial subsectors. Energy intensity is expected to have a positive relationship with emission intensities, being an obvious determinant of emission intensities. Indeed, in the case of Chinese industrial sectors Qi et al. (2016) provide evidence that CO_2 emissions have been mainly reduced by the decrease in energy intensity per output while Li et al. (2017) prove that economic scale effect and energy intensity are the major factors driving regional differences in CO_2 emissions. Controlling for energy intensity allows me to account for the effect of fossil fuels used per unit of output on the level of emissions generated for the same level of industrial output produced. Once I control for the effect of energy use on the level of emissions produced, I can also control for industrial determinants whose effect on emissions is purely related to distinct characteristics in the manufacturing process and to the economic structure within industrial sector. Thus, I review the most widely discussed and empirically tested industrial emissions determinants according to the related literature, namely physical and human capital intensity (section 2.3.2.1), capital expenditure intensity (section 2.3.2.2), total factor productivity (section 2.3.2.3), size of the firm (section 2.3.2.4), fuel substitution (section 2.3.2.5) and market concentration (2.3.2.6).

2.3.2.1 Physical and human capital intensity

The use of Physical Capital Intensity (PCI) and Human capital intensity (HCI) when studying emission intensity is related to the relationship between production inputs, including energy and therefore emissions, and the associated debate on the substitution or complementarity in the so-called KLE (Capital, Labour and Energy) literature, e.g. Koetse et al. (2014) and Thompson (2006). While results from Antweiller et al. (2001) and Cole and Elliott (2003) suggest that higher emissions are related to higher physical capital intensities, perhaps due to higher abatement costs, it is not entirely clear whether this empirical relationship would hold between emission intensity and physical capital

intensity, especially after controlling for energy intensity, a factor which is not included in neither Antweiller et al. (2001) nor Cole and Elliott (2003). After all, if higher abatement costs manifest themselves through demand for energy, so that it is more difficult for these firms to reduce emissions by substituting away from energy, a statistically significant relationship between physical capital and emission intensity might not hold once one controls for energy intensity use. CES (2005) argue that certain complex industrial processes which tend to be physically capital intensive might generate more emissions per unit of energy than less capital-intensive processes. CES (2005) also argue that human capital-intensive sectors are likely to be more efficient and by extension less energy intensive and therefore relatively clean (CES 2005). Nonetheless, it is not clear whether these plausible relationships would hold after one controls for energy intensity. CES (2005) eventually find a statistically significant positive relationship between HCI and emission intensities (after controlling for energy intensity), a result contradicting their reasoning above. Thus, I conclude that there does not seem to be sufficiently strong theoretical reasoning to expect statistically significant relationship between physical and human capital intensities, and emission intensities, especially after controlling for energy intensity.

2.3.2.2 Capital expenditure intensity

CES (2005) argue that capital expenditure intensity can be used as a measure of the vintage of production processes, under the assumption that the higher this expenditure, the more modern the equipment and machinery are likely to be, and the lower the emissions from the production process. Nonetheless, the empirical findings in CES (2005) contradict this argument, as the estimated coefficients are positive for all emission intensities although non-statistically significant. A measure of investment intensity that slightly differentiates from the one used in CES (2005) but essentially capturing the same effect is capital expenditure intensity that is measured based on Gross Fixed Capital Formation.

2.3.2.3 Total Factor Productivity

Total Factor Productivity (TFP) can be used to control for the output not explained by the amount of inputs used in the production process (Hulten, 2000). According to CES (2005), emissions are expected to be negatively correlated with TFP, as a more productive firm tends to be better managed, more resource efficient, produce less waste per unit of output and able to respond relatively quickly to any change in pollution control incentives. Although more efficient firms are likely to produce a lower level of emissions, it is not clear whether this holds once one controls for energy intensity. Cui et al. (2016) find a negative relationship between a simplified measure of TFP[13] and emission intensities. A similarly negative relationship has been estimated in CES (2005) that, unlike Cui et al. (2016), control for energy intensity.

2.3.2.4 Size of the firm

The size of the firm within the industrial subsector is used as an explanatory variable in CES (2005). The basic hypothesis is that there should be a positive relationship between a firm's total output and emissions, although diminishing at the margin, so that emission intensities decline as output increases due to economies of scale in resource use and in pollution abatement. Engineering evidence that supports lower unitary abatement costs as size of the plant increases is briefly discussed in Andreoni and Levinson (2001) but analysis of detailed US factories reveals a great diversity with regard to marginal abatement cots, i.e. some marginal costs rising with the scale of abatement while others falling. Similarly, for some sectors and some pollutants, marginal abatement costs decline across time while for others they rise across time (Hartman et al. 1997). The impact of firm size on emission intensities in Cole et al. (2013) and Gray and Shadbegian (2007) is negative, although it is not always

[13] TFP is estimated as a simple firm and industry-specific fixed effect in a linear production function comprising labour, an industry fixed effect, an industry-specific time effect and a firm and industry-specific fixed effect taken to measure TFP.

statistically significant[14]. However, none of the abovementioned studies controls for energy intensity when estimating the impact of firm size on emission intensities. As it regards to CES (2005), the impact of size is negative but statistically significant only in half of the selected final models.

2.3.2.5 Fuel substitution

As emission intensities vary across fuels, fuel substitution seems to be an obvious driver of emission intensities, especially bearing in mind that part of the emissions is calculated in ONS (2016a) by applying sector and fuel-specific emissions coefficients. According to Liaskas et al. (2000) fuel substitution from conventional fuels to natural gas in the industrial sector has resulted in the reduction of CO_2 emissions in most of the EU countries while Dachraoui and Harchaoui (2006) find that a reduction in Canadian CO_2 emission intensities has been the outcome of a combination of energy intensity and substitution effect. The fact that fuel substitution is not controlled for in CES (2005) and in any of the other contributions estimating the relative importance of the determinants of emission intensity, e.g. Cole et al. (2013), Cui et al. (2016) and Gray and Shadbegian (2007), is a shortcoming maybe related to the overall low profile of fuel substitution in the EKC literature.[15] Therefore, it is interesting to test the extent to which fuel substitution is an important factor in determining emission intensities by using the gas share, as a proxy for substitution from dirtier to cleaner fuels. One would therefore expect a negative relationship between gas share and emission intensities. Statistically significant substitution effect between coal and gas for the UK manufacturing sectors is discussed in Steinbuks (2012). The impact of switching from coal to gas on the level of CO_2 emissions is one of the generally acknowledged facts in the literature assessing the EU ETS, e.g. Chevallier (2012), while

[14] When using categorical size variables, Cole et al (2013) find that only two of the three size variables are statistically significant. Similarly, Gray and Shadbegian (2007) find that the continuous size variable used in their study is not statistically significant in the two models explaining particular matter (PM) emissions.

[15] Fuel substitution is mentioned only once, as part of the technological changes associated with the production process, in a survey of EKC (Dinda, 2004) and estimated to have a relatively overall minor impact in a number of influential articles, i.e. Stern (2002) and Stern (2004).

similarly, low coal and carbon prices has been one of the causes of the low demand for gas in Europe (Stern, 2017).

2.3.2.6 Market concentration

Market structure and concentration[16] have received considerable attention in the literature focused on the optimal choice of policy instruments aimed at maximising social welfare in presence of externalities (Baumol and Oates, 1975; Buchanan, 1969; Harberger, 1954; Oates and Strassmann, 1984). Textbook environmental economics conclude that reduction in the level of externalities is related to the reduction in economic activity brought about by any degree of market power, an established relationship which does not seem to cast much light on the relationship between emission intensity and its determinants. The empirical relationship between observed emissions and market structure or concentration is a surprisingly scarcely researched topic with very few exceptions in the electricity market. Mansur (2007) finds that exercise of market power in the Pennsylvania, New Jersey and Maryland Interconnection (PJM), i.e. the world's largest restructured wholesale electricity market, resulted in the reduction of SO_2, NO_x and CO_2 emissions. This finding is further supported by Chaton and Guillerminet (2013) with regard to CO_2 emissions, although it is not clear what the effect would have been on emission intensity. On the one hand, Asane-Otoo (2016) finds that the degree of vertical integration in OECD electricity markets was positively related to emission intensity. On the other hand, market concentration was found to be positively related to air emissions abatement control costs (per unit of economic activity), although the effect is not statistically significant (Farber and Martin, 1986). Similarly, Barrows and Ollivier (2018) show that increased competition, which one would expect from decreased market concentration, decreases aggregate emission intensity through increases in

[16] Although conceptually distinct, market structure and concentration are naturally interlinked, with the conventional understanding, e.g. Bikker and Haaf (2002), being that the greater the market share of a firm, the more concentrated an industry is and the smaller the level of competition in that industry.

aggregate productivity. As there is no established consensus in the literature, it is worth exploring the historical relationship between market concentration and emission intensity.

2.4 Socioeconomic impact and energy supply

The deployment of renewable technologies is considered as a key target in the mitigation of climate change as a higher percentage of electricity generated by renewables can substantially improve the efforts of the UK government in reducing emissions. This can be achieved through the gradual phase out of fossil intensive power generation technologies replaced by low carbon and renewable energy generation technologies in the UK power generation sector. Nonetheless, this transition from "dirty" to "clean" forms of energy raises concerns about negative socioeconomic impacts as the closure of conventional thermal power plants is expected to create redundancies in the labour market. In the same time, it is not clear whether renewable technologies will be able to create substantial long-term employment gains to counteract for the expected jobs losses. Thus, it is important to understand the underlying dynamics between the deployment of renewable technologies and employment generation. For that reason, I assess the historical trends in the UK electricity supply generated by distinct power generation technologies in section 2.4.1 and the historical employment trends in the UK power generation sector in section 2.4.2. Finally, I review in section 2.4.3 the studies estimating the employment effect of renewable energy.

2.4.1 Energy trends in the power sector

The UK electricity market was restructured in 1990 to allow private investors enter the previously nationalised electricity market through a competitive bidding system that ultimately resulted in lower energy prices (DUKES, 2017). Companies generating electricity are classified into Major Power Producers (MPPs) and Other Generators (OGs). MPPs are firms whose "primary purpose is the

generation of electricity" (DUKES, 2017), a group mainly comprising former nationalised firms responsible for the supply of electricity in the UK before 1990. On the other hand, OGs are companies that "produce electricity as part of the manufacturing or other commercial activities, but whose main business is not electricity generation" (DUKES, 2017). OGs generate electricity mostly to satisfy their industrial energy consumption needs while surplus might be exported to the grid.[17] DUKES (2017) divide electricity supply into conventional thermal, CCGT, nuclear and renewable electricity supply. Conventional thermal electricity supply includes electricity generated by turbines burning coal and oil, while CCGT is a technology that uses natural gas (or gas oil to a small extent) to produce electricity at higher efficiencies than conventional thermal technologies. Nuclear electricity is generated by nuclear power plants all of which are classified as MPPs while, according to the Directive 2009/28/EC, renewable electricity is generated by renewables non-fossil sources such as hydro, wind farms, and solar farms (DUKES 2017).[18]

Conventional thermal electricity (coal and oil), was responsible for 77% of the total electricity supply in 1990 - the year that CCGT plants introduced in the UK - but by 1999 a 42% reduction took place (see Figure 2-6) mostly due to coal being replaced by gas burnt in CCGTs, the so-called "dash for gas" (Bocse and Gegenbauer 2017) which implied a 113,000 GWh increase in CCGT generation in the same time period[19]. From 2000 to 2013, conventional thermal and CCGT power stations supplied roughly similar levels of electricity, although after the 2008 economic crisis there has been increased instability in the two series. Finally, from 2013 to 2016 conventional electricity decreased to become responsible only for 15% of electricity supply in 2016[20] while CCGT electricity has increased by 20% covering in 2016

[17] Although I have also investigated the long-term relationship between electricity supply generated by OGs and employment, I did not find any empirical evidence to support this argument. As a result, this thesis, and in particular section 5, focuses solely on MPPs whose "primary purpose is the generation of electricity" (DUKES 2017).

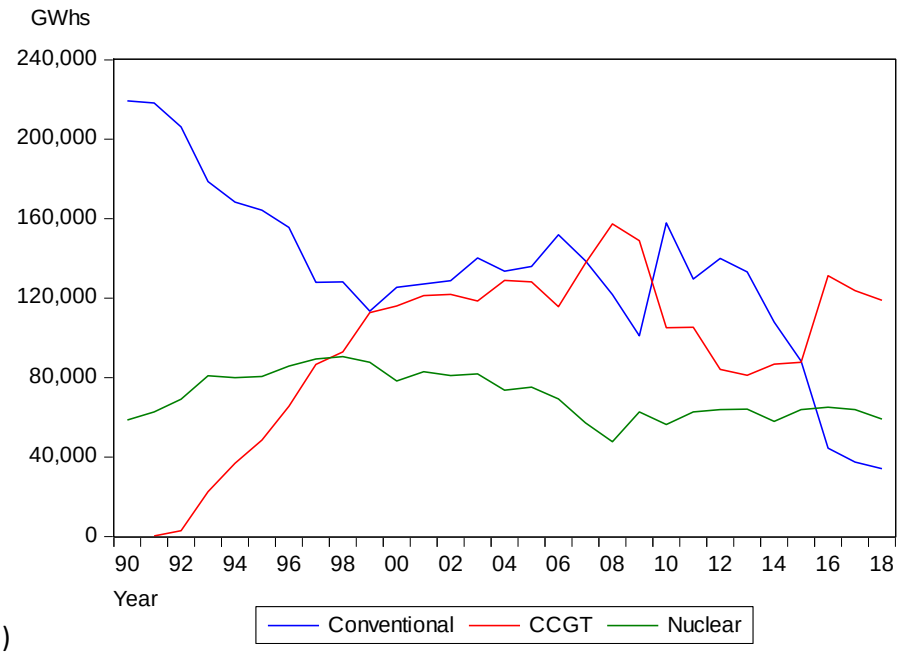
[18] There has been a major amendment in the MPPs definition in 2008 so that major wind farm companies could change classification from OGs to MPPs while the definition was further amended in 2015 to also include large scale solar farm companies which before 2015 were identified as OGs.

[19] See also the symmetric behaviour of the time series for conventional thermal and CCGT power stations between 1990 and 2000 in Figure 2-6(a).

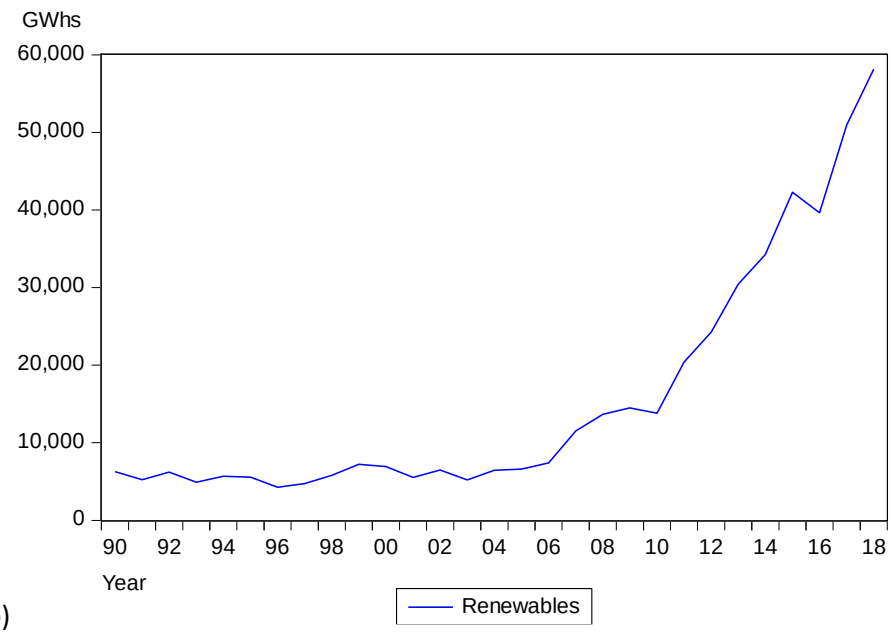
[20] This reduction is mainly due to the fact that in 2015 the carbon price floor has doubled from 9£ to 18£ per tonne of CO_2 (DUKES, 2017).

almost 50% of total UK electricity supply. From 2016 to 2018, conventional thermal, CCGT and nuclear electricity have experienced gradually declining trends.

Figure 2-6. Total annual electricity supplied (GWhs) by major power producers (MPPs) per type of electricity generation technology used in power generation process



(a)



(b)

Nuclear power stations have generated on average 23% of total UK electricity supply since 1991, with the lowest level of electricity supply being 14% in 2008 and the highest being 29% in 1997 and 1998[21]. Since 1998 several nuclear plants have been gradually decommissioned so that only eight nuclear plants were left in operation in 2017 (DUKES, 2017) out of the sixteen that were in operation in 1995, and thus explaining the overall reduction in nuclear electricity. Decline in nuclear electricity took place in correspondence to a rebound of conventional thermal electricity up to 2007.

Contribution from renewable technologies has steadily increased since the late 2000s, an outcome of national and international incentives. In 2007 the EU Renewable Energy Directive (RED) set as target by 2020 the production of 20% of electricity supply by renewable resources while in the UK the target was set in 2009 at the level of 15% of the total energy (DUKES 2017). The Energy Act 2013 established the Contracts for Difference (CfD) policy framework through which the UK government ensures secure, affordable and clean electricity supplies (Ofgem, 2018). More specifically, CfD policy incentivises business stakeholders to invest in renewable energy projects by providing them with sufficient credit to cover upfront capital costs. It further provides renewable energy generators with a fixed price and tops up the wholesale price when it is lower than the agreed price (Ofgem, 2018). As a result, renewable electricity has steadily increased up to 2018 (Figure 2-6(b)) while a small reduction in 2016 is attributed to less favourable weather conditions for wind energy in comparison to the previous years (DUKES, 2017). Increase in electricity from renewable plants has occurred in presence of shrinking production from conventional thermal plants from 2010 onwards.

To sum up, production from conventional thermal plants has decreased since the restructuring of the power market in the 1990s, so that it is reasonable to expect substitution between electricity supply generated by conventional thermal plants and other technologies. One should expect the existence of substitution between conventional thermal and CCGT, as discussed at length above. Nuclear

[21] The peak in 1997 and 1998 reflects the fact that Sizewell B has been the latest nuclear power plant to enter commercial operation in 1995.

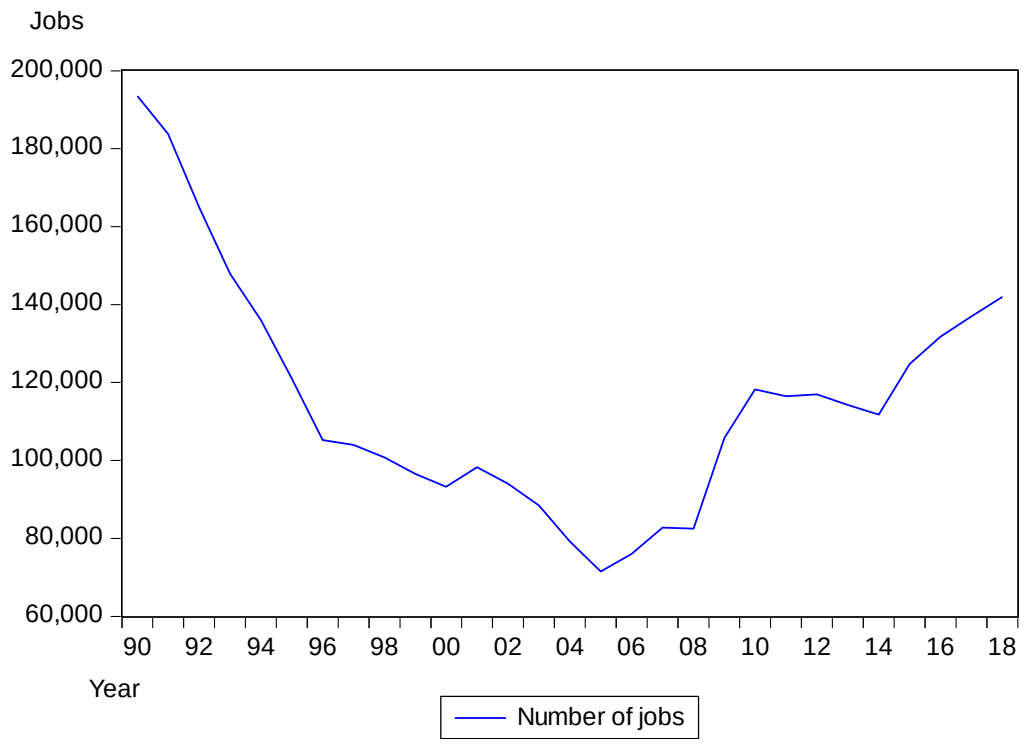
technologies have played a central role in the UK electricity market with their declining output in the 1990s initially filled by increasing production from conventional thermal plants in a way that one should expect substitution to exist between electricity generated by conventional thermal and nuclear technologies. Only nuclear and renewables can deliver CO_2-free electricity required to meet UK's CO_2 targets. Hence, it is reasonable to expect substitution between nuclear and renewable electricity, as a certain level CO_2 target can be reached by either increasing electricity from renewable or nuclear, given a certain deployment of electricity from CCGT and conventional thermal plants.

2.4.2 Employment trends in the power sector

Employment in the power generation sector steeply declines from 1990 to 1996 by 45% leading to a reduction of about 88,0000 jobs as one can observe in Figure 2-7. Total number of jobs dropped by a further 32% from 1996 till 2005 leading to a reduction of about 32,000 jobs in this time period. On the contrary, from 2005 and onwards one can observe significant employment gains. More specifically, from 2005 to 2010 there is a 65% increase in the total annual number of jobs which means that about 47,000 new jobs were created in the UK power generation sector. This bounce back effect can be linked to the substantial increase in electricity generated by renewables from 2005 to 2010 by 52% as one can observe in Figure 2-6(b). Indeed, the UK energy policy framework during the specified period has significantly incentivised the generation of renewable electricity which by extension could potentially explain the substantial employment gains observed in Figure 2-7. From 2010 to 2012 the total annual number of jobs has remained virtually constant while it slightly decreased in 2013 and 2014. This reduction could potentially be explained by the fact that the initial deployment of renewable technologies which resulted in a significant employment boost from 2005 to 2010 has reached to a certain level of maturity. This occurred while renewable electricity increased by 187% from 2010 to 2016, an increase more than three times higher than the one that occurred from 2005 to 2010. As a result, renewable electricity represented 15% of the total generation in 2015, a milestone

for renewable electricity in the UK. In fact, employment has further increased from 2014 to 2018 leading to the creation of about 30,000 new jobs, which could potentially be explained by the renewed interest in the deployment of renewable technologies induced by the establishment of renewable policy initiatives such as the CfD.

Figure 2-7. Total annual number of jobs in the UK power generation sector



2.4.3 Renewable electricity and employment impact

Jobs created by renewable technologies can be distinguished in (i) direct, (ii) indirect and (iii) induced (IRENA 2011). Direct jobs are created by the sector's core activities, indirect are those related to the supply chain of the energy sector (e.g. firms providing raw materials, regulatory bodies, banks, etc.), while induced jobs are generated by an increase in the aggregate demand stimulated by the renewable sector (Bowen and Kuralbayeva, 2015). Gross employment comprises the overall employment created by an increase in the generation of renewable energy, while net employment takes into account the missed employment which would have been generated in counterfactuals, i.e.

the employment which would have been generated by the plants which would have been built in the place of renewables.

The existing literature on the employment effect of renewable technologies – part of a wider branch assessing the employment effect of sustainable development policies (McNeill and Williams, 2007) – comprises a large number of studies employing various techniques and methodological approaches. Cameron and Zwaan (2015) identify 70 publications since the beginning of the last decade, but only a small subset can be considered as presenting original research, given the literature is affected by a high degree of recursive referencing, so that many studies merely re-use or recycle findings from earlier publications. Existing publications can be grouped into studies 1) producing forecast or simulations based on theoretical models, external estimates and conversion of values from other papers, e.g. Spalding-Fecher et al. (2012); 2) performing some form of literature review, e.g. Sheikh et al. (2016); and 3) analysing historical employment data to empirically estimate gross employment effects. The latter group of studies can be further divided in three subgroups based on the type of empirical methodology, i.e. Input-Output (IO), Computable General Equilibrium (CGE) and employment factors. More specifically:

- IO models estimate interdependencies between different economic sectors and employment effects of renewable energy, especially with regard to indirect and induced jobs such as Allan and Ross (2019), Baer et al. (2015), Lambert and Silva (2012), Markari et al. (2013), Oliveira et al. (2013) and Wang et al. (2013).
- CGE models, such as Bohlmann et al. (2019), Chatri et al. (2018) and Mu et al. (2018), are macroeconomics models that account for the economy-wide ramifications of renewable energy and provide estimates of the employment effect for induced jobs across the economy.
- Employment factors are ratios of a specific type of employment to the level/capacity of electricity generated by a specific type of renewable technology (e.g. the direct employment factor for manufacturing and installations for wind energy is measured as job/MW) (Blanco

and Rodriquez, 2009; Fanning et al., 2014; Kabayo et al., 2019; Wei et al., 2010; Zwaan et al., 2013) and mostly focus on direct job creation.

By performing a meta-analysis on studies investigating the employment effect of renewables, Stavropoulos and Burger (2020) find that the magnitude of net employment effect is mainly driven by the implemented methodology. More specifically, Stavropoulos and Burger (2020) find that studies based on IO and CGE with induced effects tend to be less favourable to net job creation while policy reports tend to be more supportive of net job creation.

Evaluating empirical results found in the literature, Cameron and Zwaan (2015) note that the employment impact varies across renewable technologies.[22] The German labour market has been in the forefront of attention as a series of studies indicates the positive effect of renewables on creating job opportunities (Lehr et al., 2008; Lutz and Lehr, 2018; Lutz et al., 2014; Lutz et al., 2015). Studies investigating the employment effect of solar industry development focus especially on Mediterranean countries (Çetin and Eğrican, 2011; Ciorba et al., 2004; Gkatsou et al., 2014; Kost et al., 2012; ILO, 2012; Moreno and López, 2008; Topcu et al., 2019; Tourkolias and Mirasgedis, 2011) and Middle East (Sohrab et al., 2019). Wind energy is expected to stimulate job creation in the European Union (EU) (Blanco and Rodriquez, 2009; EWEA, 2012) and the United States (US) (Brown et al., 2012; Yi, 2013), an argument that is specifically supported for countries such as Brazil (Gonçales et al., 2020; Simas and Pacca, 2014), Greece (Gkatsou et al., 2014; Tourkolias and Mirasgedis, 2011) and Spain (Caldés et al., 2009; ILO, 2012; Moreno and López, 2008). Nonetheless, in the case of Texas, Hartley et al. (2015) find no statistically significant impact of wind electricity on employment, revealing that the type of landscape, ownership and local participation are all crucial factors to maximise local employment effect (Ek and Persson, 2014). Similarly, Mori-Clement and Bednar-Friedl (2019) find small sectoral employment effects of Clean Development Mechanisms (CDM) projects across Brazilian municipalities.

[22] For example, solar panels can create several times more jobs than onshore wind.

Blazejczak et al. (2014) that use a macro-economic sectorial model for Germany find that renewable technologies had positive net employment effect. Although this net effect is small if labour markets are not flexible, it can become considerably high if the newly created jobs are filled with workers that have recently been unemployed. The importance of retraining workers in the transition from coal to renewable electricity is discussed in Louie and Pearce (2016). Cost-competitive wind electricity was found to produce initially low but rising benefits in terms of welfare and GDP in the case of the US economy (Cohen and Caron, 2018). On a wider scale, doubling the share of renewables in world electricity production was found to increase direct and indirect employment in the sector to 24.4 million by 2030, with most renewable jobs coming from fuel supply (bioenergy feedstocks), installations and equipment manufacturing (Ferroukhi et al., 2016). Concerning the UK job market, Fanning et al. (2014) investigate the potential employment effect in Wales by regional deployment of tidal and wave-based renewable technologies while Thornley et al. (2008) valuate the expected net employment impact of rising production and use of biomass crops in UK bioenergy plants.

From an economic theory perspective, increasing renewable electricity tends to imply higher unemployment rate (Rivers, 2013) mainly through increases in the labour tax required to fund renewable electricity schemes. Böhringer et al. (2013) confirms that labour market rigidities and existing unemployment provide some scope for a double dividend, but in practice these are likely to be limited, like in the case of the employment effects of the renewable energy expansion in Germany computed in Böhringer et al. (2013). Using a panel dataset of 80 countries, Apergis and Salim (2015) find positive impact of renewable energy consumption on unemployment in European Union and Africa while negative in Asia and Latin American countries. Perriera and Quirion (2018) describe the existence of three economic channels for job creation, so that a shift in investment towards renewables increases employment if it targets sectors with a higher share of labour compensation out of value added, lower wages or lower import rates. More specifically, Perriera and Quirion (2018) find positive employment impacts arising from weatherproofing and solar panels, a result that is robust across models used in the study. Cameron and Zwaan (2015) argue that the maturity of production

techniques, economies of scale and automatisation of industrial processes can lead to reduction of employment in the long run. Finally, a small number of studies quantifying the effect of economies of scale on long-term employment (Heavner and Churchill, 2002; Liera et al., 2013; Rutovitz and Atherto, 2009) indicate high levels of reduction in employment rates, although this subject needs to be further investigated (Cameron and Zwaan, 2015).

3 Energy price and energy efficiency

3.1 Overview

Improving energy efficiency in the industrial sector is necessary for achieving Clean Growth targets set by the UK government. The dynamics of energy efficiency in the long run are often captured by a stochastic trend component in energy consumption, but very few attempts have so far been made to connect this trend with its possible causes. Thus, this chapter responds to the first sub-research question of "*What is the importance of energy prices on long-term industrial energy efficiency?*". I develop a new approach to explore the role played by two potential sources behind the observed trend in energy consumption, economic growth and energy price. This approach creates in this way a bridge between two strands of research, one focused on the statistical properties of industrial energy demand and one analysing the underlying dynamics of industrial energy consumption. The proposed approach is based on linear state space modelling and consists in the systematic comparison between models that include alternative sets of regressors. Using this approach, I am able, first, to characterise the nature of the trend in the UK industrial energy demand, second, to assess how much of the observed shape in the trend is due to price effects, and third, to determine how much of this relation with price has changed over time. When applied on UK data for a period of almost 50 years, I find robust evidence that price is important for energy efficiency to the extent that it largely offsets the surge in energy consumption induced by economic growth. There is a remaining component of energy efficiency that is mostly imputable to technological progress, and possibly to gradual and irregular institutional changes (e.g. changes in the regulatory framework) not directly induced by the dynamics of energy prices. Finally, when I examine the stability of price elasticity, I conclude that in the UK it has remained constant over the last half a century.

3.2 Data

I use data on three non-seasonally adjusted variables, all collected from the Office of National Statistics (ONS), namely energy consumption, gross value added (GVA) and energy price, spanning the period from 1975 to 2018 and observed quarterly. More specifically:

- Energy consumption, including autogeneration[23], is obtained by summing consumption of coal, manufactured fuel, petroleum products, natural gas and electricity, all measured in tonnes of oil equivalent (toe). Data for industrial energy consumption are sourced from UK Energy Trends. The definition of the industrial sector used by the ONS for energy consumption includes the manufacturing and the construction sector.[24] Energy consumption data after 1998 can be found online, while data before 1998 has been collected from the printed version stored in the library of the University of London and the British Library.[25]
- Economic activity is captured by the index of production for the UK industrial sector measured in chain volume measure (CVM) millions of sterling.[26] Industrial GVA is constructed by aggregating the GVA of all industrial subsectors covered by the definition of energy consumption adopted by DUKES, including the construction sector.[27] This is a major difference from Hunt et al. (2003) and Agnolucci (2010), among others, who do not incorporate economic activity of the construction sector in their analysis, a shortcoming which raises (to some

[23] Autogeneration of energy by final users is included in final energy consumption while any fuel used for autogeneration by final users is reported within the transformation section (DUKES, 2018).
[24] According to DUKES (2018) Table 1G, industrial consumers of energy include 1) the manufacturing sectors (SIC 10-33) with the exception of fuel producers and processing of nuclear fuel (i.e. SIC 19 and SIC 24.46), 2) water supply, sewerage, waste management and remediation activities (SIC 36-39) and 3) the construction sector with SIC 41-43.
[25] Data on energy consumption until 1992 is expressed in million therms and therefore it is converted to thousand tonnes of oil using the DUKES conversion factor, namely 1 tonne of oil equivalent = 396.83 therms.
[26] The Index of Production (IoP) measures output in the manufacturing, mining and quarrying, energy supply, and water supply and waste management industries. IoP is an output measurement and is used as a proxy for measuring the production industry's gross value added (GVA).
[27] Although I was able to exclude fuel producers (SIC 19), this was not possible for processing of nuclear fuel (SIC 24.46).

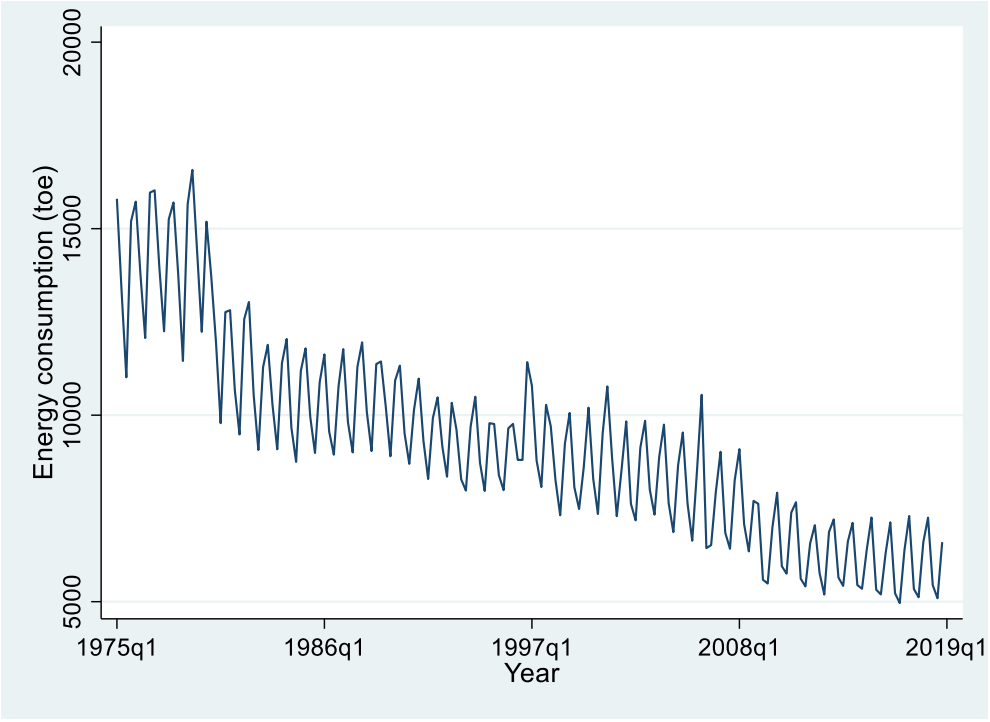
extend) concerns about model misspecification and potentially impairs the robustness of the results.

- Energy price is an index of real fuel prices of coal, heavy fuel oil, gas and electricity weighted by the share of each fuel in the total energy consumption, as defined above. All quarterly fuel prices are compiled by the UK Department for Business, Energy and Industrial Strategy (BEIS) and include the Climate Change Levy within their prices.[28] Given that nominal values for different fuels are reported in different measurement units, I express all nominal fuel prices in the same metric i.e., pence per therm. Then, I deflate nominal values using the GDP deflator and weight them by the share of each fuel in the total industrial energy consumption per year. Finally, I sum the weighted real fuel price of all fuels used in the industrial process to construct the aggregate real energy price index for the UK industrial sector.

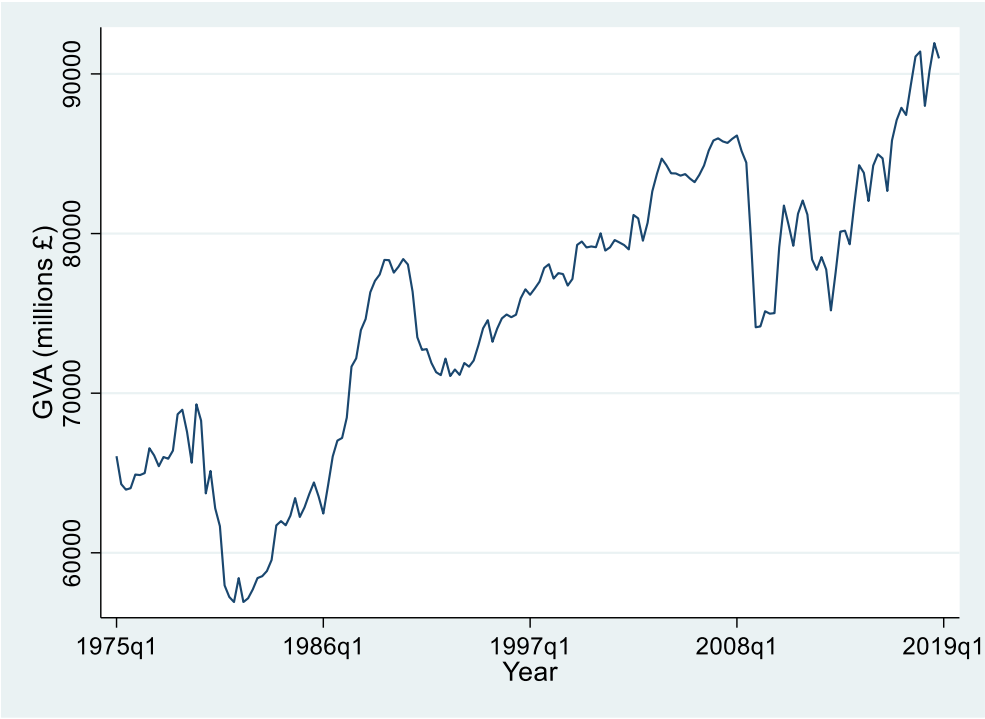
One can visually observe the time series plots of the variables used in chapter 3 in Figure 3-1, i.e. (a) energy consumption, (b) GVA and (c) energy price, while further information on the descriptive statistics of the variables can be found in the Appendix (please check Table A1).

[28] Seasonally unadjusted nominal fuel price data for the UK industrial sector on a quarterly basis are derived from DUKES table 3.3.1.

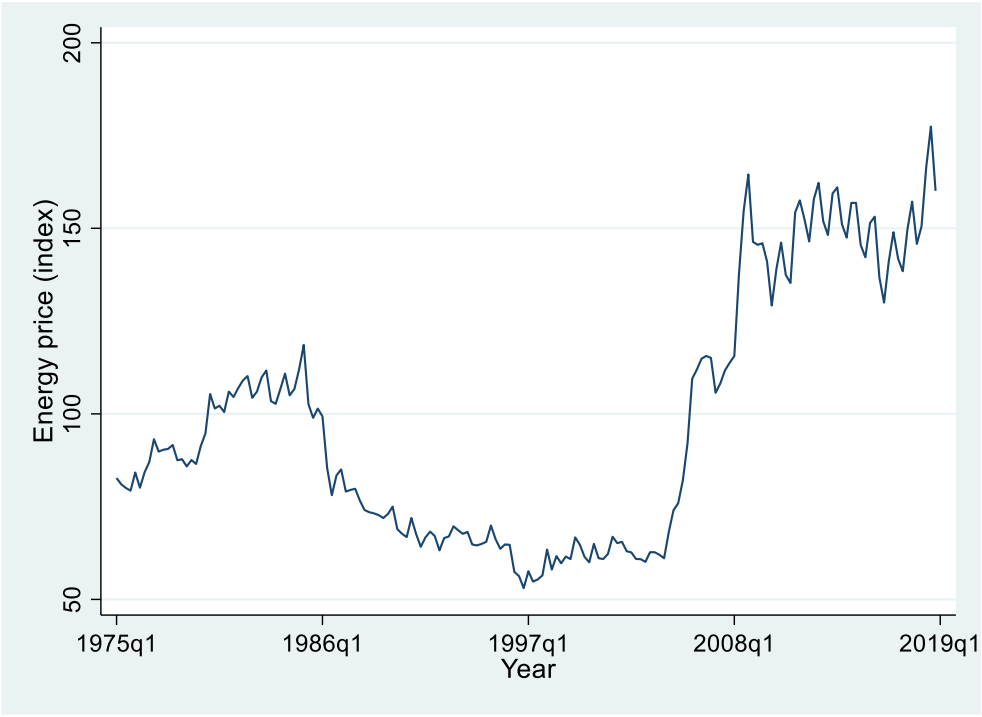
Figure 3-1. Visual representation of the time series variables used in chapter 3



(a)



(b)



(c)

3.3 Methodological approach

The proposed econometric approach enables me to assess the nature of the trend in energy consumption and the extent to which the nature and the size of the trend is affected by energy price and economic activity. This econometric framework is the general class of the Gaussian linear state space model, estimated by Maximum Likelihood through a diffuse Kalman filter (Harvey, 1989; Durbin and Koopman, 2012), an approach also known in the literature as Structural Time Series Model (STSM). This model has been introduced and advocated in the energy literature by the work of Hunt et al. (2003) through the terminology of Underlying Energy Demand Model (UEDM). Nonetheless, it is worth mentioning that the proposed approach in this chapter is more general than the UEDM, as the latter model focuses on a stochastic trend, i.e. either a stochastic level, slope or both. On the other hand, the model estimated in this chapter also allows for the introduction of stochastic coefficients representing the impact of energy drivers such as economic activity and energy price.

Following Durbin and Koopman (2012) methodology, I start by estimating a univariate model of energy consumption without any independent variable (i.e. economic activity and energy price) so that I examine the nature of the trend in energy consumption. As a second step, I add economic activity and energy price to the model selected in the first step and investigate whether the stochastic nature of the trend is affected by either or both independent variables. I finally provide a quantitative measure of the impact of economic activity and energy price on the trend in energy consumption. The following subsections (3.3.1 to 3.3.4) provide more details on the proposed econometric methodology and further discuss on the stages of the proposed empirical analysis.

3.3.1 First stage: univariate model

The aim of the first stage is to assess the nature of the trend in energy consumption which is accomplished by estimating a set of local linear trend models where the level and the slope terms are allowed to be stochastic. In this way, the general univariate model for industrial energy consumption – without any independent variable – can be defined as:

$$\begin{cases} y_t = \mu_t + \gamma_t + \varepsilon_t, & \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \\ \gamma_{t+1} = -\gamma_t - \gamma_{t-1} - \gamma_{t-2} + \omega_t, & \omega_t \sim N(0, \sigma_\omega^2) \\ \mu_{t+1} = \mu_t + v_t + \eta_t, & \eta_t \sim N(0, \sigma_\eta^2) \\ v_{t+1} = v_t + \xi_t, & \xi_t \sim N(0, \sigma_\xi^2) \end{cases} \tag{3-1}$$

where the first equation, called observation equation, describes the evolution of industrial energy consumption y_t, while the other three describe the dynamics of the states included in the trend, namely the level μ_t, the slope v_t and a set of dummies used to capture seasonality. Following Hunt et al. (2003), seasonal dummies γ_t are modelled as stochastic states to capture the variation in energy consumption across seasons. All error terms in equation (3-1) are assumed to follow independent Gaussian distributions. I estimate four specifications of the univariate model above to determine the nature of the trend, namely a univariate model with i) deterministic level and deterministic slope $\sigma_\eta^2 =$

0, $\sigma_\xi^2 = 0$), ii) stochastic level and deterministic slope ($\sigma_\eta^2 \neq 0$, $\sigma_\xi^2 = 0$), iii) deterministic level and stochastic slope ($\sigma_\eta^2 = 0$, $\sigma_\xi^2 \neq 0$) and finally iv) both level and slope as stochastic ($\sigma_\eta^2 \neq 0$, $\sigma_\xi^2 \neq 0$). To determine the nature of the trend, I perform model selection based on ***four criteria***:

1. the results of three diagnostic tests based on the standardised innovations: the Jacque-Berra test (JB) for normality, Ljung-Box (LB) test for serial correlation and the F-test for heteroskedasticity[29] (Het);
2. the value of the Akaike (AIC), Schwarz (BIC) and Hannan-Quinn (HQ) information criteria;
3. the size of the Maximum Likelihood (ML) estimate of the state error variances measured by the t-ratio, which provides an indication on the size of stochasticity;[30]
4. inspection of the plot of the smoothed states to visually verify the extent of time variation.

In the estimation process, I also include pulse dummies to treat occasional outliers identified through the plot of the auxiliary observation residuals. More specifically, I add three pulse dummies in the observation equation of the univariate model for the time periods 1980Q1, 2006Q1, 2006Q2 to deal with outliers in the observation equation auxiliary residuals, following Commandeur and Koopman (2007).[31] The outliers observed can be attributed to the 1980 oil crisis and the 2006 major increase in gas prices. The same dummies are also introduced in the multivariate model as the same outliers persist when controlling for GVA and energy price.

[29] It compares the variance of the first and last third of the sample observations (Durbin and Koopman, 2012).
[30] Following Agnolucci and De Lipsis (2019), I avoid running a test based on the ML estimate of the state error variances for two reasons. Firstly, this is a test in which the value under the null hypothesis falls in the boundary of the parameter space, which means that in most cases of interest its limiting distribution is unknown (Harvey 1989). Secondly, the test on one state of the trend implies assuming the nature of the other state, therefore limiting the application of the test unless one has theoretical reason for making such assumptions.
[31] One can visually observe the plots of the auxiliary observation residuals for the chosen model specifications in Table A4 in the Appendix A section.

3.3.2 Second stage: multivariate models

Having identified the best performing specification for the univariate model of energy demand in stage one (subsection 3.3.1) and following the methodology proposed by Agnolucci and De Lipsis (2019), the second stage involves verifying the extent to which the trend in energy consumption is influenced by the trend in any of its drivers. As a starting point, one can assume that the data-generating process for energy consumption y_t is:

$$y_t = \sum_{i=1}^{k} b_i x_{it} + u_t \tag{3-2}$$

where $u_t \sim N(0, \sigma_u^2)$ is an error term and $x_{1t}, \dots, x_{kt}$ are k exogenous variables generated by the following local linear trend models:

$$\begin{cases} x_{it} = \mu_{it} + \varepsilon_{it} & \varepsilon_{it} \sim N\left(0, \sigma_{\varepsilon_i}^2\right) \\ \mu_{it+1} = \mu_{it} + v_{it} + \eta_{it} & \eta_{it} \sim N\left(0, \sigma_{\eta_i}^2\right) \\ v_{it+1} = v_{it} + \xi_{it} & \xi_{it} \sim N\left(0, \sigma_{\xi_i}^2\right) \end{cases} \qquad i = 1, \dots, k. \tag{3-3}$$

Using a univariate representation (3-1) to describe y_t, implies that each state in (3-1) is the linear combination of the corresponding states of x_{it} in (3-3) so that the level state μ_t and the slope state v_t in y_t can be expressed as:

$$\begin{cases} \mu_t = \sum_{i=1}^{k} b_i \mu_{it} \\ v_t = \sum_{i=1}^{k} b_i v_{it} \end{cases} \tag{3-4}$$

and similarly, for the error terms:

$$\begin{cases} \varepsilon_t = \sum_{i=1}^{k} b_i \varepsilon_{it} + u_t \\ \eta_t = \sum_{i=1}^{k} b_i \eta_{it} \\ \xi_t = \sum_{i=1}^{k} b_i \xi_{it} \end{cases} \quad (3\text{-}5).$$

If one observes one of the explanatory variables in (3-2), say x_{mt}, they are able to evaluate the impact of the trend associated with x_{mt} on the trend of y_t by including such variable on the right hand side of the observation equation. More formally, by adding x_{mt} to the observation equation, one can obtain the following system:

$$\begin{cases} y_t = b_m x_{mt} + \bar{\mu}_t + \bar{\varepsilon}_t & \bar{\varepsilon}_t \sim N\left(0, \sigma_{\bar{\varepsilon}}^2\right) \\ \bar{\mu}_{t+1} = \bar{\mu}_t + \bar{v}_t + \bar{\eta}_t & \bar{\eta}_t \sim N\left(0, \sigma_{\bar{\eta}}^2\right) \\ \bar{v}_{t+1} = \bar{v}_t + \bar{\xi}_t & \bar{\xi}_t \sim N\left(0, \sigma_{\bar{\xi}}^2\right) \end{cases} \quad (3\text{-}6)$$

where:

$$\begin{cases} \bar{\mu}_t = \sum_{i \epsilon I_m} b_i \mu_{it} \\ \bar{v}_t = \sum_{i \epsilon I_m} b_i v_{it} \end{cases} \quad (3\text{-}7)$$

$I_m = \{1, \dots, k\} - m$. A similar expression to (3-7) is obtained for the error terms. As it is evident, both the level and slope states now capture the trend that is specific to all the other variables x_{it} with $i \neq m$. One can characterise the contribution of the trend in x_{mt} to the trend in y_t by looking at how the estimated states change once I control for x_{mt}. This implies examining the difference between the level and the slope states obtained without and with the inclusion of x_{mt}

$$\begin{cases} \mu_t - \bar{\mu}_t = b_m \mu_{mt} \\ v_t - \bar{v}_t = b_m v_{mt} \end{cases} \quad (3\text{-}8)$$

so that a quantitative indicator can be easily built. This quantitative indicator allows me to assess the extent of the impact of economic output and energy price on the long-run trend of industrial energy

consumption. The following subsection (3.3.3) provides more details on the proposed quantitative indicator.

3.3.3 Implementation

With regard to the trend in energy consumption assessed in this chapter, I start by selecting one of the four specifications in (3-1) based on the ***four selection criteria*** in subsection 3.3.1. Subsequently, I add GVA to the observation equation of the selected specification to explicitly control for the effect of economic activity on the trend of industrial energy consumption and I allow the impact of economic activity to change across time to capture potential non-linear effects. More specifically, I estimate the following general model:

$$\begin{cases} y_t = \tilde{\mu}_t + \tilde{\gamma}_t + \rho_t GVA_t + \tilde{\varepsilon}_t, & \tilde{\varepsilon}_t \sim N\left(0, \sigma_{\tilde{\varepsilon}}^2\right) \\ \tilde{\gamma}_{t+1} = -\tilde{\gamma}_t - \tilde{\gamma}_{t-1} - \tilde{\gamma}_{t-2} + \tilde{\omega}_t, & \tilde{\omega}_t \sim N\left(0, \sigma_{\tilde{\omega}}^2\right) \\ \tilde{\mu}_{t+1} = \tilde{\mu}_t + \tilde{v}_t + \tilde{\eta}_t, & \tilde{\eta}_t \sim N\left(0, \sigma_{\tilde{\eta}}^2\right) \\ \tilde{v}_{t+1} = \tilde{v}_t + \tilde{\xi}_t, & \tilde{\xi}_t \sim N\left(0, \sigma_{\tilde{\xi}}^2\right) \\ \rho_{t+1} = \rho_t + \psi_t, & \psi_t \sim N\left(0, \sigma_{\psi}^2\right) \end{cases} \tag{3-9}$$

with the nature of $\sigma_{\tilde{\eta}}^2$ and $\sigma_{\tilde{\xi}}^2$ determined by the specification selected for the univariate model (3-1). In model (3-9), the tilde above each parameter indicates that the incorporation of GVA implies a change in the coefficients compared to those in (3-1). The last equation in the model describes the time-varying coefficient on GVA.

Once I have estimated model (3-9), I assess whether the introduction of economic activity has contributed to a change in the stochastic nature of the trend. This implies comparing (3-9) to a) the specification selected for the univariate model (3-1), and to b) a specification of (3-9) incorporating a deterministic trend – essentially restricting $\sigma_{\tilde{\eta}}^2$ and $\sigma_{\tilde{\xi}}^2$ to zero. The reasoning is such that if the stochastic nature of the trend in (3-1) is mainly due to economic activity, the explicit incorporation of this factor in the model should eliminate the stochasticity in the trend. In that case, one would expect:

a) specification of model (3-9) with a stochastic trend to be similar to the one incorporating a deterministic trend; b) stochastic trend in model (3-9) to display markedly less time-variation compared to the specification selected for model (3-1).

I consider ***four sources of evidence*** (or similar to subsection 3.3.1 ***four criteria***) to draw conclusion on the two points above:

1. standard diagnostic tests built from the standardised innovations,
2. the gain in the fit arising from allowing a stochastic trend,
3. the change in the size of the estimate of the state error variance,
4. the plot of the smoothed state of the trend.

The importance of any residual stochasticity in the trend after controlling for the impact of economic activity is signalled by a deterioration in any of the three diagnostics in point (1), a lower value of the information criteria in point (2) when a deterministic trend is imposed, and by the size of the error variance and a pattern of the trend similar to those observed in the specification selected for the univariate model (3-1) in point (3) and (4) above.

As a next step, I add energy price to the selected specification of model (3-9) so that one obtains:

$$\begin{cases} y_t = \bar{\mu}_t + \bar{\gamma}_t + \rho GVA_t + \beta_t EP_t + \bar{\varepsilon}_t, & \bar{\varepsilon}_t \sim N(0, \sigma^2_{\bar{\varepsilon}}) \\ \bar{\gamma}_{t+1} = -\bar{\gamma}_t - \bar{\gamma}_{t-1} - \bar{\gamma}_{t-2} + \bar{\omega}_t, & \bar{\omega}_t \sim N(0, \sigma^2_{\bar{\omega}}) \\ \bar{\mu}_{t+1} = \bar{\mu}_t + \bar{v}_t + \bar{\eta}_t, & \bar{\eta}_t \sim N(0, \sigma^2_{\bar{\eta}}) \\ \bar{v}_{t+1} = \bar{v}_t + \bar{\xi}_t, & \bar{\xi}_t \sim N(0, \sigma^2_{\bar{\xi}}) \\ \rho_{t+1} = \rho_t + \psi_t, & \psi_t \sim N(0, \sigma^2_{\psi}) \\ \beta_{t+1} = \beta_t + \zeta_t & \zeta_t \sim N(0, \sigma^2_{\zeta}) \end{cases} \tag{3-10}$$

with the nature of $\sigma^2_{\bar{\eta}}$ and $\sigma^2_{\bar{\xi}}$ determined by the specification of model (3-1) and the bar above each parameter indicating that the incorporation of energy price in the model implies a change in the coefficients compared to those obtained from (3-9). The last two equations in the model describe the time-varying coefficient on economic activity and energy price, respectively. After estimating model

(3-10), I assess whether the introduction of energy price has contributed to a change in the stochastic nature of the trend. This implies comparing (3-10) to a) the specification selected for the univariate model (3-1), and to b) the specification of (3-10) incorporating a deterministic trend – essentially restricting $\sigma_{\tilde{\eta}}^2$ and $\sigma_{\tilde{\xi}}^2$ to zero. I assess the trend in the model including energy price through the same ***four sources of evidence*** discussed above in the case of economic activity.

Finally, a quantitative indicator of the impact of economic output and energy price on the long-run trend of industrial energy consumption can be obtained by taking the average difference in the smoothed slopes obtained from the univariate model (3-1), and model (3-10), respectively, calculated over the whole period:

$$\sum_{t=1}^{T}(v_t - \bar{v}_t) \Big/ \sum_{t=1}^{T} \bar{v}_t \qquad (3\text{-}11).$$

An identical computation can be implemented for univariate model (3-1) and (3-9) or model (3-9) and (3-10). This indicator measures the extent to which the observed long-run quarterly rate of change in energy consumption that can be attributed to trend in the variable which is added in the second model in any of the pairs above. In the event that the slope term being deterministic, (3-11) simplifies to $(v_t - \tilde{v}_t)/\tilde{v}_t$. For any of the comparison above, the magnitude of this indicator reveals the extent to which the trend in energy consumption can be attributed to trends in the variable (or variables) added to the second model compared to the first model.

3.3.4 Robustness analysis

The results for the procedure above can be influenced by the assumption on the impact of economic output and energy price and the fact that multivariate models have been estimated conditional on the nature of the trend obtained from a univariate model. As a robustness exercise, I tackle the abovementioned potential sources of concern as follows:

1) I replicate models (3-9) and (3-10) by assuming that coefficients β and ρ that capture the impact of economic activity and energy price, respectively, are constant across time.

2) I estimate models not incorporating the nature of the trend obtained in the univariate model (3-1) i.e. a model with stochastic level and slope, i.e. $\sigma_{\eta}^{2} \neq 0$ and $\sigma_{\xi}^{2} \neq 0$; and a model with stochastic slope only, i.e. $\sigma_{\eta}^{2} = 0$ and $\sigma_{\xi}^{2} \neq 0$.

3.4 Estimation results

As a preliminary step, I test for the existence of cointegrating relationship between the three variables used in this study, namely energy consumption, energy price and economic activity. One would expect the specification of energy demand to imply existence of a cointegrating relationship between variables such energy consumption, economic activity and price. Following textbook procedures, I perform lag order selection of a three-variable Vector Autoregression (VAR) model by using five lag length selection criteria, three of which indicating 8 lags[32] while the other two indicating 5 lags[33] (see Table A2 in the Appendix section). Subsequently, I test for the existence of a cointegrating relationship using the Johansen test in models with 5 and 8 lags and in neither of the two cases I find evidence of linear cointegrating relationship (see in Table A3 in the Appendix section). This finding, which is robust to the specification of the deterministic component of the trend (as shown in Table A3) does not necessarily contradict the presence of cointegration between GVA, energy consumption, and price in Agnolucci et al. (2017) for UK industrial subsectors. It rather indicates that the long-run relationship describing aggregate industrial energy consumption contains more factors than just GVA and price, factors that may not be observable. Therefore, I embark in the estimation of the energy demand for

[32] The sequential modified LR statistic, final prediction error and Akaike information criteria (AIC) indicate 8 lags.
[33] The Schwarz information criteria (SC) and Hannan-Quinn information criteria (HQ) indicate 5 lags.

the UK industrial sector by using a generalised state space model which can take into account unobservable stochastic factors affecting the direction of the trend in energy consumption or its level.

3.4.1 Univariate model

As a first step, I assess the nature of the trend of energy consumption by estimating the four univariate models implied by (3-1). The specifications with a deterministic level, i.e. 1.1 and 1.3 in Table 3-1, are affected by serial correlation (LB - *criterion 1* in subsection 3.3.1) but the other two specifications, i.e. 1.2 and 1.4 in Table 3-1, perform well in terms of the diagnostic tests (JB, LB and Het), so that either model can be considered an adequate characterisation of energy consumption. The three information criteria (AIC, BIC and HQ) reported in Table 3-1 point at the model 1.2 including a stochastic level and a deterministic slope, as the specification with the best fit (*criterion 2*). In addition, based on *criterion 3*, the stochastic slope in model 1.4, has negligible time variation, as testified by the size of the slope error variance (2.48E-13), and the related t-ratio (0.00). The slope term is practically constant, when allowed to be time-varying, since the difference between its maximum and minimum value is negligible (equal to 1.96E-09). This finding is also reflected by the fact that the time-pattern of the level in model 1.2 (with a deterministic slope) and model 1.4 (with a stochastic slope) is essentially identical (*criterion 4*), as shown by the complete overlap of the two series in Figure 3-2. Thus, one can confidently conclude that neither a deterministic nor a stochastic slope play any role in explaining the stochasticity in the trend, when the level is allowed to vary across time. Stochasticity of the level in model 1.2 is confirmed by i) the estimate variance (8.80E-04 in Table 3-1) and related t-ratio (*criterion 3*) and the smoothed state plot in Figure 3-2 (*criterion 4)*.

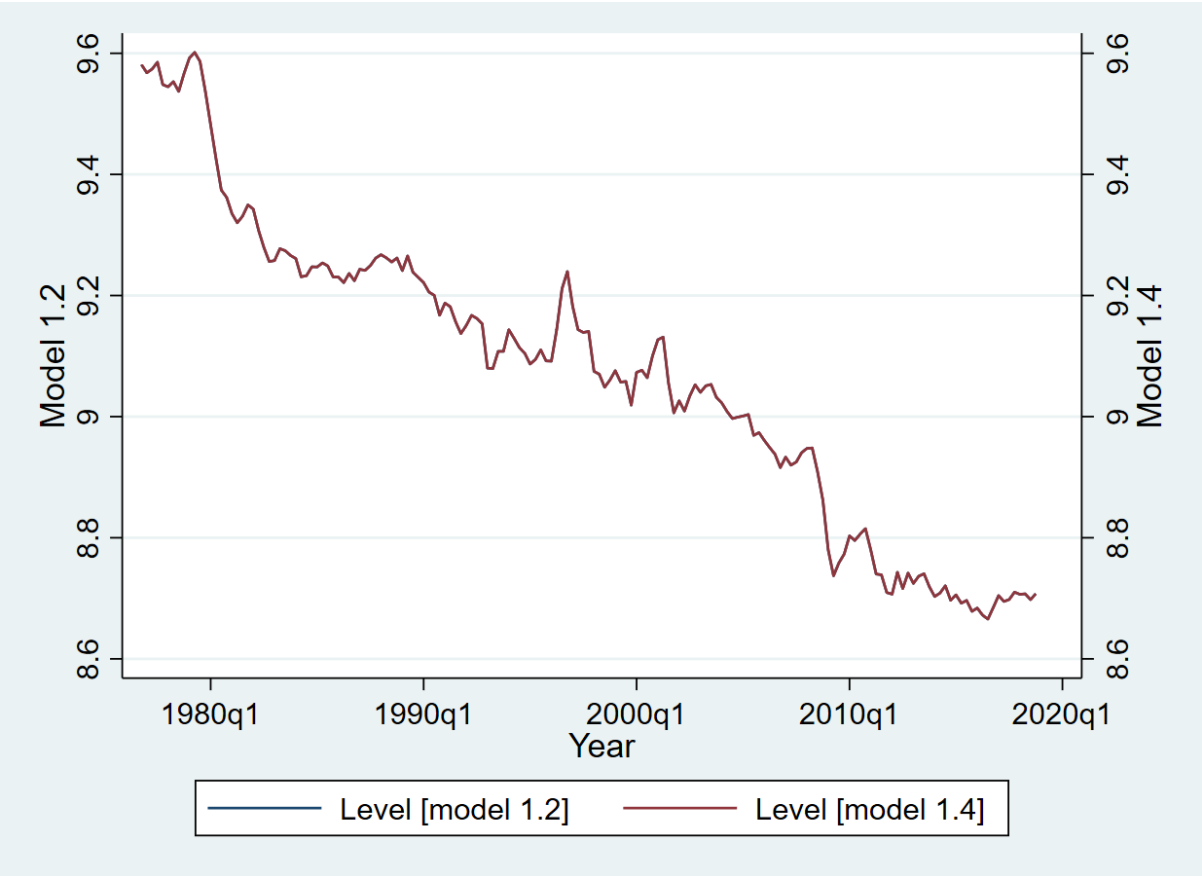
Therefore, it becomes evident that all four criteria outlined in subsection 3.3.1 (diagnostics, information criteria, state error variance and smoothed states plot) point at ***specification 1.2 being the preferred model*** which implies that **the *level is the only stochastic term of the trend in energy consumption***.

Table 3-1. Estimates, information criteria and diagnostics for univariate state space models

	State error variance			Information criteria			Diagnostics		
	Level	**Slope**	**Seasonal**	**AIC**	**BIC**	**HQ**	**JB**	**LB**	**Het**
1.1	D	D	1.01e-05 (0.71)	-2.21	-2.03	-2.13	0.35	0.00	0.06
1.2	**8.80E-04 (6.20)**	**D**	**4.58e-05 (2.84)**	**-3.30**	**-3.10**	**-3.22**	**0.18**	**0.33**	**0.65**
1.3	D	1.42E-04 (4.62)	3.71e-05 (2.47)	-3.04	-2.84	-2.96	0.15	0.00	0.75
1.4	8.80E-04 (6.20)	2.48E-13 (0.00)	4.58-05 (2.84)	-3.29	-3.07	-3.20	0.18	0.33	0.65

Notes: The values in the parentheses are the t-ratios of the ML estimates of the state error variances. Deterministic components are indicated by "D". AIC, BIC and HQ indicate the values of the Akaike, Schwarz and Hannan-Quinn information criteria. JB, LB and Het indicate the *p*-value for the Jacque-Bera test for normality, Ljung-Box test for serial correlation and F-test for heteroskedasticity.

Figure 3-2. Smoothed states of the level term of the trend from an univariate model with stochastic level (model 1.2 in Table 3-1) and with stochastic level and stochastic slope (model 1.4 in Table 3-1)



3.4.2 Multivariate models

Having chosen the preferred specification for the univariate model (model 1.2 in Table 3-1), I proceed in exploring the extent to which the stochastic nature of the trend in energy consumption is influenced by economic activity. Building on the results from Table 3-1, I estimate a model with time-varying coefficient on GVA and i) stochastic level (model 2.1 in Table 3-2), or ii) deterministic level (model 2.2 in Table 3-2). Focussing on the comparison of the two models in Table 3-2, the diagnostic tests indicate a substantial deterioration of the normality assumption (JB test) when a deterministic trend is imposed in model 2.2 (*1st source of evidence* in subsection 3.3.3).[34] In terms of the *2nd source of evidence* in subsection 3.3.3, incorporating a stochastic level in model 2.1 delivers an increase in the fit compared to model 2.2 (in which a deterministic level is imposed) as registered by all three information criteria (AIC, BIC and HQ) in Table 3-2. Moving on to the comparison of model 2.1 in Table 3-2 and the univariate model selected in subsection 3.4.1 (model 1.2 in Table 3-1), the contribution of economic activity to the stochastic trend of energy consumption is testified by the reduction in the size of the error variance of the level term from 8.80E-04 in model 1.2 to 5.68E-04 in model 2.1 (*3rd source of evidence*). On the other hand, the plot of the smoothed state of the trend confirms the presence of substantial residual stochasticity after the role of economic activity is accounted (*4th source of evidence*). In fact, the similarity of the smoothed level in model 2.1 and 1.2 in Figure 3-3 clearly indicates that the great majority of the stochastic nature of the level is not related to economic output. The main difference in the two trends occurs when a decrease in energy consumption was brought about by economic recessions, namely the early 1980s recession and the great recession. In the case of the univariate model these two events materialise themselves as a steep decline in the level, a fact that may contribute to the higher variance of the error variance registered in Table 3-1. On the other

[34] Model 2.1 is affected by serial correlation according to the LB test, as it is model 2.2, a finding most likely related to the fact that the two models are in any case misspecified due to the energy price variable being left out.

hand, no strong departure from a linearly decreasing trend can be observed in the trend of the model incorporating economic activity.

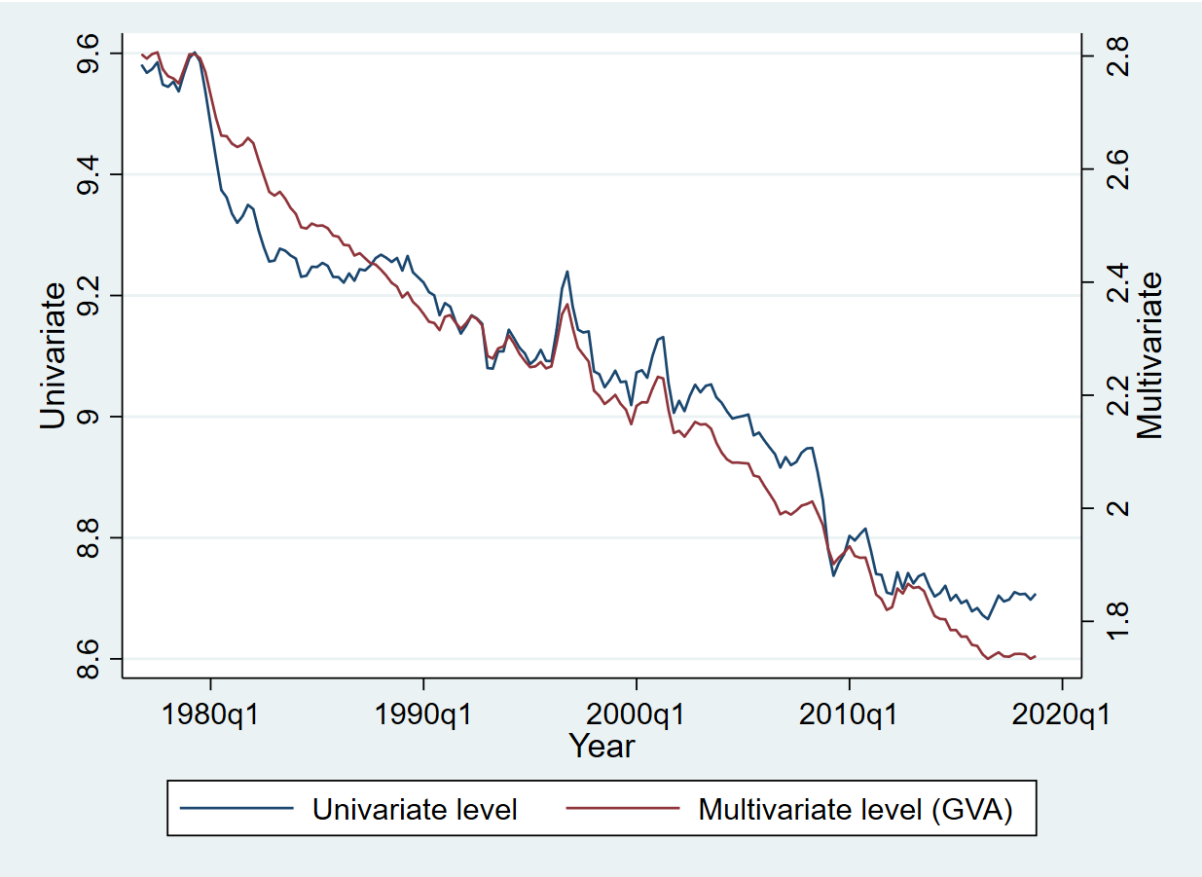
In summary, all *four sources of evidence* outlined in subsection 3.3.3 (diagnostic tests, information criteria, state error variance, smoothed states plot) clearly point at ***specification 2.1. as the preferred model***. Incorporating the effect of ***economic activity does not significantly change the stochastic nature of the trend***, although it does influence the extent of its stochasticity, as measured by the variance of the state error.

Table 3-2. Estimates, information criteria and diagnostics for state space models allowing for stochastic impact of GVA

	State error variance				Information criteria			Diagnostics		
	Level	**Slope**	**Seasonal**	**GVA**	**AIC**	**BIC**	**HQ**	**JB**	**LB**	**Het**
2.1	5.68E-04 (0.10)	D	4.92e-05 (3.06)	9.20E-09 (0.00)	-3.30	-3.07	-3.21	0.16	0.03	0.46
2.2	D	D	4.38E-05 (2.78)	4.40E-06 (5.01)	-3.28	-3.06	-3.20	0.03	0.04	0.27

Notes: Model specifications obtained by augmenting preferred univariate model in Table 3-1 with GVA. The values in the parentheses are the t-ratios of the ML estimates of the state error variances. Deterministic components are reported as "D". AIC, BIC and HQ indicate the values of the Akaike, Schwarz and Hannan-Quinn information criteria. JB, LB and Het indicate the *p*-value for the Jacque-Bera test for normality, Ljung-Box test for serial correlation and F-test for heteroscedasticity.

Figure 3-3. Smoothed states of the level from an univariate model with stochastic level (model 1.2 in Table 3-1) and a multivariate model with stochastic level and time-varying GVA (model 2.1 in Table 3-2)



The next step involves incorporating both economic activity and energy price in the univariate model selected in subsection 3.4.1 which allows me to assess the impact of these two factors on the nature of the trend of energy consumption. Similar to Table 3-2, I use the results from the univariate model in Table 3-1 as a starting point, and I estimate a model with time-varying coefficient both on GVA and energy price, and i) stochastic level (see model 3.1 in Table 3-3), or ii) deterministic level (model 3.2 in Table 3-3). Focussing on the comparison of model 3.1 and 3.2, diagnostic tests (JB, LB and Het) do not detect any substantial change when imposing a deterministic level compared to the model with a stochastic level (*1st source of evidence* in subsection 3.3.3).[35] In terms of the *2nd source of evidence*,

[35] Either model represents a considerable improvement, as far as diagnostic tests are concerned, compared to the models without energy price in Table 3-2.

incorporating a stochastic level in model 3.1 delivers an increase in the fit compared to model 3.2 (in which a deterministic level is imposed) as registered by all three information criteria (AIC, BIC and HQ) in Table 3-3. Moving on to the comparison of model 3.1 in Table 3-3 and the univariate model selected in subsection 3.4.1 (model 1.2 in Table 3-1), the contribution of economic activity and energy price to the stochastic trend of energy consumption is borne out by the reduction in the size of the estimate of the state error variance down to 6.04E-04 for model 3.1 compared to 8.80E-04 for model 1.2 (*3rd source of evidence*).[36] On the other hand, the plot of the smoothed level confirms the presence of residual stochasticity in the trend after the role of economic activity and energy price are accounted for (*4th source of evidence*). Figure 3-4 points out that the source of the stochastic nature of energy consumption well exceeds economic output and energy price. However, there is evidence of a divergence in the direction of the trend, especially from 1982 to 1989 and then from 2004 to 2009, in the model incorporating economic activity and energy price compared to the univariate model. The former time period (1982 to 1989) saw price decreasing considerably after the oil price peak in 1980 and the consequent recession, while the latter time period (2004 to 2009) saw increasing prices up to the late 2008 crash following the great recession. The decrease in the price in 1980, not taken into account in the univariate model, implies a slower year-on-year reduction in the stochastic trend so that for the following 20 years a considerable gap between the two stochastic trends in Figure 3-4 takes place. However, when price increased in early 2000s, the trend in the univariate model required a steep adjustment in its direction while no marked changes can be seen in the trend of the multivariate model.

Based on the *four sources of evidence* outlined in subsection 3.3.3, one can conclude that information criteria, state error variance and smoothed states plot clearly point at ***specification 3.1 as the preferred model***. This means that incorporating ***economic activity and energy price does not***

[36] However, it is interesting to observe that this is marginally higher than the value 5.68E-04 in Table 3-2.

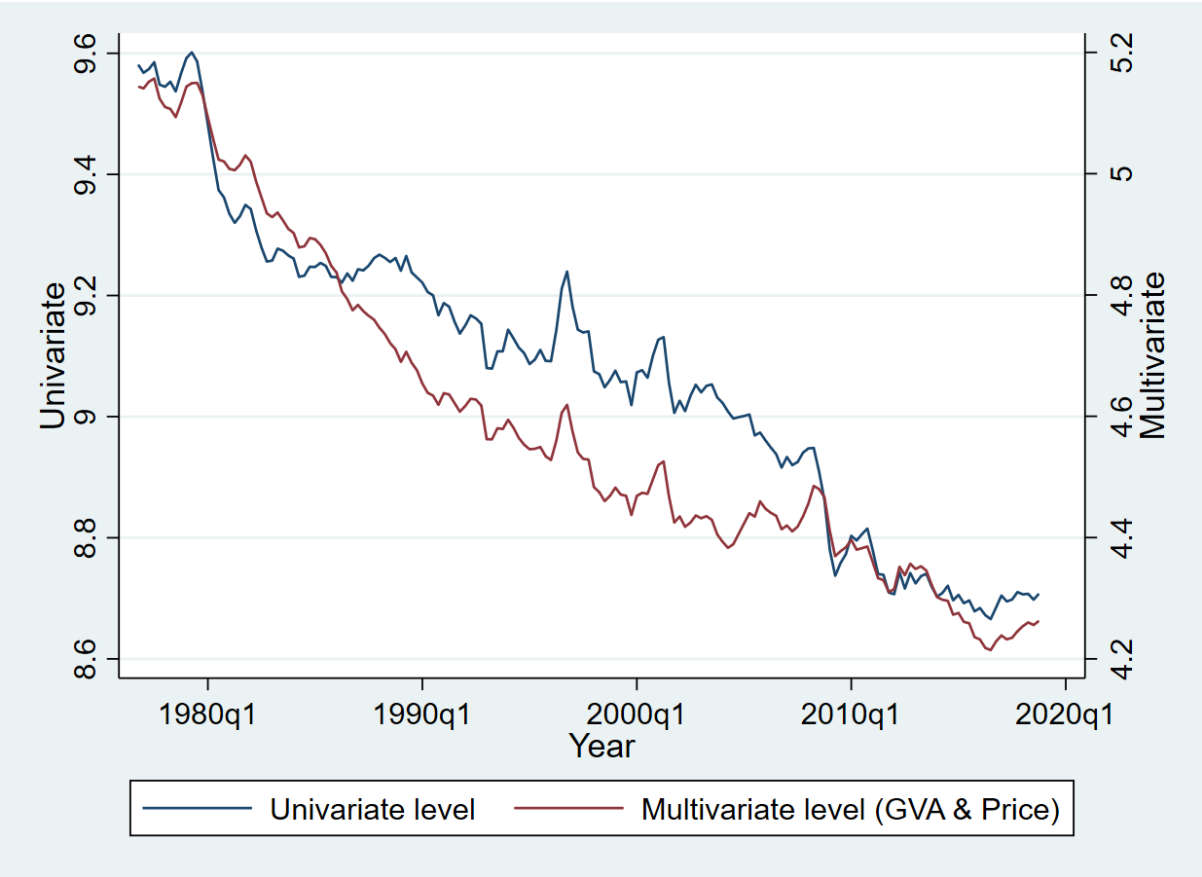
markedly change the nature of the level of the trend which continues to remain stochastic, although it does influence the extent of its stochasticity, as measured by the variance of the state error.

Table 3-3. Estimates, information criteria and diagnostics for state space models allowing for stochastic impact of GVA and energy price

	ML estimates of state error variance					Information criteria			Diagnostics		
	Level	**Slope**	**Seasonal**	**GVA**	**Price**	**AIC**	**BIC**	**HQ**	**JB**	**LB**	**Het**
3.1	6.04E-04 (1.04)	D	4.06E-05 (2.51)	1.36E-11 (0.00)	6.01E-07 (0.02)	-3.31	-3.04	-3.20	0.81	0.21	0.79
3.2	D	D	3.73E-05 (2.33)	5.04E-10 (0.00)	3.02E-05 (1.04)	-3.29	-3.04	-3.19	0.65	0.19	0.56

Notes: Model specifications obtained by augmenting preferred univariate model in Table 3-1 with GVA and energy price. The values in the parentheses are the corresponding t-ratios of the ML estimates of the state error variance. The deterministic components are reported as "D". AIC, BIC and HQ indicate the values of the Akaike, Schwarz and Hannan-Quinn information criteria, respectively. JB, LB and Het indicate the *p*-value for the Jacque-Bera test for normality, Ljung-Box test for serial correlation and F-test for heteroskedasticity, respectively.

Figure 3-4. Smoothed states of the level term of the trend from an univariate model with stochastic level (model 1.1 in Table 3-1) and a multivariate with stochastic level, time-varying GVA and time-varying energy price (model 3.1 in Table 3-3)



3.4.3 Quantitative indicator

Having established the impact of economic activity and energy price on the stochastic nature of the trend of energy consumption in the UK industrial sector, I compute an quantitative indicator to evaluate the extent to which the trend in energy consumption can be attributed to trends in economic activity and energy prices. As results in Table 3-1 to Table 3-3 indicate that the slope term is deterministic, this essentially means that the quarterly rate of change is constant across time. In particular, estimating model 1.2 (Table 3-1), model 2.1 (Table 3-2) and model 3.1 (Table 3-3) delivers estimated value of the slope equal to -4.78E-03, -5.91E-03 and -4.74E-03, respectively. Once I control for the time-varying impact of economic activity in model 2.1, I find that the negative value of the

slope decreases by 19% compared to the slope in the univariate model 1.2 (see Table 3-4). This finding is consistent with economic theory and expectations. If economic activity has a positive effect in the long term industrial energy consumption, taking into account this driver (as done in model 2.1) requires a steeper slope to deliver the decreasing trend in energy consumption in Figure 3-1, hence the decrease in the value of the estimated slope. Once I control for the time-varying impact of both GVA and energy price in model 3.1, I observe that the negative value of the slope coefficient increases by about 24% compared to model 2.1 (see Table 3-4) and becomes very similar to the slope in the univariate model 1.2. This implies that taking into account energy price among the drivers of energy consumption (as done in model 3.1) implies a flatter slope to deliver the decreasing trend in Figure 3-1. What is more interesting is that the impact of economic activity in the trend of energy consumption (obtained from comparing model 2.1 and 1.2) has historically compensated the impact of energy price on the trend (obtained from comparing model 3.1 and 2.1).

Thus, two main conclusions can be drawn from the present empirical analysis:

i) economic activity and energy price have had an impact to the stochastic nature of the trend, although considerable stochasticity in the trend remains after the impact of these two factors is taken into account;

ii) historically the impact of these two factors on the trend of energy consumption has counteracted each other as they have had an impact of similar strength and opposite direction.

Having fully accounted for the effect of energy price and economic activity on industrial energy consumption, one can argue that the great majority of the observed decrease in long-term industrial energy consumption can be attributed to **exogenous factors** that are captured by the stochastic level and the deterministic slope.

Table 3-4. Slopes and elasticities of chosen specifications

	Model type	Slope estimate	% difference from benchmark model	GVA elasticity	Price elasticity
1.1	Univariate	-4.78E-03			
2.1	Univariate + GVA	-5.91E-03	-19.12% [benchmark: 1.1]		
3.1	Univariate + GVA + Price	-4.76E-03	24.15% [benchmark: 2.1] 0.42% [benchmark: 1.1]	**0.49** **0.49**	**-0.23** **-0.23**

Notes: Model 2.1 is the preferred univariate specification in Table 3-1. Model 2.1 is the univariate model 1.1. augmented with time-varying GVA in Table 3-2. Model 3.1 is the univariate model 1.1 augmented with time-varying GVA and time-varying energy price in Table 3-3. The slope estimates remain constant over time as slope is modelled deterministic. Although GVA and energy price are modelled as time-varying, they experience negligible time variation and essentially behave as constant. Thus, columns 5 and 6 present the average elasticity across time for GVA and energy price, respectively.

As the estimates of the states of the trend depend on the implemented models, it becomes important to be confident of their plausibility. As a first test, one can assess the value of the elasticities of energy price and economic activity in model 3.1 (Table 3-3) with time-varying GVA and energy price, respectively. Interestingly, the two elasticities are essentially constant across time as a consequence of negligible time variation so that their value is equal to 0.49 and -0.23 as one can observe in Table 3-4. More specifically, the coefficient of energy price varies between the minimum of -0.230 and the maximum of -0.232 so that its range is 0.4% of the average value while variation in the coefficient of GVA is even smaller.

In terms of price elasticity, I obtain similar results to Hunt et al. (2003). This is an indication that price elasticity has been historically very stable in the UK industrial sector, given that Hunt et al. (2003) estimate UK industrial energy demand using quarterly data from 1972 to 1995 compared to the 1975-2018 timespan used in this chapter. Difference in the elasticity of economic activity between this chapter and Hunt et al. (2003) might be due to the different timespan used in the two studies or to the fact that the model in Hunt et al. (2003) does not include the construction sector in their definition of the economic variable, although it is included in their definition of energy consumption. When replicating the empirical analysis in Hunt et al. (2003) using their timespan, I find that price elasticity is equal to -0.19 and income elasticity 0.77, estimates remarkably similar to that produced by Hunt et

al. (2003) (see Table 2-2) which can be considered as an additional sign of robustness for the proposed methodological approach in this chapter. Nonetheless, I implement a more explicit robustness analysis in the following subsection, to gain further confidence in the estimates presented in this chapter.

3.4.4 Robustness analysis and discussion

3.4.4.1 Impact of economic activity and energy price on the stochasticity of the trend

In similar fashion to model 2.1 and 3.1 in which the impact of economic activity and energy price on energy consumption is allowed to be stochastic, the first robustness test is related to the assumed nature of the impact of economic activity and energy price. Thus, I proceed by implementing the methodology outlined in 3.3.4, i.e. energy price and economic activity are modelled to have a deterministic impact on energy consumption, by far the standard assumption in the energy economics literature. More specifically, Table 3-5 presents the results from models R1.1 and R1.2 that correspond to models 2.1 and 2.2 after imposing deterministic impact of economic activity, and models R1.3 and R1.4 that correspond to models 3.1 and 3.2 after imposing deterministic impact of economic activity and energy price.

As a starting point, I focus on the comparison between models with and without a stochastic level in Table 3-5, i.e. models R1.2 and R1.4 that are fully deterministic with the exception of the seasonal component and models R1.1 and R1.3 that the level term is stochastic in nature. The deterministic models R1.2 and R1.4 fail all three diagnostic tests (JB, LB and Het) as one can observe in Table 3-5 while the test failure in the models with stochastic level is confined to serial correlation in the model R1.1 that does not include energy price (*1st source of evidence* in subsection 3.3.3). With regard to *2nd source of evidence*, all information criteria (AIC, BIC and HQ) indicate that models with stochastic level (R1.1 and R1.3) perform much better than those with deterministic level (R1.2 and R1.4). Moving on to *the 3rd source of evidence* and the comparison between multivariate models with a stochastic level

and the univariate model selected in subsection 3.4.1, the introduction of energy price and economic activity delivers a reduction in the state error variances to 5.69E-04 (model R1.1) and 6.18E-04 (model R1.3), down from 8.80E-04 in model 1.2. The values of the error variances are very similar to those in models 2.1 (Table 3-2) and 3.1 (Table 3-3), a finding that further indicates that the stochasticity in the level of energy consumption is only partly related to economic activity and energy price, regardless of the assumption on the nature of the impact of economic activity and price. Considering the similarity in the variance of the level term in model 3.1 (Table 3-3) and R1.3 (Table 3-5), and variance of the level term in model 2.1(Table 3-2) and model R1.1 (Table 3-5), in accordance to the very low t-ratios on the variance of the coefficients on economic activity and price in the models where they are allowed to be stochastic (i.e. model 2.1 and 3.1), no significant difference can be observed in the time pattern of the trend of these two pairs of models. This finding further confirms the robustness of the estimates presented in this chapter. It also indicates that incorporating economic activity and energy price does not markedly change the nature of the level of the trend which continues to remain stochastic, although it has an impact on the extent of its stochasticity as measured by the state error variance. This finding is obtained regardless of whether the impact of these two factors is allowed to be stochastic or deterministic. In addition, one can conclude that both price and GVA coefficients have negligible time variation and therefore should be modelled as constant.

Table 3-5. Estimates, information criteria and diagnostics for state space models with constant coefficient for GVA and energy price, respectively

	State error variance					Information criteria			Diagnostics		
	Level	**Slope**	**Seasonal**	**GVA**	**Price**	**AIC**	**BIC**	**HQ**	**JB**	**LB**	**Het**
1.2	8.80E-04 (6.20)	D	4.58e-05 (2.84)			-3.30	-3.10	-3.22	0.18	0.33	0.65
R1.1	5.69E-04 (5.0)	D	4.92E-05 (3.07)	D		-3.31	-3.10	-3.23	0.16	0.03	0.46
R1.2	D	D	1.77E-05 (1.20)	D		-2.64	-2.44	-2.56	0.00	0.00	0.02
R1.3	6.18E-04 (4.33)	D	4.08E-05 (2.52)	D	D	-3.33	-3.10	-3.24	0.81	0.21	0.79
R1.4	D	D	1.49E-05 (1.11)	D	D	-2.56	-2.35	-2.47	0.04	0.00	0.04

Notes: The values in the parentheses are the t-ratios of the ML estimates of the state error variances. The deterministic components are reported as "D". AIC, BIC and HQ indicate the values of the Akaike, Schwarz and Hannan-Quinn information criteria. JB, LB and Het indicate the *p*-value for the Jacque-Bera test for normality, Ljung-Box test for serial correlation and F-test for heteroscedasticity.

3.4.4.2 Stochastic slope and fully stochastic trend

The multivariate models in this chapter have been estimated conditional on the nature of the trend obtained from the univariate model 1.2, i.e. stochastic level and deterministic slope. As an additional robustness exercise, I estimate models R2.1 and R2.3 in Table 3-6 with fully stochastic trend, compared to models R2.2 and R2.4 in which the nature of the level is assumed to be deterministic. Similar to the previous subsection 3.4.4.1, I start the robustness analysis by focussing on the comparison between models with stochastic level (R2.1 and R2.3) and without stochastic level (R2.2 and R2.4) in Table 3-6. The models with deterministic level (R2.2 and R2.4) have serially correlated residuals while those with fully stochastic trend (R2.1 and R2.3) perform well in terms of diagnostics tests (JB, LB and Het - *1st source of evidence* in subsection 3.3.3). With regard to *2nd source of evidence*, all information criteria (AIC, BIC and HQ) unanimously indicate that models with stochastic level (R2.1 and R2.3) perform much better than those with deterministic level (R2.2 and R2.4). Moving on to the *3rd source of evidence* and the comparison between multivariate and univariate models with fully stochastic trends, models R2.1 and R2.3 have identical state error variance (6.18E-04) which is somewhat smaller than then variance in the univariate model (1.4). In all three cases, the slope error variance is negligible,

varying between 2.48E-13 and 4.19E-10. Considering that the variance of the level term in the models R2.1 and R2.3 is identical to the one in model R1.3 in Table 3-5, and very similar to that in model 3.1 in Table 3-3, and bearing in mind the very low t-ratios on the variance of any other coefficients allowed to be stochastic (with the exception of the seasonal dummies), no significant difference can be observed in the time pattern of the trend of these two pairs of models. This finding can be considered as an additional confirmation of the robustness of the results presented in this chapter. Allowing for time variation in the slope term does not influence the stochastic nature of the level which proves that starting the multivariate analysis from a univariate model with stochastic slope and stochastic level would not have altered the conclusions obtained from this chapter. Finally, it further proves that the results are unaffected by the modelling assumption of economic activity and energy price being either time-varying or constant parameters.

Table 3-6. Estimates, information criteria and diagnostics for state space models with fully stochastic trend

	Stochastic error variance					Information criteria			Diagnostics		
	Level	**Slope**	**Seasonal**	**GVA**	**Price**	**AIC**	**BIC**	**HQ**	**JB**	**LB**	**Het**
1.4	8.80E-04 (6.20)	2.48E-13 (0.00)	4.58-05 (2.84)			-3.29	-3.07	-3.20	0.18	0.33	0.65
R2.1	6.18E-04 (1.03)	4.19E-10 (0.00)	4.08E-05 (2.51)	6.22E-15 (0.00)	4.27E-09 (0.00)	-3.30	-3.01	-3.18	0.81	0.21	0.79
R2.2	D	4.47E-06 (1.51)	1.69E-05 (1.78)	4.42E-12 (0.00)	4.51E-07 (0.11)	-3.12	-2.85	-3.01	0.75	0.00	0.76
R2.3	6.18E-04 (4.29)	2.99E-10 (0.00)	4.08E-05 (2.50)	D	D	-3.32	-3.07	-3.22	0.81	0.21	0.79
R2.4	D	3.80E-06 (2.46)	1.33E-05 (1.73)	D	D	-3.12	-2.88	-3.02	0.53	0.00	0.73

Notes: The values in the parentheses are the t-ratios of the ML estimate of the state error variances. Deterministic components are reported as "D". AIC, BIC and HQ indicate the values of the Akaike, Schwarz and Hannan-Quinn information criteria. JB, LB and Het indicate the *p*-value for the Jacque-Bera test for normality, Ljung-Box test for serial correlation and F-test for heteroskedasticity,

3.5 Discussion

3.5.1 Overview of empirical findings

This chapter assesses the determinants of energy efficiency in the UK industrial sector for over almost 50 years, the longest time period ever used in the energy economics literature. The use of a systematic model selection procedure allows me to identify and assess the nature of the trend of energy consumption. I start the analysis by identifying the exact nature of the trend of energy consumption on whether it is stochastic or deterministic. Using as evidence a number of distinct criteria, i.e. residuals diagnostic tests, information criteria, the size of the ML estimate of the variance along with the corresponding t-ratios and visual examination of the plot of the smoothed state, I find that the best performing univariate representation of industrial energy consumption is a model with stochastic level and deterministic slope. Subsequently, I control for the effect of time-varying economic activity and time-varying energy price on energy consumption and assess whether the inclusion of those two parameters changes the nature of the trend. Similar to the univariate model, this is done with the use of a number of distinct sources of evidence i.e. residuals diagnostic tests, information criteria, the change in the size of the ML estimate of the variance along with the corresponding t-ratios (in comparison to the univariate model) and visual examination of the plot of the smoothed state. Although one can observe a small decrease in the variance of the level term of the trend of energy consumption, findings indicate that the nature of the level term of the trend remains stochastic once energy price and economic activity are introduced in the model. This finding is in accordance to the related literature on the underlying energy demand model (UEDM) in the UK and it further supports the modelling choice of Hunt et al (2003) in which only trend is allowed to be stochastic and not the impact of drivers.

One could have expected that the inclusion of the level term of economic activity and energy price would affect the nature of the trend and not only the extent of its stochasticity. Nonetheless, this does not seem to be the case based on the results of the robustness analysis performed in section 3.3.4.

Information criteria indicate that model R1.3 in Table 3-5 with constant coefficients for GVA and energy price is the best representation of the UK industrial demand in the last 50 years, compared to the more general specifications including time-varying coefficients for GVA and energy price. This is because the marginal contribution of time-varying price coefficient to the model fit attracts some penalty related to additional parameters, and therefore increasing the value of the information criteria. The robustness of this finding can be further proved by the fact that the nature of the level term of the trend of energy consumption remains stochastic regardless of the assumption on the nature of the impact of economic activity and energy price. In addition, multivariate models have been estimated conditional on the nature of the trend obtained from a univariate model and throughout these robustness tests, the level term always retains a comparable variance. Another indication of robustness can be considered the fact that the level term of the trend remains stochastic in nature regardless of whether the slope term of the trend is modelled as stochastic or deterministic (see Table 3-6). In addition, the slope term of the trend has negligible variation when both the level and the slope terms of trend are modelled stochastic while the level term of the trend always retains a comparable variance to the one obtained from the univariate model.

Finally, this chapter assesses the extent to which the estimated long-run trend of industrial energy consumption can be explained by the impact of energy price and economic activity. This can be done by comparing the difference in the value of the slope term once one controls for GVA and energy price to the value of the slope term in the univariate model. Since the slope term is deterministic, it accounts for the quarterly rate of change in energy consumption which is constant across time. Controlling for economic activity results in reducing the value of the slope term of the trend by 19%. On the other hand, controlling both for economic activity and energy price results in increasing the value of the slope term of the trend by about 24%. The fact that the value of the slope in the model incorporating energy price and economic activity is almost identical to the value of the slope in the univariate model indicates that energy price has historically counteracted almost perfectly for the effect of economic activity on energy consumption. Thus, energy price is important for long run industrial energy

efficiency to the extent that it has largely offset the surge in energy consumption induced by economic activity. This is a very interesting result from a policy making perspective as it indicates that increasing energy efficiency in the industrial sector would require additional policy measures focusing on exogenous factors, which are mostly imputable to technological progress, and possibly to gradual and irregular institutional changes. For example, these policy measures could involve potential changes in the related industrial regulatory framework, specifically for energy intensive industrial facilities, so that they incentivise the corresponding firms to invest in energy saving technological improvements that could increase long run industrial energy efficiency.

3.5.2 Energy efficiency and economic interpretation

The development and adoption of energy saving technical changes in the industrial process can lead to energy efficiency gains in the long-term period. Energy efficiency gains can be either endogenously induced by changes in energy prices, or exogenously induced by changes in the corresponding regulatory framework, or more generally by institutional changes within the economy. However, the elusive nature of energy efficiency makes it very difficult to quantify and control for these factors. Decomposition analysis studies have tried to distinguish the percentage of energy use reduction that is due to structural changes, and on the other hand due to improvements in energy efficiency. However, a major modelling constraint of decomposition studies such as Hass and Kempa (2018) is that they do not explicitly control for the effect of exogenous (and/or latent) factors on energy saving technical change as they implicitly assume that all modelled factors are endogenous to the adoption of energy saving technical change. Therefore, it is not clear whether the observed long-term effect of energy price shocks on energy saving technical change would remain once I specifically control for exogenously induced adoption of energy saving technical change.

Hunt et al. (2003) introduced a stochastic linear trend term in the industrial energy demand function that accounts for unobserved factors in order to capture the elusive effect of exogenously induced

energy saving technical change. Building on Hunt et al (2003), this chapter contributes to the current understanding of relevance of price-induced against exogenous technological change by proposing a systematic econometric approach, as well as overcoming the standard restrictive assumption that energy price elasticity is modelled as a constant parameter. I present in this chapter a model that retains an agnostic approach on the underlying nature of the factors inducing the adoption of energy saving technical change. I explicitly control for endogenous factors related to energy prices – captured by the time-varying coefficient of energy price – and exogenous factors – captured by the introduction of a stochastic trend component in the linear state space model. Empirical findings in this chapter indicate that an increase in energy price can induce short-term changes in energy efficiency. Nonetheless, in the long-term period the adoption of energy saving technical change that improves energy efficiency is induced solely by exogenous factors that are not related to the dynamics of energy price. Therefore, once I explicitly control for the effect of exogenous factors on energy efficiency, Hass and Kempa (2018) finding that temporal positive shocks in energy price can have permanent effect on innovation dynamics does not hold, at least for the case of the UK industrial sector.

In other words, this essentially means that policymakers can effectively stimulate energy efficiency gains within the industrial sector through the introduction of the appropriate regulatory framework that can incentivise innovation dynamics, as argued in Malinauskaite et al (2019). Combining investment in energy saving technologies and developing the appropriate energy management practices is an effective policy approach to tackle the energy efficiency gap, specifically considering the manufacturing sector (Backlund et al 2012). Meeting Clean Growth targets requires energy intensive industrial subsectors, such as iron and steel, to particularly focus on the development of innovative practices and technological improvement of their industrial processes. The UK government can incentivise this transition by legislating the necessary regulatory framework that would incentivise energy intensive businesses to invest in research and development and boost innovation practices. In addition, the UK government could actively encourage this transition by providing financial incentives such as financial support, access to low interest borrowing, etc.

3.6 Concluding remarks

Improving industrial energy efficiency is one the key policy targets set by the UK government in the UK Clean Growth Strategy. To improve industrial energy efficiency is crucial first to identify the long-term determinants of energy efficiency and understand the relationship between energy prices and the adoption of energy saving technical change. The present chapter presents a systematic methodological approach that builds on the STSM model and more specifically on the contribution of Hunt et al (2003). The innovation of the proposed empirical model is that it controls specifically for the effect of both exogenous and endogenous factors on the adoption of energy saving technical change. Findings indicate, at least for the case of the UK industrial sector, that the adoption of energy saving technical change in the long-term period is induced solely by exogenous factors such as gradual and irregular institutional changes (e.g., changes in the regulatory framework) which are not directly induced by the dynamics of energy prices. Therefore, the UK government should incentivise and actively support the development and adoption of innovative technologies minimising emissions through the legislation of the appropriate regulatory framework and potentially, by providing sufficient financial support and technical expertise to initiate innovation dynamics within the industrial sector. In this way, they UK government could reliably improve energy efficiency in the long-term period and achieve the emissions targets set by the UK Clean Growth Strategy.

Apart from improving energy efficiency, it is important to identify and improve the distinct characteristics in the industrial process that are responsible for industrial emissions. Thus, in order to set up a reliable policy pathway towards delivering Clean Growth in the UK industry, I examine in chapter 4 the underlying dynamics behind distinct industrial characteristics and industrial emissions. Introducing new technologies that improve energy efficiency and reduce emissions could raise concerns about negative socioeconomic impacts such as job losses due to the gradual phase out of less energy efficient technologies. Thus, I assess in chapter 5 the net job impact of different types of electricity generation technologies accounting both for fossil fuels, nuclear and renewable energy.

4 Industrial determinants of emission intensity

4.1 Overview

Apart for improving energy efficiency, it also important to identify the distinct characteristics of the industrial process that can assist in reducing industrial emissions and by extension meet the Clean Growth targets set by the UK government. However, empirical assessments of the relationship between emissions from the industrial sector and the characteristics of the production process are surprisingly scarce in the literature for European countries, despite industrial sector being one of the major air polluters as discussed in section 1.1.2 and section 2.3. Thus, this chapter responds to the second sub-research question of "*what are the long-term industrial determinants of emission intensity?*". More specifically, I assess in this chapter the long-term relationship between industrial processes and air emissions by building on an existing empirical framework. This work implies re-estimating published findings for the UK industrial sector on a bigger dataset, incorporating additional observed factors which can plausibly influence the level of emissions and taking into account, for the first time in the empirical literature, unobserved common factors through cross section dependence. In comparison to previous findings, this chapter concludes that production inputs, total factor productivity and economies of scale cannot be relied upon to reduce emissions from industrial sector. I provide evidence that reduction in emissions can be reliably delivered by reducing energy consumption, encouraging fuel substitution and by encouraging market competition so that one can counteract the increase in emissions related to higher level of capital investment. Considerable similarities can be observed in the relationship between market concentration on one side and industrial emissions and innovation on the other side. This is an interesting result for the energy and environmental economic literature as the relationship between the level of emissions and market structure is a considerably under-researched area. This chapter starts with a comprehensive discussion on the variables used and their data sources in section 4.2. Section 4.3 introduces the

proposed econometric methodology. Results are presented in section 4.4 and section 4.5 discusses about their policy relevance.

4.2 Variables and data sources

Following the empirical methodology employed in CES (2005), this chapter incorporates in the empirical analysis most of the variables used in CES (2005) with the exception of R&D expenditure that is excluded due to data limitations[37]. Since I focus on the relationship between emissions and characteristics of the production process, I drop regional variables discussed in CES (2005), a decision which does not affect the comparison with CES (2005) as their results were robust to the absence of regional variables. Moreover, results in CES (2013) cast doubts on the importance of these factors, or maybe the extent to which available data enable a precise estimation, as none of the four regional variables used in CES (2013) was found statistically significant in any of the estimated models. In addition to the variables in CES (2005), I introduced two additional factors which might affect emission intensity, namely fuel substitution and market concentration, as discussed below. As emissions are compiled on the basis of Standard Industrial Classification 2007 (SIC07), I use the same industrial taxonomy to build the variables in this study which are mainly based on the ONS Input-Output Supply and Use tables that are available for the 1997-2014 time-period (ONS, 2015). As a result, the overlap between the sample used in this study and the sample used in CES (2005) is limited to two years only, i.e. 1997 and 1998. Nonetheless, this is not a limitation as the long-term relationship between industrial emissions and their determinants is expected to be constant across time.

[37] The ONS Business Enterprise R&D development dataset reports R&D expenditure data for "product groups" which is an industrial classification that classifies sectors on a more aggregated level than SIC07 two-digit classification. Therefore, SIC07 codes 10-11-12 are aggregated on one product group. The same applies to SIC07 codes 13-14-15 and 16-17-18, respectively. R&D expenditure data by product group are not directly comparable to R&D data by industrial sector according to ONS (2014). R&D expenditure data by industrial sector has started to be reported by the ONS Business Enterprise R&D development dataset only after 2010 and onwards.

The dataset used in this chapter is produced by a combination of i) publicly available datasets and ii) confidential datasets that can be accessed only by ONS Accredited Researchers under the Statistics and Registration Services Act of 2007[38]. More specifically:

i) the publicly available datasets comprises the National Atmospheric Emissions Inventory, ONS Environmental Accounts, ONS Gross Fixed Capital Formation chain volume measure, ONS Input-Output Supply and Use tables and ONS Labour Force Survey,

ii) the confidential datasets used include the ONS (2018a) Annual Business Survey (ABS) and ONS (2012) Annual Respondents Database (ARD).

This chapter uses data for all manufacturing subsectors i.e. the industrial sectors with SIC07 industrial classification from 10 to 30, for a time period that spans from 1997 to 2014. In subsections 4.2.1 to 4.2.8, I proceed in a detailed outline of the variables used and their data sources along with the way that they are computed, a helpful overview of which can be found in Table 4-1 below. Further information on the descriptive statistics of the variables can be found in the Appendix (please check Table B1).

Table 4-1. Variables definitions and data sources

Variables	Description
Emission intensity	Direct atmospheric emissions (source: National Atmospheric Emissions Inventory) divided by real GVA (source: see below). Thousand tonnes of emissions per million pounds sterling.
Energy intensity	Total fossil fuels consumption. (Source: ONS Environmental Accounts) divided by real GVA (source: see below). Thousand tonnes of fossil fuels per million pounds sterling.
GVA	Gross value added in real terms (Source: ONS Input-Output Supply and Use tables). Millions of pounds sterling (2006 base year).

[38] One can access the abovementioned Controlled Data via the UK Data Service Secure Lab on the condition that they fulfil specific requirements (for more information please check the UK Data Service webpage – see https://www.ukdataservice.ac.uk/get-data/how-to-access/accesssecurelab). UK Data Service (UKDS) Secure Lab provides access to ABS and ARD databases only to accredited researchers that have successfully completed the Safe Researcher or Safe User of Research data Environments (SURE) training course.

Gas share	Ratio of gas to total fossil fuels consumption (source: ONS Environmental Accounts). Thousand tonnes of gas per thousand tonnes of fossil fuels.
PCI	Physical capital intensity = (real GVA-real payroll)/employment. GVA (source: see above), payroll (source: ONS Input-Output Supply and Use tables), and employment (source: ONS Labour Force Survey).
HCI	Human capital intensity = (real payroll-(real unskilled wage*employment))/real GVA (source: as above).
Size	Real GVA per firm (source: ONS (2018a) Annual Business Survey and ONS (2012) Annual Respondents Database).
TFP	Total factor productivity (Olley and Pakes, 1996; Beveren, 2012) estimated using data from ONS (2018a) Annual Business Survey and ONS (2012) Annual Respondents Database.
HHI	Herfindhal-Hirschman index estimated using data from ONS (2018a) Annual Business Survey and ONS (2012) Annual Respondents Database.
Capital expenditure intensity	Capital expenditure (source: ONS Gross Fixed Capital Formation chain volume measure) divided by real GVA (source: see above). Million pounds of capital expenditure per million pounds sterling.

4.2.1 Emission intensity

Atmospheric emissions affect negatively human health in various ways. Particular matter exposition, for example, raises the risk of developing cardiovascular diseases and lung cancer (Guerreiro et al., 2016), ecosystems are affected by air pollution through acidification, eutrophication, and ground level ozone (Wald, 2016)[39] while greenhouse gases are the dominant cause of climate change (IPCC, 2014) with related impacts on health (Watts et al., 2015), the economy (Stern, 2008), and ecosystems (Walther et al., 2002). Atmospheric emissions are produced by industrial processes and direct fuel use at the point of release, including generation of electricity from primary fuels for their own use (Wakeling et al., 2016; Brown et al., 2016). Atmospheric emissions for the UK industrial sectors are computed by the National Atmospheric Emissions Inventory (NAEI) and compiled by AEA Energy & Environment on behalf of the Department for Environment, Food & Rural Affairs (DEFRA) (Wakeling

[39] Acidification occurs when acidic compounds in accord and air pollutants (such as PM_{10} and CO) are deposited on land and aquatic systems and harm soils, vegetation and wildlife. Acid rain precursors (such as NO_x and SO_2) result both to eutrophication and ground-level ozone, where the former affects the nutrients level and the wildlife in sensitive environment, while the latter damages plants, crops and forests and contributes in climate change along with greenhouse gases (such as CO_2 and N_2O).

et al., 2016; Brown et al., 2016). Essentially, the dataset on emission intensities is estimated by multiplying direct fuel use by emissions factors and subsequently adding emissions unrelated to fuel consumption. This dataset is derived from ONS Environmental Accounts (ONS, 2016a). Following CES (2005), this chapter focuses on:

- greenhouse gases (GHGs) i.e. carbon dioxide (CO_2)
- acid rain precursors i.e. nitrogen oxides (NO_x), sulphur dioxide (SO_2), and total acid precursor emissions[40] (TAC),
- other pollutants i.e. particular matter (PM_{10}) and carbon monoxide (CO).

In addition, I further add another GHG that has not been used by CES (2005), i.e. Nitrogen Monoxide (N_2O), data for which is available in the Defra dataset. All abovementioned pollutants are **divided by the level of real GVA**[41] in order to compute the emission intensities**.**

4.2.2 Energy intensity

The energy intensity variable, denominated as energy use intensity in CES (2005), is generated by dividing total fossil fuels consumption by the level of real GVA. Fossil fuels consumption measures the direct use of primary fossil fuels in the industrial process as well as some secondary fuels (e.g. from coke) and it is derived from the ONS Environmental Accounts (ONS, 2016a). The level of real GVA is obtained from the Input-Output Supply and Use tables (ONS, 2016c). Following CES (2005), the measure of energy intensity excludes consumption of electricity and hydrogen. This is because consumption of these secondary fuels does not influence the levels of direct emissions from firms in the industrial sector. I expect a positive relationship between emission and energy intensities, as an

[40]Total acid precursor emissions (TAC) are the weighted sum of SO_2, NO_x and NH_3 (ammonia) produced by industrial processes and direct fuel use at the point of release.
[41] This is derived from the Input-Output Supply and Use tables. For more information on Input-Output Supply and Use tables please check ONS (2016c).

increase in the amount of combusted fossil fuels used per unit of GVA will lead to a higher level of direct emission intensity.

4.2.3 Factor intensities

To capture the relative importance of production factors employed in the industrial production process, I incorporate two indicators employed in CES (2005), namely Physical Capital Intensity (PCI) and Human capital intensity (HCI). The former (PCI) measures the nonwage value added per worker and is produced by subtracting real GVA to total real payroll divided by employment. The other indicator (HCI) measures the share of value added paid to skilled workers and is produced by taking the difference between average and unskilled real wage times employment and dividing by real GVA. Total real payroll and GVA are obtained from ONS Input-Output Supply and Use tables (ONS, 2016c); employment from ONS Labour Force Survey[42]; unskilled real wage was produced by dividing real payroll by employment[43]; and finally, nonwage value added per worker was built by subtracting a real measure for total real payroll from real GVA (ONS, 2016c).

This chapter employs the definition of variables used in CES (2005) to facilitate the comparison of present estimates to their results, although being aware of potential minor shortcomings[44]. Alternative ways of measuring capital intensity include the capital-labour ratio, e.g. Cole et al. (2013), Ma et al. (2014), Löschel et al. (2015). Nonetheless, measures such as value added per worker (Lim, 1976) or nonwage value added per worker that is used in this chapter, are preferred when reliable

[42] For more information on the ONS Labour Force Survey please check ONS (2016d).
[43] CES (2005) define unskilled real wage using as a proxy the real wage of the "Wood and products of wood and cork" (SIC 16) sector, a strategy that I also follow as the industrial sector with the lowest real average real wage happens to be the "Wood and products of wood and cork" (SIC 16) industrial sector.
[44] The variable used as a proxy for human capital in CES (2005) includes total real wage obtained by skilled and unskilled workers. Thus, it accounts for factors related to relative scarcity of these two groups and factors related to the market structure of the sector such as imperfections and monopoly while it also accounts for differences in tax and credit policies.

data on capital stock are not immediately available (Banerji, 1976)[45]. Other measures used in the academic literature and statistical offices include the ratio between real capital stock and total value added, e.g. Ciccone and Papaioannou (2009) and ONS (2016b). With regard to human capital, data on the length of time spent in formal education, education enrolment rates, share of population (or employees) with a certain education level or share of hours worked by those with a certain education level are used in empirical studies covering countries or economic sectors (Ciccone and Papaioannou, 2009; Kottaridi and Stengos, 2014; Wood and Ridao-Cano, 1999).

4.2.4 Capital expenditure intensity

I obtained a variable measuring capital expenditure intensity by dividing Gross Fixed Capital Formation (GFCF) chain volume measure (CVM) by real GVA. Gross Fixed Capital Formation captures the annual business investment which is defined as the cost of acquisitions less proceeds from disposals of assets used in the production process (Nolan and Field, 2014). I adopted a slightly different definition for the capital expenditure intensity from the one employed in CES (2005), as Gross Fixed Capital Formation in chain volume measure is the most comprehensive deflated measure of UK capital expenditure for the industrial sectors (Nolan, 2013). After all, it is worth mentioning that results from CES (2005) point at no statistical significance for the impact of this variable on emission intensities.

[45] It is important to bear in mind that differences in the nonwage value added per employee will reflect, apart from any real difference in the sectoral PCI it is supposed to proxy for, the presence of factors such as: imperfections and monopoly (for which I account for by using the HHI - see Equation (4-2)), differences in tax and credit policies, and the degree of excess capacity. All the above-mentioned factors are likely to influence the level of nonwage value added per employee given a certain level of capital intensity, as discussed in Banerji (1976).

4.2.5 Total factor productivity

Total factor productivity (TFP) for each industrial subsector is estimated with the use of the empirical approach developed by Olley and Pakes (1996). Following Beveren (2012), I estimate sectorial TFP using real turnover based on firm-specific weights. More specifically, TFP for industrial sector i and year t is equal to $\widehat{TFP}_{it} = \sum_{i=1}^{N_t} s_{jt}\hat{\Omega}_{jt}$ where $\hat{\Omega}_{jt}$ is the firm-specific TFP residual and s_{jt} is the firm-specific weight. Firm specific weights are equal to $s_{jt} = S_{jt}/\sum_j S_{jt}$ where the S_{jt} is firm's *j* turnover for year t and $\sum_j S_{jt}$ is the sum for all firms *j* in year t. The choice to use Olley and Pakes (1996) with real turnover as a firm-specific weight is not likely to influence the findings, as CES (2005) reports little effect on the estimated coefficient on TFP when TFP data were computed using a number of different production function specifications. All production inputs and turnover are expressed in real terms, as they are deflated with the use of the ONS producer price inflation index for each industrial sector at the two-digit SIC07 level classification and transformed in their logarithmic equivalents. Firm level data for the UK industrial subsectors were derived from the Annual Business Survey and Annual Respondents Database. These datasets can be accessed only through the UK Data Service Secure lab interface and contain information for UK firms on an annual basis[46].

4.2.6 Size

The size variable is built by dividing each sector's GVA by the total number of firms in that sector and it captures the average firm size within an industrial sector. This variable is used as proxy for the effect of intra-sectoral economies of scale on emission intensities. I obtain the number of total number of

[46] In order to estimate TFP for the UK industrial subsectors, I used the following variables reported annually in the ABS and the ARD datasets: "wq550" (total turnover), "wq450" (total employment costs), "wq523" (total net capital expenditure) and "wq499" (total purchases of energy, goods, materials services). For more information on the definition of these variables please check the relevant ONS report (ONS, 2015).

firms for each sector from the ONS (2018a) Annual Business Survey and the ONS (2012) Annual Respondents Database (ONS, 2016c).

4.2.7 Fuel substitution

The fuel substitution variable is built by dividing gas consumption by total fossil fuel consumption, both of which obtained from the Environmental Accounts (ONS, 2016a), and it is used as a proxy for substitution from dirtier fuels to cleaner ones (e.g. from coal to gas).

4.2.8 Level of Concentration

Market structure and the associated level of concentration within industrial sectors can be proxied by the Herfindahl-Hirschman index (HHI), which is probably the most widely used concentration index in the empirical industrial literature. More specifically, the HHI is equal to the sum of squares of the market share of the firms in an industrial sector, with firms having a high market share influencing more than proportionally the level of the index (Ginevinius and Cirba, 2007). The HHI takes values from 0 to 1, where 0 represents perfect competition and 1 monopoly.[47] I explore the historical relationship between market concentration and emission intensity by incorporating both the logarithm of HHI and the square of the logarithm of HHI. This allows to capture evidence of non-linear effects of market concentration on innovation in the UK manufacturing sector and is very much motivated by discussion in Aghion et al. (2005) that find evidence of an inverted U-shaped relationship between market concentration and innovation in the UK industry. However, Correa (2011) argues that a structural break in the early 1980s makes Aghion et al. (2005) competition-innovation relationship

[47] In order to estimate the HHI, I use the variable "wq550" (total turnover variable) reported in both the ONS Annual Business Survey (ABS) and ONS Annual Respondents Database (ARD) (see ONS, 2015).

unstable as the author finds a positive relationship between the examined variables for 1973-1982 and no relationship for 1983-1994.

4.3 Econometric modelling

The first step of the proposed econometric methodology involves re-estimating as closely as possible the model implemented in CES (2005), i.e.

$$E_{it} = \alpha_i + \delta_t + \beta_1 EN_{it} + \beta_2 HCI_{it} + \beta_3 PCI_{it} + \beta_4 SIZE_{it} + \beta_5 TFP_{it} + \beta_6 CAP_{it} + \varepsilon_{it} \qquad (4\text{-}1)$$

for $i = 1,..,20$ industrial sectors and $t = 1,..,18$ years where the independent variable E_{it} is emission intensity, i.e. atmospheric emissions divided by real GVA. Equation (4-1) is estimated separately for sulphur dioxide (SO_2), nitrogen oxides (NO_x), total acid precursor emissions (TAC), carbon monoxide (CO), particular matter (PM_{10}), carbon dioxide (CO_2) and dinitrogen monoxide (N_2O) emission intensities. Independent variables in Equation (4-1) include energy intensity (EN_{it}), human capital intensity (HCI_{it}), physical capital intensity (PCI_{it}), size of the average firm in the manufacturing subsector ($SIZE_{it}$), total factor productivity (TFP_{it}), and capital expenditure intensity (CAP_{it}). I use the logarithms of all variables, so that the estimated coefficients can be interpreted as elasticities like in CES (2005). When estimating Equation (4-1), I choose between fixed effects (FE) and random effects (RE) estimators using the Hausman test and I use an F-test to determine the existence of time-effects, i.e. introducing time dummies if the null of the F-test is rejected. From the estimation, I obtain a benchmark model for comparison with results from CES (2005).

As a second step, I introduce in Equation (4-2) the gas share of total fossil fuel consumption (GAS_{it}) and the Herfindhal-Hirschman market concertation index (HHI_{it}), with the latter both in levels and squares to incorporate the possibly non-linear impact of market concentration on emission intensity, as discussed above.

$$E_{it} = \alpha_i + \delta_t + \beta_1 EN_{it} + \beta_2 GAS_{it} + \beta_3 HCI_{it} + \beta_4 PCI_{it} + \beta_5 SIZE_{it} + \beta_6 TFP_{it} + \beta_7 HHI_{it} + \beta_8 HHI_{it}^2 + \beta_9 CAP_{it} + \varepsilon_{it} \quad (4\text{-}2)$$

I continue by testing for the existence of CSD in the dataset which may arise from unobserved common processes or "factors" affecting both the variables and the error term, possibly to a different extent. The factors can be either strong or weak, the former representing shocks affecting all panel units, while the latter representing spillovers across panel units with strength of the dependence declining as some notion of distance between units in the panel increases (Chudik et al., 2011; Smith and Fuertes, 2016). Estimators not taking CSD into account, like the FE and RE above, produce biased and inconsistent estimates when both disturbance and regressors share a common factor (Andrews, 2005; Phillips and Sul, 2003; Phillips and Sul, 2007; Sarafidis and Robertson, 2009). One can use the CD test (Pesaran, 2004) to assess the existence of CSD, a choice motivated by the CD test being robust to structural breaks, and having good small sample properties even when *T* is small relative to *N* which might be an important feature bearing in mind the structure of this chapter's panel dataset. Thus, the third step of the proposed methodology involves the use of the Common Correlated Effects (CCE) estimator (Pesaran, 2006; Kapetanios et al., 2011) that accounts for the presence of CSD in the sample. This estimator can be algebraically derived from a multifactor error structure such as:

$$\begin{aligned} y_{it} &= \varphi_i y_{it-1} + \beta_i' x_{it} + u_{it}, \\ u_{it} &= c_{yi} + \gamma_i' f_t + \epsilon_{it}, \\ x_{it} &= c_{xi} + \Gamma_i' f_t + \varepsilon_{it}, \end{aligned} \quad (4\text{-}3)$$

where c_i=(c_{yi}, c_{xi}) is the individual specific effects, $f_t = (f_{1t}, f_{2t}, \dots, f_{mt})$ is a $m \times 1$ vector of unobserved common factors affecting both error terms u_{it} and variables with Γ_i' and γ_i' being two $m \times 1$ vectors of factor loadings of the independent variables and the error term, respectively, and γ_i' a $m \times 1$ vector of factor loadings for the dependent variable. The terms ϵ_{it} and ε_{it} are idiosyncratic errors with $E(\epsilon_{it}) = 0$, $E(\varepsilon_{it}) = 0$, $E(\epsilon_{it}^2) = \sigma_i^2$, and $E(\varepsilon_{it}^2) = \sigma_i^2$, while the covariance of error u_{it}

is determined by factor loadings Γ_i' and γ_i'. If unobserved factors f_t are correlated with the vector of the independent variables x_{it} (which is common in the economic literature) omitting f_t will result in biased and inconsistent β_i' estimates, as the resulting omitted factor will then be incorporated in u_{it}.

The CCE Pooled (CCEP), which has good small sample properties (Pesaran, 2006) in the model above even with small *T* relative to *N*, can be implemented by estimating:

$$y_{it} = \alpha_i + \beta_i x_{it} + \delta_{xi}\bar{x}_t + \delta_{yi}\bar{y}_t + u_{it}, \qquad (4\text{-}4)$$

where $\beta_i = \beta$ and $\sigma_i^2 = \sigma^2$ for all i. The CCEP estimator allows for unobserved effects to have heterogeneous impact on individual units and to be arbitrarily correlated to the individual-specific regressors (Eberhardt and Teal, 2010). $\mathrm{f_t}$ is treated as nuisance parameter while CSD is removed from the model by including $\bar{\mathrm{y}}_\mathrm{t}$ and $\bar{\mathrm{x}}_\mathrm{t}$ which are the cross-section averages of the independent (y_{it}) and the dependent variables (x_{it}), respectively. The CCE estimator remains consistent with good small sample properties when $\mathrm{f_t}$ is non-stationary and by extent when x_{it} is non-stationary (Kapetanios et al., 2011).

4.4 Estimation results

I start this section with the presentation of the results from the estimation of Equation (4-1) with a Random or a Fixed Effects estimator. It is reasonable to expect that estimated results from Equation (4-1) are close to results in CES (2005), if underlying data generation process is structurally stable across time and if CSD does not affect the estimation. As it can be seen in Table 4-2, the Hausman test indicates the selection of the RE estimator in the case of NOx, PM_{10} while for the remaining emission intensities the FE estimator is preferred. This can be considered as a departure from CES (2005) where

the Hausman test always selects the FE model.[48] Confirming results in CES (2005), all models in Table 4-2 include time dummies, with the exception of the model for N_2O (not included in CES 2005). The sign of the time dummies matches results from CES (2005) with the exception of CO_2 where time dummies are negative in CES (2005) but overall positive in the model presented in Table 4-2. As shown in Figure B1 in Appendix B section, time dummies in the models for NO_x and TAC have overall downward trends while one can see that CO_2 dummies display an upward trend. The values for SO_2, CO and PM_{10} imply U-shaped trends, with a downward trend up to around 2005 which becomes slightly upward for SO_2 and is completely reversed by 2014 for CO and PM_{10}. In the case of NO_x and TAC, one can observe similarities between the time pattern of the dummies (Figure B1) and the time pattern of emission intensities (Figure 2-4). Nonetheless, this observed similarity does not occur in the case of SO_2, CO and PM_{10} as the observed rebound in time dummies of SO_2, CO and PM_{10} does not materialise itself in the time pattern of SO_2, CO and PM_{10} intensities. Finally, emission intensity is downward sloping in the case of CO_2 even though pattern of time dummies is upward sloping.

[48] It is worth pointing out that in this analysis, contrary to evidence presented in CES (2005), the choice between FE and RE estimator does not affect the results from the estimation, as values of the coefficients and their statistical significance are fairly similar – see Table B2 and Table B3 in the Appendix B.

Table 4-2. Results from the estimation of Equation (4-1) from the Fixed or Random Effects estimator, as selected by the Hausman test

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	RE	FE	FE	RE	FE	FE
Energy Intensity	0.766***	0.787***	0.727***	0.677***	0.785***	0.904***	0.568***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital intensity	-0.098*	-0.066***	-0.053***	0.01	-0.078***	-0.004	-0.049*
	(0.086)	(0.000)	(0.005)	(0.719)	(0.001)	(0.565)	(0.076)
Human capital intensity	-0.062	-0.045***	-0.052*	-0.054	-0.107***	-0.01	-0.135***
	(0.468)	(0.000)	(0.080)	(0.203)	(0.000)	(0.326)	(0.004)
Size	0.128***	0.022**	0.041***	-0.053**	0.063***	-0.015***	-0.006
	(0.003)	(0.020)	(0.007)	(0.015)	(0.003)	(0.004)	(0.804)
TFP	-0.013	0.125***	0.039	-0.162	-0.101	-0.077***	-0.389***
	(0.949)	(0.006)	(0.570)	(0.104)	(0.318)	(0.002)	(0.001)
Capital expenditure int.	-0.087	0.018	0.047	0.044	-0.038	0.038**	0.093
	(0.588)	(0.575)	(0.392)	(0.571)	(0.569)	(0.050)	(0.202)
Constant	-6.880***	-6.139***	-5.418***	-4.435***	-8.044***	0.995***	-4.445***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel groups	19	19	19	19	19	19	19
Observations	286	300	300	300	300	300	300
CD test	X	-2.45**	-2.62***	-2.89***	-1.85*	3.23***	3.06***
CD *p*-value	(x)	(0.014)	(0.009)	(0.004)	(0.064)	(0.001)	(0.002)
R^2 between	0.807	0.935	0.947	0.862	0.766	0.963	0.559
R^2 within	0.513	0.948	0.863	0.713	0.707	0.98	0.576
R^2 overall	0.772	0.929	0.923	0.845	0.741	0.966	0.576
Hausman χ^2	31.4***	8.997	41.903***	46.009***	2.466	52.46***	11.982*
Hausman *p*-value	(0.000)	(0.174)	(0.000)	(0.000)	(0.872)	(0.000)	(0.062)
Time dummy F-test	6.024***	174.7***	9.612***	6.141***	25.88*	1.486*	0.6491
F-test *p*-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.077)	(0.099)	(0.850)
Time dummies	YES	YES	YES	YES	YES	YES	NO

Notes: Values in parenthesis are *p*-values of coefficient estimates. *, ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests regressions residuals for cross section dependence and assumes null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. FE and RE stand for fixed effects and random effects estimators, respectively. Hausman test indicates use of either FE or RE estimator where under null hypothesis RE is chosen. Rejection of null hypothesis of time dummy F-test indicates use of times dummies.

Focusing on the determinants of emission intensity, energy intensity is always positive and highly significant with values of the coefficients in the models in Table 4-2 close to those in CES (2005) for SO_2, NO_x, TAC, PM_{10} and CO_2. As a result, the difference between the estimates in this chapter and CES (2005) is at most equal to 0.18, with the exception of CO where the estimated value here is two times larger than the equivalent value estimated in CES (2005). Moving to the other determinants of emission intensity, the results indicate stronger evidence for statistical significance of PCI than CES (2005), although in this case coefficients are mostly negative and therefore contradicting findings from

CES (2005). Contradictory results are also obtained for HCI – positive impact in CES (2005) but negative in Table 4-2 – and the size – impact being negative in CES (2005) but not showing clear direction in Table 4-2). The statistically significant impact of TFP is negative in two instances, CO_2 and N_2O, and positive the case of NO_x. This is also a departure from CES (2005) which reports all coefficients being negative and statistically significant. Finally, the estimated results in Table 4-2 indicate the same difficulty that CES (2005) experienced in estimating statistically significant impact of capital expenditure intensity.

As indicated in section 4.3, the second step of the proposed econometric methodology involves estimating Equation (4-2), i.e. the specification in CES (2005) with additional variables taking into account fuel substitution and market concentration. Although the employed estimation procedure in Equation (4-2) is exactly the same to the one employed in Equation (4-1), a number of changes can be observed by comparing the results in Table 4-3 and Table 4-2. Based on the Hausman test, RE model is now selected in five of the seven intensities, i.e. all cases except CO and CO_2, a striking change from the results in CES (2005) and to a less extent those in Table 4-2. Five out of the seven models in Table 4-3, i.e. those for SO_2, NO_x, TAC, CO and N_2O incorporate time dummies. Time dummies were included in six models in Table 4-2 i.e. those for SO_2, NO_x, TAC, CO, PM_{10} and CO_2 and in all models in CES (2005). One can notice some changes with regard to the pattern of time dummies that are included in models in Table 4-3 (see Figure B2), compared to those in the models in Table 4-2 (see Figure B1).

With regard to the determinants of emission intensity, one can observe in Table 4-3 that energy intensity remains always positive and statistically significant for all emission intensities. A considerable change in the coefficient of emission intensity occurs in the case of SO_2, TAC and N_2O, with SO_2 increasing from 0.77 to 1.31, TAC from 0.72 to 1.03 and N_2O from 0.56 to 1.24. I find evidence that gas share is a negative and significant determinant of SO_2, TAC, and PM_{10}, except N_2O that is positive, but surprisingly, it is not significant in the models for the other intensities. Regarding the other determinants, PCI remains statistically significant and negative for NO_x, TAC and N_2O, as it occurred in

Table 4-2, while it becomes non-statistically significant for SO_2 and PM_{10}. The size variable remains positive and statistically significant for NO_x and TAC, negative and significant for CO and CO_2, while it becomes significant in the case of N_2O but non-statistically significant for SO_2 and PM_{10}. HCI is almost always negative and significant with the exception of SO_2. TFP becomes significant in all cases except CO and N_2O although its impact is positive in the case of SO_2, NO_x and TAC. The coefficient on the linear term of market concentration is significant in two cases (CO_2 and N_2O) while the quadratic coefficient of market concentration is significant only for N_2O. Joint significance of the two terms for market concentration using an F-test (see Table 4-3) reveals that market concentration has a statistically significant inverted-U relationship for CO_2 and N_2O (see Figure 4-1 at the end of this subsection). Interestingly a similarly shaped relationship, although non-statistically significant, occurs also in the cases of SO_2, NO_X, TAC and PM_{10}, while in the case of CO the curve is U-shaped. In all cases one can notice that this non-linear relationship is highly skewed so that the global maximum or minimum is very close to the case of no market concentration (or perfect competition). Lastly, capital expenditure intensity becomes significant and negative for NO_x and TAC while significant and positive for CO_2 and N_2O.

Table 4-3. Results from the estimation of Equation (4-2) from the Fixed or Random Effects estimator, as selected by the Hausman test

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RE	RE	RE	FE	RE	FE	RE
Energy Intensity	1.317***	0.888***	1.033***	0.678***	0.638***	0.879***	1.240***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gas share	-0.326***	0.007	-0.238***	0.06	-0.604***	-0.029	0.610***
	(0.000)	(0.860)	(0.000)	(0.505)	(0.000)	(0.168)	(0.000)
Physical capital intensity	-0.011	-0.169***	-0.097***	0.009	-0.017	0.0004	-0.185***
	(0.810)	(0.000)	(0.000)	(0.746)	(0.342)	(0.937)	(0.000)
Human capital intensity	0.043***	-0.040***	-0.026***	-0.055	-0.088***	0.002	-0.086***
	(0.008)	(0.000)	(0.000)	(0.226)	(0.000)	(0.878)	(0.000)
Size	0.084	0.086**	0.101***	-0.081*	0.016	-0.039***	0.467***
	(0.317)	(0.011)	(0.005)	(0.065)	(0.539)	(0.000)	(0.000)
TFP	0.651**	0.463***	0.458***	-0.143	-0.207***	-0.067***	-0.248
	(0.012)	(0.000)	(0.000)	(0.158)	(0.004)	(0.005)	(0.388)
HHI	0.018	-0.006	-0.016	0.036	0.002	0.020**	-0.389***
	(0.829)	(0.857)	(0.638)	(0.365)	(0.930)	(0.020)	(0.000)
HHI^2	-0.043	-0.032	-0.018	0.036	-0.016	-0.007	-0.181***
	(0.410)	(0.134)	(0.440)	(0.195)	(0.423)	(0.312)	(0.002)
Capital expenditure int.	-0.109	-0.110***	-0.063*	0.036	0.067	0.028*	0.279***
	(0.208)	(0.002)	(0.092)	(0.645)	(0.146)	(0.075)	(0.003)
Constant	-6.467***	-7.299***	-6.258***	-4.240***	-8.033***	1.094***	-5.893***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel groups	19	19	19	19	19	19	19
Observations	286	300	300	300	300	300	300
CD test	X	-2.61***	-2.19**	-2.81***	1.6	0.43	-1.23
CD *p*-value	(x)	(0.009)	(0.029)	(0.005)	(0.109)	(0.667)	(0.219)
R^2 between	0.927	0.95	0.97	0.866	0.758	0.953	0.802
R^2 within	0.477	0.906	0.843	0.716	0.765	0.979	0.368
R^2 overall	0.875	0.94	0.954	0.84	0.75	0.96	0.737
Hausman χ^2	-61.93	10.88	13.36	25.17***	-2.199	19.82**	7.64
Hausman *p*-value	(1.000)	(0.284)	(0.147)	(0.003)	(1.000)	(0.019)	(0.570)
Time dummy F-test	52.65***	31.68**	46.2***	6.1764***	8.12	1.1311	26.16*
F-test *p*-value	(0.000)	(0.016)	(0.000)	(0.000)	(0.964)	(0.324)	(0.072)
Time dummies	YES	YES	YES	YES	NO	NO	YES
HHI F-test	0.860	2.280	0.684	1.29	0.650	3.23**	24.085***
HHI F-test *p*-value	(0.650)	(0.319)	(0.710)	(0.276)	(0.722)	(0.041)	(0.000)
HHI vertex	0.05	0.04	0.03	0.02	0.04	0.17	0.01

Notes: Values in the parenthesis are *p*-values of the coefficient estimates. *. ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests the regressions residuals for cross section dependence and assumes null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. FE and RE stand for fixed effects and random effects estimators, respectively. Hausman test indicates the use of either FE or RE estimator where under the null hypothesis RE is chosen. Rejection of null hypothesis of time dummy F-test indicates use of times dummies while rejection of null hypothesis of HHI F-test indicates that market concentration effect is significant.

Results related to the CSD among the variables incorporated in this study (see Table B4) cast doubts on the results presented so far. One can also notice that CSD is left in all but three residuals of the

models presented in Table 4-2 and Table 4-3[49]. Therefore, I move on to the third step of the proposed econometric methodology that involves the use of the CEEP estimator that accounts for the existence of CSD in the sample.

Indeed, results from the re-estimation of Equation (4-1) and Equation (4-2) using the CCEP estimator cast an entirely new light on the determinants of the emission intensities. More specifically, Table 4-4 shows that accounting for CSD does not affect the statistical significance of energy intensity although it implies an average reduction in the coefficients, with those in Table 4-2 in the models for SO_2 and PM_{10} particularly affected while the coefficient in the model for NO_x virtually unaffected. The estimated results in Table 4-4 differ considerably from those in CES (2005) with regard to the coefficient for energy intensity in the SO_2 and CO models with the former being 0.44 units smaller and the latter 0.31 units larger, respectively. Coefficients in Table 4-4 are mostly higher in absolute value than those in CES (2005) with the exception of the coefficient on the SO_2 and PM_{10} models. The average difference between the coefficients in Table 4-4 and Table 4-2 is similar in absolute terms to the average difference between coefficients in CES (2005) and those in Table 4-2. Strikingly, capital expenditure intensity becomes statistically significant for all emission intensities while it was significant only for CO_2 in Table 4-2.

The remaining coefficients in Table 4-4 have overwhelmingly lost their statistical significance in contrast to the selected models in Table 4-2. More specifically, the impact of size is mostly negative but non-statistically significant in all cases except PM_{10} while the impact of TFP is mostly positive but non-statistically significant in all cases. HCI remains significant in three instances, i.e. NO_x, PM_{10} and N_2O, with estimated values in the case of PM_{10} and N_2O being almost by 50% and 33% higher, respectively than those in Table 4-2, while the value in the case of NO_x remains approximately the same. PCI remains significant only for NO_x and its estimated value increases by more than 50%. Overall,

[49] The CD test is unable to produce results for panel regression residuals in column 1 due to missing observations for SO_2 emissions.

energy intensity and capital expenditure intensity are the prevalent determinants of UK demand for manufacturing emissions in Table 4-4 once I account for CSD. The robustness of the results produced by CCEP estimator is backed up by the fact that almost all residuals in Table 4-4 are cross section independent except TAC and CO_2.[50]

Table 4-4. Results from the estimation of Equation (4-1) from the CCEP estimator

	SO_2	**NO_x**	**TAC**	**CO**	**PM_{10}**	**CO_2**	**N_2O**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CCEP	CCEP	CCEP	CCEP	CCEP	CCEP	CCEP
Energy Intensity	0.505***	0.787***	0.792***	0.557***	0.578***	0.946***	0.562***
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital intensity	0.028	-0.025**	0	-0.008	-0.023	0	-0.044
	(0.629)	(0.027)	(0.995)	(0.724)	(0.235)	(0.933)	(0.166)
Human capital intensity	0.058	-0.041**	-0.014	-0.032	-0.063**	0.005	-0.111**
	(0.467)	(0.014)	(0.601)	(0.331)	(0.034)	(0.495)	(0.037)
Size	-0.13	0.004	0.012	-0.002	-0.072*	-0.003	-0.05
	(0.222)	(0.864)	(0.762)	(0.966)	(0.099)	(0.781)	(0.448)
TFP	0.147	0.128	0.088	0.099	0.176	0.038	-0.027
	(0.706)	(0.137)	(0.527)	(0.578)	(0.263)	(0.371)	(0.914)
Capital expenditure int.	0.399**	0.064*	0.140**	0.321***	0.123*	0.032**	0.293***
	(0.012)	(0.068)	(0.014)	(0.000)	(0.056)	(0.042)	(0.001)
Constant	1.957	-0.247	0.058	-1.072	-0.091	0.379	-3.323
	(0.784)	(0.904)	(0.987)	(0.798)	(0.986)	(0.588)	(0.517)
Panel groups	20	20	20	20	20	20	20
Observations	286	300	300	300	300	300	300
CD test	X	-0.5	-1.71*	-1.35	-1.09	1.79*	1.41
CD *p*-value	(x)	(0.616)	(0.087)	(0.177)	(0.276)	(0.074)	(0.158)

Notes: Values in parenthesis are *p*-values of coefficient estimates. *, ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests regressions residuals for cross section dependence and assumes a null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. CCEP stands for Common Correlated Effect Pooled estimator.

Results from the CCEP estimator in Table 4-4 are robust to the introduction of variables taking into account fuel substitution and market concentration in Table 4-5. Energy intensity remains positive and highly significant in all cases while capital expenditure intensity remains positive and statistically significant in all cases but PM_{10}. Changes in the value of the coefficients are limited, at most by 0.11 units for CO with only exception SO_2 that increases by 0.35 units, while the average elasticity is virtually

[50] As mentioned in section 4.3, the CCEP estimator is robust to shocks affecting some or all panel units such as the 2008 economic crisis or perhaps the impact of the business cycle, the dynamics of which may very different across industrial subsectors.

identical. Elasticity of natural gas share in Table 4-5 becomes statistically significant for all emission intensities except N_2O, with considerable change in the values compared to those in Table 4-3. The biggest changes in the value of natural gas coefficient can be observed in the case of SO_2 and TAC, a change of 1.42 and 0.96 units, respectively. The average impact (in absolute value) of fuel substitution across emission intensities increases by an order of magnitude, from -0.07 in Table 4-3 to -0.79 in Table 4-5. Fuel substitution affects more severely SO_2 emission intensity as its elasticity is equal to -1.758. Given that SO_2 emissions are highly related to the level of sulphur used in the manufacturing process, this result reflects the fact that coal and oil contain high levels of sulphur while gas contains only negligible quantities (Brown et al., 2017; Wakeling et al., 2017). Fuel substitution is non-statistically significant for N_2O which confirms the fact that the main historical sources of N_2O emissions reduction have been the closure of adipic acid manufacturing plants (reflected in the time pattern of emission intensities in Figure 2-4) and the installation of abatement technologies in the largest remaining plants (Brown et al., 2017). The negative and significant impact of PCI and size elasticities for N_2O supports the findings from Brown et al. (2017) with regard to the installation of abatement technology in large plants.

Similarly to Table 4-4, one can observe in Table 4-5 that most of the remaining coefficients are non-statistically significant once I account for CSD. PCI is statistically significant in the cases of NO_x, PM_{10}, and N_2O (as just mentioned), while HCI is significant only for NO_x and CO_2, although the impact is negative in the former and positive in the latter. Size remains non-statistically significant in all cases except N_2O in Table 4-5 (which matches evidence discussed above). As suggested by both CES (2005) and Cui et al. (2016), TFP becomes mostly negative but remains non-statistically significant in all cases but for TAC. Although, the coefficient on the linear term of the market concentration variable in Table 4-5 remains significant only for N_2O, the coefficient on the squared term becomes significant in five out of seven cases - SO_2, NO_x, TAC, CO_2 and N_2O. It is interesting to note at this point that the relationship between emission intensity and market concentration is taking the shape of an upwards parabola in all cases as one can observe in Figure 4-2. An F-test on both the linear and quadratic

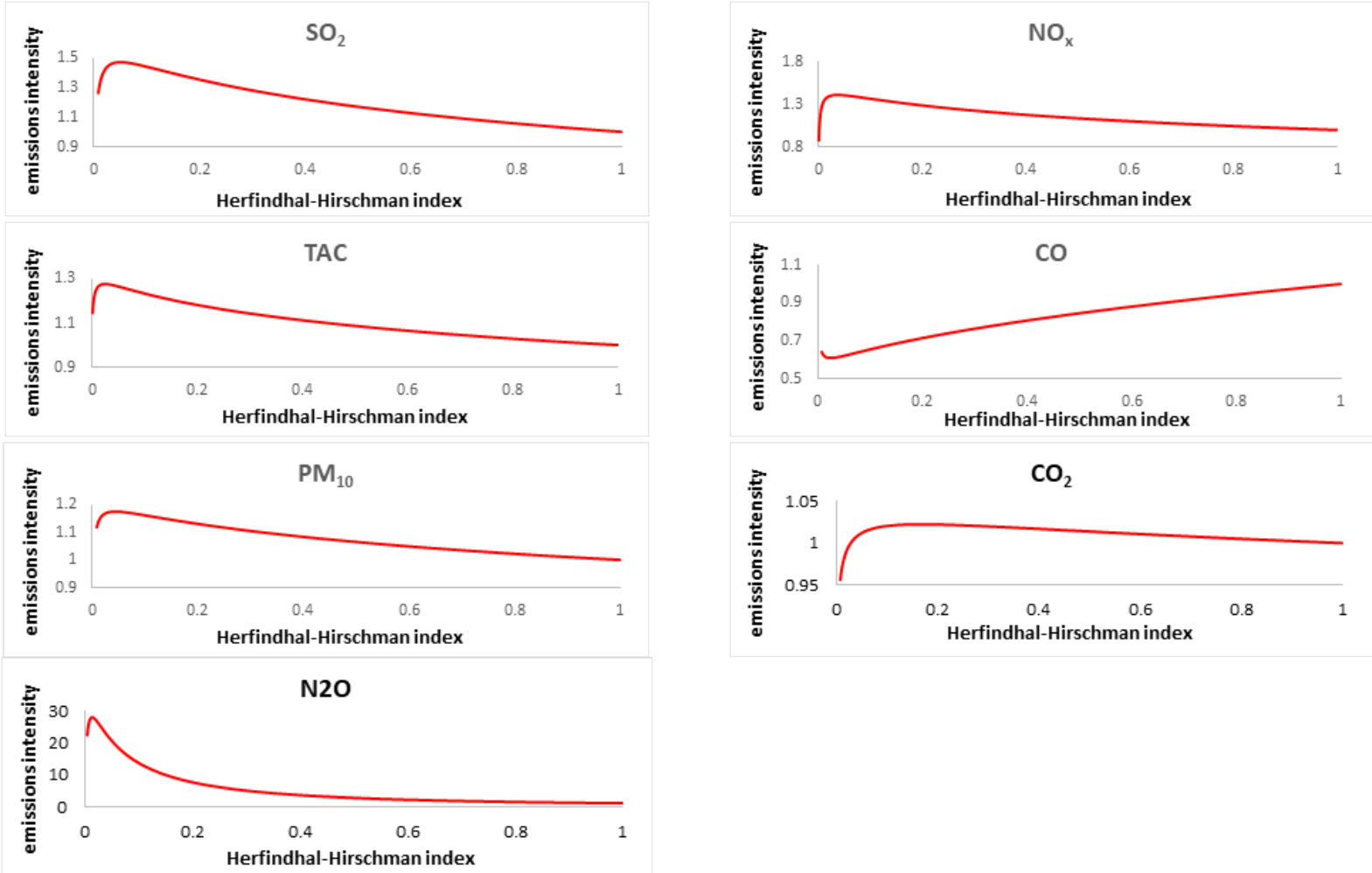
coefficients of market concentration (see Table 4-5) reveals the existence of a statistically significant relationship between concentration and intensities in three out of seven cases, namely NO_x, TAC, and N_2O. Again, this nonlinear relationship (see Figure 4-2) is greatly skewed towards zero market concentration (or perfect competition) with the highest value of the vertex being a bare 0.07. In other words, accounting for CSD, implies a change in the relationship between market concentration and emission intensities - from downward to upward parabola (see Figure 4-1 and Figure 4-2) with three of these relationships being statistically significant. The robustness of the estimated results presented in Table 4-5 is supported by the fact that the residuals of all emission intensities, except for CO_2, are now cross section independent in contrast to those is Table 4-4 where TAC and CO_2 still suffered from CSD. Since both Table 4-5 and Table 4-4 use the CCEP estimator that takes into account CSD, the cross section independence of almost all residuals in Table 4-5 indicates that the introduction of gas share and market concentration in Equation (4-2) allows the accurate identification of the long-run effect of industrial characteristics on emission intensities which has not been possible with the use of CES (2005) specification (see Equation (4-1)).

Table 4-5. Results from the estimation of Equation (4-2) from the CCEP estimator

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CCEP	CCEP	CCEP	CCEP	CCEP	CCEP	CCEP
Energy Intensity	0.855***	0.816***	0.944***	0.662***	0.662***	0.966***	0.378***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gas share	-1.758***	-0.582***	-1.201***	-0.687***	-0.916***	-0.203***	-0.261
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.201)
Physical capital intensity	0.024	-0.023**	-0.008	-0.027	-0.046**	0.004	-0.062**
	(0.731)	(0.042)	(0.679)	(0.158)	(0.037)	(0.174)	(0.024)
Human capital intensity	-0.076	-0.036**	-0.01	-0.013	-0.02	0.012***	-0.046
	(0.424)	(0.016)	(0.681)	(0.622)	(0.503)	(0.002)	(0.379)
Size	-0.003	-0.038	0.067	-0.015	0.029	0.011	-0.137*
	(0.982)	(0.202)	(0.124)	(0.751)	(0.588)	(0.103)	(0.051)
TFP	-0.567	0.034	-0.330**	-0.159	-0.176	-0.019	-0.101
	(0.252)	(0.710)	(0.024)	(0.328)	(0.338)	(0.395)	(0.632)
HHI	0.042	0.041	-0.013	0.014	-0.06	0.004	0.195***
	(0.752)	(0.102)	(0.743)	(0.734)	(0.196)	(0.521)	(0.000)
HHI^2	0.185*	0.011	0.100***	0.093***	0.061	0.008*	0.117**
	(0.068)	(0.559)	(0.001)	(0.006)	(0.106)	(0.089)	(0.013)
Capital expenditure int.	0.476**	0.063*	0.200***	0.200***	0.106	0.034***	0.270***
	(0.017)	(0.075)	(0.001)	(0.002)	(0.178)	(0.000)	(0.002)
Constant	-20.486	1.027	-0.599	1.113	-7.875	0.162	0.825
	(0.177)	(0.892)	(0.950)	(0.738)	(0.365)	(0.704)	(0.856)
Panel groups	20	20	20	20	20	20	20
Observations	283	300	300	300	300	300	300
CD test	X	-1.5	-0.81	0.19	1.28	2.73***	-0.88
CD *p*-value	(x)	(0.134)	(0.419)	(0.853)	(0.2)	(0.006)	(0.379)
HHI F-test	3.710	3.096	11.56***	7.48**	4.502	3.095	20.286***
HHI F-test *p*-value	(0.156)	(0.213)	(0.003)	(0.024)	(0.105)	(0.213)	(0.000)
HHI vertex	0.04	0.01	0.04	0.04	0.07	0.03	0.02

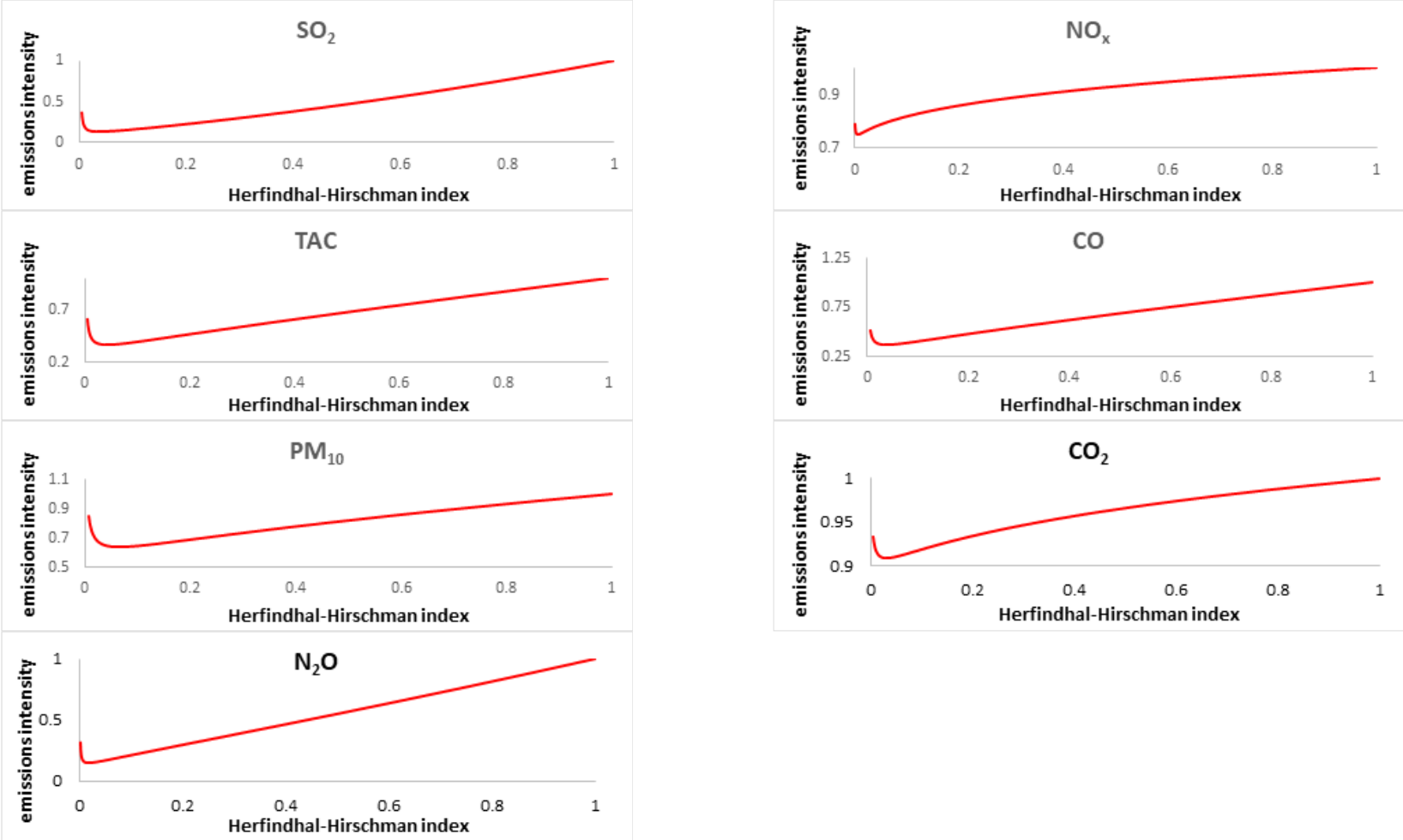
Notes: Values in parenthesis are *p*-values of coefficient estimates. *, ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests the regressions residuals for cross section dependence and assumes null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. CCEP stands for Common Correlated Effect Pooled estimator. Rejection of null hypothesis of time dummy F-test indicates use of times dummies while rejection of null hypothesis of HHI F-test indicates that market concentration effect is significant.

Figure 4-1. Relationship between market concentration and emission intensities based on the estimated models in Table 4-3



Notes: Emission intensity under perfect competition can be seen in correspondence of HHI=0 while emission intensity under monopoly can be seen in correspondence of HHI=1.

Figure 4-2. Relationship between market concentration and emission intensity based on the estimated models in Table 4-5



Notes: Emission intensity under perfect competition can be seen in correspondence of HHI=0 while emission intensity under monopoly can be seen in correspondence of HHI=1.

4.5 Discussion

The econometric analysis presented in this chapter is based on the methodological approach developed by CES (2005), augmented by two additional emission intensity determinants i.e. fuel substitution and market concentration and by taking also into account for the existence of unobserved common factors. The results indicate that a number of insights can be drawn related to the long-term determinants of emission intensity in the manufacturing sector. One can observe that energy intensity elasticities remain consistently positive and statistically significant for all emission intensities, confirming the robustness of results from CES (2005). Variation in the value of the elasticities in Table 4-2, Table 4-3, Table 4-4 and Table 4-5 is fairly limited. The highest variation can be observed for SO_2 that is equal to 0.8 points and the lowest for CO_2 that is equal to 0.09 points at most. The estimated coefficients when re-estimating the model in CES (2005) are very similar to those in CES (2005), with the difference between coefficients in Table 4-2 and those in CES (2005) being at most 0.18 units (CO being an exception with the difference equal to 0.43 units) a considerable similarity bearing in mind the difference between the two samples. The similarity between this study's results and to those presented in CES (2005) confirms that energy intensity is a positive long-term and statistically significant determinant of emission intensity, as it was originally expected based on the fact that emission data are obtained (at least in part) from energy consumption data, therefore validating the econometric approach used in this chapter.

On the other hand, this chapter's findings for physical and human capital intensities, size and total factor productivity are starkly different to those estimated by CES (2005). First of all, one can notice that the size of their elasticities is considerably lower, than the ones estimated for energy intensity in this chapter. The highest value of the estimated elasticities for physical and human capital intensities, in absolute value, is 0.18, with an average of 0.03 for physical capital intensity, and 0.13 for human capital intensity, across specifications and emission intensities. Re-estimating the methodological approach developed by approach CES (2005) implies the estimation of considerably different results

both in terms of the number of statistically significant coefficients and the sign of those coefficients. Although Physical (PCI) and Human Capital intensities (HCI) increase emission intensities in CES (2005), they take a negative coefficient in Table 4-2. This strongly contradicts results in CES (2005), as I find that HPI and PCI actually decrease emission intensities. Size and Total Factor Productivity (TFP) have a negative impact on emission intensities in CES (2005) but my findings are inconclusive with respect to the direction of the impact (when statistically significant) as one can see in Table 4-2. Considerable changes with regard to statistical significance of the variables can be observed when introducing gas share and market concentration.[51] One can interpret these results as evidence of an **unstable** relationship between emissions on one side and PCI, HCI, size and TFP on the other, pointing out that these relationships are spurious (or at least unstable) based on the dataset used by CES (2005) and this study. Further doubts are related to the presence of CSD in the residuals of the estimated models, implying that standard errors and estimated coefficients might be biased. On top of that, statistical significance almost completely disappears after taking into account unobserved factors, fuel substitution and market concentration[52]. Thus, it is to safe to conclude that the elasticities of emission intensities with respect to emission determinants such as PCI, HCI, size and TFP are small, and mostly non-statistically significant, especially when implementing more comprehensive econometric approaches. This implies that relationship between capital, labour and emissions cannot be relied upon to produce certain environmental benefits from policies changing either the labour or the capital intensity of an industry, trying to increase total factor productivity or size of the manufacturing sector.

Indeed, estimated results point at fuel substitution being an important factor in reducing emissions from UK manufacturing, with the exception of N_2O. This finding – that echoes results from energy demand and ETS literature (Chevallier, 2012; Steinbucks, 2012) – has surprisingly not been previously

[51] The number of instances in which coefficients are statistically significant changes from 5 to 3 in the case of physical capital intensity, from 4 to 5 in the case of human capital intensity, from 6 to 5 in the case of size variable and from 3 to 5 in the case of TFP, as one can see by comparing Table 4-2 and Table 4-3.

[52] Exception to this finding can be observed in very few instances in Table 4-5: i.e. for PCI in the cases of NO_x, PM_{10}, and N_2O, HCI in the cases of NO_X and CO_2, size in the case of N_2O and TFP in the case of TAC.

explored in the related literature focusing on the determinants of emission intensities (CES, 2005; Cole et al., 2013; Cui et al., 2016; Gray and Shadbegian, 2007). The value of elasticities and statistical significance are considerably influenced by taking unobserved factors into account, as one can conclude by comparing results in Table 4-3 and Table 4-5, a sign that these unobserved factors are correlated to the time pattern of the gas share. In Table 4-5, elasticities are all negative, as one would expect based on natural gas being a cleaner fuel than oil and coal. The plausibility of this finding is further supported by the fact that the coefficient with the highest absolute value is observed in the case of SO_2 emissions, i.e. the emissions for which natural gas delivers the highest savings (Wakeling et al., 2017; Brown et al., 2017). The non-statistically significant impact of fuel substitution on N_2O is reflective of the fact that historical reduction in N_2O emissions has been mainly delivered by the closure of adipic acid manufacturing plants and the installation of abatement technologies (Brown et al., 2017).

Similar to CES (2005), this chapter's results confirm the difficulty in estimating the statistical significance and the direction of the impact of capital expenditure intensity on emission intensity when re-estimating the econometric methodological employed in CES (2005). The impact remains positive and becomes statistically significant only after controlling for unobserved factors-with the use of the CCEP estimator, highlighting the importance of adopting a comprehensive and robust econometric approach. Including fuel substitution and market concentration affects the size but not the direction and statistical significance of the impact, with only exception that of PM_{10}.

When it comes to market concentration, results indicate the existence of a quadratic functional relationship between market concentration and emission intensities. The shape of this relationship changes from a downwards parabola in Figure 4-1 – when implementing fixed and random effect models – to an upwards parabola in Figure 4-2 – when taking into account unobserved factors through CSD – an outcome that shows once again the importance of adopting a comprehensive and robust econometric approach. In the latter case, market concentration impacts emission intensities through

an initial dip and then a steady increase up to the maximum level of emissions observed in the case of monopoly. Market concentration is statistically significant in the cases of CO, N_2O and TAC emissions. Given TAC is the weighted sum of SO_2, NO_x and NH_3 emissions, this finding indicates the existence of a statistically significant relationship between market concentration and acid rain precursors. In all cases and regardless of statistical significance, one can observe a similar non-linear shape of the functional relationship between market concentration and emission intensities which further confirms the robustness of the estimated results. In fact, this nonlinear relationship between market concentration and emission intensity is greatly skewed towards perfect competition in all cases which implies that increased concentration in the market increases emission intensity. The only exception to this finding comes at a point when the market is at perfect competition and at which point a small reduction in competition delivers increasing environmental benefits. The finding that increased level of market competition reduces emission intensity could potentially be explained by increased productivity, or CSR performance. In fact, Fernández-Kranz and Santaló (2010) shows that a number of market concentration proxies and widely used CSR measures are inversely related so that an increase in concentration deteriorates the CSR performance of firms to an extent that firms in more competitive environment have a superior environmental performance, measured by firm pollution levels. Considering that I have already accounted for both energy intensity and fuel substitution effects, a superior performance of firms in more competitive environments can be the reflection of superior innovation performance, if innovations tends to be emission savings, an assumption which is supported by the results in CES (2005).

Results presented in this chapter are strikingly similar to Aghion et al. (2005) that assesses the relationship between competition and innovation. Aghion et al. (2005) estimated an inverted-U relationship between market competition and innovation that is greatly skewed towards perfect competition. Following Aghion et al. (2005), firms in highly competitive markets are “prevented” from innovating, and therefore abating emissions due to low profit margins. Reduction of competition allows firms to increase their margins, innovate to be ahead of the curve and eventually increase the

abatement of emissions. Nonetheless, this incentive decreases as market concentration increases above a certain threshold due to market power guaranteeing profit margins. The vertex of this relationship is fairly close to the case of perfect competition both in this chapter and in Aghion et al. (2005), where in the latter it takes the value of 0.95 with perfect competition being equal to one – the inverse to this chapter that perfect competition is equal to zero. To the best of my knowledge, this is the first empirical research that provides evidence on the impact of increasing market competition on emission intensities in the UK industry.

4.6 Concluding remarks

Improving energy efficiency in the industrial sector can assist the efforts towards achieving Clean Growth in the UK industry. However, apart from improving energy efficiency, it is equally important to identify the distinct characteristics of industrial process, not directly related to energy use, that are responsible for reducing industrial emissions in the long-term period. Building on existing studies in the literature, this chapter examines the relationship between industrial processes and air emissions. I start by re-estimating published findings for the UK industrial sector on a bigger dataset. I further add additional observed factors which can plausibly influence the level of emissions and taking into account, for the first time in the empirical literature, unobserved common factors through cross section dependence. Empirical findings indicate that that reduction in industrial emissions can be reliably delivered by reducing energy consumption, encouraging fuel substitution and by encouraging market competition so that one can counteract the increase in emissions related to higher level of capital investment. This essentially means that policymakers should incentivise the transition towards cleaner fuels while removing entry barriers for new businesses – such as for example start-ups with innovative clean processes – as they can stimulate Clean Growth and assist the efforts towards achieving the emission targets set by the UK government. Nonetheless, the development and adoption of novel, clean technologies raises concerns over negative socioeconomic impact such as job losses, specifically within local communities relying on energy intensive industrial subsectors for job

opportunities. For that reason, I assess in chapter 5 the employment effect of renewable technologies and estimate the employment impact for future UK decarbonisation scenarios. Proving the positive socioeconomic impact of renewable technologies can enhance public support towards the wider adoption of energy saving technical change within the industrial sector.

5 Renewable electricity and employment impact

5.1 Overview

The adoption of energy saving technical change and the improvement of industrial processes in the industrial sector can assist the efforts towards meeting the Clean Growth targets set by the UK government. However, the transition towards clean energy and the gradual phase out of fossil-fuel based technologies raises concerns over jobs loses. Hence, it is important to assess the employment impact of renewable technologies and estimate their impact on future UK decarbonisation scenarios. This chapter responds to the third sub-research question of "*What is the long-term employment effect of renewable electricity?*". Assessment of the employment impact of renewable electricity technologies is generally implemented through either complex and data-intensive methods (such as Computable General Equilibrium models) or simplistic approaches normally focused on specific energy generation technologies (such as employment factors) as discussed in section 2.4.3. In contrast, this chapter proposes a transparent and easily reproducible econometric methodology based on the Vector Error Correction (VECM) model that uses aggregated and widely available data. I apply the proposed approach to the UK power generation sector using annual data from 1990 onwards and provide evidence that the long-term employment impact of renewable technologies is much higher than the impact arising from deploying nuclear or natural gas technologies. The impulse response function analysis indicates that a permanent 1 GWh increase in annual electricity supply generated by renewable technologies creates 3.5 jobs in the long-term period. I further derive the implications of the findings in the context of decarbonisation scenarios for the UK power sector and assess the extent to which decarbonisation pathways based on renewable rather than nuclear technologies contribute to stimulating employment in the generation sector. On average renewable technologies are expected to generate net employment effect in the UK power sector by 2030 equal to about 55,000 jobs, while under the most conservative and most optimistic scenarios is expected a net employment effect of

about 12,000 and 150,000 jobs, respectively. This chapter starts by providing details on the employed variables in section 5.2, it outlines the methodological approach in section 5.3 and presents results in section 5.4. Section 5.5 discusses on the policy relevance of the presented results, while 5.6 applies results to national decarbonisation scenarios for 2030 to estimate the potential future net employment effect.

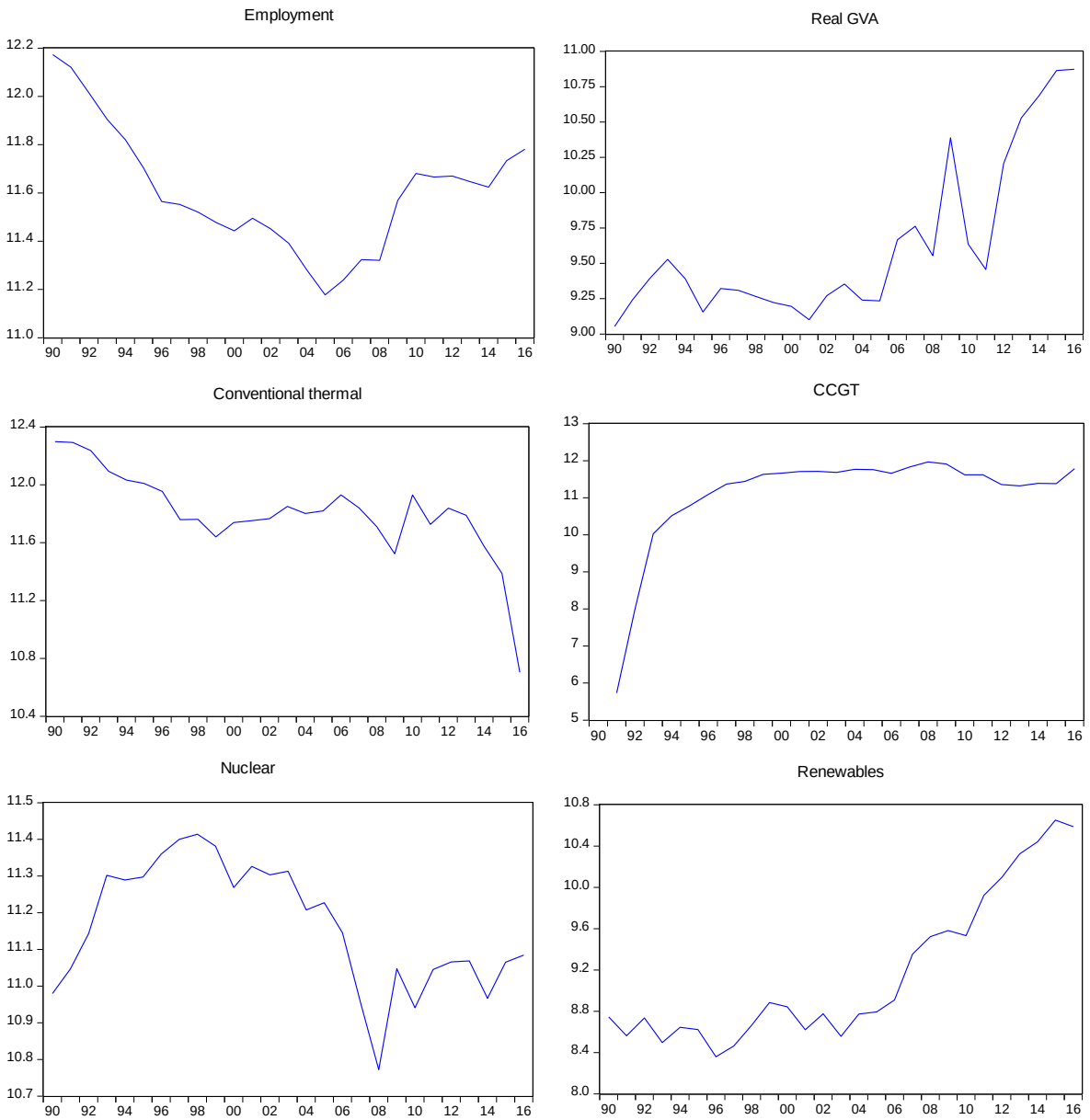
5.2 Data

The dataset used in this chapter includes six variables, namely a) number of jobs, b) GVA, and electricity supply generated by c) conventional thermal, d) CCGT, e) nuclear and f) renewable technologies at an annual frequency from 1990 to 2016. More precisely:

- Employment is measured by the number of "workforce jobs," or to be more precise, number of jobs in the UK major power producing (MPP) firms. Workforce jobs are sourced from employer surveys like the ONS Labour Force Survey (ONS, 2018a) on a quarterly basis from which I compute yearly averages. Full-time and part-time jobs are measured by workforce jobs without any distinction for the two types of jobs or the skill level of the job position. Workforce jobs data are available for the sector with SIC industrial classification "D" that incorporates all UK MPP firms, or more generally, firms active in "electricity, gas, steam and air conditioning" supply.
- Data on GVA related to the "D" industrial sector are published in annual figures by the ONS (Lee et al., 2015) and expressed in terms of 2010 prices (measured in million pounds). GVA measures the national level of economic activity or output of the related industrial sector.
- Electricity supply is equal to the total annual level of electricity supplied to end users in the UK generated by MPPs and it is reported separately for each type of energy generation technology. Electricity supply data for conventional thermal, CCGT, nuclear and renewable technologies, respectively, is obtained from DUKES that provide the longest time series on UK electricity supply measured in GWhs on an annual basis.

All data are converted into logarithms and thus estimated coefficients represent the elasticities of the variables. One can visually observe the time series of the variables used in this chapter in Figure 5-1 below, while further information on the descriptive statistics of the variables can be found in the Appendix (see Table C1).

Figure 5-1. Visual representation of the time series variables used in chapter 5 expressed in logarithms



5.3 Methodological approach

The methodological approach of this chapter comprises two steps. The first step (section 5.3.1) establishes a theoretical framework for the reduced form model that explains how the future number of jobs in the representative power producing firm is determined by the firm's expectation of future electricity demand. The second step (section 5.3.2) involves the empirical implementation of the theoretical model with the use of econometric modelling and can be further divided in: (a) unit root testing, (b) cointegration testing, (c) VECM modelling, (d) impulse response function (IRF) analysis.

One can use as a starting point the consideration, supported by DUKES (2017, p.113) that UK electricity system is driven by demand which, in other words, means that UK electricity supply is competitive in nature. Indeed, the wholesale electricity market in the UK is moderately concentrated while according to Ofgem (2018) the degree of market concentration[53] has significantly decreased during the last decade. Overall, the installed capacity has increased during the last decade mainly due to policies such as the CfD which support the investment in renewable technologies (Ofgem, 2018). This allows the related labour market to be fully flexible and competitive enough to efficiently accommodate changes in the energy mix of electricity generation.[54]

5.3.1 A theoretical framework

A representative firm in the electricity generation market chooses labour inputs (L_t) at time *t* based on its expectations (E_{t-1}) at time *t-1*, using all available information (I_{t-1}) at time *t-1* of the electricity it will supply (e_t) at time *t*. This can be expressed as:

$$L_t = f(E_{t-1}[e_t|I_{t-1}]) \tag{5-1}$$

[53] The degree of market concentration is measured by Ofgem with the use of the Herfindahl-Hirschman index.
[54] Employment depends both on installed and operating capacity of distinct renewable technologies. Since this chapter focuses on the macro level of the economy and uses aggregated data, it seems more sensible to look at the generation. It would be interesting in the future to use installed capacity data instead.

The firm's expectation in relation to electricity supply at time *t* can be further distinguished into the sum of expectation for conventional thermal electricity $E_{t-1}[con_t|I_{t-1}]$, CCGT electricity $E_{t-1}[ccgt_t|I_{t-1}]$, nuclear electricity $E_{t-1}[nuc_t|I_{t-1}]$ and renewable electricity $E_{t-1}[ren_t|I_{t-1}]$ at time *t-1* so that:

$$E_{t-1}[e_t|I_{t-1}] = E_{t-1}[con_t|I_{t-1}] + E_{t-1}[ccgt_t|I_{t-1}] + E_{t-1}[nuc_t|I_{t-1}] + E_{t-1}[ren_t|I_{t-1}]. \quad (5\text{-}2)$$

The representative firm forms its expectation about electricity supply at time *t* by taking into account demand for electricity observed at time *t-1* and in all past years, with diminishing weights attributed to the past years used to form the expectation. Thus, an increase in electricity demand at time *t-1* – and by extent an equal increase in electricity supply – implies an increase in the representative firm's expectations of electricity demand at time *t* with expectations adjusted by a parameter β which takes values between 0 and 1. The parameter takes the role of an "error-adjustment" term reflecting the deviations between expectation at *t-2* of electricity consumption at *t-1*, $E_{t-2}[e_{t-1}|I_{t-2}]$, and actual consumption of electricity at *t-1,* e_{t-1}:

$$E_{t-1}[e_t|I_{t-1}] = E_{t-2}[e_{t-1}|I_{t-2}] + \beta(e_{t-1} - E_{t-2}[e_{t-1}|I_{t-2}]) \quad (5\text{-}3)$$

As under the assumption of adaptive expectations, the expectation of the future value of a variable is based on all past observations, equation (5-3) can iteratively be expressed as follows:

$$E_{t-1}[e_t|I_{t-1}] = \beta(\textstyle\sum_{j=0}^{\infty}(1-\beta_1)^j\, e_j), \quad (5\text{-}4)$$

for years *j* in the past. Distinct technologies within the same energy generation category (for example solar, wind, etc.) have different employment effect and one should also bear in mind that the magnitude of the employment effect from a given technology is likely to vary across the stages of the technological development. One of the advantages of the approach of this study is that it estimates the average employment effect without having to focus on the characteristics of individual generation

technologies. Given that a positive employment effect might not only be the outcome of higher electricity consumption but also of higher economic activity, I control for Gross Value Added (GVA) in the electricity generation sector.

5.3.2 Econometric modelling

The first step of the empirical modelling consists in testing the stationarity of the variables using the Dicky-Fuller Generalised Least Squares (DF-GLS) test (Elliott et al., 1996), a choice motivated by high size-adjusted power in finite samples. If the DF-GLS test cannot reject the null of nonstationary, I implement the Zivot and Andrews (1992) test that allows for series to have a break at an unknown point in time. The choice of the deterministic component used in the test is determined based on the results of Akaike and Bayesian information criteria on two separate specifications (one with intercept only and the other one with intercept and linear trend) and secondly by visual inception of the series (Figure 5-1). The choice of the appropriate lag length is based on modified Akaike information criterion (Ng and Perron, 2001).

Since I find evidence of the variables being integrated of order I(1), and of cointegration among them (section 5.4), I focus on cointegrating VAR as econometric methodology. This implies implementing a cointegration analysis using a VAR approach (Johansen, 1988; 1991), and estimate a Vector Error Correction (VECM) model of order *p*, where all variables are treated as endogenous:

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

where x_t is a 6 x 1 vector containing the logarithms of employment, GVA, and electricity generated by 1) conventional thermal, 2) CCGT, 3) nuclear and 4) renewable technologies, Π and Γ_i are 6 x 6 coefficient matrices and Γ_0 contains the deterministic terms. I employ the trace and the maximum eigenvalue tests to explore the appropriate number of cointegrating vectors. Regarding the

deterministic terms in the cointegrating vectors, the choice of whether or not to include a linear trend is based on estimation of a model with intercept only and one with intercept and trend (following Johansen 1992). Once the long-term relationship between employment, output and electricity supply is identified, [55] I use the IRF analysis to compute the effect of a positive permanent shock in each type of electricity generation technology at time *t* on employment from time *t* to *t + n*. In this way, I can examine the response of employment to a 1 GWh increase, independently taking place in each electricity production technology. As this is a reduced form model, the generalised IRF (Koop et al., 1996) is employed because it is invariant to the ordering of the variables in the VAR and "fully takes into account the historical patterns of the correlation observed amongst the different shocks" (Pesaran and Shin, 1998; Pesaran and Smith, 1998).

5.4 Estimation results

The results from unit root testing (Table C2) indicate that all variables are non-stationary as they are of order I(1). The DF-GLS unit root test[56] indicates that only 3 of the 6 variables are I(1) (Table C2), namely employment, GVA and renewable electricity supply. Therefore, the remaining variables (conventional thermal, CCGT and nuclear electricity supply) are assessed by implementing the ZA test that allows for an unknown break in the series, a choice validated by the graphical visualisation of the series (Figure 5-1)[57]. The results of the ZA test confirm the existence of breaks and the fact that conventional thermal, CCGT and nuclear electricity supply are of order I(1) allows me to proceed with the VECM methodology. As the cointegration tests indicate the existence of four cointegrating vectors

[55] Results from the cointegration testing, discussed below preclude us from using the bound testing approach of Pesaran et al (2001), as this can be implemented only in the case on one cointegrating vector.
[56] This is a unit root test where the null hypothesis of non-stationarity is rejected when the test statistic is larger (in absolute values) than the critical value (Elliott et al., 1996).
[57] This is a unit root test with structural breaks where the null hypothesis of non-stationarity is rejected in favour of the break-stationary alternative when the test statistic is larger (in absolute values) than the critical value (Zivot and Andrews, 1992). The ZA test indicates the existence of a break in the series of conventional thermal, CCGT and electricity supply at the year 2013, 1995 and 2006, respectively, which can also be confirmed by visual inception of the abovementioned series in Figure 5-1.

in the estimated system (Table C3)[58], the specified restrictions in the cointegrating vectors are based on both economic theory, i.e. the scale effect between output and employment represented in the first cointegrating vector β_1, and the historical relationships between the four electricity production technologies discussed in section 2.4.1 in the three remaining cointegrating vectors. More specifically, vector β_2 is used to capture the substitution between conventional thermal and CCGT electricity supply, β_3 the substitution between conventional thermal and nuclear technologies and β_4 to capture the substitution between nuclear and renewable electricity plants.

The resulting long-run component of a VECM with trends included in all cointegrating vectors turns out to be stable and with coefficients having reasonable signs and values (VECM 1 - Table 5-1). The cointegrating vector capturing the scale effect indicates the existence of a positive long-term coefficient equal to 0.96 for the relationship between output and employment. When it comes to relationship between different electricity generation technologies, long-term coefficients are all negative as one would expect, with the long-term coefficient of CCGT (β_2) taking the value of -0.31, that of nuclear (β_3) -1.36 and the coefficient capturing the substitution between nuclear and renewables (β_4) being equal to -0.22. The trend in β_1, β_3 and β_4 is positive and equal to 0.35, 0.12 and 1.02, respectively, while the trend in β_2 is negative and equal to -0.89. The unexpectedly high values (in absolute terms) of the trend in β_3 and β_4 vectors raise some initial concerns on the indication of four cointegrating vectors from the tests.

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

Table 5-1. Cointegrating vectors β from specifications VECM 1 and VECM 2

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

I assess the statistical significance of the coefficients in the four cointegrating vectors with the use of the Likelihood Ratio (LR) test (Table 5-2) where a *p*-value lower than 0.05 indicates that the coefficient is statistically significant at the 5% significance level. The long-term coefficients are all strongly statistically significant, while the trend coefficient of the β_1 vector is statistically significant only at 5% significance level and that in β_4 at 10% significance level. I also check the validity of VECM 1 in Table 5-2 by implementing the Lagrange Multiplier (LM) test for serial correlation in the residuals and the White test for heteroskedasticity. Table 5-3 reveals that the cointegrating VAR has homoscedastic residuals, while the null of no serial autocorrelation is rejected at 5% significance level in the case of LM test. To further test the validity of a model with four cointegrating relationships, I estimate two slightly modified specifications (VECM 1A and VECM 1B in Table C4) where the trend coefficients in β_2 and β_3 are imposed to be zero, therefore enforcing the results from the LR tests in Table 5-2. One can see that in both VECM 1A and VECM 1B specifications, the exclusion of only one trend coefficient in each of the models has considerable impact on the value of the long-term coefficients. More specifically, the scale effect takes the values of 0.73 and 1.03 in the VECM 1A and VECM 1B specifications, respectively (see Table C4), in contrast to VECM 1 that is equal to 0.96. The substitution between conventional and CCGT electricity supply changes from -0.31 in VECM 1 to -0.56 and -0.35 in VECM 1A and VECM 1B, respectively. Similarly, the coefficient in β_3 changes from -1.36 in VECM 1 to -

1.30 and -1.15 in VECM 1A and VECM 1B, respectively. Finally, the substitution effect between nuclear and renewables changes from -0.22 in VECM 1 to -0.64 and -0.27 in VECM 1A and VECM 1B, respectively. The remaining trend coefficients in VECM 1A and VECM 1B have in most cases different signs and markedly different values from those in VECM 1, although they remain statistically significant (Table C5). More specifically, the trend coefficient in the β_1 cointegrating vector changes from 0.35 in VECM 1 to -0.05 and -0.21 in VECM 1A and VECM 1B, respectively. The trend coefficient in β_2 changes from -0.89 to 0.30 in VECM 1B while that of β_3 changes from 0.12 to -0.03 in VECM 1A. Finally, the trend coefficient in β_4 changes from 1.02 in VECM 1 to 0.02 and -0.37 in VECM 1A and VECM 1B, respectively. The residuals in the alternative specifications VECM 1A and VECM 1B remain non-heteroskedastic similar to VECM 1, while they become non-serially correlated in VECM 1A (Table C6). Most importantly, both specifications VECM 1A and VECM 1B are not stable as they have one root out of the unit root circle, a pattern also observed for any examined specification except VECM 1.

Table 5-2. *P*-values of the Likelihood Ratio (LR) tests for the coefficients in the cointegrating vectors in Table 5-1

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

The fact that restricting one coefficient in VECM 1 produces considerable instability in the values of the other long-term coefficients, changes in their signs and ultimately explosive behaviour in the restricted models is taken as an indication that the result of four vectors from cointegration testing is spurious. Therefore, I re-estimate VECM 1 with only two cointegrating vectors, by assuming that β_1 captures the scale effect between employment and GVA as before, and β_2 capturing the substitution effect between conventional thermal on one side (i.e. historically the main electricity generation technology used in the UK)[59] and CCGT, nuclear and renewables on the other side.

[59] As it has already been discussed in section 2.4.1, conventional thermal technologies have generated the largest amount of electricity supply in relation to independently each one of the other electricity generation

Table 5-3. Diagnostic tests for the residuals of the VECMs cointegrating vectors in Table 5-1

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

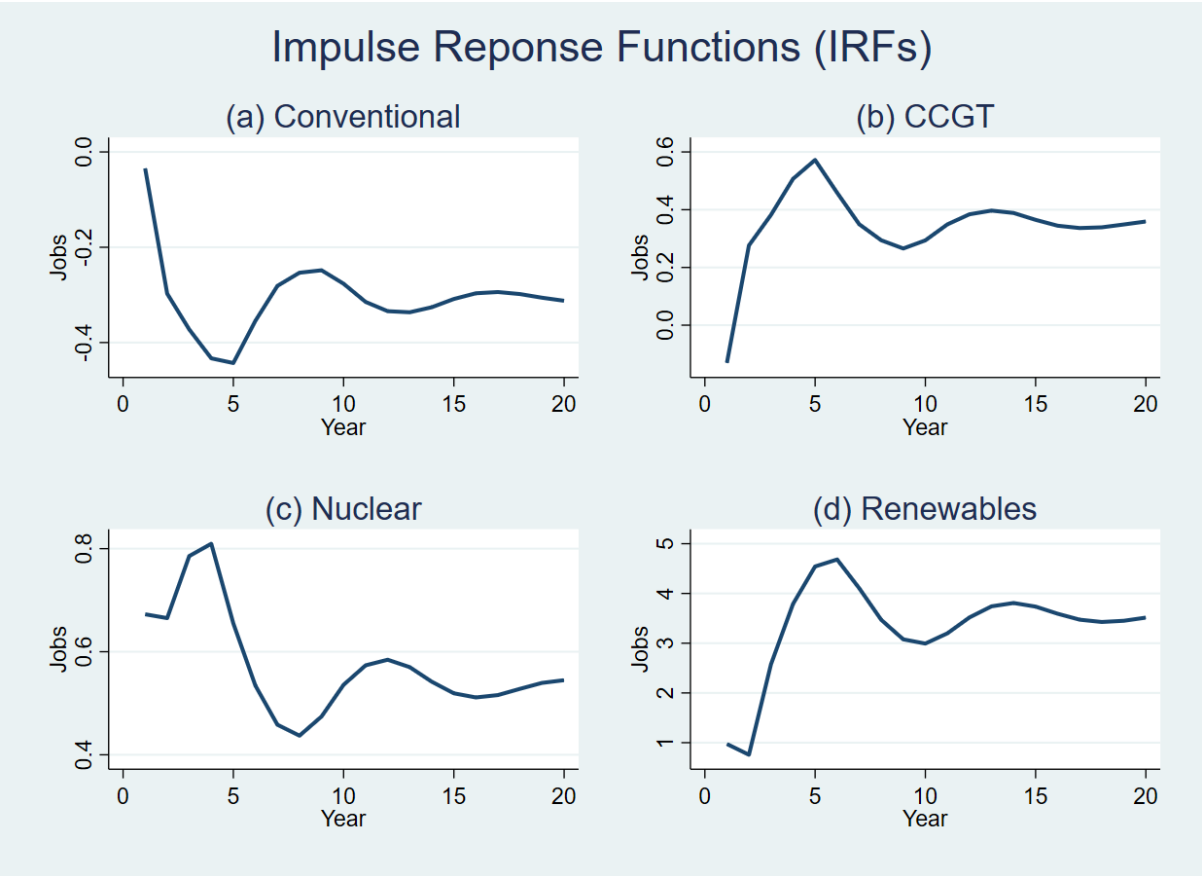
The resulting specification (VECM 2 in Table 5-1) is stable and has coefficients in the cointegrating vectors of the same sign and value similar to those in the model with four cointegrating vectors (VECM 1). More specifically, the scale effect between employment and GVA remains positive with value equal to 1.06 (Table 5-1) which is fairly similar to the 0.96 value in VECM 1. Concerning the substitution effect, the coefficients for CCGT and renewables (-0.46 and -0.30, respectively) are also close to those in VECM 1. The only exception is the long-term coefficient of nuclear electricity which is equal to -0.76, i.e. half the value of the coefficient in VECM 1. The trend coefficient in β_1 is equal to -0.06 while that in β_2 is almost equal to zero (0.001). The coefficients in the two cointegrating vectors are strongly significant – LR test in Table 5-2 – with only exception the trend coefficient in β_2. The validity of VECM 2 specification is supported by the failure to detect heteroskedasticity and serial correlation in the residuals (Table 5-3). Finally, I examine the validity of the assumption of two cointegrating vectors by assessing its robustness and estimating an alternative specification of VECM 2 where the non-statistically trend term in the β_2 is dropped from the model. The results (VECM 2A in Table C4) indicate that this change leaves all long-term coefficients in both vectors virtually unaffected so that their values and signs are almost identical to those in VECM 2 (Table 5-1). The β coefficients in VECM 2A are strongly statistically significant (Table C5) while the diagnostic tests fail to detect heteroskedasticity and serial correlation in the residuals (Table C6). The stability of the system is not affected by this restriction.

The last step involves the implementation of a 1 GWh shock on each type of technology, separately, and the assessment of the resulting impact on employment for a time horizon of twenty years starting

technologies throughout the whole timespan with the exception of the years 2007, 2008 and 2016 onwards (see Figure 2-6).

from year one - when shock occurs. Results indicate that employment responds negatively to a 1 GWh permanent increase in annual conventional thermal electricity supply (Figure 5-2(a)) reaching the value of -0.3 in the long-term. This is a counterintuitive result which I attribute to the fact that the most recent conventional thermal plant built in the UK predates the start of the sample and that production of electricity from coal plants has largely been decreasing since 1990. In other words, it is unlikely that moderate increases in generation would change expectations of generators on the decreasing share of this technology. In panel (b), one can observe that the employment effects related to a shock in conventional thermal and CCGT technologies seem to have roughly symmetrically opposite shapes, although the employment effect to a shock in conventional thermal is lower in absolute value compared to the impact of a shock to electricity produced from CCGT. This finding seems to reflect the considerable pattern of substitution observed in Figure 2-6(a). One can also observe that the impact of an increase in CCGT production builds up across time after it takes place and results in an even higher employment effect in the following 4 years where employment reaches its peak value of 0.6 jobs. In the case of a shock in nuclear supply, employment effect reaches a value of 0.5 jobs in the long-term. However, contrary to the impact of CCGT, the size of the impact decreases across time from an initial impact of 0.7. Finally, regarding the employment effect to a shock in renewable electricity, Figure 5-2 (d) indicates that the immediate impact of 1 job reaches the peak of 4.7 jobs after 6 years and eventually stabilises near 3.5 jobs.

Figure 5-2. Impulse response functions (IRF) for VECM 2 in Table 5-1



Notes: The graphs reveal the employment effect of a 1GWh permanent increase in electricity supply for each type of power generation technology.

5.5 Discussion

Starting with the scale effect, Table 5-1 confirms a positive relationship between GVA and employment, a result supported by Narayan and Smyth (2005) and in general by the extensive literature on the causal relationship between electricity use and economic growth[60]. The long-term elasticity of GVA takes the values 0.96 and 1.06 in the case of VECM 1 and VECM 2, respectively, hinting at a positive one-to-one relationship between output and employment. Regarding the relationship between different types of electricity, findings indicate that CCGT, nuclear and renewable electricity plants are all substitutes of conventional thermal. As there is sufficient evidence to conclude that the

[60] See Payne (2010) for a review on the causal relationship between electricity use and economic growth.

indication of four cointegrating vectors is likely to be spurious, the focus is placed on the results produced by VECM 2 (Table 5-1) where I assume two cointegrating vectors. Electricity generated by CCGT power plants is a long-term substitute of electricity generated by conventional thermal power plants, with elasticity equal to -0.46, a result supported by the literature related to interfuel substitution in the power industry[61]. Results further indicate that electricity supply generated by both nuclear and renewable technologies is a substitute of electricity generated by conventional thermal processes with elasticity equal to -0.76 and -0.30, respectively.

As mentioned in section 2.4.3, there is a certain debate on whether jobs created by the deployment of renewable technologies can be sustainable in the long-term period. After examining the historical relationship between employment and electricity supply in the UK, findings indicate (Table 5-1) that a permanent 1 GWh increase in annual electricity supply generated by renewable technologies creates 4.7 new jobs in the short-term period while 3.5 jobs in the long-term. Thus, 3/4 of the jobs created by the deployment of renewable technologies are sustainable in the long-run. Regarding nuclear electricity supply, a 1 GWh increase creates 0.8 jobs in the short-term period – 6 times lower than those created by an equally sized increase in renewable electricity – while in the long-term period employment stabilises at 0.5 jobs, i.e. 2/3 of the created jobs are sustainable in the long-run. Thus, the employment effect of nuclear electricity is not only much smaller in absolute terms than that of renewables but also less sustainable. When it comes to CCGT technologies, the short-term employment effect is 0.6 jobs – 8 times lower to the that created by an equal sized increase in renewable electricity – while the long-term effect is 0.4 jobs. The fact that capacity utilisation is normally lower for renewable electricity technologies compared to other technologies might have a role in explaining the higher employment impact of renewables, as a higher level of capacity needs to

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

be built and maintained, compared to other technologies, in order to produce a given amount of electricity.

The similarity between this chapter's results and those estimated by Hondo and Moriizumi (2017) that use an Input-Output model for Japan can be interpreted as evidence of robustness of the proposed approach. Hondo and Moriizumi (2017) find that the potential for job creation over the life cycle of different renewable technologies is estimated to range between 1.04 and 5.04 person-years per GWh. Older studies find similar but lower in magnitude effect for countries such as Brazil and Greece. Simas and Pacca (2014) find that the total employment effect for brazil is equal to 1.09 persons-years per GWh while Tourkolias et al. (2011) find that total employment effect for Greece ranges between 0.26 to 1.50.

5.6 UK 2030 decarbonisation scenarios

From a policy perspective and as a way of testing the proposed methodology, I investigate the potential future employment effect from a set of scenarios for electricity generation in 2030 – produced by the UKTM model (Watson et al., 2018)[62] – by using the estimated long-run employment effect (Table 5-1). I use as a counterfactual the "Energy island" scenario which is the only one to assume that conventional thermal technologies will continue to be used until 2030. Table 5-4[63] reveals that "Low carbon (no Bioenergy with Carbon Capture Storage (BECCS))" and "Low carbon" are the only scenarios in which there is positive employment effect related to CCGT technologies equal to the creation of about 15,000 and 4,500 jobs, respectively. Nuclear technologies have a positive employment effect, equal to about 19,000 jobs, under the counterfactual in which 43% of total

[62] For more information on the UKTM model scenario assumptions please check Appendix D section and more specifically Table D1 (Watson et al., 2018).
[63] I do not incorporate conventional thermal in Table 5-4 as the last coal plant has been commissioned in 1987, and since then, the UK power generation sector has significantly reduced its reliance to conventional thermal technologies.

electricity supply is generated by nuclear. “Low carbon (no CCS)” scenario assumes that nuclear technologies will generate in 2030 the same amount of electricity as in 2016 which leads to no employment effect. The rest of the scenarios share the same assumption about the amount of electricity generated by nuclear technologies in 2030, which results in the same negative employment effect equal to -19,089 (Table 5-4). Renewable technologies are expected to create from a minimum of about 16,000 jobs to a maximum of about 186,000 jobs under the “Low carbon (no BECCS)” and “Low carbon (no Carbon Capture Storage (CCS))” scenarios, respectively. The “Low carbon (no BECCS)” scenario is the most conservative in terms of electricity generated by renewables as only 29% of the electricity is generated by renewable technologies while the “Low carbon (no CCS)” assumes that 64% of the electricity is generated by renewable technologies and overwhelmingly by wind turbines. The rest of the scenarios, excluding “Energy island”, assume that on average 48% of the total electricity is generated by renewables. The key role of renewable energy in generating a significant number of jobs in the long-run is the reason why employment effect in the “Low carbon” scenario is substantially lower than the impact in the “Low carbon (no CCS)” as in the former negative emissions[64] are delivered through CCS technologies.

Table 5-4. Employment effect for the UK Times (UKTM) energy security scenarios (Watson et al., 2018)

Scenario	CCGT	Nuclear	Renewables	Net employment
1) Energy island	-21,492	19,303	-10,219	-12,408
2) Slow decarbonisation	-9,278	-19,089	60,034	31,668
3) Low carbon	4,499	-19,089	53,549	38,960
4) Low carbon (no CCS)	-32,931	0	185,594	152,539
5) Low carbon (no BECCS)	14,956	-19,089	16,124	11,992
6) Technology optimism	-17,886	-19,089	75,136	38,162

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

In contrast to the counterfactual, all scenarios generate positive net employment effect which takes the minimum value of about 12,000 and maximum of about 152,500 jobs under the "Low carbon (no BECCS)" and "Low carbon (no CCS)" scenarios, respectively. The rest of the scenarios indicate that net employment in the long-term period is expected to vary between about 31,000 to 39,000 jobs.[65] Overall, the results indicate that further support of policies supporting the deployment of renewable technologies in the UK (e.g. CfD) can boost employment significantly in the power generation sector.

5.7 Concluding remarks

Improving industrial energy efficiency through the development and adoption of clean industrial processes can stimulate Clean Growth dynamics within the UK industrial sector. For that reason, it is important to invest in and develop novel technologies with energy saving technical properties. Nonetheless, this transition towards clean energy and the gradual phase out of fossil-fuel based technologies raises concerns over jobs loses. For that reason, I estimate in this chapter the employment effect of different energy generation technologies and compare their long-term impact on the UK job market. To do that, I develop a transparent and easily reproducible econometric methodology based on the Vector Error Correction (VECM) model, that uses aggregated and widely available data and I apply the proposed approach to the UK power generation sector. Empirical findings clearly indicate that renewable technologies have significant long-term employment impact in the UK power generation sector. This essentially means that incentivizing the wider adoption of renewable technologies can lead to net job creation in the UK power sector of up to 152,500 jobs by 2030, although the estimated overall net employment gains depends on the energy mix of the corresponding decarbonisation scenario for the UK in 2030. Hence, this chapter provides evidence that Clean Growth can have significant positive long-term employment impact, and thus the UK

[65] Although I am aware of potential limitations due the implicit assumption of linearity in the effects, the plausibility of the results presented in Table 5-4 indicates the robustness of the suggested approach.

government should actively encourage the development and adoption of low carbon technologies that are capable of minimising emissions.

6 Conclusions and policy implications

6.1 Key research findings

6.1.1 Overarching research question and policy implications

Clean growth has been identified by the UK government as one of the four grand challenges for the UK industry, indicating the importance of developing industrial policies able to not only stimulate economic growth but also to reduce emissions. Nonetheless, delivering long-term industrial Clean Growth is not a straightforward process, as it has been already highlighted by the lack of a clear policy pathway towards achieving those goals. Hence, this thesis responds to this challenge by answering the following key overarching research question:

What are the long-term drivers of Clean Growth in the UK industry?

In order to develop the appropriate policy pathway that can facilitate Clean Growth, first it is important to identify the enabling factors that can deliver long-term Clean Growth in the UK industrial sector. My research findings can substantially contribute to the shaping of a clear policy agenda towards stimulating and supporting economic growth within the industrial sector while also reducing emissions. The key research findings and their policy relevance in relation to the key overarching research question in the present thesis can be summarised as follows:

1. In the long-term period, the UK government should incentive and actively support the development and adoption of innovative technologies that improve energy efficiency as they can reliably minimise emissions and by extension deliver Clean Growth.
2. Although in the short-term period encouraging fuel switching from carbon fuels to cleaner fuels and reduce energy consumption can support the efforts towards achieving Clean Growth, this is not sufficient for achieving Clean Growth targets in the long-term period.

3. Clean Growth can have significant positive long-term employment impact, and thus the UK government should actively encourage the development and adoption of technologies that improve energy efficiency and minimise emissions.

Hence, it is important that policymakers adjust accordingly the associated regulatory framework in the industrial sector to actively encourage the development and adoption of novel technologies that can significantly minimize emissions. To achieve this, policymakers could use policy incentives such as reduction in taxation, support in credit access, etc., while as well they could directly fund research and development practices within businesses. In addition, the UK government should remove any existing entry barriers within industrial subsectors with increased market concentration, to incentivise the formation of new, innovative businesses. Highly energy intensive subsectors such as iron and steel are in the forefront of this discussion. Short term policies based on energy price signals and incentives to use cleaner fuels cannot be used to support long-term transition towards Clean Growth. Achieving emissions targets set by the Clean Growth Strategy would require significant changes in the technologies involved in the production process. A good example would be to incentivize the wider experimentation on how renewable energy could be used in the long-term for energy intensive industrial processes such as the warming of iron smelting furnaces (given they require extremely high temperatures to function properly). Significant technological changes within industrial subsectors could however raise concerns among employees and local communities that might fear potential job losses and financial uncertainty. Nonetheless, this transition towards renewable technologies is estimated to have positive long-term employment impact. Thus, policymakers should communicate this message to the wider public and develop associated skill development programs that can support the retraining of employees. This is particularly relevant for jobs related to fossil-fuel technologies that are subject to gradual phasing out under the current UK government industrial plans.

Having outlined the key research findings and how they respond to the key overarching research question, I now focus on the more detailed research findings that respond to the three sub-research

questions and present the methodological contribution of my thesis to the wider energy and environmental economics literature.

6.1.2 Sub-research questions and key findings

To minimize industrial emissions while as well increase economic growth, it is important first to identify the underlying factors that can enable long-term Clean Growth dynamics in the UK industry. For that reason, I comprehensibly assess the underlying dynamics behind the enabling factors of Clean Growth in the UK industry by addressing the three sub-research questions outlined in section 1.2. More specifically, I respond to the first sub-research question of *"What is the importance of energy prices on long-term industrial energy efficiency?"* by developing a new econometric approach based on linear state space modelling technique to explore the role of economic activity and energy price on historical trend in energy efficiency in the industrial sector. I respond to the second sub-research question of *"What are the long-term industrial determinants of emission intensity?"* by employing a panel time series methodology that tackles cross sectional dependence to identify the industrial characteristics of production process that are directly responsible for reducing emissions. I respond to the third sub-research question of "*What is the long-term employment effect of renewable electricity?"* by developing a novel methodological approach, based on the Vector Error Correction model, to estimate the net employment impact from the further deployment of renewable technologies in the UK power sector. By addressing the abovementioned sub-research questions, I am able to provide credible policy recommendations on the ways through which the UK government can achieve Clean Growth in the UK industry by stimulating economic growth while substantially reducing industrial emissions. The key research findings of this thesis and their policy relevance in the relation to the three sub-research question can be summarized as follows:

1. energy price is important for industrial energy efficiency to the extent that it has historically largely offset the surge in energy consumption induced by economic activity,

2. the remaining part of industrial energy efficiency that is not directly induced by the dynamics of energy prices, is mostly imputable to technological progress, and possibly to gradual and irregular institutional changes,
3. industrial price elasticity has remained constant over the last half century in the UK, taking the value of -0.23,
4. industrial emissions are driven by energy consumption, fuel substitution, market concentration and capital expenditure,
5. there is no empirical evidence that production inputs, total factor productivity and the size of a typical firm within industrial subsector are robust determinants of industrial emissions,
6. reducing market concentration within industrial subsectors reduces industrial emissions probably through stimulating the adoption of innovation processes towards clean technologies,
7. reducing energy consumption, encouraging transition to cleaner fuels such as natural gas and increasing competition within industrial subsectors can reliably reduce industrial emissions and counteract for an increase in emissions due to higher capital expenditure,
8. increasing annual renewable electricity supply by 1 GWh can create 3.5 jobs in the long run in the UK power sector,
9. increasing renewable electricity can stimulate 6 times higher long-term employment impact in the UK power sector than an equivalent increase in nuclear electricity and 8 times higher than an equivalent increase in CCGT generated electricity,
10. incentivizing the wider adoption of renewable technologies can lead to net job creation in the UK power sector of up to 152,500 jobs by 2030, with an average of about 55,000 jobs, depending on the energy mix composition of the UKTM decarbonisation scenarios.

In order to cast more light on the enabling factors that can deliver long term Clean Growth in the UK industrial sector, I proceed to the following discussion of the main research findings and key policy

recommendations for each one of the three main chapters – i.e. chapter 3, 4 and 5 – in subsection 6.2, 6.3 and 6.4, respectively.

6.2 Energy price and energy efficiency

The historical reduction in the UK industrial energy consumption could have been the outcome of both improvements in the energy efficiency and structural changes within the UK industry. Nonetheless, the literature indicates that structural changes have had only negligible influence in this historical reduction in energy consumption with only exemption certain crisis that have driven structural changes that stabilised in the post crisis period. Energy efficiency can be induced both by endogenous factors, i.e. energy price and economic activity, and exogenous factors such as the introduction of energy saving technical changes and institutional changes.

Chapter 3 contributes to the understanding of the underlying forces that have historically affected energy efficiency in the UK industrial sector, using data for over almost 50 years, the longest time period ever used in the literature. The chapter employs a systematic model selection procedure to identify and assess the nature of the long-term trend in the UK industrial energy consumption. First, the proposed methodology is performed on the univariate model and results indicate that a model with stochastic level and deterministic slope is the best univariate representation of the industrial energy consumption. This finding is supported by a number of distinct criteria i.e. residuals diagnostic tests, information criteria, size of the ML estimate of the variance along with the corresponding t-ratios and visual examination of the plot of the smoothed state. Subsequently, the proposed methodology is employed in the multivariate model that controls for the effect of time-varying economic activity and time-varying energy price on long term industrial energy consumption. The results indicate that there is no change in the nature of the level term of the trend which remains stochastic, although it can be observed a small decrease in the size of the variance. This finding clearly supports the modelling choice of Hunt et al. (2003), and in general the literature related to the

underlying energy demand model (UEDM), in which the trend is the only parameter allowed to be stochastic. The nature of the level term of the trend remains stochastic and retains a comparable variance size across a number of alternative specifications used as a robustness exercise in chapter 3. Modelling economic activity and energy price as deterministic parameters affects neither the nature of the level term of the trend that remains stochastic, nor the size of its variance which retains remarkably similar variation to that in the univariate model. As a matter of fact, one can observe that the specification with deterministic factors has a better model fit than the specification with stochastic factors.

I respond to the key issue of assessing the extent to which the estimated long-run trend of industrial energy consumption can be explained by the impact of energy price and economic activity. When controlling only for economic activity, the value of the slope term of the trend that captures the quarterly rate of change in energy consumption decreases by 19%. Once I account for both economic activity and energy price, the value of the slope term of the trend increases by 24% and becomes identical to the equivalent value of the slope term in the univariate model. Therefore, this finding indicates that energy price has historically counteracted almost perfectly for the effect of economic activity on energy consumption for the last 50 years in the UK industry. From a policy perspective, this is an important finding as it indicates that increasing energy efficiency in the UK industrial sector would require policy measures focusing on exogenous factors thar are mostly imputable to technological progress, and possibly to gradual and irregular institutional changes.

Future studies could further support these policy efforts to increase industrial energy efficiency by focusing more in depth and further investigating the dynamics underpinning the relationship between energy efficiency and those exogenous factors. Identifying potential metrics that might be able to control for energy saving technological progress and irregular institutional changes could potentially allow the modelling of those factors within the traditional industrial energy demand function as additional determinants of long-term industrial energy consumption. It would also be very interesting

to assess the nature of the long-term trend in the industrial energy consumption and the determinants of long-run industrial energy efficiency for other countries that share similar characteristics to the UK using the proposed methodology and compare results to those estimated in this thesis.

6.3 Industrial emission determinants

Lacking an established and generally accepted theoretical framework on the relationship between emissions and characteristics of the production process in the manufacturing sector, this thesis has investigated the long-term determinants of emissions by assessing the robustness of established findings in the literature such as those in Cole et al. (CES) (2005). The first step of the methodological approach outlined in chapter 4 implies, i) re-estimating a specification as close as possible to CES (2005) using observations from 1997 to 2014 instead of the original sample of 1990-1998, and ii) adding two factors which might have an impact on emissions from the manufacturing sector, namely fuel substitution and market concentration. Long-term determinants of emissions are expected to be reasonably robust to changes in the estimation sample and the addition of a limited number of explanatory variables. The second step of the proposed methodological approach involves exploring the impact of unobserved factors through cross sectional dependence (CSD) on the difference between my results and those in CES (2005). As expected, I find that energy consumption is positive and significant determinant for all emission intensities, with values of estimated elasticities similar to those in CES (2005). However, once I account for CSD, physical and human capital, size and total factor productivity (TFP) become overwhelmingly non-statistically significant for most of the emissions assessed in this study. Results indicate that factors such as production inputs i.e. labour and capital, total factor productivity and size of typical firm are not robust determinants of emissions from industrial sector. On the other hand, energy intensity, fuel substitution, capital expenditure intensity and market concentration are long-term determinants of industrial emissions across the pollutants assessed in this study. This implies that the relationship between emissions on one side and physical

and human capital, size of the typical firm and TFP cannot be relied upon to produce certain environmental benefits from policies aimed at changing any of these factors.

A sustained reduction in emissions from the manufacturing sector needs to be delivered through the leverages of reduced energy consumption and increased adoption of cleaner fuels, therefore indicating the crucial role of energy efficiency policies and those facilitating adoption of cleaner fuels (such as the Climate Change Levy), in reducing emissions. On the other hand, increases in capital expenditure intensity brought about by policies facilitating investments, for example to increase productivity, have an adverse impact on emissions, therefore pointing at a trade-off between economic growth and environmental quality. Investing in new capital equipment and machinery should not per se be considered equivalent to investing in cleaner technologies, therefore contradicting the assumption in CES (2005). The fact that I find evidence that capital expenditure intensity has increased all emissions of all pollutants except PM_{10} indicates the importance of redirecting capital investment towards "green" industrial technologies. On the other hand, changing level of competition through a change in market concentration delivers emissions savings probably through an increasing level of innovations documented in Aghion et al (2005). This implies that reduction of entry barriers for firms in the manufacturing sector delivers environmental benefits which are consistent across emissions assessed in this study, perhaps through stimulating rate of innovation in the sector.

From an academic perspective, it would be interesting to explore the extent to which the results on the limited importance of physical and human capital, size and total factor productivity are robust across time, countries and regulation environments. One would also want to assess whether the estimated relationships are confirmed when using microdata rather than observations aggregated to industrial subsector. By matching patent and emissions datasets observed at firm level, one would be able to test the conjecture that innovation processes directed toward reducing emissions are responsible for the hump-shaped relationship between market concentrations and emissions.

From an environmental policy perspective, industrial policy planning in the short-term should continue to encourage fuel switching from carbon fuels to cleaner fuels and reduce energy consumption. As possibilities of switching to low carbon fuels and energy efficiency might be limited after sustained efforts in this direction are undertaken by the manufacturing sector, long-run industrial policy planning should focus on development and adoption of technologies minimising emissions so as to counteract increases brought about by the scale of economic activity and capital expenditure. The results pointing at environmental benefits arising from increased competition in the market place highlight potential synergies between policies focused on industrial strategy, market completion and environmental welfare. Reduced emissions observed in presence of increased competition is likely to be due to the pressure to innovate taking place in competitive markets so that adoption and development of emissions saving technologies can reduce abatement cost, and achieve positive brand recognition and a competitive advantage in the supply chain. The relationship between emissions abatement and market concentration through innovation is likely to become more important in delivering reduction in industrial emissions, especially because estimated autonomous technological change (measured through a time effect) only rarely shows a distinct trend towards reducing emissions.

Future studies could further investigate the dynamics underpinning the relationship between emissions and innovation practices, utilising data sources not accessed in this thesis due to data constraints. Examples could involve data on firm R&D expenditure, patents data and potentially distinct corporate social responsibility (CSR) policies. To that aim, and specifically considering CSR polices, it could be worth employing a case study approach and particularly focusing on large corporations and industrial conglomerates. Finally, it would be interesting to assess the long-term determinants of industrial emission intensities for other countries that share similar characteristics to the UK and compare results to those estimated in this thesis.

6.4 Renewable electricity and employment impact

Chapter 5 proposes a transparent and easily replicable methodology to estimate the employment effect of electricity generation technologies by using aggregated data on economic activity and employment in the power generation sector, and amount of electricity produced by different technologies. This thesis is the first to provide empirical evidence on the long-term impact of renewable electricity supply on net employment while also accounting for the employment effect of conventional thermal, natural gas and nuclear electricity supply through standard cointegration analysis. I analyse the UK power sector, using annual data from 1990 to 2016, although the proposed approach can be easily applied to other countries. The validity of long-run estimates is assessed through robustness analysis and results of diagnostic tests. I resorted to generalised IRF to compute the employment response to an increase in electricity supply generated by different types of technologies.

Results indicate positive scale effect between output and employment in electricity generation revealing an approximate one-to-one relationship between percentages increases in GVA and jobs. I further find that evidence of substitution between conventional thermal electricity supply on the one side and gas, nuclear and renewables on the other side. In terms of the employment implications of electricity generation technologies, I find that a 1 GWh permanent increase in renewable electricity creates 3.5 jobs in the long-term, i.e. about six times the number of jobs created by an equally sized increase in nuclear generation. The similarity of the presented results with existing Input-Output employment effect estimates indicates the robustness of the proposed approach. It also indicates that although simple, this approach is equivalently powerful to complex methods such as Input-Output or CGE models. Results also indicate that the jobs created by the deployment of renewable technologies are the most sustainable in the long-term.

Finally, I apply the estimated long-run employment effect to a set of scenarios for electricity generation in 2030 produced by the UKTM model (Watson et al., 2018) so as to analyse the

employment implications of those scenarios. The scenario that assumes that electricity generation is based overwhelmingly on renewable electricity results in a positive net effect of up to 152,000 jobs while the rest of the scenarios assuming a moderate increase in renewable electricity result in an average positive net effect of about 36,000 jobs. In contrast, the scenario where power generation relies mainly on nuclear technologies results in a negative net effect of about 12,000 jobs. Bearing in mind recent reduction in the cost of solar generation technology and the fact that the UK has largest global capacity in off-shore wind energy (BEIS, 2018), it becomes evident that renewable electricity supply can have a considerable positive long-term employment effect. It is crucial that policymakers incentivise and support the further deployment of renewable electricity technologies as I find robust evidence of their employment impact in scenarios aimed at progressing the decarbonisation of the UK economy. Nevertheless, it has to be taken into account that the results presented in chapter 5 focus on the electricity generation sector and therefore I do not identify potential indirect job employment effects (for example in the manufacturing sector). Since the focus is on the aggregate level of the UK economy, the model cannot control for structural changes on the micro level of the labour market such as changes in wages and opportunity costs, changes in competitiveness due to demographic factors and potential supply constraints.

Future studies should try to address the limitations of the current implementation and develop reduced-form models able to identify the broader employment effect of the deployment of renewables technologies in sectors such as manufacturing, construction or services. In particular, it would be helpful if technological change influencing the composition of renewable generation, e.g. a further shift toward solar PV, or the labour intensity of the renewable technologies, could be incorporated in the model, perhaps through a non-observable factor approach. Collection of data for smaller geographical areas would enable the estimation of 'local' models that can effectively tackle the issue of job displacement in which one geographical area can be taking away jobs from another area. Thus, these 'local' models could take into account the fact that the employment effect of renewables might be influenced by the location of the technology on the grid or their distance from

the shore, in case of offshore wind. Similarly, collection of data for periods shorter than one year, such as quarter, would enable the analysis of seasonal effects in the employment which could be expected for technologies affected by rough wintery conditions, such as offshore wind. On the other hand, it is also possible that the schedule of regular maintenance in the summer period, could make up for the increase in unforeseen repairs likely to be observed in the winter season. Based on purely statistical considerations, access to more granular data would increase the size of the sample available for empirical analysis, therefore probably increasing the confidence in the obtained estimates of the employment effects discussed here, while reducing loss of information related to heterogeneity of the effect across time and space. It would also help if future studies could implement this approach, perhaps while tackling some of the limitations pointed above, to other countries to increase the empirical evidence base on the employment effect but also to explore the extent to which the effect varies across countries. It is reasonable to expect differences in the employment effect of renewables across countries due to: i) differences in the composition of the renewable sector; ii) in the phase of renewable deployment (i.e. some countries are at an advanced stage, while others less so); iii) in the share of renewable electricity production which is exported; and finally iv) in terms of industrial and labour policy.

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Appendix

A Supplementary material for chapter 3

Table A1. Descriptive statistics of variables used in chapter 3

	Levels			Logs		
	Energy consumption	GVA	Price	Energy consumption	GVA	Price
Obs.	176	176	176	176	176	176
Mean	9,264	74,940	97.51	9.09	11.22	4.52
St. Dev.	2,679	8,647	34.12	0.29	0.12	0.34
Min	4,963	56,916	53.07	8.51	10.95	3.97
Max	16,576	91,936	177.42	9.72	11.43	5.18
Skewness	0.64	-0.32	0.59	-0.01	-0.52	0.26
Kurtosis	3.05	2.24	2.00	2.47	2.38	1.72

Table A2. Lag length selection criteria

Lag	LR	FPE	AIC	SC	HQ
0	NA	0.00	-1.46	-1.41	-1.44
1	1,263.06	0.00	-9.06	-8.84	-8.97
2	56.49	0.00	-9.30	-8.91	-9.14
3	219.39	0.00	-10.58	-10.03	-10.36
4	156.52	0.00	-11.49	-10.76	-11.19
5	69.99	0.00	-11.84	-10.95*	-11.48*
6	24.65	0.00	-11.90	-10.84	-11.47
7	19.63	0.00	-11.93	-10.70	-11.43
8	26.98*	1.23e-09*	-12.01*	-10.61	-11.44

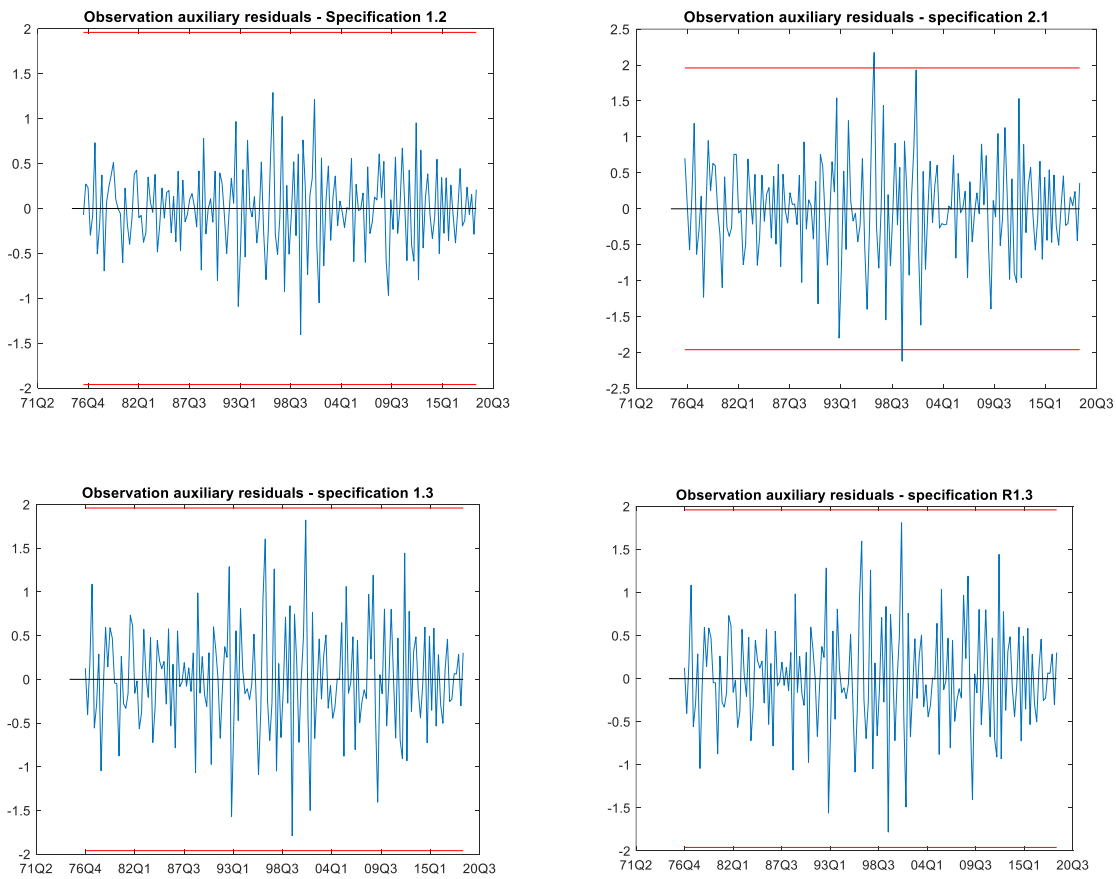
Notes: (*) Indicates the lag length selected by the criterion. LR stands for the sequential modified LR test statistic (each test at 5% statistical significance level), FPE for final prediction error, AIC for Akaike information criteria, SC for Schwarz information criteria and HQ Hannan-Quinn information criteria.

Table A3. Johansen test results on the existence of cointegrating relationships

		Lag 5		Lag 8	
		Cointegrating relationships	***p*-value**	**Cointegrating relationships**	***p*-value**
H1	Trace	0	(0.92)	0	(0.70)
		1	(0.96)	1	(0.86)
	Max Eigenevalue	0	(0.88)	0	(0.64)
		1	(0.96)	1	(0.86)
H*	Trace	0	(0.40)	0	(0.44)
		1	(0.82)	1	(0.53)
	Max Eigenevalue	0	(0.26)	0	(0.52)
		1	(0.82)	1	(0.53)

Notes: H1 stands for the specification with intercepts in the cointegrated series and deterministic linear trends in the level. H* stands for the specification with intercept and linear trend in the cointegrated series and deterministic linear trend in the levels of the data.

Table A4. Observation auxiliary residual plots for specifications 1.2, 2.1, 3.1 and R1.3 in Table 3-1, Table 3-2, Table 3-3 and Table 3-5, respectively



Notes: According to Harvey and Koopman (1992), one can use the observation auxiliary residuals to identify potential outliers in the time series.

BSupplementary material for chapter 4

Table B1. Descriptive statistics of variables used in section 4

Variables in levels

Variables	*Obs.*	*Mean*	*St. Dev.*	*Min*	*Max*	*Skewness*	*Kurtosis*
SO_2 emission intensity	330	0.004	0.012	8.05E-06	0.118	5.202	37.177
NO_x emission intensity	360	0.002	0.004	4.83E-05	0.037	4.612	34.183
TAC emission intensity	360	0.006	0.015	8.36E-05	0.156	5.317	39.989
CO emission intensity	360	0.010	0.028	1.38E-04	0.284	5.006	34.803
PM_{10} emission intensity	360	4.04E-04	0.001	8.19E-06	0.007	3.643	22.590
CO_2 emission intensity	360	1.433	3.221	0.034	33.742	4.941	37.365
N_2O emission intensity	360	0.025	0.125	1.74E-04	1.569	9.126	99.287
Energy intensity	360	0.595	1.679	0.014	19.108	6.212	53.544
Gas share	360	0.583	0.233	0.018	0.974	-0.813	2.886
Physical Capital Intensity	360	0.033	0.084	-0.110	1.111	7.568	83.333
Human Capital Intensity	360	0.290	0.228	-0.428	2.348	2.811	23.618
Size	354	88.723	274.207	0.227	3727.647	8.197	94.566
Total Factor Productivity	351	4.949	1.025	2.081	8.621	0.577	3.742
HHI	352	0.085	0.135	0.005	0.763	3.175	13.641
Capital expenditure int.	342	0.198	0.494	0.010	9.067	17.018	305.879

Variables in logs

Variables	*Obs.*	*Mean*	*St. Dev.*	*Min*	*Max*	*Skewness*	*Kurtosis*
SO_2 emission intensity	330	-7.934	2.135	-11.730	-2.137	0.670	2.647
NO_x emission intensity	360	-7.198	1.306	-9.938	-3.291	0.513	2.711
TAC emission intensity	360	-6.732	1.613	-9.390	-1.860	0.796	2.935
CO emission intensity	360	-6.347	1.655	-8.886	-1.259	0.924	3.250
PM_{10} emission intensity	360	-8.953	1.503	-11.713	-4.992	0.348	2.406
CO_2 emission intensity	360	-0.872	1.446	-3.375	3.519	0.720	2.860
N_2O emission intensity	360	-5.916	1.624	-8.658	0.451	1.138	4.839
Energy intensity	360	-1.847	1.409	-4.272	2.950	0.903	3.582
Gas share	360	-0.703	0.719	-4.007	-0.027	-2.183	7.448
Physical Capital Intensity	340	-4.155	1.170	-9.696	0.106	0.097	5.611
Human Capital Intensity	341	-1.787	2.852	-19.816	0.854	-5.450	32.449
Size	354	3.195	1.419	-1.484	8.224	0.364	4.943
Total Factor Productivity	351	1.578	0.207	0.733	2.154	-0.152	3.521
HHI	352	-3.219	1.172	-5.362	-0.271	0.471	2.572
HHI^2	352	0.698	1.026	2.09E-07	6.401	2.545	10.594
Capital expenditure int.	342	-1.942	0.687	-4.637	2.205	0.211	7.286

Table B2. Results from estimation of Equation (4-1) when using a Fixed Effects estimator

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FE	FE	FE	FE	FE	FE	FE
Energy intensity	0.766***	0.724***	0.727***	0.677***	0.702***	0.904***	0.525***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital intensity	-0.098*	-0.058***	-0.053***	0.01	-0.066***	-0.004	-0.036
	(0.086)	(0.000)	(0.005)	(0.719)	(0.004)	(0.565)	(0.252)
Human capital intensity	-0.062	-0.042**	-0.052*	-0.054	-0.098***	-0.01	-0.126**
	(0.468)	(0.019)	(0.080)	(0.203)	(0.007)	(0.326)	(0.013)
Size	0.128***	0.013	0.041***	-0.053**	0.052***	-0.015***	-0.017
	(0.003)	(0.145)	(0.007)	(0.015)	(0.004)	(0.004)	(0.495)
TFP	-0.013	0.093**	0.039	-0.162	-0.201**	-0.077***	-0.353***
	(0.949)	(0.023)	(0.570)	(0.104)	(0.016)	(0.002)	(0.003)
Capital expenditure int.	-0.087	0.072**	0.047	0.044	-0.064	0.038**	0.107
	(0.588)	(0.028)	(0.392)	(0.571)	(0.331)	(0.050)	(0.247)
Constant	-6.880***	-6.034***	-5.418***	-4.435***	-7.964***	0.995***	-4.448***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel groups	19	19	19	19	19	19	19
Observations	286	300	300	300	300	300	300
R^2 between	0.807	0.931	0.947	0.862	0.755	0.963	0.562
R^2 within	0.513	0.95	0.863	0.713	0.711	0.98	0.593
R^2 overall	0.772	0.923	0.923	0.845	0.731	0.966	0.575
CD test	X	-2.51**	-2.62***	-2.89***	-2.27**	3.23***	1.28
CD *p*-value	(x)	(0.012)	(0.009)	(0.004)	(0.023)	(0.001)	(0.199)

Notes: Values in parenthesis are *p*-values of the coefficient estimates. *, ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests regression residuals for cross section dependence and assumes a null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. FE stands for Fixed Effects estimator. Time dummies are included in all regressions.

Table B3. Results from estimation of Equation (4-1) when using a Random Effects estimator

	SO_2	NO_x	TAC	CO	PM_{10}	CO_2	N_2O
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	RE	RE	RE	RE	RE	RE	RE
Energy intensity	0.923***	0.787***	0.842***	0.920***	0.785***	0.919***	0.566***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital intensity	-0.072	-0.066***	-0.045**	-0.036	-0.078***	-0.008	-0.028
	(0.172)	(0.000)	(0.012)	(0.170)	(0.001)	(0.212)	(0.349)
Human capital intensity	0.01	-0.045***	-0.033*	-0.147***	-0.107***	-0.028***	-0.100**
	(0.857)	(0.000)	(0.057)	(0.000)	(0.000)	(0.000)	(0.012)
Size	0.140***	0.022**	0.053***	-0.029	0.063***	-0.011**	-0.014
	(0.001)	(0.020)	(0.000)	(0.234)	(0.003)	(0.038)	(0.588)
TFP	0.047	0.125***	0.09	0.052	-0.101	-0.067***	-0.342***
	(0.812)	(0.006)	(0.211)	(0.661)	(0.318)	(0.008)	(0.003)
Capital expenditure int.	-0.133	0.018	-0.002	-0.078	-0.038	0.027	0.104
	(0.375)	(0.575)	(0.974)	(0.244)	(0.569)	(0.162)	(0.245)
Constant	-6.610***	-6.139***	-5.343***	-5.002***	-8.044***	0.923***	-4.377***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel groups	19	19	19	19	19	19	19
Observations	286	300	300	300	300	300	300
R^2 between	0.908	0.935	0.962	0.904	0.766	0.973	0.622
R^2 within	0.509	0.948	0.86	0.692	0.707	0.98	0.593
R^2 overall	0.842	0.929	0.939	0.88	0.741	0.971	0.617
CD test	X	-2.45**	-2.66***	-2.76***	-1.85*	3.84***	1.36
CD *p*-value	(x)	(0.014)	(0.008)	(0.006)	(0.064)	(0.000)	0.173

Notes: Values in the parenthesis are *p*-values of coefficient estimates. *, ** and *** indicate 10%, 5% and 1% stat. significance, respectively. CD test (Pesaran, 2004) tests regression residuals for cross section dependence and assumes a null of cross section independence. CD test cannot produce result for column 1 because of SO_2 missing values. RE stand for Random Effects estimator. Time dummies are included in all regressions.

Table B4. CD test for regressors specified in Equation (4-1) and Equation (4-2)

Variables	CD test	*p*-value	Variables	CD test	*p*-value
SO_2 emission intensity	X	(X)	Gas share	2.73***	(0.00)
NO_x emission intensity	27.97***	(0.00)	Physical Capital Intensity	8.03***	(0.00)
TAC emission intensity	24.65***	(0.00)	Human Capital Intensity	6.88***	(0.00)
CO emission intensity	9.95***	(0.00)	Size	1.03	(0.301)
PM_{10} emission intensity	12.01***	(0.00)	Total Factor Productivity	6.26***	(0.00)
CO_2 emission intensity	15.94***	(0.00)	HHI	4.87***	(0.00)
N_2O emission intensity	15.36***	(0.00)	HHI^2	3.08***	(0.002)
Energy intensity	17.53***	(0.00)	Capital expenditure int.	15.26***	(0.00)

Notes: CD test (Pesaran, 2004) tests regressors for cross section dependence and assumes null of cross section independence. CD test cannot produce result for SO_2 emission intensity because of missing values. Values in the parenthesis are *p*-values of CD test statistics. *, ** and *** indicate 10%, 5% and 1% stat. significance, respectively.

Figure B1. Time effects from models presented in Table 4-2

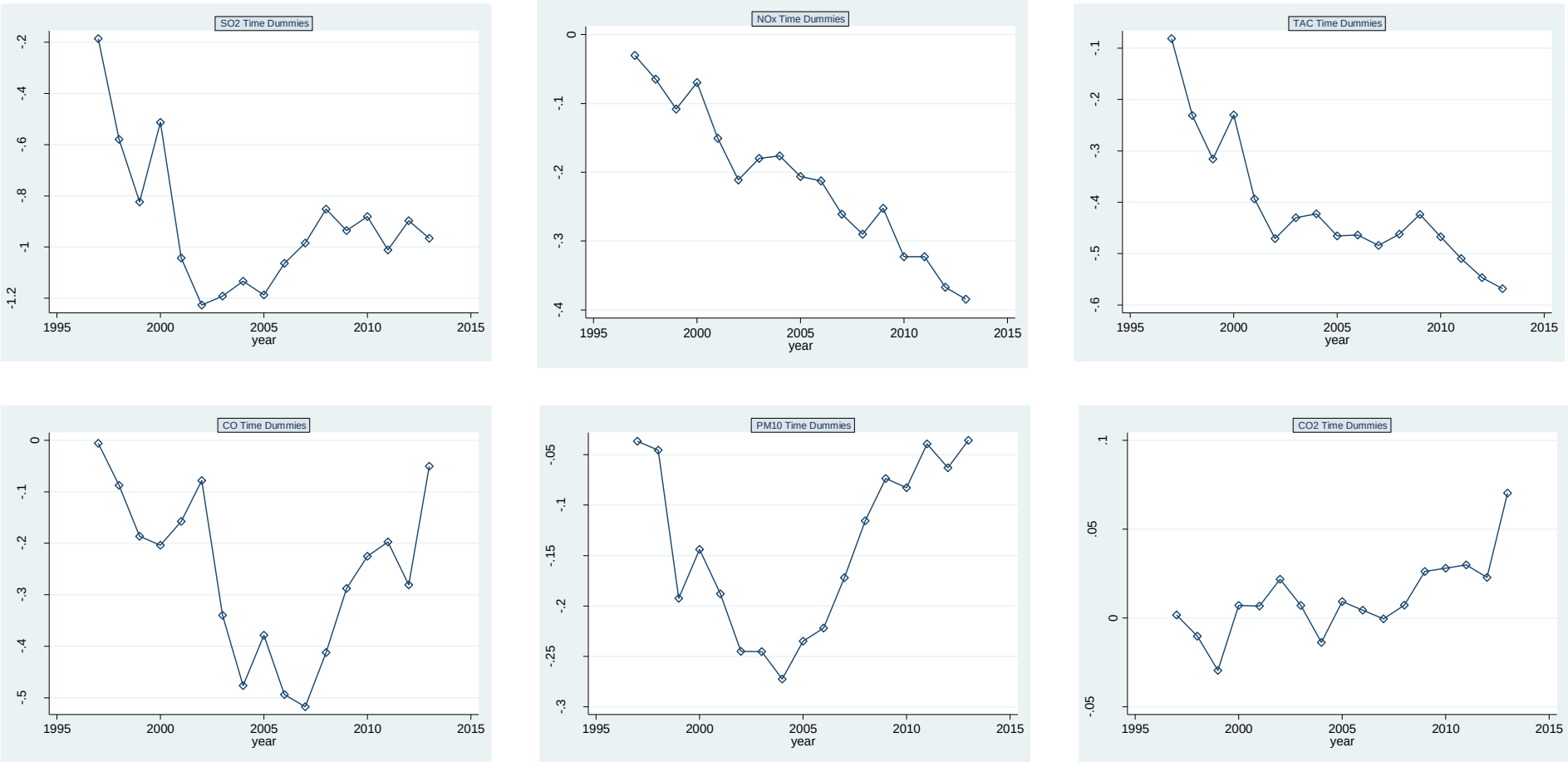
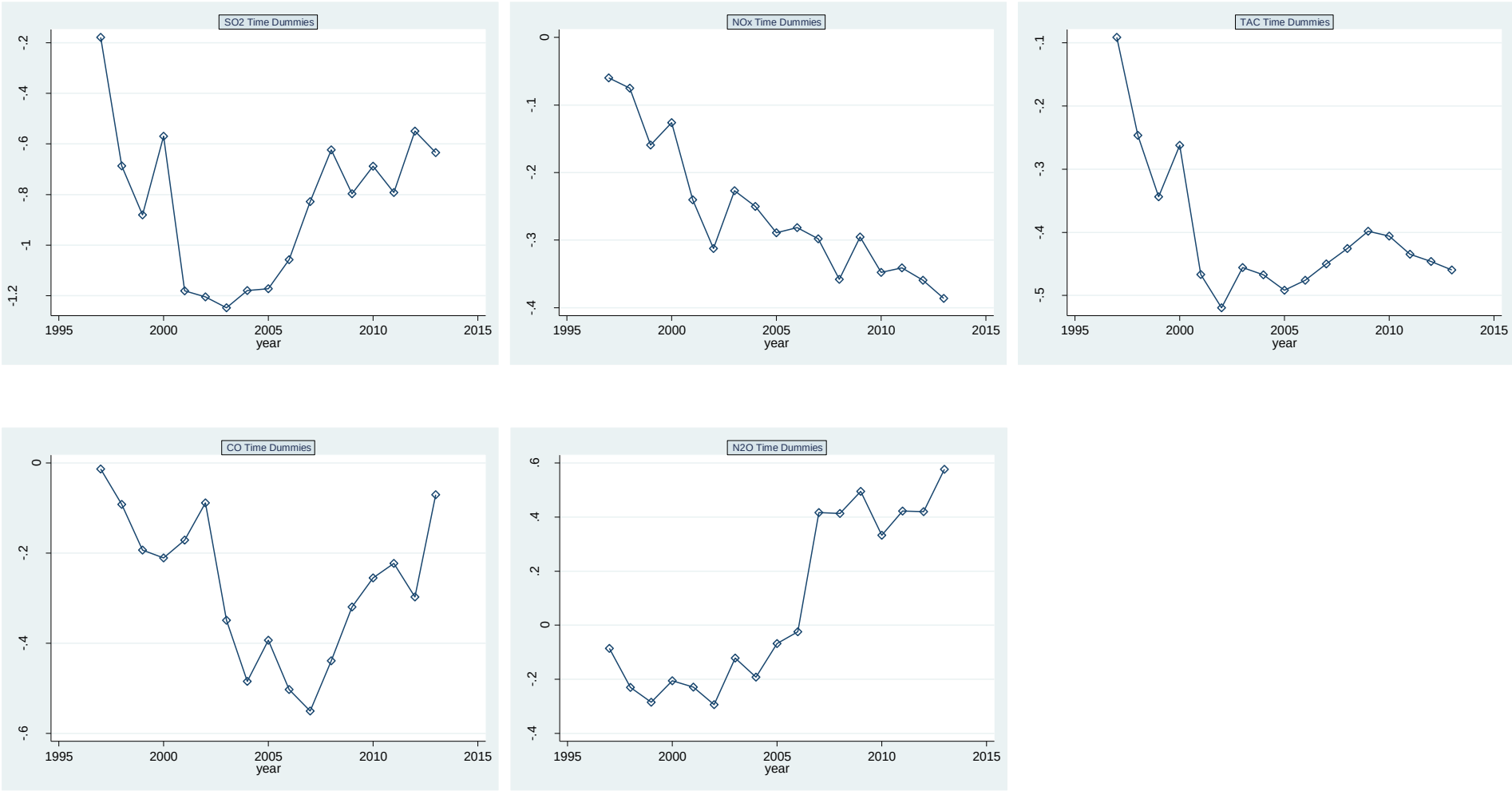


Figure B2. Time effects from models presented in Table 4-3



CSupplementary material for chapter 5

Table C1. Descriptive statistics of variables used in chapter 5

	Levels						Logs					
	Jobs	GVA	Conv. thermal	CCGT	Nuclear	Renewables	Jobs	GVA	Conv. thermal	CCGT	Nuclear	Renewables
Obs.	27	27	27	26	27	27	27	27	27	26	27	27
Mean	113,287	18,201	139,651	94,686	71,472	12,787	11.60	9.62	11.80	11.10	11.16	9.16
St. Dev.	30,870	13,370	37,655	42,603	11,749	11,395	0.25	0.56	0.30	1.36	0.16	0.72
Min	71,500	8,554	44,543	309	47,673	4,270	11.17	9.05	10.70	5.73	10.77	8.35
Max	193,500	52,741	219,364	157,416	90,590	42,281	12.17	10.87	12.29	11.96	11.41	10.65
Skewness	1.07	1.64	0.19	-0.84	-0.04	1.50	0.48	1.19	-1.44	-2.95	-0.29	0.89
Kurtosis	3.69	4.29	3.87	2.87	1.91	3.90	2.79	2.99	7.38	11.26	2.22	2.35

Table C2. Unit root test results for Major Power Producers (MPPs)

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

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

Table C3. Johansen test cointegration results

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

Notes: Results from the Trace and Max Eigenvalue cointegration tests. (+), (*), (**) in the superscripts indicate significance of the test statistics of the unit root tests at 90%, 95% and 99% significance level, respectively.

Table C4. Cointegrating vectors *β* from alternative VECM specifications to those presented in Table 5-1

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

Notes: VECM 1A: specification as in VECM 1 in Table 5-1 with trend in β_2 restricted to zero. VECM 1B: specification as in VECM 1 in Table 5-1 with trend in β_3 restricted to zero. VECM 2A: specification as in VECM 2 in Table 5-1 with trend in β_2 restricted to zero.

Table C5. *P*-values of the Likelihood Ratio tests for the coefficients in the cointegrating vectors *β* presented in Table C4

	GVA	CCGT	NUC	REN	Trend β_1	Trend β_2	Trend β_3	Trend β_4	All trends
VECM 1A	0.00	0.00	0.00	0.00	0.01		0.00	0.40	0.00
VECM 1B	0.00	0.00	0.00	0.00	0.02	0.00		0.00	0.00
VECM 2A	0.00	0.00	0.00	0.00	0.00				

Table C6. Diagnostic tests for the residuals of the VECMs cointegrating vectors presented in Table C4

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

D Decarbonisation scenarios for the UK

Scenarios used in chapter 5.6 were developed by the UK Energy Research Centre (UKERC) to assess the energy security implications of different energy futures based on a set of six UK energy scenarios (Watson et al., 2018). The scenarios consist of qualitative narratives and quantitative analysis using an energy system model: UK TIMES. UK TIMES is a bottom-up, cost optimisation energy system model that is often used to explore the implications of different energy futures and identify pathways that achieve carbon reduction targets. As not all the parameters used to develop the qualitative narratives could be modelled in UK TIMES, some components of the narratives, such as governance or environmental awareness, are not reflected directly.

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

The variants of those key components and the combinations within each scenario narrative are summarised in Table D1 which is taken from Watson et al. (2018). The remainder of this section briefly describes the six scenarios. A much more detailed description of the scenarios and a discussion of the findings can be found in Watson et al. (2018).

Scenario 1: Energy island

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

Scenario 2: Slow decarbonization

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

Scenario 3: Low carbon

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

increasing role in the electricity generation. This is the only scenario that estimates negative emissions by 2030.

Scenario 4: Low carbon (no CCS)

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

Scenario 5: Low carbon (no BECCS)

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

Scenario 6: Technology optimism

The "Technology optimism" is a more decentralised scenario in which more powers are given to devolved administration and local government while a new deal with the EU provides full access to the single market. Under this scenario there are rapid reductions in the cost of renewable

technologies, especially solar PV which leads to sustained government support for the deployment of low carbon technologies.

Table D1. Summary of 2017 UKERC scenarios – table taken from Watson et al. (2018)

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

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