Three essays on applied energy econometrics with policy implications

Three Essays on Applied Energy Econometrics with Policy Implications

by

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Dedication

To

Anu, Opeoluwa and Olaoluwa

Thank you for your unconditional love and sacrifice.

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Abstract

This thesis examines the implications of econometric estimation of energy demand in three separate empirical chapters. In particular; the issues addressed are: (i) the extent in which inappropriate modelling techniques could impact energy demand estimates, (ii) the relationship between energy demand estimates and carbon emissions and (iii) the relationship between the decomposition of derived energy input and carbon emissions. The research begins with the estimation of industrial energy demand across 29 European countries over the period 1995–2009 using both the generalised method of moments (GMM) and the dynamic multilevel model (DMM) that accounts for the hierarchical structure of the data used. The main results indicate that the long run income and price elasticities of the standard dynamic model, that is, the GMM, which does not account for the hierarchical structure of the data used, are overestimated.

The second empirical chapter carries out an exploratory investigation on the impact of energy demand elasticities on carbon emissions across Chinese sectors. The study allows for a structural change by dividing the period under consideration into period before (1995–2001) and after (2002–2009) China's accession to WTO. This chapter estimates/demonstrates how to compute a range of elasticities by estimating a translog model, and then examines the impact of these elasticities on industrial carbon intensity. Findings suggest that there is a moderately negative relationship between energy substitution and carbon emissions, more especially after the structural change.

The third chapter combines the first two chapters into a single study by adopting a two-stage procedure to measure the implications of inappropriate energy modelling technique/energy demand estimates on carbon emissions. The study is based on industry level data across Europe over the period 1995–2007. Firstly, the study decomposed energy estimates into substitution and output effects with a multilevel model and iterated seemingly unrelated regression (iSUR). The second stage examines the impact of the decomposition effects with other competing forces on carbon emissions. Findings reveal that the substitution effect dominates the output effect and is inversely related to the carbon emissions. For the output effect, the results derived from both techniques differ, as the output effect from the iSUR show a positive sign; however, the output effects from the multilevel model show a negative relationship with carbon emissions, which is more consistent with the ideal practice of a cost minimising firm.

Key words: multilevel model, energy demand, long-run elasticities, substitution elasticities, World Trade Organisation, carbon emissions, decomposition effects.

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Chapter 1 Introduction

1.1 Background

It is not an overstatement that energy is an important ingredient in the day-to-day running of economies globally, given its usefulness within the production technology and its contributions to the production of goods and services for mankind. More specifically, energy contributes to consumer welfare through end-use services such as cooling, heating, cooking, driving and so forth. However, some of the most crucial global development issues such as poverty and climate change are related to energy use. Poverty is linked to limited energy access (energy poverty), while climate change is largely attributed to greenhouse emissions resulting from energy use as energy-related CO_2 emissions account for about 61% of global greenhouse gases (Lescaroux, 2011). As a result, never has it been more important for governments and policy makers around the world to devise methods and policy actions to manage economic prosperity through adequate and affordable access to energy, while also curbing greenhouse emissions.

More importantly, the devastating impact of CO_2 emissions resulting from increasing energy consumption has motivated many researchers and policymakers to look for a long-lasting solution to reduce energy consumption by using reliable estimates in making appropriate predictions about future energy use and associated carbon emissions. Further, for the sake of providing guidance for policy makers in designing appropriate policies, accurate prediction of how energy consumers react to changes in price, economic activity and other indicators is necessary. It is in this context that estimated energy parameters become valuable tools in formulating energy related policies.

Energy estimates provide relevant information with respect to the sensitivity of consumers' behaviour to changes in important explanatory variables (e.g. energy price, income, non-energy inputs and even weather). In the field of energy demand modelling, it is now a major challenge for applied energy economists/ econometricians and modellers to determine energy demand elasticities that are useful for policy design and strategic decision-making of utilities, technology manufacturers, and other relevant stakeholders. In addition, the assessment of the relationship between energy use, economic activity and emissions is valuable for an appraisal of potentially conflicting policy objectives, such as the trade-off between energy conservation and economic growth, economic growth and greener environment, and energy conservation and sustainable environment[1].

With the primary purpose of generating more reliable energy estimates, econometric studies still seem to dominate the applied research done in empirical analysis of energy demand and its implications. In recent years, importantly, new econometric techniques (e.g. panel data analysis) have become more and more popular among researchers and analysts alike, and increasingly applied, while at the same time interest in the estimation of elasticities for industrial energy use and fuel types seems not to have diminished. However, both policy-makers and decision-makers in industry alike, and energy modellers providing model-based insights, rely on reliable estimates of the sensitivity of energy demand in reaction to changes in important variables shaping energy demand.

The main arguments of this thesis are at least fourfold: (1) to describe and apply recent econometric techniques for estimating elasticities of energy demand; (2) to produce reliable energy estimates by estimating sectorial energy demand for own/cross-

[1] The conflicting interest in the energy-income nexus is rooted in four alternative economic hypotheses namely the conservation hypothesis, the growth hypothesis, feedback hypothesis and the neutrality hypothesis. While the environmental Kuznets hypothesis largely describes the expected relationship between income and emissions

price elasticities and income elasticities; (3) to compare and contrast the empirical results obtained from different model specifications, estimation techniques and data samples; and (4) to measure the implications of the elasticities of energy demand obtained from different model specifications and techniques mainly on carbon emissions.

1.2 Motivations and contributions

They are two major motivations that have prompted the research discussed in this thesis. First, from the policy point of view, policy based on wrong or inaccurate energy demand estimates is very likely to be misleading. Hence, the main economic motivation of this thesis is to produce more reliable estimates by estimating energy demand functions with econometric methods that are more suitable to the industry-level data used. This motivation is driven by the fact that reliable econometric estimates of energy demand elasticities are rare, and research interest appears to have dwindled in recent years, despite an increasing stock of data and the acknowledgement that a better understanding of energy consumer behaviour is crucial for decision support in the energy domain (Bhattacharyya, 2011).

The second motivation for the research discussed here is driven by Greening et al. (2007) as they concluded their article by hoping new research would be forthcoming on energy demand modelling. In response to this challenge, this research introduces a multilevel model, an established method of analysis in other branches of economics, but new in energy demand literature to the best of my knowledge[2]. The aim is to show that the application of this model can provide new insights on the estimation of energy

[2] Multilevel modelling approach forms the bedrock of the empirical analysis discussed in this thesis, especially, in the first two empirical chapters. The approach is discussed in a more detail in chapters three and four.

demand and its implications like never before. This motivation is driven by the availability of detailed data for industrial subsectors.

With respect to contributions to the existing literature, this research contributes significantly to the literature on applied energy econometrics by providing new insightful information about the policy and environmental relevance of energy demand elasticities. Specifically, the three main contributions of this research are discussed as follows.

First, generally, the econometric estimation of energy demand estimates has such a long history, going back as far as the early 1950s. While the oil shocks in 1970s prompted the interest in modelling industrial energy demand following the seminal work of Berndt and Wood (1975). In the interest of generating reliable energy estimates, many econometric estimation techniques have been employed ranging from estimating a system of cost equations (Christensen et al., 1973; Fuss, 1977; Uri, 1982) and to a single-equation model (Hunt et al., 2003a; Adeyemi and Hunt, 2007; Agnolucci, 2009). The research discussed here belongs to the latter category given the relative scare of the application of the single method approach in the literature of energy demand modelling as compared to the former. On a different terrain, empirical evidences have shown that hierarchical data such as industry-level data is very likely to suffer from potential cluster-level heterogeneity (Lee, 1997; Steenbergen and Jones, 2002). Hence, it is imperative to control for potential heterogeneity across different levels of the dataset. The first paper of this thesis combines the two arguments discussed above and demonstrates that failure to account for the cluster-level heterogeneity in energy data could severely produce bias the estimated energy demand elasticities.

Secondly, literature reveals that energy demand elasticities are indirectly related to the feasibility of the stated goals of emission reductions as they could serve as policy instruments. Hence, this research is worthwhile undertaking, which is rooted in the global agenda on climate change. As such, the link between global environmental challenges and energy consumption is well documented in the energy literature, given that energy consumption is arguably the main source of CO_2 emissions. In an attempt to overcome notable environmental challenges like global warming, improvement in energy-saving in terms of capital-energy substitution is considered as a key measure[3]. The aim is to reduce energy consumption by using more non-emission inputs and consequently reducing CO_2 emissions. Theoretical demonstration shows that a high elasticity of substitution (ES, hereafter) between energy and other inputs could lead to a large reduction in carbon, while a small ES between energy and other inputs could proves otherwise. However, there is no concrete empirical evidence to support these claims in the literature. Therefore, an empirical assessment of the implication of ES between energy and other inputs would help in understanding the relevance of the ES in reducing carbon emissions. This forms the second contribution of this thesis.

In the literature of econometric estimation of energy demand, ES between energy and other inputs has remained a popular empirical research area with a strand in the literature arguing that energy and capital are substitutes, while other strand claims they are complements. However, the ES fails to represent a complete picture of inputs adjustment as it is based on the assumption of constant level of output. In reality, producer tends to adjust output in response to changes in relative factor prices and market conditions. The output effect represents a more complex picture of inputs

[3] This measure has two main advantages. First, it removes over-reliance of continuing increase in energy prices as a way of stimulating improvement in energy efficiency. Second, it represents a way of relaxing the pressure of increasing global energy consumption and regarded as a natural way of reducing greenhouse gases.

adjustments as it accounts for a non-constant level of output. Therefore, it is essential to factor in this argument while examining the implication of ES on carbon emissions. This research addresses this issue by examining the implications of substitution and output effects alongside with other factors on carbon emissions. This constitutes the third main contribution of this thesis.

1.3 Research questions

This thesis comprises three essays exploring important aspects of econometric estimation of energy demand elasticities using sector level data. To achieve the aims and objectives of this research, the following as-yet unanswered research questions are addressed:

1. To what extent would inappropriate econometric techniques impact energy demand elasticities?
2. What is the relationship between estimated energy demand elasticities and carbon emissions?
3. What is the relationship between the decomposition of derived energy input and carbon emissions?

1.4 Thesis plan

This thesis is dedicated to answering the above research questions in three different empirical chapters.

The first empirical chapter addresses research question 1 and the analysis undertaken in this chapter further leads to the following additional questions.

Q1.1: Is there a significant difference between industry-level and country-level energy demand estimates?

Q1.2: Is heterogeneity in energy use more associated with between-industry or between-country differences?

In the first empirical chapter, the issue of generating unreliable estimates by using inappropriate econometric method is addressed. This chapter uses sector level data across 29 European countries to demonstrate the consequence of ignoring the hierarchical structure of industry-level energy data. As having accurate information on income and price elasticities is important for policy making, this paper introduces a dynamic multilevel model to estimate energy demand function. The long-run elasticities of the multilevel model are then compared to that of the generalized method of moment approach.

Question 2 is addressed in second empirical-chapter (Chapter 3). In additional to the main question, this paper provides answers to the following specific questions.

Q2.1: Are energy and non-energy inputs substitutes or complements?

Q2.2: What are the main drivers of carbon intensity?

More specifically, chapter 3 adopts a two-step procedure to address the relationship between the elasticities of factor substitution and CO_2 emissions. Having motivated by the inconclusive evidence about the ES in the literature, this chapter derives a range of elasticities of substitution and complementarity by estimating a translog cost function in the first step. In the second step, the estimated factor substitution with other potential determinants are therefore analysed as drivers of carbon intensity having accounted for structural change in Chinese production sector. The empirical analysis is based on a rich Chinese sector-level data over the period of 1995–2009.

Question 3 is addressed in chapter 4. In additional to the main question, this chapter provides answers to the following specific questions.

Q3.1: What are the estimates of the substitution and output effects?

Q3.2: Which of the two effects dominates?

In the production context, producer is likely to adjust output in response to changes in relative factor prices. More specifically, this chapter relaxes the assumption of constant level of output under pure substitution elasticity by decomposed derived energy input into substitution and output effects. Using sector-level data across Europe, this paper estimates a translog cost function with seemingly unrelated regression (SUR) and multilevel model. Then, the paper examines implications of the decomposition effects alongside with other competing forces on carbon emissions.

The remainder of this thesis is organized as follows. Chapter 2, 3 and 4 contain the empirical chapters of this thesis. Chapter 5 summarises the main findings and offers remarks pertaining to the policy implications of the research questions/objectives highlighted in Chapter 1. This chapter also offers suggestions for future research.

Chapter 2 Econometric Estimation of Industrial Energy Demand: A Dynamic Multilevel Modelling Approach[4]

2.1 Introduction

The estimated long-run elasticities derived from energy demand functions have retained energy demand modelling as an area of interest in the literature. This is because these elasticities serve as important tools for the policy makers in making appropriate predictions about future energy use and energy related policies, Hunt and Ninomiya (2005). This subsequently highlights the potential implications of energy related policies based on inaccurate energy demand estimates, which are very likely to be misleading or inappropriate. Numerous approaches have been employed to derive energy demand estimates ranging from aggregate level to sectoral level analyses, but majority of the existing literature generate their energy demand estimates from aggregate demand models[5]. Although, energy demand estimates derived from aggregate energy demand functions are useful in formulating macroeconomic policies related to energy security and carbon emissions, but as such analysis fails to capture the potentially more diverse energy consumption behaviour of disaggregated units in the economy. Consequently, detailed information and understandings required in formulating specific energy related policies are lost (Bhattacharyya, 2011). This in turns highlights the importance of estimating industrial energy demand as it avoids masking the difference in the production process across the various productive sectors.

[4] A revised version of this Chapter has been published as: Sharimakin, A., Glass, A. J., Saal, D. S. and K. Karligash (2018), "Dynamic multilevel modelling of industrial energy demand in Europe", *Energy Economics*,

[5] [5] Lee and Lee (2010) list studies that have estimated aggregate energy demand function. In addition; York (2007), Adeyemi et al. (2010) and Lee and Chiu (2011) estimate aggregate energy demand function.

The purpose of this Chapter is to analyse industrial energy demand across 29 European countries over the period 1995–2009. The main contribution of this study over the existing literature in industrial energy demand modelling is the introduction of the dynamic multilevel model that controls for the hierarchical structure of industry level data, given that failure to control for the multilevel structure of hierarchical dataset could produce unreliable estimates, Steenbergen and Jones (2002). The methodology adopts in this study subsequently highlights the implications of ignoring the hierarchical structure of industry level data while modelling industrial energy demand. Specifically, we analyse energy demand function for the sectors as a whole and for different sector types by classifying the sectors into primary, manufacturing and service sectors respectively. The categorising of the whole sample into three different sectors allows the estimation of price and income elasticities for each of the sectors, which in turn provide insightful information in formulating specific sector's energy related policies. The estimation method employed in this paper is sensible as Lee (1997) demonstrates that the estimates from a model using only aggregated industrial data might be biased.

The remainder of this Chapter is organised as follows. Section 2.2 presents the overview of existing literature in industrial energy demand. Section 2.3 introduces the dynamic multilevel econometric methodology and discusses our application of it to industrial energy demand. Section 2.4 describes the data used for the estimations. The empirical results are then discussed in Section 2.5. Section 2.6 presents the concluding remarks and avenues for further research.

2.2 Related literature on industrial energy demand

The research interest in modelling industrial energy demand has increased in recent years owing to the fact that industrial energy consumption accounts for about one third of the global energy consumption (Greening et al., 2007). Further, as noted by Agnolluci et al. (2017) the contribution of industrial energy consumption to global energy consumption has remained constant over the years fluctuating around 33% and 27% in 1971 and 2013 respectively (IEA, 2016). In the last three decades, tremendous efforts have been taken to empirically model industrial energy demand. The closest relatives to this study falls into two categories: (i) empirical modelling of industrial energy demand using a system of cost share with a translog specification and (ii) empirical modelling of industrial energy demand using a single-equation model[6]. In respect to the former, existing literature in industrial energy demand modelling primarily focuses on the elasticities of substitution (ES) and complementarity (EC) between factor inputs/or fuel types owing to the seminar work of Berndt and Wood (1975). Among others, Berndt and Wood (1975), Fuss (1977), Anderson (1981), Prywes (1986), Arnberg and Bjøner (2007) and Tovar and Iglesias (2013) find capital and energy to be complements. However, some existing studies on industrial energy demand refute the claim that capital and energy are substitutes, and therefore argue that capital and energy are complements. These include Griffin and Gregory (1976), Uri (1982), Kim and Heo (2013), Haller and Hyland (2014), Lin and Ahmad (2016) and Li and Lin (2016).

In addition to the analysis of factor substitution, some studies simultaneously highlight the importance of the price elasticities. Floros and Vlachou (2005) modelled the Greek industrial energy consumption using a two-stage translog model for the period 1982–1998. Their results suggest that energy price elasticities vary markedly between – 1.13 and – 0.02, with upper bound decreasing to –0.04 when the model only

[6] We classified models that are not system cost-share translog models such as fixed effect, random effect models and GMM etc. as single-equation model.

contains statistically significant elasticities. Kim and Heo (2013) estimate a translog cost function for the manufacturing sectors of 10 OECD countries and find energy price elasticities to be inelastic ranging between –0.08 and –0.76. Haller and Hyland (2014) also employ translog function to model production in the Irish manufacturing sector over the period 1991-2009 and find price to be elastic with an estimated elasticity −1.46. Similarly, Li and Lin (2016) estimate both static and dynamic tranglog cost function to analyse inter-factor/inter-fuel substitution in China over the period 1985–2012. The authors find own price elasticities for electricity, coal, and oil to be −0.72, −0.76 and −0.74 respectively. We acknowledge that the system based estimation of the translog cost model has remained a popular method to model industrial energy demand, because of the flexibility of the translog specification as well as this approach is consistent with microeconomic theory related to cost minimization. However, notwithstanding this popularity, most of the studies that model industrial energy demand using cost functions mainly focus on inter-factor and/or inter-fuels substitution possibilities rather than energy price or income/output estimates.

In contrast, studies that have modelled industrial energy demand with the single-equation model have focused more on investigating the implication of energy price and economic activity on energy demand by estimating long-run energy price and economic activity elasticities of energy demand. Bjøner and Jensen (2002) employ fixed effect model to analyse the survey data for 8 Danish industrial companies between 1983 and 1997. They find average price elasticity –0.44 for the whole industry, while price elasticities vary between industries ranging from –0.69 and –0.21. The elasticities of economic activity vary between 0.44 and 0.65 with an average of 0.54 for the whole industry. The elasticities of energy price and economic activity produce by Agnolluci et al. (2017) are almost identical as the authors find average elasticities with respect to energy price –0.41 and economic activity 0.57 for UK industrial subsectors. These average elasticities are somewhat similar to the average elasticities with respect to energy price and economic activities produce in Agnolucci (2009, 2010). Hunt et al. (2003a) demonstrate the importance for allowing for inherent underlying forces that can be stochastic in nature in energy demand modelling. Structural Time Series Model (STSM) of Harvey (1989) was used to estimate energy demand for the UK as a whole and for different sectors using a quarterly data for the period 1971q1 to 1997q4. Their findings suggest that energy demand models that fail to allow for these underlying forces are likely to produce biased estimates. In a very similar study, Dimitropolous et al. (2005) reconfirmed the importance for allowing for the inherent underlying forces in industrial energy demand modelling using an annual UK data for the period 1967–2002 across different sectors. They find the elasticity with respect to energy price between –0.11 and –0.23 and the elasticity with respect to economic activity between 0.34 and 0.81. Similarly, Dilaver and Hunt (2011) investigate the impacts of energy price and economic activity on the Turkish industrial electricity consumption using STSM. Having controlled for the underlying forces that could affect electricity consumption in the model; they find both output and price to be inelastic with estimated elasticities 0.15 and –0.16 respectively– value close to Dimitropolous et al. (2005) when considering only price.

One strand in the literature of energy demand argues that there is a difference between the impacts of an increased energy price and a decreased energy price- the concept of asymmetric methodology introduced by Dargay and Gately (1995). With respect to industrial energy demand, Adeyemi and Hunt (2007) consider the APR methodology to demonstrate that the use of single-equation model had become a standard procedure while modelling industrial energy demand for a panel of 15 OECD countries. They argue on the basis that the procedure is simple, straightforward and required limited data. The long-run elasticities with respect to economic activity for the two models estimated are 0.76 and 0.56. The estimated long-run price elasticity when assuming no asymmetric response is −0.22, though not statistically significant; when assuming asymmetric price responses, the elasticities for price-maxima, price-recoveries and price-cuts are −0.52, −0.68 and −0.30 respectively. In a similar approach, Adeyemi and Hunt (2014) use the same set of 15 OECD countries explored in Adeyemi and Hunt (2007) to model the industrial energy demand using time series analysis over the period 1962–2010. The authors account for both APR and underlying trend in their models, and find estimated long-run income elasticities in the range of 0.34 to 0.96; estimated long-run price-maximum elasticities in the range of −0.06 to −1.22; estimated long-run price-recovery elasticities in the range of 0.00 to −0.27; and estimated long-run price-cut elasticities in the range of 0.00 to −0.18.

Two key points can actually be drawn from the literature. First, existing literature on industrial energy demand that in principle heavily rely on industry/sectoral level data do not normally account for the hierarchical structure of the industry level data used and consequently likely to produce unreliable estimates. Second, despite the huge existing literature on energy demand modelling, studies primarily focusing on European industrial energy demand remain relatively scarce in the literature given the fact that most previous studies rather focused on modelling energy demand for OECD countries[7] or a single country. Therefore, first, this paper aims to contribute to the existing literature by estimating industrial energy demand with a dynamic multilevel model. Multilevel model is very popular among social scientists and has been widely used in other branches of economics. For instance, in education economics, Konishi et al.

[7] In addition to the studies mentioned above, Hass et al. (1998), Griffen and Schulman (2005) Filippini and Hunt, (2011) and Lee and Chiu, 2013) have also modelled energy demand for OECD countries.

(2010), Ronfeldt et al. (2013) and Voyer and Voyer (2014) have employed multilevel model to analyse the determinants of student achievement. Moreover, multilevel modelling has been widely used in social and health economics to analyse the relationship between social capital and health (Islam et al., 2006; Mohnen et al., 2011; Layte, 2011; Murayama et al., 2012). In regional economics, multilevel model has also been used to control for the nesting of regions within countries (Srholec, 2007; Rentfrow et al., 2013). Given the wide use of multilevel models in other branches of economics, we can conclude that multilevel model is in fact an established method of analysis in economics, the benefits of which are transferable to energy economics. Second, we extend the existing literature by modelling the European industrial energy demand.

2.3 Empirical method

2.3.1 Multilevel modelling

Multilevel modelling aims to model the relationship between a response variable and a set of explanatory variables, but differs from standard regression analysis by modelling units of observation at different 'levels'. In particular, multilevel analysis is applied to a hierarchical data structure. For instance, in the context of this study, we have a longitudinal data[8] that is viewed as three-level or clustered data with occasions (that is, time period) nested in subjects (that is, industries) which are in other hand nested in countries. Following Rabe-Hesketh and Skrondal (2012) we use the term "occasions" i for level-1 units, "industries" j for level-2 units and "countries" k for level-3 units. In other words, this implies that the individual observations are in general not absolutely independent. That is, industries interact with and are influenced by the

[8] For interested reader on multilevel modelling for longitudinal or repeated measures data see Rabe-Hesketh and Skrondal (2012).

economic environment to which they belong, and that national economies are in turn influenced by the industries that make them up.

More importantly, one can associate differences in energy consumption between industries to the countries where they are located, but industries located in different countries may have different energy consumption behaviour even though they have similar industrial features. This could arise as a result of diversity in energy prices, climate, economic growth and technological progress across countries. In other words, the energy consumption behaviour of a typical industry operating in a given country can be influenced by the consumption behaviour of another industry operating in a different country. In other hand, industries located in the same country tend to have common energy consumption behaviour even though they have different industrial characteristics given the fact they face the similar economic and social situations. This could be referred as the consumption patterns of clusters, that is, industries with different characteristics. Steenbergen and Jones (2002) discuss the statistical problems inherent in clustered data and demonstrate that models that do not control for this clustering tend to produce unreliable estimates in terms of incorrect standard errors.

In this study, we control for clustering in our data by using multilevel model that can explicitly accounting for the multilevel structures of the data. Multilevel modelling allows us to disentangle the clustering at different levels by including the explanatory variables and the disturbance term at every level. That is, our models incorporate predictors at each of the levels. This allows us to indirectly control for the heterogeneity of the relationships between the response variable and the explanatory variables among clusters- of industries and countries. Consequently, we are able to identify the unexplained heterogeneity associated with each level. Another advantage of using multilevel regression is to remove the "Robinson effect" after Robinson (2009). This is often referred as dis-aggregation bias or ecological fallacy where an analyst wrongly analyses data at one level and formulates conclusions at another level. Hox et al. (2010, pp. 2-4) discusses the major statistical problem associated with this Robinson effect by arguing that when data is aggregated substantial information about underlying economic relationships is lost and the statistical analysis loses power, leading to a high potential for spurious results. Multilevel modelling is therefore explicitly designed to remove this biasedness as it provides a tool for analysing hierarchical data structures.

2.3.2 Dynamic multilevel modelling of industrial energy demand

The microeconomic model underlying our econometric specification of European industry energy demand is a modification of Medlock (2009) and is specified as follows, where i is a time index, j is an industry index and k is a country index:

$$E^* = E(Y, P, D_i) \tag{2.1}$$

where E^* is the energy demand, Y is output, P is the price of energy and D_i is the time dummies. We acknowledge that some existing literature considered the methodology of APR (Adeyemi et al., 2010; Adeyemi and Hunt, 2014) on the basis that there is a difference between the impacts of an increased energy price and a decreased energy price. Although, Griffin and Schulman (2005) refute this claim by arguing that the APR is only capturing energy saving technical progress endogenously, but Huntington (2006) replied by arguing that there is role for both the APR and technical progress while estimating energy demand model. In this paper, we are in favour of the former (Griffin and Schulman, 2005) as we do not considered APR like some existing literature on energy demand such as Hunt et al. (2003); Agnolucci, (2009, 2010); Lee and Lee (2010) and Lee and Chiu (2013). In a separate strand of the literature, the importance of allowing for the underlying nonlinear forces related to energy consumption has been considered (Hunt et al., 2003a; Dimitropoulous et al., 2005) with a mechanism termed as Underline Energy Demand Trend (UEDT)[9]. As noted by Adeyemi et al., (2010), the UEDT is regarded as a measure of energy saving technical progress and is captured by the time dummies in a panel data analysis, following the argument of Griffin and Schulman (2005). Following these arguments and the importance of allowing for the technical progress in energy demand model, we allow for the UEDT in our analysis and is captured by the time dummies, D_i.

We employ a dynamic multilevel model (DMM hereafter) and generalised method of moments (GMM hereafter) estimators (Arellano and Bond, 1991)[10] in estimating Eq. (2.1). However, we only discuss the DMM as the GMM has been extensively used and explicitly discussed in the literature. Given the structure of our dataset- a hierarchical structure with a balanced panel of multiple years of data on industries nested within countries, we apply a 3-level dynamic multilevel model in estimating European industrial energy demand where the numbers of occasion are regarded as level-1, the industries as level-2 which are nested in countries, level-3. Given our fully balanced panel data base, the general 3-level DMM is specified as follows:

$$E_{ijk} = \alpha E_{i-1,jk} + X_k^{(3)} u_k^{(3)} + X_{jk}^{(2)} u_{jk}^{(2)} + D_{ijk} + \in_{ijk} \tag{2.2}$$

where $k = 1, \ldots, K$, $j = 1, \ldots, J_i$, and $i = 1, \ldots, I_{jk}$. D_{ijk} is the time dummies. For example, the dependent variable E_{ijk} denotes the energy consumption for industry j operating in country k in time period (or occasions) i. Each j and k group consists of i observations, while E_{ijk} and $\in_{ijk}$ each have row dimension I. $X_k^{(3)}$ is the $I \times K$ design

[9] Hunt et al., (2003a) demonstrate the importance of allowing for inherent underlying forces that are nonlinear to energy demand and argue that any energy demand model that fail to allow for these nonlinear forces might produce biased estimates.

[10] The GMM is recognised as the baseline model for comparison. The GMM is known for controlling for endogeneity in the model and we also control for the unobserved country- and time-specific effects by including country dummies and time dummies. The industry-specific effects are automatically control for in the GMM given the fact that the industries represent our identifiers.

matrix for the third-level random effects $u_j^{(3)}$, and $X_{jk}^{(2)}$ is $J \times K$ design matrix for the second-level random effects $u_{jk}^{(2)}$. The random terms are assumed to be identically independently distributed

$$u_k^{(3)} \sim N(0, \sigma_v^2); \qquad u_{jk}^{(2)} \sim N(0, \sigma_u^2); \qquad \in_{ijk} \sim N(0, \sigma_\in^2)$$

For the purpose of estimation, we redefined Eq. (2.2) through a three-stage formulation using the notation of Bryk and Raudenbush (1992). The level-1 model for occasions i, industry j, and country k is a linear regression on time and is specified as:

$$E_{ijk} = \pi_{0jk} + \pi_{1jk} D_{ijk} + \varepsilon_{ijk} \tag{2.3}$$

where D_{ijk} is the time dummies and ε_{ijk} is the level-1 residual. The intercept π_{0jk} in the level-1 model vary between industries according to the following level-2 model:

$$\pi_{0jk} = \alpha_{00k} + \alpha_{01} E_{i-1,jk} + \alpha_{02} Y_{jk} + \alpha_{03} P_{jk} + \delta_{0jk} \tag{2.4}$$

where $E_{i-1,jk}$ is one period lagged value of energy use, Y_{jk} stands for output at industry-level, P_{jk} energy price at industry-level and δ_{0jk} is a level-2 random intercept. Further, we can introduce the country-level predictors by modelling the industry-level intercept, α_{00k}:

$$\alpha_{00k} = \beta_{000} + \beta_{001} Y_k^c + \beta_{002} P_k^c + \nu_{0k} \tag{2.5}$$

where Y_k^c stands for output at country-level, P_k^c energy price at country-level and ν_{0k} is a level-3 random intercept.

Substituting the level-3 model into the level-2 model gives

$$\pi_{0jk} = \beta_{000} + \beta_{001} Y_k^c + \beta_{002} P_k^c + \alpha_{01} E_{i-1,jk} + \alpha_{02} Y_{jk} + \alpha_{03} P_{jk} + \nu_{0k} + \delta_{0jk} \tag{2.6}$$

By making assumptions that the effect of industry-level variables are fixed (i.e., $\alpha_{0x} = \beta_{01x}$ for $x = 0$) and that the effect of the level-1 variable is fixed as well (i.e.,

$\pi_{1jk} = \beta_{100}$), then the substitution of level-2 model into level-1 model results to our 3-level model given as:

$$E_{ijk} = \beta_{000} + \beta_{001}Y_k^c + \beta_{002}P_k^c + \beta_{010}E_{i-1,jk} + \beta_{020}Y_{jk} + \beta_{03}P_{jk} + \beta_{100}D_{ijk} + \nu_{0k} + \delta_{0jk} + \varepsilon_{ijk} \quad (2.7)$$

where $\nu_{0k} \sim N(0, \sigma_\nu^2)$, $\delta_{0jk} \sim N(0, \sigma_u^2)$ and $\varepsilon_{ijk} \sim N(0, \sigma_\varepsilon^2)$.

This model has unique features as it brings together the predictor at different levels and it assumes that the error terms are uncorrelated across levels. A typical multilevel model normally consists of two parts: the fixed part, which shows the relationship between the predicted value of the dependent variable and the explanatory variables, and the random part, which shows the estimates of the group effects on the response variable. In principle, by simply including the lagged of the dependent variable into a static model such as Eq. (2.7), we are making a very strict assumption of no correlation between the lagged response and the residuals (that is, $\text{Cov}\,(\varepsilon_{ijk}, E_{i-1,jk}) = 0$). Therefore, estimating Eq. (2.7) directly without correcting for the potential correlation between the residuals and the lagged dependent variable is a very naïve way of estimating a dynamic model and this may consequently lead to biased and inconsistent estimates (Nickell 1981).[11] This is described as the problem of initial conditions in the literature. However, Steele (2008) and Crouchley et al. (2009) have argued that the problem of initial conditions is difficult to justify in practice as it only arises if the length '*T*' period of the study is relatively small because the problem is wiped out over a relatively long period of time. That is, in a longitudinal study with a relatively long time period, the problem of initial conditions might not occur. But unfortunately, none of these papers suggest an appropriate time period that is long enough for the problem

[11]By ignoring the possibility of correlation between the dependent variable and the residuals and estimate Eq. (2.7) might lead to upward biasedness of the coefficient of the state dependency (β_{010}) and the downward biasedness of the estimate of the unobserved heterogeneity $\sigma_{\nu0}^2$.

of initial conditions not to be of concern. Given the above argument, we control for the potential correlation that might occur between the lagged dependent variable and the residuals by adopting the joint working models proposes by Heckman (1981a) following Skrondal and Rabe-Hesketh (2014)[12].

The problem of initial condition arises when response at initial period does not coincide with the start of the process under study. In theory, response at the initial period E_{0jk} plays a crucial role in dynamic/transition models as subsequent responses (i.e., E_{1jk}, E_{2jk},..., E_{njk}) depend on it[13]. The basic idea of Heckman (1981a) is to model the initial response, jointly with the subsequent responses. In practice, Eq. (2.7) is a as model at a later occasion (i.e., when *i=1,...,I-1*) and since we have on-going data process where initial response E_{0jk} is considered to be affected by random intercept $\delta_{0jk}$and pre-sample $E_{-1,jk}$ response, thus, there is need to jointly model initial response E_{0jk} and subsequently responses. An unrefined starting point would be to specify a similar version of Eq. (2.7) using the initial response E_{0jk} as the dependent variable as a function of the predictors, but without the lagged response and the time dummies, since we only have initial time period here. This model is regarded as when *i=0* can be specified as:

$$E_{0jk} = \gamma_{000} + \gamma_{001} Y_k^c + \gamma_{002} P_k^c + \gamma_{020} Y_{jk} + \gamma_{03} P_{jk} + \nu_{0k} + \delta_{0jk} + \varepsilon_{0jk} \qquad (2.8)$$

where $\nu_{0k} \sim N(0, \sigma_v^2)$ and $\delta_{0jk} \sim N(0, \sigma_u^2)$ as given above, and $\varepsilon_{0jk} \sim N(0, \sigma_{0\varepsilon}^2)$.

It is important to point out that the remaining disturbance terms at subsequent period, that is, $i > 0$ and the initial period, that is, i=0 are not equal (that is $\sigma_\varepsilon^2 \neq \sigma_{0\varepsilon}^2$). This is

[12] The approaches discuss in this paper are for binary response models, but they can also be adopted for continuous response models. Moreover, interested readers may see Kazemi and Crouchley (2006), Crouchley et al. (2009; Chapter 11) for other approaches.
[13] See appendix A1 for the technical notes.

simply because the variance of the residuals of subsequent responses E_{ijk} condition on the covariates $\boldsymbol{X}_{ijk}$ and the lagged response $E_{i-1,jk}$ is different from the variance of the residual of initial responses E_{0jk} which is condition on the covariates $\boldsymbol{X}_{0jk}$ only. In other words, the residual in the initial period is related to the explanatory variables of initial period, while the residuals of the subsequent period are related to the explanatory variables at subsequent period, $\boldsymbol{X}_{ijk}$ and the lagged response, $E_{i-1,jk}$. Since Eq. (2.8) for initial response E_{0jk} and Eq. (2.7) for response E_{ijk} shared the same industry (i.e., δ_{0jk}) and country (i.e., ν_{0k}) random effects therefore, they must be jointly estimated.

For estimation purposes, we create a time period indicators that distinguishes the initial period (i=0) coded as w_1 from the subsequent periods (i > 0) coded as w_2. The time period indicator w_1 is coded as 1 for i=0 and 0 otherwise. The time period indicator w_2 is coded as 1 for i > 0 and 0 otherwise. Then, we interact w_1 with the predictors in Eq. (2.8) and interact w_2 with the predictors in Eq. (2.7). Both models for i=0 and i > 0 are therefore jointly specified as one model as follows:

$$\begin{aligned} E_{ijk} = \gamma_{000}w_1 + \gamma_{001}w_1Y_k^c + \gamma_{002}w_1P_k^c + \gamma_{020}w_1Y_{jk} + \gamma_{03}w_1P_{jk} + \beta_{000}w_2 \\ + \beta_{001}w_2Y_k^c + \beta_{002}w_2P_k^c + \beta_{010}w_2E_{i-1,jk} + \beta_{020}w_2Y_{jk} + \beta_{03}w_2P_{jk} \\ + \beta_{100}w_2D_{ijk} + \nu_{0k} + \delta_{0jk} + \epsilon_{ijk} \end{aligned} \tag{2.9}$$

where $\nu_{0k} \sim N(0, \sigma_v^2)$, $\delta_{0jk} \sim N(0, \sigma_u^2)$ and the estimated variance for level-1 residual ϵ_{ijk} is decomposed into $\varepsilon_{0jt} \sim N(0, \sigma_{0\varepsilon}^2)$ and $\varepsilon_{ijt} \sim N(0, \sigma_\varepsilon^2)$ by defining groups based on w_1. It is worth pointing out that Eqs. (2.7), (2.8) and (2.9) are interrelated by substitution. If w_1 and w_2 are substituted as 0 and 1 respectively into Eq. (2.9) that gives Eq. (2.7), and If w_1 and w_2 are substituted as 1 and 0 respectively into Eq. (2.9) that gives Eq. (2.8). Ultimately, the model of interest is Eq. (2.7) when i > 0, that is, when $w_1 = 0$ and $w_2 = 1$ in Eq. (2.9) as it relates to the time period of our analysis. The inclusion of model 2.8, (i.e., when $i = 0$) becomes imperative only for controlling for the initial conditions problem. Hence, only the results for $i > 0$ in Eq. (2.9) will be presented in the analysis section.

2.4 Data

The main source of data for the emprical analysis is World Input-Output Database (WIOD) (Timmer et al., 2015)[14]. The WIOD is based on national accounts data and it provides a comprehensive, harmonized dataset that allows comparison of specific environmental indicators like sectoral energy use over the years covered by the database (1995 to 2009). The WIOD has two advantages with respect to existing data sources as suggested by Voigt et al. (2014)[15]. First, the harmonization procedures undertaken throughout the data collection minimize the risks of measurement errors. Moreover, the consistence in data collection and comparability across countries describes the data efficiency gains at the sectoral and global levels. Second, the WIOD provides data on sectoral price deflators. This allows for the retaining of important information and variations with respect to price development, which is an advantage over the use of aggregate national price deflators in sectoral analysis.

The empirical analysis is based on a fully balanced sample of industries[16] at three- and four-digit level using International Standard of Industrial Classification (ISIC) Rev.4, which is consistent with NACE Rev.2 across 29 European countries[17] over the

[14] This study obtained data from the three major accounts of the WIOD, the National Input-Output Tables (NIOT) released in November 2013, Environmental Accounts (EA) released in March 2012 and the Socio-Economic Accounts (SEA) released in July 2014. Data downloaded from these accounts are available at www.wiod.org

[15] Other studies that have also obtained energy data from WIOD include: Hübler and Glas (2014), Kaltenegger et al. (2017) and Loschel et al. (2015).

[16] In the interest of balanced panel data and reliable estimates, sectors without data on energy use were excluded from our analysis and all the 34 sectors are listed in the appendix.

[17] The 29 EU countries comprises Austria, Belgium, Bulgaria, Cyprus, Czec Rep, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta,

sample period 1995–2009. Data on purchasing power parity exchange rates (US$) are taken from Penn World Table (PWT 7.1). Industry energy use (e) in terajoule (TJ) is taken from the Environmental Accounts of WIOD, 2012. Industry output is measured as gross output by industry at current market prices in millions of national currency, and data is taken from the Socio-Economic Accounts of WIOD, 2014. To generate the real output (y), we deflated the gross output using the price index of gross output (1995=100) obtained from the SEA of WIOD, 2014. In order to express the real output in international monetary unit, we used the purchasing power parity taken from the Penn World Table (PWT7.1) to convert the real output in national currencies to international units (US$). Since there is no ready-made data on industry price of energy from data sources, we therefore follow a similar process adopted in Adetutu et al., (2016) to generate the price of energy. The real price of energy (p) is computed as the ratio of energy input expenditure at constant prices in US$ to energy use in TJ. Energy input expenditure is computed as the addition of the value of expenditure on coke, refined petroleum, nuclear fuel, electricity and gas supply purchased domestically and internationally (millions of US$). Data on the energy commodities are taken from the National Input-Output Tables (NIOT) of the WIOD, 2013. To derive the real price of energy in US$, we deflated the energy expenditure by constant unit (1995=100), and then divided the real energy expenditure by energy use in TJ.

Table 2.1 Descriptive statistics of variables used in the analysis.

Description	Variable	Mean	Std. Dev	Min	Max
Energy consumption in TJ	E	117125.8	396875.4	42.69	3109309
Industry real energy price in US$/ TJ	P	1.59	2.36	0.002	16.01
Industry real output in US$	Y	19230.86	37032.64	11.97	206776
Country real energy price in US$/TJ	P^c	1.59	1.78	0.004	14.91
Country real output in US$	Y^c	19230.86	28886.28	29.32	123376

Netherlands, Poland, Portugal, Romania, Russia, Slovak Rep, Slovania, Spain, Sweden, Turkey and United Kingdom.

2.5 Empirical analysis

This section discusses the results of the models estimated and all variables estimated are in their natural logarithm. We employ the GMM and DMM to estimate Eq. (2.9) for all sectors as a whole and also separately for primary, manufacturing and service sectors[18]. For straightforward interpretation, we centred the industry-level variables on the log of their group means (country-level)[19] so that the coefficients of the industry-level and country-level variables can be interpreted as the within-country (or between-industry) and between-countries elasticities. We present the parameter estimates of the GMM and DMM estimators in Tables 2.2 and 2.3 respectively, for the sectors as a whole and in the restricted samples. Unlike the initial DMM (model 2.7) the GMM does not suffer from the endogeneity problem of the correlation of the lagged response and the disturbance term that could result to a biased and inconsistent estimate. However, the GMM is not an estimator specifically designed to control for cluster-level heterogeneity resulting from hierarchical data and consequently not an estimator suitable to analyse multilevel model. This is simply because the GMM can only automatically control for a given level of heterogeneity at the level of the data in which the identifiers are based on.

Since our analysis is based on industry data, therefore our identifiers are based on industry rather than country. This implies that the GMM automatically controls for heterogeneity across industries only and consequently might produce unreliable estimates. Generally, we acknowledged the fact that other unobserved heterogeneity (e.g., country-specific and time-specific effects in our analysis) could also be controlled for in the GMM by introducing dummies into the estimated models, but the models

[18] The classifications of the sectors into primary, manufacturing and service sectors are listed in the appendix.
[19] Henceforth, we shall interchangeably use contextual variables as country-level variables.

becomes very unlikely to analyse when the size of the sub-units (e.g country and time period) are very large[20]. Besides, the DMM does not only account for heterogeneity across all the sample units, but also produces random-effect results which provide information about the extent of unobserved heterogeneity across the sample units. Given the above argument, we choose the DMM as our preferred model and hence, we discuss the DMM result in much more detail. Nevertheless, our discussions of the estimated results start with the GMM results.

2.5.1 Discussion of the estimated GMM results

The estimated GMM results for model 2.9 for the sectors as a whole and for different sectors are reported in Table 2.2. We account for the country-specific and time-specific effects by incorporating country and time dummies into models estimated, while the industries heterogeneity is accounted for by demeaned the industry level variables. Given the fact that the two-step GMM estimator produces asymptotic efficiency gains over the one-step estimator, especially in large samples; we therefore employ the two-step estimator[21]. As the estimated standard errors from GMM otherwise tend to be underestimated, we use the robust standard error option throughout. As display in Table 2.2, all estimated models pass all the diagnostic tests (no autocorrelation at first difference, valid instruments and valid over-identifying restrictions) as none of the tests is statistically significant. As pointed out in the empirical model section, we test for the importance for allowing for the underlying nonlinear forces in our model by performing a restriction test between the unrestricted model (that is, models with time dummies) and restricted model (without time dummies) using a χ^2-Test. In other words, this

[20] This situation is similar to the issue discussed in Wooldridge (2009) when using pooling regression to control for fixed specific-effect.
[21] It is worth noting to point out that we employ one-step estimator to analyse the primary sector energy demand because its sample size is relatively small.

imposes the null hypothesis restriction that the coefficients on the time dummies are equal to zero (H0: β_{100}=0) that is, there is no importance for allowing for the underlying nonlinear forces in the estimated energy demand models. For all models estimated, our results support the importance for allowing for the underlying nonlinear forces in energy demand model by rejecting the null hypothesis that the coefficients on the time dummies are statistically equal to zero. This result is in line with the outcome suggested by Adeyemi and Hunt (2007 and 2014).

The primary results derived from the estimated GMM are as follows. First, majority of the estimated variables are statistically significant with expected signs across board while none of the intercepts is statistically significant with mix signs and relatively large values. Of course, the negative intercepts would have been difficult to justify, if they were statistically significant as this would have been interpreted that the expected demand for energy by industries with no influence from economic activity and energy price is negative. With the exception of the between-country output elasticity for the primary sector, the statistically significant of all other estimated elasticities suggest that both industry-level and country-level economic activities and energy prices influence industrial energy demand. Further, in general, the values of the between-industry price elasticities and between-country price elasticities are largely not different across the board. This suggests that there is no substantial difference on average, between the influence of industry-level energy prices and country-level energy prices on industrial energy use. For the whole sector, the coefficient on the industry-level energy price of about –0.30 suggests that a 1% increase in within-country energy price is associated with a –0.30% reduction in within-country energy use in the short-run. Whereas the coefficient on the country-level energy price of about –0.29 suggests that a 1% increase in between-country energy price is associated with a –0.29% reduction in between-country energy use in the short-run. However, our results suggest otherwise in the case of output elasticities as the coefficients of between-industry and between-country output elasticities differ in most cases across board.

Table 2.2 Estimated generalized method of moment (GMM)

Variables	All Sectors	Primary Sector	Manufacturing Sector	Service Sector
Intercept	−8.94	10.95	−5.69	−0.69
	(48.95)	(39.29)	(54.48)	(0.38)
Industry level variables				
$E_{i-1,jk}$	0.67***	0.23***	0.39***	0.91***
	(0.25)	(0.09)	(0.10)	(0.02)
Y_{ijk}	0.46***	0.41***	0.46***	0.06***
	(0.14)	(0.11)	(0.15)	(0.14)
P_{ijk}	−0.30***	−0.21*	−0.33***	−0.11***
	(0.06)	(0.10)	(0.08)	(0.02)
Country level variables				
Y_k^c	0.58**	0.43	0.87***	0.17***
	(0.22)	(0.29)	(0.29)	(0.05)
P_k^c	−0.29***	−0.36***	−0.47***	−0.10***
	(0.06)	(0.14)	(0.13)	(0.02)
Diagnostic Tests:				
Arellano-Bond test AR(2)	0.89	0.36	0.18	0.14
Sangan/Hansen test	0.06	0.99	0.64	0.13
Hansen exogeneity Test	0.98	0.99	0.12	0.13
Restriction test (H0: D_i=0)	χ^2(12)=75.5	χ^2(12)=33.5	χ^2(12)=46.0	χ^2(12)=112.8
	(0.00)***	(0.00)***	(0.00)***	(0.00)***
Sample size	12779	754	6006	6019
Number of instruments	210	207	197	464
Long-run elasticities				
Income	1.41	0.54*	0.75*	0.68*
	(0.74)	(0.15)	(0.18)	(0.16)
Energy price	−0.91	−0.27	−0.54*	−1.21*
	(0.61)	(0.14)	(0.07)	(0.13)

***, ** and * represent statistically significant at 0.1%, 1% and 5% level of significance respectively. $LR = \frac{\delta_x}{1-e_{i-1,jk}}$ $x = Y_{ijk}, P_{ijk}$. Standard errors are in parentheses

For the estimated long-run elasticities, most of the estimated long-run elasticities are inelastic with majority being statistically significant with expected signs across the board[22]. Specifically, to the whole sector, neither the output elasticity (1.41), nor the price elasticity (−0.91) is statistically significant with both relatively have huge values

[22] We find the coefficient on the lagged response for the service sector to be relatively big compare to other sectors. One possible explanation for this outcome may be the difference among the sectors as the industries in the service sector tend to be more associated with previous energy use.

compared to the elasticities derived for different sectors with the exception of service sectors' estimated long-run price elasticity (−1.21). The huge difference in the values of the estimated long-run elasticities for the whole sector, and those derived from sector types is an issue of concern. This is because in principle, the estimated long-run elasticities for the whole sector is expected not to be too far away from the average of the estimated long-run elasticities of the sector types. Our results show that the estimated long-run output elasticity for European industries (1.41) is substantially larger than the average of the estimated long-run output elasticities of the sector types (0.66) by 75%. Our results also show a similar pattern in the price elasticity as the estimated long-run price elasticity (−0.91) is larger than the average (0.67) of the sector types by about 23%. A possible explanation for the difference in values between the estimated long-run elasticities for the sector as a whole and the sector types may be the fact that the GMM is not an appropriate estimator to analysis data with a hierarchical structure as it fails to appropriately account for the multilevel structure of the data. These results again raise the concern about the appropriateness of GMM in estimating energy demand model using hierarchical data.

Generally, we find the long-run output elasticities ranging from 0.54 to 1.41 to be larger than the estimated long-run price elasticities ranging from −0.27 to −1.21. The relatively large value of the output elasticities to the price elasticities suggests that across all the classifications of sectors, industries are more sensitive to changes in economic activity than to changes in energy price in terms of their energy consumption.

2.5.2 Discussion of the estimated DMM results

We estimated Eq. (2.9) for the sector as a whole and for the sector types using the DMM and the results are reported in Table 2.3. Although, it is difficult to statistically demonstrate that the DMM is superior to the GMM in estimating an energy demand function, but we nonetheless again emphasize that the DMM controls for the hierarchical structure of the data used in this paper, and for this, we consider the DMM as the best modelling technique for our analysis.

Table 2.3: Estimated dynamic multilevel model (DMM)

Variables	All Sectors	Primary Sector	Manufacturing Sector	Service Sector
Fixed part:				
Intercept	0.72***	1.12***	1.91***	1.10***
	(0.09)	(0.24)	(1.15)	(0.11)
Industry level variables				
$E_{i-1,jk}$	0.66***	0.57***	0.57***	0.69***
	(0.01)	(0.02)	(0.01)	(0.01)
Y_{ijk}	0.28***	0.29***	0.36***	0.18***
	(0.01)	(0.02)	(0.01)	(0.01)
P_{ijk}	–0.23***	–0.22***	–0.33***	–0.15***
	(0.00)	(0.02)	(0.01)	(0.01)
Country level variables				
Y_k^c	0.29***	0.37***	0.25***	0.20***
	(0.01)	(0.03)	(0.01)	(0.01)
P_k^c	–0.17***	–0.19***	–0.14***	–0.13***
	(0.01)	(0.01)	(0.01)	(0.01)
Random part:				
σ_v^2	0.09*	0.14*	0.15*	0.05*
	(0.03)	(0.04)	(0.04)	(0.02)
σ_u^2	0.09*	0.03*	0.16*	0.06
	(0.00)	(0.01)	(0.02)	(0.01)
σ_ε^2	0.03*	0.02*	0.03*	0.03*
	(0.00)	(0.00)	(0.00)	(0.00)
$\sigma_{0\varepsilon}^2$	0.44*	0.25*	0.35*	0.45*
	(0.02)	(0.05)	(0.03)	(0.03)
ICC	0.44	0.74	0.44	0.39
Restriction tests				
H0: D_i=0	$\chi^2(13)$=570.7	$\chi^2(13)$=80.8	$\chi^2(13)$=219.9	$\chi^2(13)$=342.2
	(0.00)***	(0.00)***	(0.00)***	(0.00)***
H0: β_{001}=β_{002}=0	$\chi^2(2)$=1260.5	$\chi^2(2)$=193.4	$\chi^2(2)$=354.4	$\chi^2(2)$=457.9
	(0.00)***	(0.00)***	(0.00)***	(0.00)***
Long-run elasticities				
Income	0.81*	0.67*	0.83*	0.58*
	(0.02)	(0.04)	(0.02)	(0.03)
Energy price	–0.68*	–0.52*	–0.77*	–0.49*
	(0.11)	(0.04)	(0.01)	(0.02)

***, ** and * represent statistically significant at 0.1%, 1% and 5% level of significance. Intra-class correlation coefficient $(ICC) = \frac{\sigma_v^2}{\sigma_v^2+\sigma_u^2+\sigma_\varepsilon^2}$ and $LR = \frac{\delta_x}{1-e_{i-1,jk}}$ $x = Y_{ijk}, P_{ijk}$. Standard errors are in parentheses.

The DMM results reported in Table 2.3 consist of the fixed part where the estimates of the explanatory variables estimated are presented and the random part where the results of the random unobserved heterogeneity are presented. Unlike the GMM, all estimated parameters of the DMM are statistically significant with expected signs inclusive the estimates of the random part. As carried out in the GMM, we also test for the importance for allowing for the underlying nonlinear factor in the DMM using the χ^2-Test. The DMM results across all sector types also support for allowing for the underlying nonlinear factors while estimating energy demand by rejecting the null hypothesis that the coefficients on the time dummies are statistically equal to zero (that is, H0: β_{100}=0) at 0.1% significant level. The primary results derived from the DMM models estimated are as follows.

First, the statistical significance of the coefficients on all the country-level variables reported in Table 2.3 for the whole sector and sector types emphasize the important roles of aggregate activities on industrial energy use. Given the statistical significance of the contextual variables, the result suggests that industries are not operating in isolation as aggregate economic activities evidenced to influence the energy consumption of industries. For robustness check on the importance of the country-level explanatory variables in the models estimated, we perform a restriction test using the χ^2-Test to test the null hypothesis that the coefficients on the country-level variables are jointly statistically not different from zero (that is, H0: β_{001}=β_{002}=0). In all models estimated, our results reject the null hypothesis that the contextual variables are not statistically different from zero at 0.1% level of significance. This outcome thus reinforces the importance of controlling for the country-level variables while estimating industrial energy demand with industry-level data as failure to do so may lead to biased energy demand elasticities. Second, the difference between the size of the within-country and between-country elasticities provides important information about the extent of the relationship between energy and the explanatory variables. Across board, the relationship between energy and output is the same at industry-level and country-level by looking at the difference between the average of the within-country output elasticity 0.27 and between-country output elasticity 0.27. However, this is not the case if will consider individual sector type. For instance, for the primary sector, the relative size of the within-country income elasticity 0.29 to its corresponding between-country income elasticity 0.37 indicates that the relationship between energy and income is stronger at the aggregate level than industry level, but otherwise in the manufacturing sector. In general, the within-country price elasticity is larger in value than its corresponding between-country price elasticity in all models estimated. For price elasticity across board, the average elasticity of the within-country price 0.23 and its corresponding average elasticity of the between-country price 0.16 suggest that the relationship between energy and own-price is stronger at the industry level by 7%. One possible explanation for this might be that industries are more sensitive to changes in local energy prices as they can alter their input use combination than a change in national energy price.

In addition, we can also infer from the results reported in Table 2.3 that the values of the estimated short-run price elasticities and short-run output elasticities for the all sectors and primary sector are somewhat similar. However, this is not the case in comparison, especially with the short-run elasticities for the service sector as the short-run elasticities for the manufacturing sector in some cases somewhat similar in values to that of the all sectors and the primary sector[23]. For instance, the short-run estimated within-country output elasticity for the all sectors and the primary sector are 0.28 and 0.29 respectively. This result indicates that a 10% increase in output is associated with about 2.8% and 2.9% increase in the energy consumption of the all sector and primary

[23] We do not find this kind of similarity in the estimated GMM reported in Table 2.2 as we find the short-run elasticities across different models estimated to be considerably differs in most cases.

sector respectively. This suggests that the impact of a change in the economic activity on the energy consumption of the primary sector and that of European industry as a whole is almost the same. The implication of this result is that a change in energy consumption of the primary sector is largely associated with a change in the energy consumption of the European industry as the degree of responsiveness of the primary industry resulting from a change in price or output is similar to that of the industry as a whole. For the price elasticity, the short-run estimated within-country price elasticity for the all sectors and primary sector are –0.23 and –0.22 respectively, suggesting that a 10% rise in energy price is associated with about 2.2% and 2.3% reduction in energy consumption of the sectors as a whole and the primary sector respectively.

We now focus on the results of the random part of the estimated DMM reported in Table 2.3. The information provided by the results of the random part allows us to demonstrate the strengths of multilevel modelling in terms of its ability to account for and separate the unobserved heterogeneity at different levels of the data, which single-level models such as GMM and fixed effect will overlook. As argued earlier, we would like to emphasize that failure to account for the cluster level of the data may lead to unreliable estimates. The results of the random part reported in Table 2.3 explain the unobserved cluster level heterogeneity in our models. The disturbance terms σ_v^2, σ_u^2 and σ_ε^2 represent country-differences, industry-differences and time-differences and they measure the changes in energy consumption with respect to differences in- country, industry and time respectively. Our results show that all estimated disturbance terms reported in Table 2.3 are statistically significant. Specifically for the whole sector, although, the statistical significance of the coefficients on unobserved terms σ_v^2=0.09, σ_u^2=0.09 and σ_ε^2=0.03 demonstrate the importance of country, industry and time variations to changes in European industrial energy consumption, but we are very much interested to measure the role of country differences in energy consumption. To measure the extent of contextual effects in determine European industrial energy consumption, we employ the intra-class correlation coefficient (ICC). The coefficient of the ICC 0.44 suggests that 44% of the unexplained variations in industrial energy use in Europe are traceable to between-country differences. In other words, the differences in energy use by industries are to some reasonable extent affected by aggregate indicators.

The ICC for the manufacturing and service sectors are very similar to that of the whole sector, implies that the differences in energy use of these sectors are to some meaningful extent characterised by aggregate activities. However, the results of the random part of the primary sector prove otherwise as the ICC (0.74) suggests that about 74% of the unobserved variations in energy use of the primary sector are traceable to between-country differences rather than between-industry difference. In other words, industries in the primary sector are largely tied to their respective country. One possible explanation for this strong relationship between the primary sector and their respective aggregate activities may be because of the strong role of the government in industries such as the agriculture, fishing and forestry, which form the major part of the primary sector. For this reason, they are likely to be more sensitive to changes in macroeconomic policies[24].

The estimated long-run elasticities derived from energy demand functions have retained energy demand modelling as an important area of interest in the literature. This is because these elasticities have served as important tools for the policy makers in making appropriate predictions about future energy use and energy related policies. This subsequently highlights the potential implications of energy related policies based

[24] Interestingly, *The Economist* (2017) emphasised the danger for UK farmers that they may be among the first to feel the effects of Brexit as UK agriculture is heavily reliant of foreign workers and they may not be available for long.

on inaccurate estimates, which are very likely to be misleading or inappropriate. In respect to this argument, we now discuss the estimated long-run income and price elasticities reported in Table 2.3. Unlike the estimated GMM long-run elasticities, all estimated DMM long-run elasticities reported in Table 2.3 are statistically significant with expected signs. Our results show that the European industrial energy demand is income-inelastic with an estimated long-run elasticity 0.81 and also price-inelastic with estimated price elasticity –0.68. The results indicate that a 10% rise in income and in price is associated with 8.1% rise and 6.8% reduction respectively in European industrial energy consumption on average in the long-run. In terms of the elasticity of economic activity, our value is similar to that of Dimitropoulous et al. (2005). Our income elasticity 0.81 is almost the same of the average income elasticity 0.76 for the UK manufacturing and transport sector obtained in Dimitropoulous et al. (2005). However, they obtained average price elasticity –0.11, a value smaller to ours –0.68. The value of our long-run price elasticity –0.68 is almost identical to the price elasticity –0.64 obtained in Agnolucci (2009) for the British and German industrial sector[25].

The relative big value of the estimated income elasticity (0.81) compare to the price elasticity (–0.68) in absolute terms suggests that European industrial energy demand is more responsive to changes in economic activity than to changes in energy price. For the subsectors, we find the price elasticity of energy demand for the primary, manufacturing and service sectors to 0.67, 0.83 and 0.58 respectively. Further, the long-run price elasticities for these sectors are −0.54, −0.77 and −0.49 respectively. The results show that the long-run elasticities of the manufacturing sector are markedly higher than the long-run elasticities of other sector types. This is reasonable, as we

[25] However, we advised that one should be exercise caution when comparing our estimates to Dimitropoulous et al. (2005) and Agnolucci (2009) due to differences in scope, data and econometric methodology employed.

would expect the considered largest energy-consuming sector (manufacturing) to be more sensitive to change in energy price and economic activity relative to other sectors.

By comparing the long-run elasticities of the sector types, our results show that the DMM long-run output elasticities reported in Table 2.3 are somewhat similar in values to that of the GMM, reported in Table 2.2. However, with the exception of the service sector, the estimated DMM long-run price elasticities for the primary (−0.52) and manufacturing (−0.77) sectors are bigger in absolute value than their corresponding estimated long-run price elasticities derived from the GMM (−0.27, −0.54). Therefore, in general, one would have expected the estimated GMM long-run price elasticity −0.91 for the whole sector (however, not statistically significant) to be smaller than that of the DMM −0.68 in absolute terms, but it is otherwise. This is due to the large value of the service's sector price elasticity −1.21 reported in Table 2.2. This is an intriguing finding suggesting that estimates derived from a model using industry-level data that fails to control for the multilevel structure of the data may be unreliable as in the case of the GMM. Further, the whole sector's estimated long-run income 1.41 derived from the GMM, though, not statistically significant is again larger the value obtained in DMM 0.81. This further reinforces our argument that failure to account for the underlying multilevel structure of the data may lead to unreliable estimates in form of overestimation or underestimation.

2.6 Conclusion and policy implications

Given the pivotal role energy plays in the process of economic development and the continuation of economic growth, especially in modern industrialised countries, its absence or shortage (of course) is expected to cause nothing but a serious damage to the production processes and consequently retards economic growth and standard of living.

However, rapid economic growth or sustainable growth is associated with an increase in energy use that typically results in higher carbon and particulate emissions. The devastating impact of increasing emissions therefore requires accurate projections of future energy demand, which are necessary in order to understand and address issues relating to energy security, resource planning, trans-boundary emissions, etc. Thus, the improved energy demand parameters provided by our dynamic multilevel modelling approach should be seen as significant tools for policymakers.

This chapter employs a dynamic multilevel model and GMM estimator to analyse industrial energy demand across European countries for the period 1995 – 2009. The energy demand model specified allow for the underlying non-linear forces that might influence the energy demand estimates as pointed out in the literature. In all models estimated, our findings are in the body of evidence in the literature by supporting the fact that it is important to allow for the inherent underlying non-linear forces in the energy demand model. Further, to a meaningful extent, we confirm that the DMM performs better than the GMM in terms of the estimated parameters that are statistically significant. Moreover, we would also like to reiterate that, unlike the GMM, our dynamic multilevel model controls for the hierarchical structure of the data used in the analysis by assigning disturbance terms to each level of the data. Given the advantages of the DMM over the GMM within the context of this study, we chose the DMM as our preferred choice of modelling technique.

The preferred model reveals that the European industrial energy consumption is significantly influenced by the country-level variables given the statistically significant of the estimated country-level variables. This result is reinforced by the result of ICC in the DMM (0.44), suggesting that about 44% of the unexplained variations in industrial energy consumption are traceable to between-country differences. Moreover, we find

European industrial energy demand to be both income- and price-inelastic with estimated long-run elasticities of 0.81 and –0.68 respectively. However, the long-run elasticities generated from the alternative model, although not statistically significant, but are substantially overestimated with estimated income and price elasticity 1.41 and –0.91 respectively. This is an intriguing finding demonstrating that unless energy demand models using industry-level data are formulated to allow for the multilevel structure of the data, the estimated income and price elasticities could be seriously biased.

Our findings have some policy implications. To start with, this chapter does not only introduced a new method of modelling energy demand, but also highlights the need for more sophisticated modelling of energy demand if policy makers seek to formulate appropriate policies related to energy security and climate change. This is because; any energy-related policy based on inaccurate energy estimates is very likely to be misleading or inappropriate. Moreover, given the importance for controlling for the hierarchical structure of data while using industry energy data as demonstrated in this study, we argue that it is imperative that future industry level energy demand studies account for the hierarchical structure of the data. This is to prevent energy policy making being based on industry level evidence that substantially inflates the responsiveness of long run energy demand to income and price changes. In addition, the difference in the magnitude of the long-run price elasticities of demand for the sector types suggests that the degree of responsiveness of industry to changes in energy price differ. From the policy perspective, this suggests that any policy being targeted to increase energy price with the intention to reduce energy consumption/increase in energy-saving is not very likely to produce desirable result in some industries as we find in the service sector with an estimated elasticity of –0.49. We therefore argue that it is important to consider the characteristics of the sectors while formulating energy related policy. Also, as the preferred model indicates relatively large long-run income elasticity, this suggests that European industries are more responsive to changes in economic activities. However, despite the relatively lower estimated long-run price elasticity in our preferred model, the results still suggest that policy responses influencing energy prices are likely to be effective in reducing energy consumption. More importantly, the main result drawn from this research suggests that controlling for the hierarchical structure of the energy data is imperative if European policy makers wish to make more appropriate predictions about future energy use and associated carbon emissions. We hope that our findings would be a blueprint for other developed countries.

With respect to further research, we hope that future studies will extend this work by estimating household energy demand and make appropriate predictions about future household energy use and emissions, which can help in policy making.

Chapter 3 Applied Econometrics to Factor Substitution with Implications for Carbon Intensity: Evidence from China's Accession to the WTO

3.1 Introduction

The growing concern about the devastating impacts (e.g., global warming and acidic rain) of increasing anthropogenic greenhouse gases (GHGs) has motivated governments, institutions and researchers to look for a long-lasting solution in reducing CO_2 emissions. Since CO_2 emissions account for half of the anthropogenic contribution to GHGs (Floros and Vlachou, 2005) therefore, reduction in CO_2 emissions could be considered as a good measure of dealing with the rising effects of climate change on environment and people's livelihood. Among available measures, energy saving is seen as a key in reducing CO_2 emissions via reduction in energy consumption in the energy-emissions literature. Of course, in practice, energy saving could be in form of energy efficiency or energy substitution. In particular, the latter allows firms/industry to substitute from the use of CO_2 intensive fuels and towards the use of low carbon intensive fuels and factors.

According to World Bank (2009), the increase in global CO_2 emissions in recent decades is linked to the fast growing of the emerging economies notably China. The drastic increase in China's CO_2 emissions in recent years has been characterised by her increase in energy consumption with a staggering consumption of 119.67quadrillion BTU (IEA, 2015) because of rapid economic growth with an annual increase in GDP of 6.8% from 1989–2017 and. In 2008, China became the world's largest emitter of CO_2 emissions by overtaking the United States and China's CO_2 emissions account for about one third (28%) of global CO_2 emissions (IEA, 2015). Besides the rapid economic growth, China's exports have also been regarded as a crucial contributor to China's CO_2 emissions as more energy is being utilised to meet increasing exports (Weber et al., 2008; Yungfeng and Laike, 2010). In 2014, China surpassed the US to become the world's largest merchandise trader with foreign trade amounted to 43 billion US dollars according to World Trade Organisation (WTO). As the world's largest exporter, China exports were worth US$2.119 trillion across the globe in 2016. This accounts for about 13.1% of the global exports estimated at US$16.236 trillion in 2016. These figures demonstrate that China has substantially benefited from its vast trade surplus. However, the benefits associated with China's trade surplus are at the expense of the environment. Given the connection between energy substitution and the environment, thus, an exploratory analysis of energy substitution effects of trade would help in understanding the extent of factor substitution that is induced by trade.

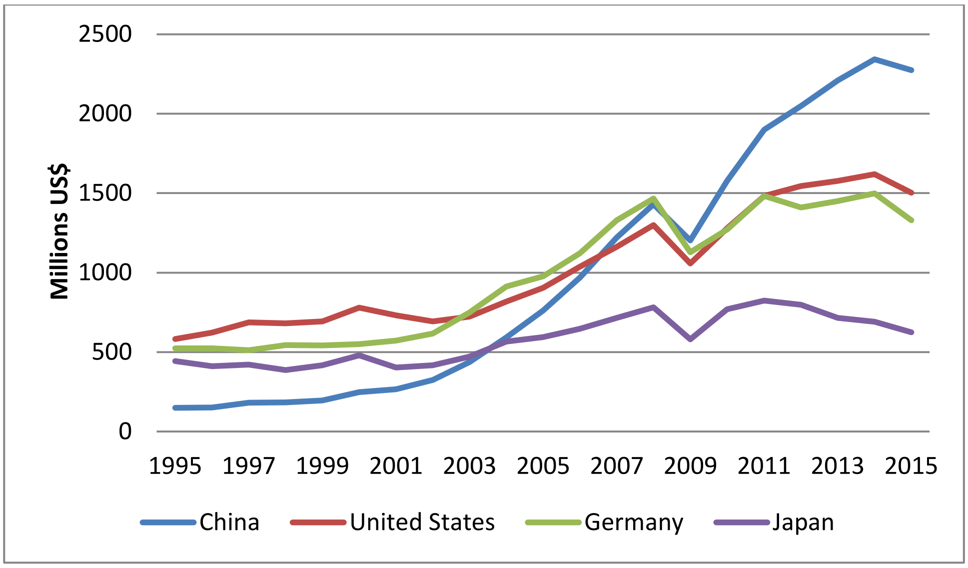


Figure 3.1: China's export in comparison to Germany, Japan and US

Source: World Trade Integrated Solution, World Bank

Arguably, the rise in China's trade surplus in recent years can be traced to China's accession to the WTO in December 2001. As a result, China's production related energy use has increased. Zhang and Lahr (2014) argue that about 26.6% of the increase in China’s production-related energy use is because of increase in exports between 2002 and 2007. In these 5 years, exports rose faster than immediate past 15 years in total with an average annual rate of 19.6% in exports, a number that almost doubled the previous annual average growth of 11.6%. The trade effects of WTO membership on trade flows are well documented in the literature (Shafaeddin, 2003 and 2004; Rose, 2004 and 2005; Tomz et al., 2007; Subramanian and Wei, 2007; Eicher and Henn, 2011). Fig. 4.1 presents the historical trend of China’s exports in comparison to US, Germany and Japan. In comparison to those of other countries, China’s export has drastically increased since becoming a member of the WTO. Hence, a two-separate period (before and after joining the WTO) analysis would offer an in-depth understanding of trade’s effects on factor substitution. In this regard, this chapter extends the literature of factor substitution by deriving a range of elasticities of substitution (ES) and elasticities of complementarity (EC) rather than focusing on a single ES/EC like extant literature for China for the period before (1995–2001) and after (2002–2009) joining the WTO.

Existing literature on factor/or fuel substitution for China includes Ma et al. (2008 and 2009), Smyth et al. (2011), Su et al. (2012), Lin and Wesseh Jr (2013), Zha and Ding (2014), Yang et al. (2014) Li and Lin (2016) and Ma and Stern (2016). However, none of these studies (i) explored the richness in the theoretical literature of elasticities of substitution and complementarity (Hicks, 1932; Robinson, 1933; Lerner, 1933; Allen, 1934, 1938; Uzawa, 1962; Syrquin and Hollender, 1982; Sato and Koizumi, 1973; Bertoletti, 2005; Stern, 2010) by estimating a range of elasticities as is done in this study; (ii) considered the implications of increasing China’s exports since joining WTO for production factor substitution. In this regard, this study provides new insights to the exiting literature by reaffirming the importance of the theoretical exposition on elasticities of substitution and complementarity with a rich history for exertions that address extant issues. This chapter builds on the work of Stern (2010) and computes ten elasticities of substitution (ES) and complementarity (EC) for Chinese industry before and after gaining access to WTO. The following are the ten ES and EC derived from the translog cost functions, which we shall discuss in details in due course: (i) Allen (1934; 1938)-Uzawa (1962) elasticity of substitution (AES); (ii) Morishima (1967) elasticity of substitution (MES); (iii) Hotelling (1968)-Lau (1978) elasticity of substitution (HLES); (iv) Shadow elasticity of substitution (McFadden, 1963) (SES); (v) Morishima gross elasticity of substitution (MGES) (Mundlak, 1968; Davis and Shumway, 1996); (vi) Antonelli elasticity of complementary (AEC) and (vii) Morishima elasticity of complementary (MEC) (Blackorby and Russell, 1981; Kim, 2000); (viii) Hicks (1970) elasticity of complementarity (HEC) (Sato and Koizumi, 1973); (ix) Pigou (1934) elasticity of complementarity (PEC) and (x) Shadow elasticity of complementarity (SEC) (McFadden, 1963).

We compute these elasticities by adopting a simplified approach that is based on the AES. This is because from the AES we can derive the MES, HLES, SES, AEC and HEC. The MEC and SEC are derived from the AEC, while the PEC and MGES are easily derived from the HEC and HLES respectively. Since each of these elasticities provides different information on substitution (a case where a pair of inputs are (price) p-substitutes or p-complements) and complementarity (a case where a pair of inputs are (quantity) q-complements or p-substitutes) therefore, no single elasticity is preferred in all situations.[26]

[26] Two inputs are p-substitutes (complements) if an increase in the price of one input increases (reduces) the quantity of the other. An increase in a q-substitute (complement) reduces (increases) the marginal product of the other substitutable (complementary) input.

Secondly, this chapter contributes to existing literature of energy and environment by exploring the extent in which energy demand estimates in form of ES can impact carbon emissions, which has not been empirically tested until now, but has an established theoretical background as noted by Saunders, (2009). Specifically, the estimated results of the ES are further applied to carry out an exploratory analysis on the driving forces of Chinese industries' carbon intensity (the amount of CO_2 emissions emit per unit of industrial output) having controlled for other competing factors[27].

China has been increasingly under international pressure to reduce its CO_2 emissions in recent years, and in response the Chinese government intended to reduce its carbon intensity by 40% – 45% in 2020 in comparison to 2005 level. To achieve this objective as well as for global environmental advantages given China's contribution to global anthropogenic GHGs, it is therefore necessary to examine the driving forces of China's carbon intensity and simultaneously investigate the relative effects of factor substitution and technological progress. In regard to existing literature on carbon intensity, Fan et al. (2007) use divisia index decomposition approach to measure the main drivers of China's energy-related carbon intensity between 1980 and 2003. They find that about 90% reduction in China's carbon intensity is associated with a decrease in energy intensity. The authors further advocate that reduction in energy intensity is not sufficient enough for continuing reduction in emissions intensity and should be supplemented with changes in energy mix[28].

In a study similar to Fan et al. (2007) in terms of methodology, Tan et al. (2011) investigate the driving forces of China's carbon intensity for the period 1998–2008

[27] The analysis involved in second contribution is regarded as exploratory as this is the first empirical study (as far as we know) that would examine the impact of ES directly on carbon emissions.
[28] This can be characterized as shifting away from the use of high carbon intensive fuels such as coal or even changes in input mix that is, substituting non-energy inputs for energy inputs.

using logarithmic mean divisia index approach. To help in their investigation, the authors further decomposed emissions intensity into the effects of energy intensity of power generation, energy intensity of GDP, electricity intensity of GDP, provincial structural change and energy consumption ratio. They find that decrease in China's energy intensity in general accounts for 96.4% reduction in carbon emissions intensity, which fell by 29.14% during the period of observation. Ouayang and Lin (2015) also conclude that decrease in energy intensity is the key to reduction in carbon intensity in China. The authors investigate the determinants of Chinese industrial carbon intensity and show that a 1% increase in energy use and fuel consumption is associated with about 0.55% and 0.66% increase in energy-related industrial CO_2 emissions respectively. These findings are similar to those reported in Chang and Lahr (2016), and the authors further advise the Chinese government about their trade policies as it is counterproductive in terms of carbon intensity. On the basis of decomposition of energy share equation derived from a translog cost function, Li and Lin (2007) observed that carbon intensity of China decreased by 60.1% between 1986 and 2012 as a result of factor substitution, which mainly results from the substitution of labour for energy, and technological progress. The findings are reinforced in Wang et al. (2017) as the authors argue that from 2000 to 2009, China's carbon intensity decreased from 2.341 to 2.088 ton/10^3US$, equivalently 89%, which is largely associated with energy reduction.

Give the above discussion; we can deduce that this research is worth considered as it could offer insightful information via an exploratory analysis on the extent in which energy estimates impact of energy substitution on carbon emissions. The remainder of this chapter is organised as follows. Section 2 presents the theoretical specifications of the translog cost function. Section 3 presents the general formula for each of the elasticities of substitution and complementarity computed and then describes the data used for the estimations. Section 4 consists of two parts. The first part presents the results of both the estimated cost function and the elasticities of substitution and complementarity. In the second part, we attribute the driving forces of carbon intensity in terms of the estimated ES and other competing factors. In particular, we present the model specifications for the carbon intensity and subsequently present the results of the model estimated. Section 5 presents the concluding remarks by providing key insights for the China industry on changes in inter-factor substitution and complementarity, and also suggests possible future research.

3.2 Modelling framework: Translog cost function

Let $w \in \mathbb{R}$ be the set of K inputs, indexed $k = 1, \dots, K$, a representative producer uses to produce Y output. The firm's production function can be expressed as follows:

$$y = h(w_1, \dots, w_k, A), \tag{3.1}$$

where A represents the technical change. The function $h(.)$ assumes a production technology where all inputs levels are varied. Under the duality theory, the cost function is regarded as a true dual of the production function, Shephard (1970). That is, the corresponding cost function is also twice differentiable if the production function is twice differentiable.

Under the assumption of perfectively competitive markets for inputs, a standard cost function can be written as follows:

$$c(y, p) \equiv \min_w \{p \cdot w\} \; s.t. \; y = h(w_1, \dots, w_k, A) \tag{3.2}$$

where $p \in \mathbb{R}$ is the set of K input prices, w's represent capital, energy, labour, material, and $c = \sum_{k=1}^{K} p_k \, w_k$ is the total expenditure on inputs. In conformity to microeconomics theory, the cost function specified possesses the following four properties: (i) non-decreasing in p, $\partial c(y,p)/\partial \ln p_k \equiv \eta p_k \geq 0$, where ηp_k is elasticity with respect to kth input; (ii) non-decreasing in y, $\partial c(y,p)/\partial \ln y \equiv \eta y \geq 0$; homogenous of degree one in p, $c(y,tp) \equiv tc(y,p)$ for $t > 0$; (iv) concave and continuous in p, $c(tp + (1-t)p' \geq tc(y,p) + (1-t)c(p',y)$ for $0 \leq t \leq 1$ and for $p \gg 0$.

For the purpose of estimation, we employ a flexible functional form with no a *priori* restrictions of the ES among factors and economic of scale. Although, they are various flexible functional forms in the literature, but we employ the translog function proposed by Christensen et al. (1973). This is because the translog function remains as the most widely used flexible function in the literature. Also, our translog function imposes the fundamental restrictions of symmetry ($\delta_{ij} = \delta_{ji} \forall_{ij}$) and linear homogeneity in input prices ($\sum_{i=1}^{n} \delta_i = 1$; $\sum_{i=1}^{n} \delta_{ij} = \sum_{i=1}^{n} a_Y = \sum_{i=1}^{n} \delta_{i\tau} = 0$). Since we estimate a few model specifications, we also follow the conventional practice by normalized one input price each time we estimate the cost function concurrently with the share equations. That is, we jointly estimated the cost function and three cost share equations in each case. Although, all estimated variables were mean-adjusted, which at least control for a minimum level of sectorial heterogeneity, but further controlled for potential heterogeneity across the sectors by including additional sectorial characteristics. In this regard, a categorical variable is included to indicate a similarity in production technology by classifying the sectors into primary, manufacturing and service sectors[29]. Also, a dummy is added to indicate a sector with multiple production units. These are all comprised in z_t in Eq. (3.3). Our translog cost function is therefore specified as follows:

[29] The classification of the sectors to primary, manufacturing and service sectors can be found in the appendix.

$$\ln C_{it} = a_0 + a_Y \ln Y_{it} + \sum_{i=1}^{n} \delta_k \ln P_{kit} + \delta_t t + \frac{1}{2}\delta_t t^2 + \frac{1}{2}\delta_{YY} \ln(Y_{it})^2$$
$$+ \sum_{i=1}^{n} \delta_{kY} \ln P_{kit} \ln Y_{it} + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \delta_{kj} \ln P_{kit} \ln P_{jit} + \delta_{Yt} \ln Y_{it}\, t$$
$$+ \sum\nolimits_{i=1}^{n} \delta_{k\tau}\, t \ln P_{kit} + z_t + \varepsilon_{it} \qquad (3.3)$$

where i is the number of industries indexed $i = 1, \ldots., N$ that operate over the time period. C is the total cost; Y is output; t is time trend, which captures technical progress; Ps are the input prices as previously defined and ε_t is the residual. The factor share input demand functions can be derived using Shephard's lemma by differentiating Eq. (3.3).

$$S_{kit} = \delta_k + \delta_{k\tau}\tau + \textstyle\sum_{j=1}^{3} \delta_{kj} \ln P_{jit} + \delta_{kY} \ln Y_{it} + \lambda_{it} \qquad (3.4)$$

where S_{kit} is the factor share equation of *kth* input. Eqs. (3.3) and (3.4) are jointly estimated using the iterated seemingly unrelated regression (iSUR) technique given its ability to account for potential correlation of the error terms across the equations.

3.3 Elasticities of substitution and complementarity

Until now the focus has been on the presentation of the translog cost function. This section presents the ten elasticities derived from the estimated cost function Eq. (3.3) and the factor share equations (3.4). The theoretical and methodological presentations of these elasticities of substitution and complementarity are motivated by several existing literature, but in particular Stern (2011). For clarity purposes, the presentation of these elasticities is written in terms of two inputs w_j and w_k from the input vector w.

1. *Symmetric Allen-Uzawa Elasticity of Substitution (AES)*: The AES is commonly regarded as the most popular ES in the literature originally proposed by Allen (1934;

1938) (i.e., the primal AES) before Uzawa (1962) demonstrate how the AES can be derived from a fitted cost function (the dual AES). The AES is a partial elasticity as it measures the change in k if the price j changes. The AES classifies inputs as p-complements if, AES <0 and inputs as p-substitutes if, AES >0. Following Uzawa (1962) presentation of the dual AES, we have.

$$AES_{jk} = \frac{C(y,\boldsymbol{p})\dfrac{\partial^2 C(y,\boldsymbol{p})}{\partial p_j \partial p_k}}{\dfrac{\partial C(y,\boldsymbol{p})}{\partial p_j}\dfrac{\partial C(y,\boldsymbol{p})}{\partial p_k}} = \frac{1}{S_k}\frac{\partial \ln X_j\,(y,\boldsymbol{p})}{\partial p_k} \tag{3.5}$$

For the purpose of estimation, we compute the AES_{jk} from the estimated Eqs. (3.3 and 3.4) in our empirical analysis as follows:

$$AES_{jk} = \frac{\delta_{jk} + S_j S_k}{S_j S_k} \tag{3.6}$$

where S_j and S_k are the estimated cost shares for inputs *j* and *k* respectively. Since our estimations are based on the sample mean, then $S_j = \delta_j$ and $S_k = \delta_k$ given that the quadratic and interaction terms in Eqs. (3.3 and 3.4) are equal to zero at the sample mean.

2. As*ymmetric Morishima Elasticity of Substitution (MES)*: The MES is initially owing to the work of Morishima (1967), but Blackorby and Russell (1975) proposes a popular formula for the MES that is identical to the Robinson's (1933) definition of ES (i.e., changes in input ratio with respect to price ratio while holding output constant).

$$MES_{jk} = \frac{\partial \ln\left(\dfrac{\partial C(y,\boldsymbol{p})}{\partial p_j} \Big/ \dfrac{\partial C(y,\boldsymbol{p})}{\partial p_k}\right)}{\partial \ln(p_k/p_j)} \tag{3.7}$$

Following Blackorby and Russell (1989), for a change in p_j Eq. (3.7) can be specified as follows:

$$MES_{jk} = \frac{p_j\left(\frac{\partial^2 C(y,\boldsymbol{p})}{\partial p_j \partial p_k}\frac{\partial C(y,\boldsymbol{p})}{\partial p_j} - \frac{\partial^2 C(y,\boldsymbol{p})}{\partial p_j^2}\frac{\partial C(y,\boldsymbol{p})}{\partial p_k}\right)}{\frac{\partial C(y,\boldsymbol{p})}{\partial p_j}\frac{\partial C(y,\boldsymbol{p})}{\partial p_k}} = \frac{\partial \ln X_k\,(y,\boldsymbol{p})}{\partial p_j} - \frac{\partial \ln X_j\,(y,\boldsymbol{p})}{\partial p_j} \tag{3.8}$$

where $X_j(y,\boldsymbol{p})$ and $X_k(y,\boldsymbol{p})$ are factor input demand functions from Eq. (3.4). Eq. (3.8) presents the MES between inputs k and j in terms of the function of the cross-price elasticity of the AES. The asymmetric nature of the MES implies that $MES_{kj} \neq MES_{jk}$. For analytical purpose, the MES between two inputs while holding output constant can be expressed in terms of the AES: $MES_{jk} = S_j(AES_{jk} - AES_{jj})$.

3. *Asymmetric Morishima Gross Elasticity of Substitution (MGES)*: Further to the proposition of MES, Mundlak (1968) proposes the gross version of the MES[30]. Under the assumption of cost minimization with output and all input prices held constant, Davis and Shumway (1996) present a unique generalized factor ratio elasticity of substitution (FRES) $\frac{\partial \ln X_k(w,\boldsymbol{p})}{\partial p_j} - \frac{\partial \ln X_j(w,\boldsymbol{p})}{\partial p_j}$, where the demand function for w as the variable of interest is conditioned in a situation beyond the Mundlak (1968) ES. By modifying the FRES, by substituting q for w we have the MGES as follows:

$$\frac{\partial \ln X_k\,(q,\boldsymbol{p})}{\partial p_j} - \frac{\partial \ln X_j\,(q,\boldsymbol{p})}{\partial p_j} \tag{3.9}$$

4. *Symmetric Shadow Elasticity of Substitution (SES)*: McFadden (1963) presents the SES that later observed by Mundlak (1968) under the assumption of constant cost. The SES measures the input substitution along the isocost curve, which can be expressed as the share-weighted average of two MES (Chambers, 1988) or three AES (Stern, 2011). Unlike the MES that is asymmetric, the SES is symmetric because of the constant cost restriction. The SES can be specified as follows:

[30] Blackorby et al. (2007) provide detail discussion of the MGES.

$$SES_{jk} = \frac{\partial \ln\left(\frac{\partial C(y,\boldsymbol{p})}{\partial p_j} \Big/ \frac{\partial C(y,\boldsymbol{p})}{\partial p_k}\right)}{\partial \ln\left(p_k/p_j\right)} \backslash C$$

$$= \frac{-\frac{(\partial^2 C(y,\boldsymbol{p}))/\partial p_j^2}{\frac{\partial C(y,\boldsymbol{p})}{\partial p_j}\frac{\partial C(y,\boldsymbol{p})}{\partial p_j}} + 2\frac{(\partial^2 C(y,\boldsymbol{p})/\partial p_j \partial p_k}{\frac{\partial C(y,\boldsymbol{p})}{\partial p_j}\frac{\partial C(y,\boldsymbol{p})}{\partial p_k}} - \frac{(\partial^2 C(y,\boldsymbol{p})/\partial p_k^2}{\frac{\partial C(y,\boldsymbol{p})}{\partial p_k}\frac{\partial C(y,\boldsymbol{p})}{\partial p_k}}}{\frac{1}{(\partial C(y,\boldsymbol{p})/\partial p_j)p_j} + \frac{1}{(\partial C(y,\boldsymbol{p})/\partial p_k)p_k}} \tag{3.10}$$

Stern (2011) presents an easily computational form of Eq. (3.10), which is expressed as the share-weighted average of three AES. In our empirical analysis we derive the SES using this computational form, which is written as follows:

$$SES_{jk} = \frac{S_j S_k}{S_j + S_k}\left(-AES_{jj} + 2AES_{kj} - AES_{kk}\right) \tag{3.11}$$

5. *Symmetric Hotelling-Lau Elasticity of Substitution (HLES)*: This is the gross version of the AES, introduced by Mundlak (1968) and Lau (1978), but termed as Hotelling-Lau elasticity of substitution by Bertoletti (2005). In comparison with Syrquin and Hollender (1982), Bertoletti (2005) demonstrates the duality between the HLES and the HEC (Hicks Elasticity of Complementarity) and then argues that this dual relationship represents the final piece of the Hicks with respect to ES argument. The HLES interprets substitution inform of between gross p-substitutes and complements. The formula for the HLES is as follows:

$$HLES_{jk} = \frac{\Pi(q,\boldsymbol{p})\frac{\partial^2 \Pi(q,\boldsymbol{p})}{\partial p_j \partial p_k}}{\frac{\partial \Pi(q,\boldsymbol{p})}{\partial p_j}\frac{\partial \Pi(q,\boldsymbol{p})}{\partial p_k}} = \frac{\Pi}{p_k w_k}\frac{\partial \ln X_j\,(q,\boldsymbol{p})}{\partial \ln p_k} \tag{3.12}$$

where Π is the profit function and q is the price of output. This elasticity is also valid for a price vector $\mathbf{q}$ like MGES, HEC and PEC (Pigou elasticity of complementarity). For empirical computation we obtain the HLES from the AES following the formula presents in Bertoletti (2005).

$$HLES_{jk} = \left(\frac{\partial \ln C}{\partial \ln y} - 1\right)\left(AES_{jk} - \frac{\partial \ln X_j / \partial \ln y}{\partial \ln C / \partial \ln y} \frac{\partial \ln X_k / \partial \ln y}{\partial \ln \mu / \partial \ln y}\right) \tag{3.13}$$

where μ is the marginal cost of the translog function, $\frac{\partial \ln \mu}{\partial \ln y} = -1 + \frac{\partial \ln C}{\partial \ln y} + \frac{\delta_{YY}}{\partial \ln C / \partial \ln y}$ and $\frac{\partial \ln X_j}{\partial \ln y} = \frac{\partial \ln C}{\partial \ln y} + \frac{\delta_{jY}}{S_j}$

6. *Symmetric Antonelli Elasticity of Complementarity (AEC)*: Blackorby and Russell (1981) originally derive this elasticity and argues is the true dual of the AES under non-constant return to scale. Kim (2000) further develops this elasticity using the Antonelli substitution matrix of Antonelli (1886). To measure the response to a change in the input quantity w_k the formula of AEC is:

$$AEC_{jk} = \frac{D_{\mathrm{I}}(y, \boldsymbol{w}) \dfrac{\partial^2 D_{\mathrm{I}}(y, \boldsymbol{w})}{\partial w_j \partial w_k}}{\dfrac{\partial D_I(y, \boldsymbol{w})}{\partial w_j} \dfrac{\partial D_I(y, \boldsymbol{w})}{\partial w_k}} = \frac{1}{S_k} \frac{\partial \ln P_j\,(y, \boldsymbol{w})}{\partial \ln w_k} \tag{3.14}$$

The AEC is a net elasticity as it distinguishes between the net q-complements (positive value) and q-substitutes (negative values). To derive the AEC_{jk} in our empirical analysis, we draw on the description in Broer (2004) by using the inverse matrix of the AESs.

$$\begin{bmatrix} \boldsymbol{AEC} & \iota \\ \iota' & 0 \end{bmatrix} = \left[diag(S_1, \ldots., S_n) \begin{bmatrix} \boldsymbol{AES} & \iota \\ \iota' & 0 \end{bmatrix} diag(S_1, \ldots., S_n)\right]^{-1} \tag{3.15}$$

where ι is the column vector of ones and the elements of **AEC** and S_n are obtained as discussed above.

7. As*ymmetric Morishima Elasticity of Complementarity (MEC)*: Blackorby and Russell (1981) and Kim (2000) introduced the complementary version of the Morishima elasticity based on the inverse demand function derived from an input distance function. Since the EC measures a change in quantity of an input, therefore, the MEC measures a change in the price ratio when one of the inputs in a fixed ratio changes while holding

output and all other inputs constant. The MEC is like the AEC as it does not measure substitutability along the efficient frontier. This is because the substitution along the efficient frontier requires changes in the distance for only one input to change while holding output constant. For a change in the quantity of input w_k, the formula for MEC is as follows:

$$MEC_{jk} = \frac{\partial \ln\left(\frac{D_I(y,\boldsymbol{w})}{\partial w_j} \Big/ \frac{D_I(y,\boldsymbol{w})}{\partial w_k}\right)}{\partial \ln\left(w_k/w_j\right)} = \frac{\partial \ln P_k\,(y,\boldsymbol{w})}{\partial \ln w_j} - \frac{\partial \ln P_j\,(y,\boldsymbol{w})}{\partial \ln w_j} \tag{3.16}$$

8. S*ymmetric Hicks Elasticity of Complementarity (HEC)*: This elasticity is owing to the work of Hicks (1970) and is being regarded as the first elasticity of complementarity to be discovered. The initial motivation behind the proposition of the HEC was to be the true dual of the AES and thus expected to mirror the change in the price ratio for a change in the input ratio while holding the quantities of other inputs and the price of output constant. However, Syrquin and Hollender (1982) and Blackorby and Russell (1981) both argue that the HEC is not the true dual of the AES under non-constant returns to scale, but the dual of the gross version of the AES- HLES (Bertoletti, 2005). Sato and Koizumi (1973) present the formula for the HEC as follows:

$$HEC_{jk} = \frac{Y(\boldsymbol{w})\dfrac{\partial^2 Y_{jk}(\boldsymbol{w})}{\partial w_j \partial w_k}}{\dfrac{\partial Y_j(\boldsymbol{w})}{\partial w_j}\dfrac{\partial Y_k(\boldsymbol{w})}{\partial w_k}} = \frac{qY}{p_k w_k}\frac{\partial\, ln\, P_j\,(q,\boldsymbol{w})}{\partial\, ln\, w_k} \tag{3.17}$$

where *Y(x)* is the production function. We can derive the general form of HEC for a case of multiple outputs by substituting the revenue function for qY in Eq. (3.17):

$$HEC_{jk} = \frac{R(\boldsymbol{q},\boldsymbol{w})}{p_k w_k}\frac{\partial\, ln\, P_j\,(\boldsymbol{q},\boldsymbol{w})}{\partial\, ln\, w_k} = \frac{RR_{kj}}{R_j R_k} \tag{3.18}$$

We derive the HEC in our empirical analysis following Syrquin and Hollender (1982) as follows:

$$HEC_{jk} = \frac{\sum_{jk}}{S_j S_k} - \frac{\partial \ln \mu}{\partial \ln y} \tag{3.19}$$

where:

$$\Sigma = \begin{bmatrix} \boldsymbol{AES} & [\nabla_{\ln y} \ln \boldsymbol{X}]' \\ \nabla_{\ln y} \ln \boldsymbol{X} & 0 \end{bmatrix}^{-1} \tag{3.20}$$

9. S*ymmetric Shadow Elasticity of Complementarity (SEC)*: This elasticity is relatively recent compared to other elasticities discussed in this study. Stern (2010) proposes the SEC with the intention of developing an elasticity that can fit into the modern framework of elasticity of complementarity. The SEC measures the optimal response of the shadow factor price ratio to the change in the ratio of two input quantities while holding the quantities of other inputs, output and the distance constant. Unlike the AEC and the MEC that do not measure input substitution along the efficient frontier as output level adjusts optimally to the change in the input quantity, the SEC is referred as movements along the input distance frontier. Hence, under the assumption of fixed distance the SEC measure input substitution when production is technically efficient. Stern (2010) presents the formula for the SEC as follows:

$$SEC_{jk} = \frac{\partial \ln\left(\frac{D_I(y,\boldsymbol{w})}{\partial w_j} \Big/ \frac{D_I(y,\boldsymbol{w})}{\partial w_k}\right)}{\partial \ln\left(w_k / w_j\right)} \setminus D_I$$
$$= \frac{-\frac{\partial^2 D_I(y,\boldsymbol{w})/\partial p_j^2}{\frac{\partial D_I(y,\boldsymbol{w})}{\partial w_j}\frac{\partial D_I(y,\boldsymbol{w})}{\partial w_j}} + 2\frac{\partial^2 D_I(y,\boldsymbol{w})/\partial w_j \partial w_k}{\frac{\partial D_I(y,\boldsymbol{w})}{\partial w_j}\frac{\partial D_I(y,\boldsymbol{w})}{\partial w_k}} - \frac{\partial^2 D_I(y,\boldsymbol{w})/\partial w_k^2}{\frac{\partial D_I(y,\boldsymbol{w})}{\partial w_k}\frac{\partial D_I(y,\boldsymbol{w})}{\partial w_k}}}{\frac{1}{(D_I(y,\boldsymbol{w}))/\partial w_j) w_j} + \frac{1}{\left(\frac{D_I(y,\boldsymbol{w})}{\partial w_k}\right) w_k}} \tag{3.21}$$

where $D_I(y, \boldsymbol{w})$ is the input distance function and the SEC is the true dual of SES, Eq. (4.10). As in Eq. (4.22) we derive the SEC as the share-weighted average of the AECs (Stern, 2010) in our empirical analysis:

$$SEC_{jk} = \frac{S_j S_k}{S_j + S_k}\left(-AEC_{jj} + 2AEC_{kj} - AEC_{kk}\right) \tag{3.22}$$

10. As*ymmetric Pigou Elasticity of Complementarity (PEC)*: This elasticity is originally proposed by Pigou (1934) following his awareness that elasticities of substitution and complementarity are asymmetric in general. In this regard, Pigou (1934) developed two possible elasticities in which the first of these elasticities was based on the concept on Hicks ES, holding the quantities of other inputs and output constant. The second elasticity termed as the Pigou elasticity of partial productivity by Hicks (1936) was based on the assumption that output and all inputs apart from one of the two in the input ratio under consideration are held constant. Later, Hicks demonstrates how this elasticity can be derived from a production function or profit function as HEC, which is written as a function of own quantity and cross-quantity elasticities. This elasticity was renamed as the "Pigou elasticity of complementarity" in a more recent literature of ES and EC (Stern, 2010). To measure the response to a change in w_j the formula for the SEC is as follows:

$$PEC_{jk} = \frac{\partial \ln\left(\frac{R_j(q,\boldsymbol{w})}{\partial w_j} \Big/ \frac{R_k(q,\boldsymbol{w})}{\partial w_k}\right)}{\partial \ln\left(w_k/w_j\right)} = \frac{\partial \, ln\, P_k\,(q,\boldsymbol{w})}{\partial \, ln\, w_j} - \frac{\partial \, ln\, P_j\,(\boldsymbol{q},\boldsymbol{w})}{\partial \, ln\, w_k} \tag{3.23}$$

Eq. (3.23) shows that the PEC is the difference between two cross-quantity elasticities based on the inverse demand functions derived from the revenue function. Unlike the MEC, the PEC measures the optimal response of input shadow price ratio to a change in input quantity ratio with all other input quantities and the price of output being held constant, but while varying the quantity of output and all input prices.

3.4 Data

This study estimates a few model specifications for two different time periods using annual balanced panel data. The first period covers 1995–2001, which is before the

China accession to the WTO and the second period is 2002–2009, which covered China accession to the WTO[31]. The Chinese sectors covered in this paper comprises 33 sectors at two-and three-digit level using International Standard of Industrial Classification (ISIC) Rev. The industrial classification of the sectors is listed in the appendix. The raw data are mainly obtained from the World Input-Output Database (WIOD) (Timmer et al., 2015)[32]. CO_2 emissions in Gg (kt) and energy use in TJ are taken from the EAs of the WIOD. Except energy expenditures that are expressed in millions of US$ at current prices, all other monetary series are in millions of national currencies at current prices. Output is measured in terms of gross output (y) of individual sector. Energy expenditures expressed in millions of US$ are calculated as the addition of expenditures on energy inputs purchased domestically and internationally. Material expenditures are calculated as expenditures on intermediate inputs, while capital expenditures and labour expenditure are measured in terms of capital compensation and labour compensation respectively.

All the series at current prices were converted to constant prices by using the related prices indices. Gross output is deflated by using the price index of gross output (1995=100). The gross output at constant prices is then converted to international monetary unit US$, using the purchasing power parity exchange rates obtained from the Penn World Table (PWT7.1). Similarly, producers' input expenditures at current prices were converted to constant (1995=100) prices by applying the implicit prices deflator for that sector and thus converted the constant series to US$ using the purchasing power parity exchange rates. The total cost and input prices are then derived as follows. The

[31] We acknowledge the relevance for allowing for a transition period in our analysis, but given the short span of the data and with the intention to have a more robust result, we categorised the transition period as part of the time period 2002–2009.

[32] We used data from the three major accounts of the WIOD, the National Input-Output Tables (NIOT) released in November 2013, Environmental Accounts (EAs) released in March 2012 and the Socio-Economic Accounts (SEA) released in July 2014.

total cost represents the addition of capital, energy, labour and material expenditures. The price of capital is derived as the ratio of capital compensation to real fixed capital stock; the price of labour is computed as the ratio of labour compensation to number of persons engaged in thousand; the price of energy is generated as the ratio of energy input expenditures to gross energy use in TJ and the price of material is computed as the ratio of the value of intermediate material input expenditure to intermediate material volume. For estimation purposes and smoothing interpretations, all variables estimated are naturally logged and mean-adjusted, so that the first order coefficients in the model can be interpreted as elasticities at the sample mean.

Table 3.1: Variable descriptions and summary statistics

Variable description	Before joining the WTO (1995 – 2001)		After joining the WTO (2002 – 2009)	
	Mean	St. Dev.	Mean	St. Dev.
CO2 emissions in Gg (kt)	85204	220626	117223	366450
Energy (in terajoule)	1490264	3208284	2663665	6492539
Output (millions US$)	195836	170977	481537	512147
Price of capital (in millions of US$)	9.38	6.09	15.79	16.79
Price of labour (in millions of US$)	3.97	2.88	6.32	4.49
Price of energy in (millions US$/per TJ)	17.39	10.97	31.81	21.21
Price of material (in millions of US$)	8.92	8.06	8.67	7.85
Capital expenditure/cost	0.22	0.13	0.23	0.16
Labour expenditure/cost	0.19	0.11	0.15	0.11
Energy expenditure/cost	0.01	0.00	0.01	0.01
Material expenditure/cost	0.59	0.15	0.61	0.19

3.4 Empirical analysis

3.4.1 Estimated results of the translog cost function

The estimated translog/share-cost functions for model specifications (3.3 and 3.4) for the period before China's accession to WTO (1995 – 2001) and for the period covers China's accession to WTO (2002–2009) are presented in Table 2, where labour is the normalized input. Although, it is possible to derive the coefficient of the normalized input (labour) from the results since the sum of all the coefficients of the inputs equals one, but the estimation of the coefficients where labour is interacted with other variables is not practically feasible. Hence, we also estimated model specifications where other inputs (capital, energy and material) are normalized since we are interested in the ES and EC among the four inputs.

Table 3.2: Estimated results

Before joining the WTO (1995 – 2001)			After joining the WTO (2002 – 2009)		
Variable	Coefficient.	Std. Err.	Variable	Coefficient.	Std. Err.
y	0.251***	0.026	y	0.301***	0.029
y^2	–0.041**	0.017	y^2	–0.045**	0.021
yt	0.009	0.009	yt	0.022**	0.012
yp_k	0.023**	0.011	yp_k	–0.017	0.013
yp_e	–0.001**	0.001	yp_e	–0.003***	0.001
yp_m	–0.068***	0.015	yp_m	0.017	0.017
p_k	0.214***	0.007	p_k	0.219***	0.008
p_e	0.005***	0.000	p_e	0.007***	0.000
p_m	0.600***	0.009	p_m	0.619***	0.011
p_k^2	0.043***	0.001	p_k^2	0.043***	0.008
p_e^2	–0.001**	0.000	p_e^2	–0.003***	0.000
p_m^2	0.116***	0.009	p_m^2	0.059***	0.011
p_kp_e	0.001**	0.000	p_kp_e	0.000	0.001
p_kp_m	–0.076***	0.007	p_kp_m	–0.052***	0.009
p_ep_m	–0.001	0.000	p_ep_m	–0.000	0.001
p_kt	–0.001	0.004	p_kt	–0.003	0.004
p_et	0.000	0.000	p_et	0.001***	0.000
p_mt	0.010**	0.005	p_mt	0.008	0.005
t	0.046***	0.009	t	0.079***	0.009
t^2	–0.007**	0.003	t^2	–0.003	0.004
id	0.003	0.002	id	0.027***	0.004
$idg(2)$	0.141***	0.054	$idg(2)$	–0.095	0.090
$idg(3)$	0.029	0.079	$idg(3)$	–0.387***	0.134
idp	0.049	0.027	idp	0.114**	0.048
$Intercept$	–0.198**	0.054	$Intercept$	–0.336***	0.086

*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels respectively.

To reiterate, all variables estimated are in their natural log (therefore all variables reported in Table 3.2 in lower case letters) and mean-adjusted to control for heterogeneity across the sectors and allows the first order coefficients to be interpreted as elasticities at the sample mean. In addition to mean-adjusted of estimated variables we further control for heterogeneity across the sectors through a set of z variable. That is a dummy variable (idp) indicates sectors with multiple production units and a categorical variable that group sectors according to production technology (idg).

For statistical justification of dividing data used into two sample periods, we performed a restriction to verify if a structural change did exist when China started gaining access to the WTO using χ^2~Test. The restriction test imposes a null hypothesis restriction that the estimated parameters are the same for the entire sample period (1995–2009). The results of the $\chi^2 \sim$ (32; 0.00) reject the null hypothesis that the estimated parameters are the same for the entire sample period. In other word, there is a structural change when China gained access to the WTO. The results for the two sample periods reported in Table 3.2 show that most of the estimates are statistically significant with output and inputs having the expected (positive) signs. The results suggest that as producer increases output level by using more inputs, the producer's cost of production also increases. To observe the performance of the estimated cost function as required, we verified the monotonic property of the fitted cost function both at the sample and outside the sample mean. At the sample mean the fitted cost function for both sample periods in Table 3.2 produces positive output elasticities and positive input elasticities all through. Therefore, the results indicate that the estimated cost function satisfy the condition of monotonicity at the sample mean. Similarly, the results of the monotonicity property outside the sample mean indicate that the fitted cost function strongly satisfied the monotonicity property with 80% of the data points, on average are monotonic. The negative elasticities of the output squared (y^2) for both sample periods are sensible as this suggests that in the long-run cost of production declines as output expands. From the estimates of the fitted cost function for the two sample periods, we observe evidence of strong economies of scale with values of 3.98 for the period 1995–2001 and 3.32 for the period 2002–2009. These results (of course) seem questionable, but our evidence of strong economies of scale of the pre– and post– China accession to the WTO is consistent with existing literature that estimated a translog cost function for China (Adetutu et al., 2016)[33]. This suggests for the sample average production sector in China that an increased production level in both sample periods would lead to a substantial proportionate saving in cost. One possible explanation could be the relative cheap cost of abundant labour input in China; therefore, narrowing down the production cost as more people are employed as output level rises.

Having considered only the significant parameters of the *t*, our results suggest a negative (positive) relationship between the deterministic trend and the production cost for the period 1995–2001 (2002–2009)[34]. This suggests that in the face of technical progress the production cost was shifting upwards since China gained access to the world trade. This is an interesting result as one would have expected otherwise (like the result before access to the world trade), but the result reinforces the role of economies of scale and factor accumulation as opposed technical progress because of China's economic growth in recent years. The result is similar to Adetutu et al. (2016) as they argue that the results support the view of Accumulationists that argue in favour of increased use and accumulation of inputs in form of investment rather than increased in

[33] We observe that existing literature on China using a translog function either assume a constant return to scale (Ma et al., 2009; Symth et al., 2012; Ma and Stern, 2016) or do not report the estimates of the translog function (Lin and Wesseh Jr, 2013; Li and Lin, 2016).

[34] E.g., the value of the time trend for period 1995–2001 is calculated as: $\frac{dC}{dt} = 0.046 - 2(0.007)t + p_s$.

productivity as what determines growth (Young, 1992, 1995; Krugman, 1994; Crafts, 1999a, 1999b). To complete the discussion of the fitted cost function, attention is turned to the estimates of the z variables. Majority of the z variables meant to control for heterogeneity across the sample sectors are significant at 0.1% level. For instance, the coefficient of idp (0.11) for sample period 2002–2009 indicates that sectors with multiple production units are associated with a more increasing of about 11% than sectors with single production unit. The estimate of $idg3$ (–0.39) indicates that the service sector shifts the cost function downwards by approximately 39% more than that of the primary sector.

3.4.2 Results of the elasticities of substitution and complementarity

For the pre-accession to the WTO (1995–2001) and for the post-accession to the WTO (2002–2009), at the sample mean we derive ten elasticities of substitution and complementarity (AES, MES, MGES, SES, HLES AEC, MEC, HEC, SEC, PEC) discussed in Section 3.3 following the estimation of Eqs. 3.5 to 3.6. These elasticities between production factors are reported in Tables 3.3 and 3.4 and we compute the standard errors for the elasticities of substitution using the delta method.[35] To recap, and based on different assumptions, each of the elasticities discussed in this study possesses specific theoretical contributions to the literature of elasticities of substitution and complementarity and for this, no single elasticity is preferred in all circumstances. Further, it is often the case to compare different estimated elasticities of substitution and complementarity in the literature, however, given the wide range of elasticities presented here, it is therefore somewhat difficult to compare and contrast the elasticities

[35] The computation of the standard errors of the elasticities of complementarity requires the estimation of the corresponding production function, but since the derivation of these elasticities relies heavily on the AES (we use the matrix inversion in Eq. (3.15) to derive the AEC from the AES in which we build on to compute other EC) derived directly from the estimated cost function, it is impossible to compute the standard errors of the EC.

of substitution and complementarity reported in Tables 3.3 and 3.4. That being said, we provide to a reasonable extent a comparative description of the reported elasticities of substitution and complementarity in our empirical analysis.

The ES reported in Table 3.3 provide information about the relationship between production inputs in form of p-substitutes (positive value) or p-complements (negative value). To start with, the AES are all positive and significant at 0.1% level for both sample periods. This suggests that energy and other inputs are p-substitutes. The magnitudes of the AES are similar on average for both sample periods. In terms of magnitude, our results are similar to Stern (2011) and Adetutu et al. (2016) as they find relatively strong p-substitutability between energy and other inputs. The shadow elasticity of substitution (SES) also shows that energy and capital are p-substitutes in both sample periods, but not statistically significant. Further, we observe that the values of the SES for the two periods are almost identical, but generally smaller than AES. With respect to positive values, our SES estimates are similar to Zha and Ding (2014), but relatively small in size, however, bigger than the SES reported in Stern (2011). In comparison to the AES, the SES estimates display a bit strong and less substitutability in both sample periods. For instance, the substitutability between energy and capital before China's accession to the WTO is stronger for the AES (1.91) and stronger for the SES (1.38) after China's accession to the WTO.

Stern (2011) argues that the MES (likewise the MEC) is not a good measure of ES when production technology consists of more than two inputs because it erroneously classifies all inputs as p-substitutes as the own-price elasticity tends to be greater in absolute value than the cross-price elasticities (Frondel and Schmidt, 2002). However, we still report the MES (and the MEC) given their popularity in the literature of ES, appealing asymmetric feature and to point out the implications of erroneously using the

MES and its dual when using more than two inputs in production. As expected, the MES are all positive with the majority of the elasticities close to or greater than one in both sample periods. The MES indicates capital and energy as strong p-substitutable in both sample periods having observed a similarity in their sizes. In contrast, the gross version of the Morishima elasticity (MGES), which allows for output adjustment in response to changes in factor prices are all negative and significant at 0.1% level for both sample periods. This suggests that production inputs are p-complements and we observe no significant different in terms of size of the elasticities in most cases between the two sample periods. The HLES (the gross version of the AES) yield similar results in terms of sign as all elasticities are negative indicating p-complementarity and significant at 0.1% level for both sample periods. Our results differ to that of Stern (2011) especially in terms of magnitude as the reported HLES in Table 3.3 are generally larger. The magnitudes of the HLES differ between the two-sample periods relatively to other ES reported. For instance, the HLES indicates a strong p-complementarity between energy and capital for the period 1995 – 2001, which indicates a moderate p-complementarity between energy and capital for the period 2002 – 2009.

Table 3.3: Elasticities of substitution between sample periods

	Before joining the WTO (1995–2001)					After joining the WTO (2002–2009)				
	AES	MES	SES	MGES	HLES	AES	MES	SES	MGES	HLES
K-L	1.26***	0.91***	0.89***	–0.65***	–1.50***	0.76***	1.00***	0.89**	–0.70***	–0.67***
	(0.14)	(0.04)	(0.28)	(0.05)	(0.00)	(0.17)	(0.04)	(0.33)	(0.07)	(0.01)
K-E	1.91***	1.40***	1.39	–1.05***	–1.42***	1.07***	1.40***	1.38	–0.98***	–0.67***
	(0.38)	(0.06)	(0.76)	(0.10)	(0.02)	(0.40)	(0.06)	(0.79)	(0.12)	(0.02)
K-M	0.41***	0.45***	0.62***	–0.40***	–0.47***	0.62***	0.67***	0.70***	–0.41***	–0.63***
	(0.06)	(0.03)	(0.11)	(0.03)	(0.00)	(0.06)	(0.04)	(0.13)	(0.04)	(0.01)
L-K	1.26***	0.86***	0.89***	–0.67***	–1.50***	0.76***	0.75***	0.89**	–0.52***	–0.67***
	(0.14)	(0.04)	(0.28)	(0.06)	(0.01)	(0.17)	(0.05)	(0.33)	(0.08)	(0.01)
L-E	2.72***	1.41***	1.40***	–1.05***	–2.02***	3.83***	1.42***	1.42	–0.99***	–2.60***
	(0.32)	(0.06)	(0.63)	(0.10)	(0.02)	(0.41)	(0.06)	(0.81)	(0.12)	(0.02)
L-M	0.64***	0.59***	0.75***	–0.53***	–0.69***	1.12***	0.98***	1.04***	–0.63***	–0.99***
	(0.06)	(0.04)	(0.12)	(0.03)	(0.00)	(0.07)	(0.05)	(0.15)	(0.04)	(0.01)
E-K	1.91***	1.00***	1.39	–0.65***	–1.42***	1.07***	0.82***	1.38	–0.52***	–0.67***
	(0.38)	(0.08)	(0.76)	(0.06)	(0.01)	(0.40)	(0.09)	(0.79)	(0.08)	(0.02)
E-L	2.72***	1.18***	1.40***	–0.74***	–2.02***	3.83***	1.48***	1.42	–1.00***	–2.60***
	(0.32)	(0.06)	(0.63)	(0.05)	(0.02)	(0.41)	(0.07)	(0.81)	(0.07)	(0.02)
E-M	0.76***	0.66***	1.39***	–0.46***	–0.56***	0.97***	0.89***	1.40***	–0.37***	–0.57***
	(0.16)	(0.10)	(0.32)	(0.03)	(0.01)	(0.14)	(0.08)	(0.27)	(0.04)	(0.01)
M-K	0.41***	0.67***	0.62***	–0.45***	–0.47***	0.62***	0.72***	0.70***	–0.52***	–0.63***
	(0.06)	(0.03)	(0.11)	(0.06)	(0.00)	(0.06)	(0.04)	(0.13)	(0.08)	(0.00)
M-L	0.64***	0.80***	0.75***	–0.50***	–0.69***	1.12***	1.06***	1.04***	–0.75***	–0.99***
	(0.06)	(0.04)	(0.12)	(0.05)	(0.00)	(0.07)	(0.04)	(0.15)	(0.07)	(0.00)
M-E	0.76***	1.40***	1.39***	–0.05***	–0.56***	0.97***	1.40***	1.40***	–0.98***	–0.57***
	(0.16)	(0.06)	(0.32)	(0.10)	(0.01)	(0.14)	(0.06)	(0.27)	(0.12)	(0.01)

Note: Capital (K), Labour (L), Energy (E) and Material (M).
Standard errors in parentheses for the elasticities of substitution are calculated using the delta method.
*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels respectively.

Table 3.4: Elasticities of complementarity between sample periods

	Before joining the WTO (1995–2001)					After joining the WTO (2002–2009)				
	AEC	MEC	SEC	PEC	HEC	AEC	MEC	SEC	PEC	HEC
K-L	0.16	1.05	1.14	0.98	2.88	1.24	0.19	0.23	0.98	1.57
K-E	–0.32	0.71	0.72	0.72	0.94	0.95	0.01	0.01	0.72	0.48
K-M	1.95	1.89	1.69	3.12	2.72	1.48	0.91	0.48	1.08	2.09
L-K	0.16	1.23	1.14	1.31	2.88	1.24	0.27	0.23	1.44	1.57
L-E	–0.70	0.71	0.71	0.72	0.82	–0.93	–0.01	0.02	0.71	–1.37
L-M	1.65	1.72	1.41	3.13	2.65	0.89	0.55	0.22	0.80	1.68
E-K	–0.32	1.13	0.72	1.07	0.94	0.95	0.21	0.01	1.21	0.48
E-L	–0.70	0.90	0.71	0.60	0.82	–0.93	–0.14	0.02	0.71	–1.37
E-M	1.51	1.63	0.73	2.04	0.87	1.04	0.65	0.01	0.33	0.92
M-K	1.95	1.61	1.69	1.42	2.72	1.48	0.32	0.48	1.17	2.09
M-L	1.65	1.32	1.41	1.18	2.65	0.89	0.14	0.22	0.71	1.68
M-E	1.51	0.72	0.73	0.72	0.87	1.04	0.01	0.01	0.71	0.92

Note: Capital (K), Labour (L), Energy (E) and Material (M).

The elasticities of complementarity reported in Table 3.4 provide information about the relationship between production inputs in form of q-complements (positive value) or q-substitutes (negative value). Unlike the AES that indicate energy and capital as p-substitutes for both sample periods, the AEC indicates that energy and capital are q-substitutes (–0.32) for the period 1995 – 2001, but that indicates energy and capital are q-complements (0.95) for the period 2002 – 2009. The size of the AEC differs significantly in most cases between the two sample periods. Our results for the period 1995 – 2001 perfectly match Stern (2011) in terms of sign, but generally smaller in value. For the period 1995 – 2001, the MEC indicates that energy and other inputs are q-complements, however, for the period 2002 – 2009, energy and labour are q-substitutes. We observe a relatively weak elasticity between inputs after China joined the WTO.

As theoretically expected, the SEC is positive for all input combinations in both periods under study, indicating the relationship between inputs as q-complements. Again, we also observe a relatively weak elasticity between inputs after China joined the WTO. One possible explanation is that increased in alternative fuel source and technology as a result of increase in output/export level has reduced the degree at which one input needs to complement the others since China gaining access to the world trade. The PEC also indicates that input combinations are q-complements for the two sample periods as all values are positive. Both the MEC and the PEC demonstrate a reasonable degree of asymmetric unlike the MES and the MGES. For the HEC, except for the energy and labour for the period 2002 – 2009, which indicates q-substitutes like Kim (2000), the HEC is positive for all input combinations indicating input combinations as q-complements. The HEC demonstrate considerable variations in terms of size between the two periods under investigation. In general, the elasticities of complementarity reported in Table 3.4 are relatively small to Kim (2000) and Stern (2011).

3.4.3 ES-economic activity-emission: Theoretical interactions

Mainstream neoclassical economics looks at energy and the environment as 'inputs' into consumption or production activities. Energy is an input produced from natural resources (such as fossil fuels), and the environment is also considered as an 'inputs' in the sense that it can act as a 'sink' for production activity wastes. The limited supply and non-renewable nature of some of the energy resources can put a limit on the capacity of the economy to sustain growth in the long term. The natural environment also has a limited capacity to absorb 'wastes' from economic activities and therefore this can act as a constraint on long-term sustainable economic growth. To demonstrate the relationship between ES, economic activity and emissions we begin with the simplest possible way to look at ES in form of energy efficiency in a production setting. We modify the production function in Eq. (3.24) as follows:

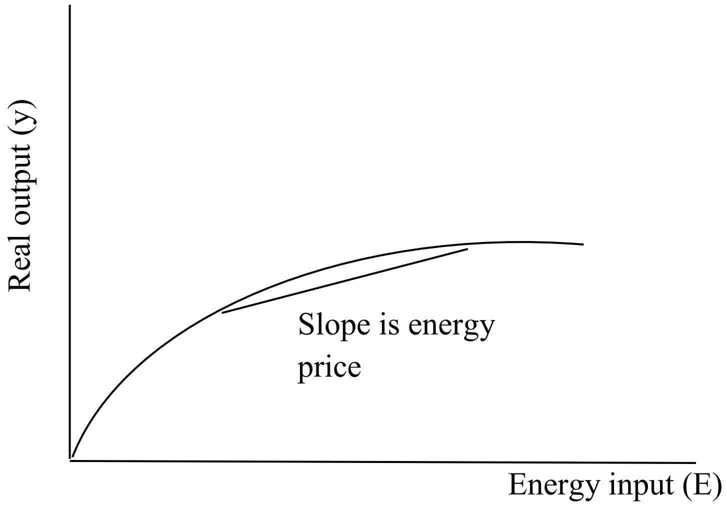
$$Y = f(E, R) \tag{3.24}$$

where Y represents real output, E represents the amount of energy used in production and R is the quantity of other inputs used (capital, labour and materials). The energy efficiency in the production of the output can be characterised by the E/Y ratio[36]. The aim is to know how and why this ratio might differ for different production settings and it may differ over time, for example due to gains in energy efficiency in form of ES of non-energy inputs for energy inputs. A simple way to look at this question as demonstrated by Hogan and Manne (1977) is shown in Figure 3.2. The Figure shows that reducing the energy input does not result in a one-for-one loss in output, while

[36] The ratio E/Y is often called as 'energy intensity', which is the unit of energy per unit of output.

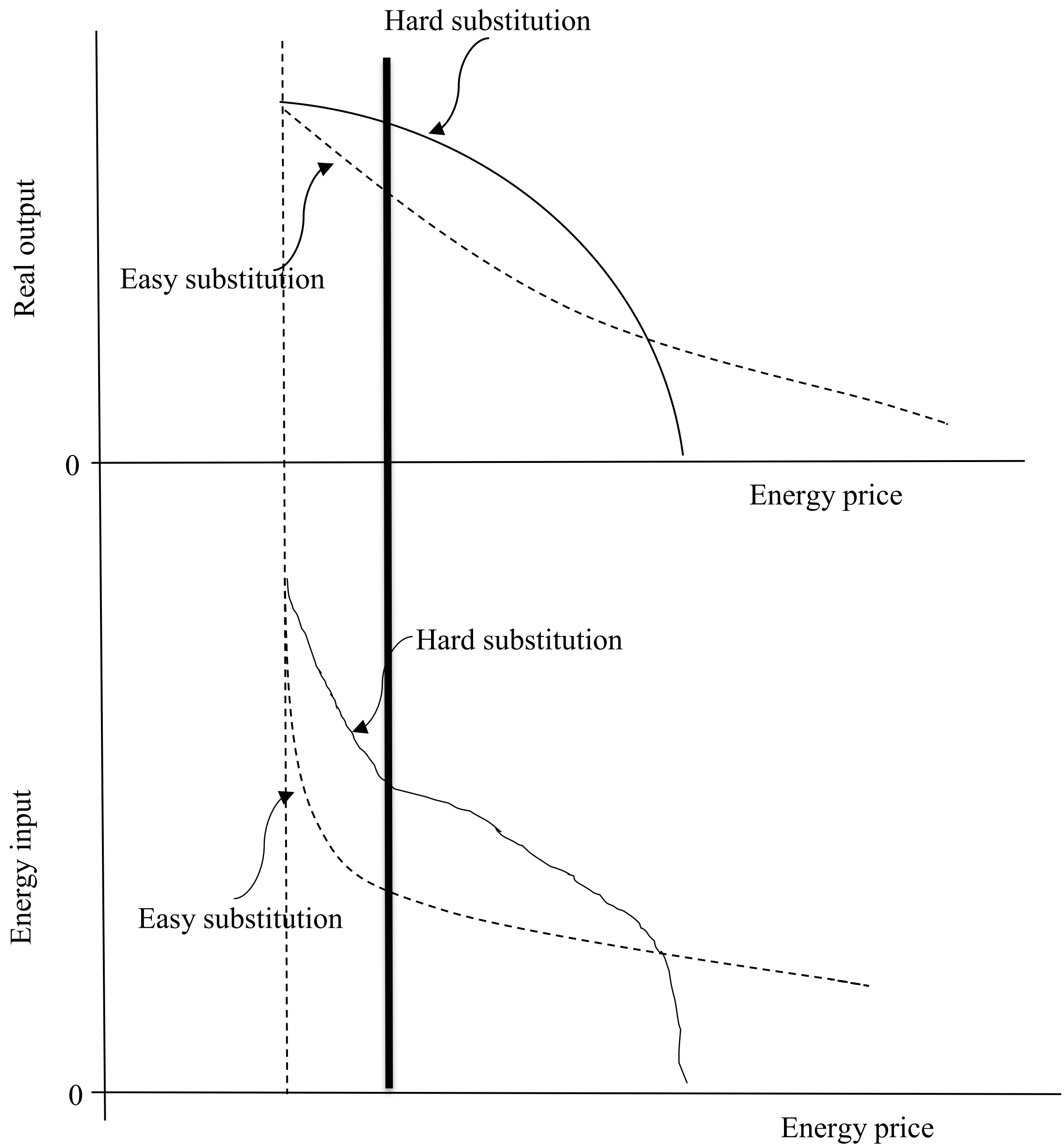
holding other inputs (R) constant for simplicity. The exact shape of this curve will depend of course on how we characterise the function f. The movement along this curve involves technology change or input adjustment. A good example is substituting more building insulation for heating oil use or using more labour in production setting. This is characterised in Figure 3.2, which shown that ratio E/Y can be reduced through energy efficiency gains, by substituting non-energy inputs for energy, which can be induced by increase in energy price.

Figure 3.2: Economic output and energy input



The reduction in ratio E/Y has implications for major environmental problems, such as global warming remedies. A Favoured remedy is the substitution of capital for energy, which can be induced by carbon tax or high energy price. The key element that drives the magnitude of this effect as pointed out by Hogan and Manne (1977) is the degree of substitutability between energy and non-energy inputs as illustrated in Figure 3.3. Thus, if the objective is to reduce carbon emissions from energy use via a carbon tax, then we hope that easy substitution is possible in the real-world production setting. If this is the case, the economic cost (environmental benefit) of achieving any energy use target will be lower (higher). On the other hand, if substitution is more difficult, we have a situation illustrated by the top curve where a given reduction in energy input has a larger negative effect on output and environmental benefit.

Figure 3.3: Substitution potential and carbon taxes



However, easy substitution is not always likely to yield greater environmental benefit or low economic cost with a given level of energy price (carbon tax). This may seem counterintuitive, but Figure 3.3 illustrates this. For instance, if the energy price starts out at a level corresponding to the dashed line running through both panels of the figure and is then increased to a level illustrated by the solid line, one can see that with easy substitution economic output is reduced more than it would be with hard substitution (top panel). Of course, the increase in energy price will also lead to a lower energy use (lower panel).

The main issue here, as discussed above is that one of the crucial parameters that determines sustainable-growth and-environment is the elasticity of substitution between energy and non-energy inputs. It is in this context, that an exploratory analysis of the relationship between ES and the environment is worth to be considered as presented in Section 3.4.4.

3.4.4 Elasticity of substitution and carbon emission: Empirical specification

Following the theoretical exposition presented in Section 3.4.3, this section presents an exploratory analysis on the relationship between carbon emissions and the estimates of factor substitution reported in Section 3.4.3 having controlled for other competing factors. Although, this is an exploratory analysis, but we acknowledge that by mere using the estimates of energy substitution as a measure of substituting one input for another is not the true measure of substitution among production factors in practice. However, for the analysis carried out here, the most feasible and closest measure of substitution possibility between energy and non-energy inputs we could use is the ES reported in Table 3.3. Notwithstanding the justification for analysing the estimates of capital-energy substitution directly on carbon emissions, we advise that our results should be interpreted with cautions either for scholarship or policy-making purposes.

So far, we have only discussed the estimated elasticities of substitution and complementarity reported in Tables 3.1 and 3.2. Now, the aim is to analyse the relationship between carbon intensity and the ES with other competing factors. To attribute the Chinese industrial carbon intensity to various competing driving forces (particularly in terms of estimated factor substitution, energy intensity and technical progress), we firstly represent the carbon intensity as follows:

$$\frac{CO_2}{Q} = \frac{E}{Q} * \frac{CO_2}{E} \tag{3.25}$$

where CO_2 is carbon emissions, Q is the output and E energy input. Eq. (3.24) expresses carbon intensity in terms of energy intensity $(\frac{E}{Q})$ and fuel mix $(\frac{CO_2}{E})$. This analysis is motivated particularly by Welsch and Ochsen (2005) and Li and Lin (2016) as they attribute changes in energy/carbon intensity to factor substitution and technological progress. In combination with energy intensity and technical progress, we specify the driving forces of carbon intensity as in Eq. (3.24) by expressing the fuel mix in a simplest term of the estimated factor substitution derived from Eqs. (3.3 and 3.4).

$$co_{2,it} = \alpha_i + \pi e_{it} + \gamma_0 \sigma_{it}^{ke} + \gamma_1 \sigma_{it}^{kl} + \gamma_2 \sigma_{it}^{le} + \gamma_3 \sigma_{it}^{km} + \gamma_4 \sigma_{it}^{em} + \gamma_5 \sigma_{it}^{lm} + \theta D_t + z_t + \epsilon_{it} \tag{3.25}$$

where:

c_{it} is the natural logarithm of carbon intensity for industry *i* for time period *t*.

e_{it} is the natural logarithm energy intensity for industry *i* for time period *t*.

σ_{it}^{ke} is the estimated AES between capital and energy for industry *i* for time period *t*.

σ_{it}^{kl} is the estimated AES between capital and labour for industry *i* for time period *t*.

σ_{it}^{le} is the estimated AES between labour and energy for industry *i* for time period *t*.

σ_{it}^{km} is the estimated AES between capital and material for industry *i* for time period *t*.

σ_{it}^{em} is the estimated AES between energy and material for industry *i* for time period *t*.

σ_{it}^{lm} is the estimated AES between labour and material for industry *i* for time period *t*.

D_t is the time dummies representing technical progress.

z_t represents a dummy and categorical variable to control for sectors' heterogeneity

ϵ_{it} is the error term.

With respect to factor substitution, it is clearly observable from model (3.25) that our analysis is based on the popular AES. The decision to use the AES among the estimated elasticities of substitution reported in Table 3.2 is due to a number of compelling factors and advantages. Firstly, the AES formed the bedrock for the derivation of all other elasticities reported in Tables 3.3 and 3.4. Secondly, the AES allows us to assume for simplicity that the substitutability between two factors is symmetric in our analysis. Therefore, the γ_s can be interpreted as the extent in, which the substitution between two factors affect carbon intensity. Thirdly, the estimation of the σ_s in Eq. (3.25) requires the computation of the σ_s outside of the sample mean, but the AES is arguably the only elasticity that could be derived logically outside of the sample mean. Unlike the other ES, the AES (3.6) is directly derived from the estimates of the translog cost function reported in Table 3.2.

To control for potential endogeneity, we estimated Eq. (3.25) with a GMM estimator (Arellano and Bond, 1991) and we control for time-specific effects by including time dummies, which also serve as the technical progress[37]. To recap, we control for possible heterogeneity among the sectors by including a z_t variable in model 3.25. This consists of a dummy (idp) indicating 1 for sectors with multiple production units and 0 otherwise; and a categorical variable that categorised sectors according to production technology (idg). That is primary sector ($idg1$), manufacturing sector ($idg2$) and service sector ($idg3$). We also verify the importance for allowing for structural break in our data using the χ^2~test. The result of the χ^2~(52; 0.00) reject the null hypothesis that the estimated parameters are the same for the entire sample period. The estimated GMM

[37] The coefficients of the time dummies reported in Table 3.5 are not directly estimated. Since they are dummies and to avoid the problem of dummy trap they are derived as the sum of the constant and the addition of all the coefficients of the time dummies in each of the model estimated.

results for model 3.23 for different sample periods are presented in Table 3.5. As reported in Table 3.5, all estimated models pass all the diagnostic tests of no autocorrelation AR (2) and the Sangan/Hansen instrument test as none of these tests is statistically significant.

Table 3.5: Estimated results for China's carbon intensity

Variable	Before joining the WTO (1995 – 2001)	After joining the WTO (2002 – 2009)
Constant	–3.506 ***	–1.212 ***
	(0.121)	(0.196)
Energy intensity	1.111***	1.062***
	(0.018)	(0.009)
$\sigma_{Captial-Energy}$	–0.080***	–0.079***
	(0.012)	(0.000)
$\sigma_{Captial-Labour}$	0.005***	0.012***
	(0.001)	(0.004)
$\sigma_{Energy-Labour}$	–0.026***	–0.016***
	(0.007)	(0.005)
$\sigma_{Captial-Material}$	–0.018***	–0.035***
	(0.006)	(0.011)
$\sigma_{Energy-Material}$	–0.009***	0.029
	(0.003)	(0.015)
$\sigma_{Labour-Material}$	0.686***	–0.902***
	(0.152)	(0.147)
Time dummies	–3.262***	–0.264***
	(0.092)	(0.047)
$idg2$	–0.500***	–0.982***
	(0.107)	(0.073)
$idg3$	0.023	–0.509***
	(0.102)	(0.073)
idp	0.261***	0.367***
	(0.034)	(0.075)
Diagnostic Tests:		
Arellano-Bondtest AR(2)	0.257	0.729
Sangan/Hansen test	0.357	0.999

*, ** and *** denote statistical significance at the 5%, 1% and 0.1% levels respectively. Standard errors are in parentheses

For the period before China's accession to the WTO, Table 3.5 shows that the results are somewhat differ to the results for the period 2002–2009. Most estimated variables are statistically significant at 0.1%. As expected, energy intensity places itself as the main contributor to China's carbon intensity with an estimated elasticity 1.11, indicating that a 10% rise in energy intensity is associated with a rise of about 11% in carbon intensity. The result is similar to that of Fan et al. (2007) and Tan et al. (2011) as they both argue that the main determinant of carbon intensity is energy intensity.

We observe that the substitution between energy and other inputs is inversely associated with carbon intensity, given the negative coefficients of the parameters reported in Table 3.5. However, their effects are weak in general. For instance, the substitution of capital for energy with an estimate –0.08 suggests a 10% in capital-energy substitution is associated with a decrease of about 0.8% in China's carbon. This suggests that Chinese industries have started adopting less-carbon intensive equipment, which is embedded in capital equipment even before China got access to the WTO. This could be driven by the fact that China recognised the potential damage associated with its increasing energy consumption as the economy is growing. Also, this could be because of the international pressure China is facing to cut down its emission since signing the Kyoto protocol in 1998, however, China only ratified this agreement in 2002[38].

The negative effect of technical progress on carbon intensity is massive given its large coefficient –3.26. A possible explanation for the large coefficient could be because of the small sample period, which ordinarily fails to capture the relative long-term effect of the technical progress on carbon intensity. The coefficients of the z_t are also statistically significant at 0.1% level and possess the same sign as that of the other sampled period.

The results for the period China's accession to the WTO (2002–2009) somewhat differ to that of the sample period 1995–2001 in terms of the magnitude of the estimates.

[38] The Kyoto protocol (1997) is an international agreement linked to the United Nation framework convention on climatic change that sets a minimum target for 37 industrialised economies including the European Union to reduce CO2 emissions to 5% lower than the 1990 level between 2008 and 2012.

Majority of the estimated variables are statistically significant at 0.1%. We also observe that energy intensity is the main driver of carbon intensity with an estimated elasticity 1.06. On the other hand, the substitution effect of non-energy inputs for energy is associated with a decrease in China's carbon intensity given the negative sign of the estimates. The magnitude of the substitution effect of capital for energy is weak like the other sample period. This is consistent with the findings of Li and Lin (2016) as their findings suggest that the substitution effect of capital for energy decreases carbon intensity. The substitution effect between energy and material, though not statistically significant, but indicates a rise in carbon intensity. This is contrary to the period before China's accession to the WTO. The substitution effect between labour and material is relatively substantial compared to other factor substitution effects. The coefficient is negative (–0.90) and statistically significant at 0.1%. This indicates that a 10% increase in substitution between labour and material is associated with a 9% reduction in carbon intensity. This is expected as both inputs could be considered as low emission or emission free-inputs.

Expectedly, technological progress is negatively related to carbon intensity given its significant negative coefficient (–0.26). The effect is (of course) relatively small to that of the period before China's accession to the WTO. On the other hand, the negative effects of the z_t variables are much larger for the period 2002–2009. For instance, the significance of the coefficient $idg2$ (–0.98, which indicates that an increase in the number of manufacturing industries is associated with a reduction in carbon intensity) is almost twice of that of the period 1995–2001. However, like other sample period, (idp) displays a positive association with China's carbon intensity given its positive coefficient (0.37). This suggests that sectors with multiple production units have tendency to increase China's carbon intensity.

3.5 Conclusion and policy implications

This chapter analyses the factor substitution for pre-and post-China's accession to the WTO, and further carries out an exploratory investigation on the relationship between the factor substitution and the Chinese industrial carbon intensity. It is important that industries understand how increase in export and growth has affected their energy-saving technology in terms of capital-energy substitution since China gaining access to the world trade. To carry out our analysis, we use a rich data source that has been applied to similar issue to date. We use a sector level data for China for the period 1995–2009. Our analysis focuses on two different sample periods: pre- (1995–2001) and post- (2002–2009) China's accession to the WTO. To analyse factor substitution, we estimated a translog cost function in which we accounted for potential heterogeneity across sectors by including additional sectoral characteristics. Moreover, for an in-depth analysis of ES we compute ten elasticities of substitution and complementarity where each of the elasticities computed possesses specific theoretical contributions to the literature, and hence, no single elasticity is preferred in all circumstances.

Our results show some disparities mainly in terms of the magnitude of the elasticities of substitution and complementarity for the pre-and post-China's accession to the WTO, but in general we find a relatively strong substitution possibility among production factors. This in turn suggests that China's accession to the WTO is a motivation for embarking on a journey of energy-savings in form of capital-energy substitution. In particular, our results indicate that energy and non-energy inputs are strongly substitutable (positive ES) for both sample periods based on the computed AES, Morishima and SES given the magnitude of the majority of the elasticities greater than one. The AES, Morishima and the SES are based on the assumption of constant level of in the face of changes in factor prices. However, as output is allowed to adjust in response to changes in relative factor prices as the case of MGES and HLES, our results indicate negative ES. The statistically significant of the negative estimates of the MGES and the HLES indicates that energy and non-energy inputs are complements as output changes in response to changes in factor prices.

Having analysed the elasticities of substitution, we then carried out an exploratory investigation on the driving forces of Chinese carbon intensity for two different sample periods. In the empirical analysis, we attribute Chinese industrial carbon intensity to various competing driving forces namely; factor substitution, energy intensity and technical progress. We estimated the model for carbon intensity with a GMM estimator to accounts for potential endogeneity in the model. We also control for potential heterogeneity across sectors by adding different sectoral characteristics to the model. In general, our findings show that energy intensity is the main contributor to carbon intensity. This is consistent with the body of evidence in the literature. On the other hand, our results show that technological progress has key role to play in reducing carbon intensity.

With respect to factor substitution, the results for the pre- and post-China's accession to WTO differ in most cases either in terms of signs or the magnitude of the estimates reported in Table 3.5. Generally, although, we find that the substitution of non-energy for energy is negatively related to carbon intensity in both sample periods considered, but the effect is relatively small compared to the effects of technological progress and energy intensity. Specifically, the substitution between labour and materials has the greater impact on carbon intensity with the result for the post-WTO period suggests a negative relationship with carbon intensity while the result for the pre-WTO suggest otherwise (positive sign).

In summary, despite some variations in the magnitude of the elasticities while holding output constant, the substitutability between energy and non-energy inputs is strong across the sample periods. However, energy and non-energy inputs are complements while output is free to adjust in response to changes to factor prices. Energy intensity serves as a major contributor to carbon intensity; however, factor substitution and technical progress reduce carbon intensity. These findings reinforce that China's reduction in carbon emissions is largely associated with reduction in energy consumption, technological progress and to some extent energy-saving methods in form of factor substitution.

The policy implications that can be drawn from our findings are as follows. For instance, if one thinks of the substitution potential in the production setting or economy, one hopes that substitution potential is easy if producer wishes to reduce energy use to some specific target level- as this will require a smaller carbon tax and will results in less loss of economic output. In this situation, any energy related policy design to reduce carbon emissions is less likely to affect production level. However, if one imagines that substitution potential may be different sectors of the economy, which is likely the case in general, a uniform carbon tax applied to all sectors will hurt more sectors that deliver the greatest reduction in energy use. This curious result would likely strike most unfair. In addition, it may run counter to welfare maximization or cost minimisation. Since in general, producer should able to find for any target reduction in energy use via a combination of differentially applied carbon taxes resulting in less loss of output than one would obtain with a uniformity applied tax, whichever sector may be thereby favoured. This suggests a possible policy solution that would apply different levels of carbon taxes to different sectors.

In addition, our findings reveal that China’s accession to the world trade is a motivation for energy-savings and subsequently carbon reduction, given the strong ES between capital and energy after the structural break. One would expect this outcome given the international pressure China is facing to reduce its emissions level. Therefore, our findings should serve as a blueprint for other emerging economies.

With respect to further work, we are hoping that future research could focus on the analysis of interfuel substitution rather than the approach adopted in this research. The findings from such research would provide new insight about the potential implications for different sources of energy.

Chapter 4 Econometric Decomposition of Derived Energy Input with Implications for CO_2 Emissions[39]

4.1 Introduction

Oil price shocks and subsequently the growing awareness about the increasing greenhouse gases have initiated serious concern about energy security and environmental degradation. In particular, CO_2 emission is one of the major environmental threats as it accounts for almost half of the anthropogenic greenhouse gases (Floros and Vlachou, 2005). On the other hand, technological improvement in terms of energy-savings is considered as an important way of mitigating greenhouse gases. This practice therefore reduces the sensitivity of consumers to increase in energy prices. To some extent, especially in the production setting, the substitution of non-energy input for energy input can be characterised as a way of energy-savings or improvement in energy efficiency[40]. The positive implications of substituting non-energy input for energy input can be categorised into two parts. Firstly, it removes over-reliance of continuing increase in energy prices as a way of stimulating improvement in energy efficiency. Secondly, the measure could be considered as a natural way of reducing greenhouse gases with some social environmental benefits. Therefore, one can argue that one of the motives behind capital-energy substitution is to improve the quality of our environment by reducing energy consumption, which in turn leads to reduction in greenhouse gases.

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[39] A revised version of this chapter has been submitted as Akinsehinwa Sharimakin "The Decomposition of Derived Energy Input with Implications for CO_2 Emissions" *The Energy Journal.*

[40] However, a range of mechanisms, commonly grouped under the heading of rebound effects may reduce the size of the 'energy savings' achieved.

In fairness, empirical investigation of the substitution possibilities among factor inputs in the literature is highly recognised. In fact, the elasticity of substitution among production inputs plays an important role in firms' decision making when the price of an input changes. In production settings, this allows a representative producer to adjust inputs demand and minimise cost by purchasing more of less expensive inputs to cover for the more expensive input(s). However, the elasticity of substitution may not provide a complete picture of inputs adjustment resulting from a relative change in input prices. This is because the pure elasticity of substitution assumes that the producer's output is constant over time whereas, producers may adjust output in response to changes in relative factor prices and market conditions in practice. Chambers (1982) argues that the addition of the output effect to the substitution effect is likely to produce a more representative picture of inputs adjustments within a production function. This is because the output effect takes account of the fact that producers are not operating under the assumption of constant level of output unlike the substitution elasticities. Given the connection between changes in factor price and the producer's reaction to these changes, therefore, an empirical assessment of both the substitution and output effects to changes in factor price is likely to provide a more representative picture of inputs adjustment. More importantly, it is an attempt to evaluate whether the inclusion of the 'output' effects is warranted.

This chapter applies a two-stage procedure by firstly presenting the decomposition analysis of the change in energy demand resulting from changes in energy price. Secondly, this chapter carries out an exploratory investigation (as justified in chapter 3) about the implications of the output and substitution effects on CO_2 emissions using industry level data for a sample of European countries for the period 1995–2007. Specifically, this chapter explores the substitution possibilities between energy and other factors under the assumption of constant level of output and subsequently relax this assumption by decomposing changes in energy demand into substitution effect and output effect under the assumption that producer adjusts the level of output in response to changes in factor prices. Having analysed the decomposition effects, this study further carries out an exploratory investigate the impacts of both the substitution effect and output effect with other competing factors on carbon emissions.

Arguably, we could present the reaction of a representative producer to changes in energy prices in terms of input substitution and output adjustment as the producer is expected to reduce energy consumption as energy price increases. This is achievable by altering production system through the substitution of other factor inputs for energy, if substitution is possible, which is termed as pure technical substitution adjustment. However, in reality, an increase in energy prices would not only lead to inputs demand substitution, but also output adjustments as producers are expected to adjust output accordingly in response to relative changes in input price. For instance, if the price of an input increases, the expectation is that the total cost of the producer will also rise.

Similarly, substitution between production inputs allows producers to minimise cost by consuming more of those inputs that are cheaper and less of that input(s) with higher price(s). This implies that the producer's cost of production is affected by the elasticity of substitution between factor inputs. This process of input adjustment can increase the total cost of the producer or leave the producer at the same cost before the increase in price. For instance, if substitution between energy and non-energy is very strong, then a relative increase in energy price to other inputs' prices may not affect the cost of the producer as the producer can easily alter their inputs by using more of non-energy inputs that are relatively cheaper. However, if substitution possibility between inputs is weak, then a relative increase in factor price is very likely to increase the cost of the producer, which might force such producers to cut down production (output adjustment).

Despite the shortcoming associated with the elasticity of substitution among production factors, it remains an interesting research area in the academic literature. This is because the elasticity of substitution provides insightful information about the likely effect of relative changes in factor prices and relevant to policy questions related to the management of demand and supply for factor inputs (Kotse et al., 2008). Since the seminal work of Berndt and Wood (1975), the substitutability between capital and energy remained a subject of controversy as one strand in the literature suggests that energy and capital are substitutes, while another strand suggests they are complements. Berndt and Wood (1975) employ the translog model initially proposed by Christensen et al. (1973) to investigate the possibility of factor substitution and find capital and energy as complements. This argument is reinforced in Fuss (1977), Anderson (1981), Prywes (1986), Arnberg and BjØner (2007), and Tovas and Iglesias (2013) as shown in chapter 2. However, chapter also discusses that another strand in the literature refuted the claim that energy and capital are complements by arguing that they are substitutes (Cameron and Schwartz (1979); Uri (1979; 1982); Kim and Heo (2013) and Lin and Ahmad (2016)).

The above arguments imply that there is no consensus in the literature about the substitution possibilities between energy and other factor inputs. Ironically, the inconclusive evidence about the substitutability between capital and energy makes it a popular research area in academic literature. Notwithstanding the popularity of the elasticity of substitution between production factors, the fact remains that it may not provide a complete picture of input adjustments as it ignores the output effect to changes in relative input price. From consumers' perspectives, Ashenfelter and

Heckman (1974) build on the theory of consumer behaviour to analyse the income and substitution effects of negative income tax for US household labour supply. A more connected work to this study is Kako (1978) where the author analysed the growth of rice production in Japan by decomposed labour input demand into output effect, factor substitution effect and technical effect. The author finds technical change as the main reason why labour input declines and that the labour-saving effect from factor substitution are relatively small compared to the output effect. Chambers (1982) presents the theoretical and empirical exposition of the importance of output effects of changes in relative input prices by demonstrating how to use estimates of dual cost functions to generate the compensated and uncompensated elasticities. The author finds only capital and materials as complements when considering the pure substitution effect. However, materials and all other inputs are complements, when the level of output is free to adjust in response to changes in factor price. The author further highlights the importance of the output effect in terms of the difference between the compensated and uncompensated elasticities. More recently, Adetutu et al. (2016) empirically investigate the substitution and output effects of changes in energy input demand for the individual BRIIC countries[41]. Their findings suggest that the substitution effect dominates the output effect in the BRIIC countries with estimated elasticities ranged from –0.007 to –0.020 for the period under consideration.

Having reviewed the literature, this study is motivated by two key points. First, there are very limited studies on the decomposition analysis of derived demand for production factors. Second, as far as we know, no existing study on the assessment of the implications of decomposed demand for factor inputs on the environment. This chapter makes a significant contribution to the decomposition analysis for production

[41] Adetutu et al. (2016) defines the BRIIC countries as Brazil, Russia, India, Indonesia and China.

factor by decomposing derived energy demand into substitution and output effects, and further empirically investigating the implications of these effects on industrial CO_2 emissions across Europe. In this chapter, we perform empirical analysis for the industry as a whole and for different sector types by classifying the industry into primary, manufacturing and service sectors respectively. From a policy point of view, we believe that the categorisation of the entire industries into different sector types would assist in formulating sector specific energy/climate change policies as we expect our results to provide insightful information about different production technologies.

The remainder of this chapter proceeds as follows. Section 4.2 outlines the theoretical and econometric models used for the analysis. Section 4.3 describes the dataset. Section 4.4 consists of two parts. The first part presents the elasticities of substitution among factors and that of the decomposition effect, while the second part analyses the impact of the decomposition effect with other relevant factor on carbon emissions. Section 4.5 provides the concluding remarks and policy implications.

4.2 Empirical method

4.2.1 Modelling framework: Translog cost function

To investigate the substitution possibility between production factors, we employ the translog cost model among available functional forms such as Cobb Douglas, Leontief and Constant Elasticity of Subtitution (CES). Our modelling choice is motivated by the fact that the translog cost function remains as the most popular in the academic literature since its introduction by Christensen et al. (1973) due to its flexible nature, which limits any a priori restriction on factor inputs relationships. Our translog model allows for non-neutral technical change and non-constant return to scale in order to capture the role of economies of scale and technical progress within the production settings with capital, energy, labour and material as input factors. The corresponding input prices are: p_k, p_l, p_e, p_m. In addition, our translog model imposes the fundamental restriction of symmetry ($\beta_{zf} = \beta_{zf} \forall z, r$) and linear homogeneity ($\sum_i \alpha_i = 1; \sum_i \delta_i = \sum_i \varphi_i = 0 ; \sum_i \beta_{zf} = \sum_f \beta_{fz} = 0$) in the input prices. For estimation purposes, we follow the conventional practice by normalised the cost and input prices with the price of material (p_m). For simplicity, we defined the normalised input prices as $\left(\frac{p_z}{p_m} = w_z\right)$ where z= capital, energy and labour.

Unlike previous studies, in our empirical analysis we recognise the fact that industries are not operating in isolation as their activities are clearly interrelated with the activities of economy as a whole. In this context, we control for the interactions between the industries and the economy by incorporating country level variables together with their interactions with the industry level variables in our translog cost function. Furthermore, we understand that the characteristics and activities of the sampled industries are not homogenous. As a result, we control for the heterogeneity across the industries by mean-adjusted all industry level variables to at least account for a minimum level of heterogeneity across sampled industries. We further account for industries heterogeneity by include a categorical variable for classifying industries based on similarity in production activity (that is, primary, manufacturing or service sectors). Again, we include a dummy variable with "1" for industries with a multiple production unit and "0" for industries with a single production unit. Both the categorical and dummy variables are in the vector π_t as in Eq. (4.1). In addition, we account for the country-specific effects, by adding countries dummies (z_t) into our translog cost function. We incorporate the above information by specifying Eq. (4.1) as follows:

$$
\begin{aligned}
\ln\frac{C_{ijt}}{p_{m,ijt}} = {} & \alpha_0 + \alpha_y \ln y_{ijt} + \frac{1}{2}\alpha_{yy} \ln y_{ijt}^2 + \sum_{z=i}^{3} \delta_z \ln y_{ijt} \ln w_{z,ijt} + \sum_{z=1}^{3} \alpha_z \ln w_{z,ijt} \\
& + \frac{1}{2}\sum_{z=1}^{3}\sum_{f=1}^{3} \beta_{zf} \ln w_{z,ijt} \ln w_{z,ijt} + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2 + \alpha_{yt} \ln y_{ijt}\, t \\
& + \sum_{z=1}^{3} \varphi_z \ln w_{z,ijt} t + \alpha_Y \ln Y_{jt} + \alpha_{yY} \ln y_{ijt} \ln Y_{jt} + \sum_{z=1}^{3} \alpha_{zY} \ln w_{z,ijt} \ln Y_{jt} \\
& + \alpha_{tY} \ln Y_{jt}\, t + \sum_{r=1}^{4} \alpha_r \ln W_{r,jt} + \sum_{r=1}^{4} \alpha_{yW} \ln y_{ijt} \ln W_{r,jt} \\
& + \frac{1}{2}\sum_{z=1}^{3}\sum_{r=1}^{4} \beta_{rz} \ln w_{z,ijt} \ln W_{r,jt} + \sum_{r=1}^{4} \alpha_{tW} \ln W_{r,jt}\, t + \pi_t + z_t \\
& + v_{it} \qquad (4.1)
\end{aligned}
$$

where $z = k, l, e$; $r = k, l, e, m$; lower and upper case letters represent industry-level and country-level variables respectively. Ln denotes the natural log; *i* represents industries; C is the total cost; *y* is output; *t* is time trend which captures technical progress; v_{it} is the residual and *w's* are input prices as previously defined. *Y* is the output at country level; *W* is the input prices at country level. The cost minimising input demand function can be derived using Shepherd lemma by differentiating Eq. (4.1) and this gives the input demand function in terms of cost share equations as:

$$
\begin{aligned}
S_{z,ijt} = {} & \alpha_z + \varphi_z t + \sum_{f=1}^{3} \beta_{zf} \ln w_{z,ijt} + \delta_z \ln y_{i,j,t} + \alpha_{zY} \ln Y_{jt} + \sum_{r=1}^{4} \beta_{rz} \ln w_{r,jt} \\
& + \lambda_{it} \qquad (4.2)
\end{aligned}
$$

Eqs. (4.1) and (4.2) can be jointly estimated using the popular Zellner's iterated seemingly unrelated regression (iSUR) technique given its ability to increase efficiency by controlling for potential correlation of the error terms across the cost share equations. However, given the hierarchical structure of our data where industries nested in countries over time, and the potential cluster-level heterogeneity usually associated with hierarchical data, it is very likely that the iSUR technique may produce unreliable estimates[42]. In addition, it is worth noting that the inclusion of the country level variables and their interactions suggest a necessity to account for the country level residual, which might not be possible with the iSUR[43]. In order to account for the hierarchical structure of the data as well as controlling for potential cluster-level heterogeneity, we therefore also estimate the cost function with a multilevel modelling. Multilevel modelling is a maximum likelihood estimation that aims to model the relationship between a response variable and a set of explanatory variables but differs from standard regression analysis by modelling units of observation at different 'levels'. Specifically, multilevel modelling is predominantly for modelling hierarchical datasets, as the model possesses the ability to disentangle the clustering at different levels by including a disturbance term at each level of the data.[44] Unlike the iSUR, multilevel modelling is not an approach purposely meant to jointly estimate a system of equations as it requires the estimation of only Eq. (4.1), but its ability to control for the hierarchical structure of the data and cluster-level heterogeneity is a significant advantage[45]. Moreover, it allows us to introduce a model that incorporates the structure of our data.

On the other hand, Berndt and Christensen (1973) noted a notable shortcoming that might be associated with the use of single-equation models such as multilevel modelling and OLS if employ to estimate a system of equations like the translog cost function. The authors argue that since such modelling techniques would relax the restrictions imposed on the translog cost function and thus, only estimate Eq. (4.1) as in our own case,

[42] Steenbergen and Jones (2002) discuss the statistical problems and consequences inherent in hierarchical data and demonstrate that failure to control for the hierarchical structure of the data will lead to biased and inconsistent estimates.
[43] The inclusion of both explanatory variables and error term at each level enables us to measure the unexplained heterogeneity associated with each level.
[44] For interested readers on multilevel modelling see Rabe-Hesketh and Skrondal (2012) and Hox et al. (2010).
[45] This means $\pi_t = z_t = 0$ while estimating Eq. (4.1) with a multilevel model.

without simultaneously estimating the cost share equations (4.2), then the validity of such translog cost function could be violated and needs to be verified. However, Barten (1969) investigate the properties of maximum likelihood and that of translog equations and concludes that there is no difference between their estimates. Kmenta and Gilbert (1968); Dhrymes (1971) support this claim as noted by Berndt and Christensen (1973) by demonstrating that the iSUR and the maximum likelihood estimators are computationally equivalent. Notwithstanding, the arguments by Barten (1969); Kmenta and Gilbert (1968); Dhrymes (1971) we responded to the potential shortcoming noted by Berndt and Christensen (1973) by also verified the validity of our translog cost function with the iSUR technique. As a result, we estimated our translog cost function with both estimation techniques. Furthermore, since our data is regarded as three-level hierarchical dataset where the number of observations is regarded as a level 1, the industries being regarded as level 2, which are nested in countries, that is, level 3, we therefore estimate Eq. (4.1) with a three-level multilevel model. In the case of multilevel model, we control for potential cluster-level heterogeneity in our dataset by decomposing the error term in Eq. (4.1) as follows: $v_{ijt} = u_j^{(3)} + u_{ij}^{(2)} + \epsilon_{ijt}$. Where $u_j^{(3)}$ is the random term for the jth country, $u_{ij}^{(2)}$ denotes the nested effect of ith industry within the jth country, and ϵ_{ijt} is the remaining disturbance term for each observation in the sample.

4.2.2 Elasticities of substitution

The elasticity of substitution (ES) between energy and non-energy inputs can be computed using the estimated parameters from the cost function Eq. (4.1) and the predicted cost shares Eq. (4.2). We apply the most three popular methods of measuring the elasticity of substitution in the literature, that is, the Allen-Uzawa elasticity of substitution (AES), cross-price elasticity (CPE) and the Morishima elasticity of substitution (MES). Although, each of these elasticities of substitution has unique features, but they are interrelated as both the CPE and the MES could be derived from the AES[46]. Allen (1934 and 1938) initially proposed the AES, and then Uzawa (1962) later demonstrated the empirical estimation of the AES from a fitted cost function. The AES is a partial elasticity as it measures the change in input *K* (capital) if the price of input *E* changes. For simplicity purposes, we refer to only inputs *K* and *E* (energy) when presenting our elasticities of substitution and the decomposition effects (when necessary). The AES considers inputs as complements if ES denotes by σ less than zero (that is σ < 0 and inputs as substitutes if, σ > 1. The formula for the AES is written as follows:

$$\sigma_{EE}^{AES} = \frac{\beta_{EE} + S_E^2 - S_E}{S_E^2}; \qquad \sigma_{EK}^{AES} = \frac{\beta_{EK} + S_E S_K}{S_E S_K} \tag{4.3}$$

where S_E and S_K are the estimated factor shares for energy and capital respectively and β_s are the parameter estimates from the translog cost function. The main argument against the use of AES in the literature is the fact that it fails to provide information on relative factor shares since the impact is on actual price changes rather than relative price changes. In addition, the symmetric nature of the AES (i.e.,σ_{EK}=σ_{KE}) makes it a limited measure of ES as it fails to capture the curvature properties of the production function (Blackorby and Russell, 1981). Although, the CPE and AES have similar features as both measure absolute change in input demand rather than relative change, unlike the AES the CPE is asymmetric, that is, $\sigma_{EK} \neq \sigma_{EK}$. The asymmetric property of the CPE is therefore an added advantage. The CPE is written in terms of the AES as follows:

[46] Broadstock et al. (2007) provide detailed explanation on the relationship between the AES, CPE and MES.

$$\eta_{EE} = s_E \sigma_{EE}^{AES}; \quad \eta_{EK} = s_K \sigma_{EK}^{AES}. \tag{4.4}$$

where η_{EE} is the own-price elasticity of energy input and η_{EK} is the cross-price elasticity between capital and energy.

Given the shortcomings associated with AES and CPE, Blackorby and Russell (1981) proposed the use of MES as a more appropriate measure of ES. They argued that the MES is theoretically superior to the AES and CPE as it is closer to the original definition of ES proposed by Hicks (1932) as noted in Haller and Hyland (2014)[47]. In addition, MES does not only allow for inputs adjustments while holding output constant, but also allows for the evaluation of the elasticity of change in input ratios with respect to price ratios for a given level of output (Stern, 2011). The MES can be written in terms of the AES as follows:

$$\sigma_{EK}^{MES} = s_K(\sigma_{EK}^{AES} - \sigma_{KK}^{AES}). \tag{4.5}$$

where all notations remained as previously defined. The MES measures the change in the ratio of two inputs (*E/K*) when the price of *K* changes. If an increase in the price of *K* stimulates an increase in *E/K* input ratio ($\sigma_{EK}^{MES} > 0$) then *E* and *K* are substitutes. On other hand, if $\sigma_{EK}^{MES} < 0$ where an increase in the price of *K* reduces *E/K* input ratio, then *E* and *K* are complements. Unlike the AES the MES is asymmetric in nature ($\sigma_{EK}^{MES} \neq \sigma_{KE}^{MES}$) depending on which input price changes.

4.2.3 Energy demand decomposition effect

To this point, we mainly focused on the substitution possibilities among factors if the price of input changes by assuming that output level in unchanged. To recap, Chambers (1982) argues that these substitution elasticities may not represent the true

[47] However, Frondel (2004) argues that the CPE is preferable on the basis that it is more applicable in practice given the fact that it is an absolute measure of ES rather than relative measures of ES.

characteristics of a cost minimising firm as it fails to account for the output effects of a change in input price. In other words, producers do not adjust their output as factor prices change. However, in principle, this assumption undermines the true nature of firm behaviour because in practice, producers adjust output not only to changes in factor price, but also to changes in technology, external shocks and etc. Therefore, making the estimation of the output effect in addition to the substitution effect likely relevant as it may provide the missing point in input adjustments rather than estimating only the ES. To do this, we use the Slutsky equation in microeconomic theory to decompose the reaction of a representative firm resulting from changes in factor price into substitution and output effects. Specifically, our interest is own-decomposition of derived energy input to changes in own-price. To do so, we draw on duality theory by using the uncompensated (Marshallian) and compensated (Hicksian) input demand functions where we assume that firms' minimize cost (c) subject to a given level of output (y):

$$c(y, \boldsymbol{w}) = c = \min_{x'}[\textstyle\sum_z \boldsymbol{w}_z x_z] \text{ subject to } y = f(\boldsymbol{x}) \tag{4.6}$$

where $c(y, \boldsymbol{w})$ is the targeted total cost of producing output y given input prices $\boldsymbol{w}$. In microeconomic theory, the Marshallian demand function ($x_z = g_z(c, \boldsymbol{w})$) that expresses the input demand in terms of the total cost and a vector of input price is actually the true dual of the Hicksian demand function ($x_z = h_z(y, \boldsymbol{w})$) where the firm's input demand is written in terms of output and a vector of input price instead[48]. By substituting the cost function into the Marshallian demand function and using the implicit relationship between the Marshallian and the Hicksian functions, the total effect of changes in price is as follows:

$$x_z = h_z(y, \boldsymbol{w}) = g_z(c(y, \boldsymbol{w}), \boldsymbol{w}) \tag{4.7}$$

[48] The Hicksian functions present the amount of input (x_z) demanded at each possible price (w_z) holding output constant. Thus, the Hicksian function only depicts the substitution effects of a change in relative prices.

By differentiating Eq. (4.7) with respect to w_z we have: $\frac{\partial x_z}{\partial w_z} = \frac{\partial h_z}{\partial w_z} \equiv \frac{\partial g_z}{\partial w_z} + \frac{\partial g_z}{\partial c} \cdot \frac{\partial c}{\partial w_z}$. Since $c = c(q, \boldsymbol{w})$ and also by Shepard's Lemma, $\frac{\partial c}{\partial w_z} = x_z$, then Eq. (4.7) is re-arranged and written in terms of substitution and output effects of changes in input price as in Eq. (4.8):

$$\frac{\partial g_z}{\partial w_z} = \frac{\partial h_z}{\partial w_z} - \frac{\partial g_z}{\partial c} x_z \tag{4.8}$$

Eq. (4.8) decomposes the uncompensated price response ($\frac{\partial g_z}{\partial w_z}$) into a substitution effect ($\frac{\partial h_z}{\partial w_z}$) and an output effect ($-\frac{\partial g_z}{\partial c} x_z$). The substitution effect implies, if the price of one input changes, its relative price also changes, which results in a fall in demand for that input whose price increases and an increase in demand for inputs that are substitutable for it. The output effect captures the change in real output as a result of a change in input price. In our empirical analysis, we write the compensated cross-price elasticity between inputs *E* and *K* by converting Eq. (4.8) to Mundlak (1968) elasticity form as follows:

$$\eta_{EK} = \eta_{EK}^{c} - S_K \eta_E \tag{4.9}$$

where η_{EK}^{c} captures the substitution effect and η_E captures the output effect, which consists of two components. S_K is the cost share of input *K* to total expenditure and η_E is the expenditure elasticity of input demand. For own-price elasticity, which is more relevant to this paper, Eq. (4.9) is written as follows:

$$\eta_{EE} = \eta_{EE}^{c} - S_E \eta_E \tag{4.10}$$

The substitution effect is non-positive ($\eta_{EE}^{c} \leq 0$), but the output effect can be negative or positive. If the output effect is positive (that is, $-S_E \eta_E > 0$), this implies that the input is an inferior good; while a negative output effect ($-S_E \eta_E < 0$) suggests that the input is a normal good. The former case suggests that an increase in the price of energy would have a positive impact on the output level of the producer. The latter suggests that the output level of the producer reduces as energy price increases. The substitution and output effects can be generated from the estimated translog model as follows. The substitution effect, η_{EE}^{c} can be derived by taking the second-order derivatives of the estimated cost function with respect to energy price, that is: $\eta_{EE}^{c}=\frac{\partial^2 \ln c}{\partial \ln w_E^2}$. The output effect consists of two components: S_E is the cost share of energy input to total cost; η_E, which is the expenditure elasticity of energy input demand and can be derived from the implicit relationship between the Marshallian and Hicksian functions in Eq. (4.10). That is $\eta_E=\frac{\partial \ln x_E}{\partial \ln c}=\left(\frac{\partial \ln x_E}{\partial \ln y}\right)\left(\frac{\partial \ln y}{\partial \ln c}\right)$.

4.3 Data

This study is based on a panel of 34 industries across 29 European countries[49] over the period 1995–2007[50]. Majority of our series are obtained from World Input-Output Database (WIOD) (Timmer et al., 2015). Temperature and purchasing power parity exchange rates are taken from the Climate Research Unit and Tyndall, and Penn World Table (PWT 7.1) respectively. CO_2 emissions in Gg (kt) and energy use in (TJ) are obtained from the environmental accounts of WIOD. Energy input expenditure is calculated as the addition of the value of expenditure on energy inputs (coke, refined petroleum, nuclear fuel, electricity and gas Supply) purchased domestically and internationally in national currency. Material input expenditure is calculated as the expenditure on intermediate inputs at current national currency. Temperature is measured as the average annual temperature for each country, while the measure of

[49] The industries are listed in the appendix and 29 European countries consist of Austria, Belgium, Bulgaria, Cyprus, Czec Rep, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Russia, Slovak Rep, Slovania, Spain, Sweden, Turkey and United Kingdom.

[50] We are constrained to this period, as some of the series used in our estimation are not available beyond 2007.

output (y) is gross output that is expressed in millions of national currency at current prices and employees are in thousand. Energy input expenditure; material input expenditure, capital compensation and labour compensation are in millions of national currency at current prices while numbers of persons engaged are in thousands. We deflated gross output using the price index of gross output (1995=100). Then used the exchange rates to convert the series to US$. Similarly, we convert the producers' input expenditures to constant (1995=100) prices in each country by applying the implicit price deflator for that industry in each country. We then convert the constant series to US$ using the purchasing power parity exchange rates.

The input prices are therefore computed as follows. The real price of energy (pe) is computed as the ratio of intermediate energy input expenditure at constant prices to energy use in TJ. The real price of capital (pk) is calculated as the ratio of capital compensation to real fixed capital stock; the real price of labour (pl) is computed as the ratio of labour compensation to number of persons engaged and the real price of material (pm) is derived as the ratio of value of intermediate material input expenditure to intermediate material volume.

Table 4.1: Variable descriptions and summary statistics

Variable	Obs.	Mean	Std. Dev.
CO_2 emissions in Gg (kt)	12662	5144.84	29901.7
Energy (in terajoule)	12662	148958.6	743730.6
Output (millions US$)	12662	195836	170977
Price of capital (in millions of US$)	12662	9.38	6.09
Price of labour (in millions of US$)	12662	3.97	2.88
Price of energy in (millions US$/per TJ)	12662	17.39	10.97
Price of material (in millions of US$)	12662	8.92	8.06
Capital expenditure/cost	12662	0.22	0.13
Labour expenditure/cost	12662	0.19	0.11
Energy expenditure/cost	12662	0.01	0.00
Employee	12662	0.59	0.15
Temperature	12662	10.05	4.58

4.4 Empirical analysis

4.4.1 Estimated results and elasticities of substitution

Given the significant intuition of the parameter estimates of the translog cost function, we therefore reported the results of the estimated cost function in Tables 4.2 and 4.3. We estimated the specified translog model with both iSUR[51] and multilevel modelling techniques for the entire industries and for sector types with all estimated variables in their natural logarithm. We control for heterogeneity across the industries and countries by incorporating additional industry and country characteristics ($\pi_t$and z_t) respectively in Eq. (4.1). By mean-adjusted the industry level variables, we can therefore interpret the ES as elasticities at the sample mean. Although, the results reported in the appendix show that majority of the estimated parameters are statistically significant with expected signs, we observe that the multilevel modelling performs better in terms of the numbers

[51] We estimated the cost share equations while using the iSUR.

of significant estimates across the board[52]. The results of the estimated cost function lead to the discussion of the elasticities of substitution discussed above. However, it is necessary to discuss the curvature properties of the estimated cost function before analysing the ES as it provides information about the performance of the fitted cost function.

In principle, a well-behaved cost function must possess an economic property that satisfies the condition of monotonicity at both samples mean and outside the sample mean. Given the positive and statistically significant of the coefficients of the output and input prices at the industry level as reported in Tables 4,2 and 4.3, our results suggest that the estimated cost functions strongly satisfied the condition of monotonicity at the sample mean. Further, we also test these curvature properties of the fitted cost function by verifying if the condition of monotonicity is also satisfied outside the sample mean. Our analysis shows that monotonicity is strongly satisfied outside the sample mean with on average 76% of the data points is monotonic[53]. The monotonic condition suggests that our estimated cost functions are non-decreasing in both output and input prices.

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[52] Specifically, most of the estimates at country-level and their interactions with industry-level are significant. This reinforces the argument stated above that industries are not operating in isolation as their activities are closely integrated with aggregate activities, thus, there is a need to control for aggregate effects.

[53] As the entire sample comprises data points for the primary, manufacturing and service sectors, we verified the monotonic condition outside the sample mean with the entire sample only and the results are available on request.

Table 4.1: Estimated translog cost function with multilevel modelling

Variable	Whole	Primary	Manufacturing	Service
Fixed part:				
Intercept	–0.20***	0.28**	–0.25	–0.01
ly1_y	0.65***	0.63***	0.66***	0.63***
ly11_y^2	–0.02***	0.00	–0.01***	–0.02***
ly1t_yt	0.01***	0.01*	0.01***	0.00
ly1w1_yk	–0.00	0.06***	–0.00	0.00
ly1w2_yl	–0.06*	–0.01	0.02***	–0.03***
ly1w3_ye	–0.01	–0.01	–0.01**	0.00
w1_k	0.14***	0.23***	0.16***	0.11***
w2_l	0.27***	0.30***	0.30***	0.29***
w3_e	0.05***	0.01***	0.04***	0.03***
w11_k^2	0.02***	0.04***	0.03***	0.02***
w22_l^2	0.00	–0.03***	0.01***	–0.02***
w33_e^2	–0.01***	0.00	–0.01***	0.00
w12_kl	–0.03***	–0.01	–0.05***	–0.02***
w13_ke	0.00**	–0.01	0.01***	–0.01***
w23_le	0.03***	–0.03**	0.03***	0.03***
w1t_kt	0.00***	0.01***	0.01***	0.00***
w2t_lt	–0.00***	0.00	0.00	–0.01***
w3t_et	0.00***	0.01***	0.00	0.00***
t	0.02***	0.02***	0.02***	0.03***
tsq_t^2	0.00***	0.00***	0.00	0.00
Country-level variables				
Y	–0.21***	–0.27***	–0.22***	–0.14***
W1-K	–0.11***	–0.07***	–0.14***	–0.06***
W2-L	–0.12***	–0.09***	–0.16***	–0.08***
W3-E	0.02***	–0.01	–0.02***	0.01
W4-M	–0.41***	–0.09	–0.36***	–0.51***
Industry-country interactions				
Yt	–0.01***	0.00	–0.01***	–0.01***
Yy	0.06***	–0.01	0.05***	0.06***
Yw1_Yk	0.01***	–0.01	0.02***	0.01
Yw2_Yl	0.01***	0.00	0.01	0.02***
Yw3_Ye	0.01	0.01	–0.01*	–0.03***
W1t-Kt	0.00	0.00	0.00	0.00
W2t-Lt	0.00	0.01***	0.00*	0.00
W3t-Et	–0.01***	–0.01**	–0.01***	–0.01***
W4t-Mt	0.01***	0.00	0.00	0.00
W1y-Ky	0.02***	–0.02	0.02***	0.00
W2y_Ly	–0.02***	–0.02	–0.05***	0.02***
W3y_Ey	0.01***	–0.05***	0.01***	0.01
W4y_My	–0.02***	0.06***	–0.01	–0.03***
W1w1_Kk	–0.04***	–0.05***	–0.05***	–0.03***
W2w1_Lk	0.04***	0.00	0.03***	0.04***
W3w1_Ek	–0.00***	–0.01**	0.00*	0.00***
W4w1_Mk	0.00	0.04***	0.02***	0.00
W1w2_Kl	0.05***	0.13***	0.06***	0.03
W2w2_Ll	0.03***	0.00	0.01	0.08***
W3w2_El	–0.01***	–0.07***	–0.01***	0.00***
W4w2_Ml	–0.05***	–0.05**	–0.05**	–0.08
W1w3_Ke	0.01***	–0.02***	0.00	–0.01
W2w3_Le	–0.05***	–0.02	–0.04***	–0.09***
W3w3_Ee	0.01***	0.03***	0.01***	–0.00**
W4w3_Me	0.03***	0.04*	0.02**	0.07***
Intra-class correlation	0.77*	0.55*	0.82*	0.80*

Table 4.2: Estimated translog cost function with iSUR

Variable	Whole	Primary	Manufacturing	Service
Cost share equation for capital				
ly1	0.02***	0.03***	–0.00	0.05***
w1	0.02***	0.02***	0.03***	0.02***
w2	–0.00***	0.02***	–0.01***	0.02***
w3	–0.00**	–0.01***	–0.01***	–0.00***
t	0.00***	0.01***	0.00***	0.00***
Y	0.01***	0.00	0.03***	–0.01**
W1	–0.04***	–0.05***	–0.04***	–0.03***
W2	–0.00	–0.00	0.01***	–0.03***
W3	0.01***	0.00***	0.02***	0.01***
W4	–0.01***	0.01	–0.02***	–0.01***
Intercept	0.16	0.20***	0.13***	0.19***
Cost share equation for labour				
ly1	0.03***	0.07***	0.01***	0.03***
w1	–0.00***	0.02***	–0.01***	0.02***
w2	0.01***	0.01***	0.00	0.01***
w3	0.01***	0.00	0.01***	0.00***
t	0.00***	–0.00	0.00***	–0.00**
Y	–0.03***	–0.03***	–0.01***	–0.04***
W1	0.05***	0.06***	0.07***	0.03***
W2	0.04***	0.04***	0.05***	0.05***
W3	–0.07***	–0.06***	–0.08***	–0.05***
W4	0.01***	–0.01**	–0.01***	0.02***
Intercept	0.30***	0.36***	0.26***	0.36***
Cost share equation for energy				
ly1	0.00**	0.00**	–0.00	–0.01***
w1	–0.00**	–0.01**	–0.01***	–0.00***
w2	0.01***	0.00	0.01***	0.00***
w3	–0.00***	–0.01***	–0.00***	0.00***
t	–0.01***	–0.00***	–0.00	–0.00***
Y	0.00	0.00	0.01***	0.01***
W1	0.01***	0.01***	0.02***	0.01***
W2	–0.03***	–0.03***	–0.04***	–0.02***
W3	0.01***	0.01***	0.01***	0.01***
W4	0.01***	0.00	0.00	0.00***
Intercept	0.04***	0.04***	0.04***	0.03***
Cost share equation for material				
ly1	0.02**	0.04**	–0.00	–0.02***
w1	–0.00**	–0.03**	–0.01***	–0.04***
w2	0.01***	0.00	0.21***	0.00***
w3	–0.00***	–0.01***	–0.10***	0.30***
t	–0.03***	–0.00***	–0.00	–0.02***
Y	0.00	0.20	0.01***	0.01***
W1	0.01***	0.01***	0.02***	0.01***
W2	–0.03***	–0.03***	–0.04***	–0.02***
W3	0.01***	0.01***	0.01***	0.12***
W4	0.01***	0.01	0.04	0.02***
Intercept	0.14***	0.12***	0.10***	0.15***

***, ** and * represent statistically significant at 0.1%, 1% and 5% level of significance

Following the estimation of the translog cost function, we verified the possibility of factor substitution by computing the AES, CPE and MES using Eqs. (4.3 to 4.5). We used the estimated parameters of the iSUR and the multilevel model reported in Table 4.2 and 4.3 in computing the substitution elasticities[54]. Empirical elasticities at the sample mean are presented in Table 4.4 and 4.5. Majority of the estimates of the AES reported in Table 4.4 are positive and statistically significant. The positive estimates of our elasticities indicate that energy and non-energy inputs are substitutes in most cases, though; we find capital and energy as complements for the manufacturing sector with multilevel modelling. Our estimates indicate a relatively strong ES between energy and non-energy inputs as most of the elasticities reported in Table 4.4 are close to or greater than one. However, our results display a weak/moderate ES between capital and energy for the Primary and Service sectors. As theoretically expected, the estimates of the MES are positive across board and statistically significant. The MES reinforces that energy and non-energy inputs are substitutes across sectors. Furthermore, the estimates of the AES and the MES show that the substitution between energy and labour is relatively stronger compared to others ES, while capital and labour are the least substitutes. Specific to the MES, the elasticity of substitution η_{EL} = 1.74 suggests that a 1% increase in the price of labour is associated with about 1.7% increase in energy-labour input ratio. The estimates of our ES are in line with existing literature. For the AES, our estimates are closer to Adetutu et al. (2016) and for the MES; our estimates are similar to Haller and Hyland (2014).

For comparison purposes, the elasticities reported in Table 4.4 indicate that the values of the AES are bigger than that of the MES. The results suggest that the AES demonstrate a stronger technical substitution between factor inputs than the MES. One reason that might account for the difference between the values of the AES and MES

[54] However, substantial part our explanation is limited to the elasticities of substitution derived from the estimates of the multilevel modelling as this is our model of interest. Further, unlike chapter 3, since the purpose of this chapter is to analyse the decomposition effect rather than estimating ES, thus, we didn't compute the ES for the normalised input (materials) as shown in Tables 4.4 and 4.5.

could be because of the restrictive symmetric relationship exhibits in input combinations under the AES, as it explains the potential input adjustment relative to factor share, if the price of other input changes. While, in contrast, MES exhibits a flexible asymmetric relationship in input combinations, as it captures the change in the ratio of two inputs when the price of one of the inputs changes. Ideally in practice, the producers are more concerned with the relative change rather than actual change in input demand when the price of one input changes. Therefore, the restrictive assumption of actual change in input demand under the AES rather than the relative change in input as other input price rises might be a possible explanation for the overstate of the AES.

The own and cross-price elasticities for different sectors are reported in Table 4.5. We find majority of the elasticities reported in Table 4.5 statistically significant across board. As expected, all own-price elasticities are negative and significant. With few exceptions, the estimates of the CPE generally indicate that factor inputs are substitutes given their positive coefficients. However, we observe a relative weak substitutability among factors in CPE compared to the AES and MES as majority of the CPE less than 0.5. This suggests that the substitution possibility among factors is predominantly weak, with the substitution of capital for energy (η_{KE}) demonstrates the weakest, while the substitution of energy for labour (η_{EL}) demonstrates the strongest in general. Moreover, the elasticities reported in Table 4.5 demonstrate considerable variations in terms of asymmetric from factor to factor. For instance, although, the demand for labour demonstrates a weak response to changes in energy prices (η_{LE} = 0.13), the demand for energy displays a strong response to changes in labour prices (η_{EL} = 1.05). Further, in most cases, our results show considerable differences in the estimates of the CPE derived from the iSUR and the multilevel technique. For instance, the elasticities from the iSUR (multilevel) indicate substitutability (complementarity) between capital and energy for the manufacturing sector. In contrast, although, not statistically significant, the elasticities from the iSUR indicates complementarity while that of the multilevel technique indicates substitutability between capital and energy for the service sector.

Across the board, our estimated elasticities indicate that energy is the most price responsive input, with average estimated own-price elasticities of about -0.94 and -1.07 from the iSUR and multilevel techniques respectively. In contrast, we find labour as the least price responsive input with average estimated elasticities of about -0.65 and 0.68 from the iSUR and multilevel techniques respectively. These results are consistent with Haller and Hyland (2014) as they find energy as the most price responsive input with an estimated elasticity of -1.46%, and labour as the least price responsive input with an estimated elasticity of -0.48%. Also, Griffin and Gregory (1976); Nguyen and Streitwieser, (1999) find energy as the most price-elastic input with Griffin and Gregory (1976) find labour as the least price-elastic input with an average estimated elasticity -0.23, which is similar to Arnberg and Bjørner (2007).

Table 4.4 Elasticity of substitution estimates.

	Elasticities with iSUR estimates				Elasticities with multilevel model estimates			
	Whole	Primary	Manufacturing	Service	Whole	Primary	Manufacturing	Service
Allen-Uzawa elasticities								
$\sigma_{KL} = \sigma_{LK}$	0.95***	1.25***	–0.43***	1.26***	0.35***	0.87***	0.72***	0.76***
$\sigma_{KE} = \sigma_{EK}$	0.82***	0.43***	2.57***	0.66**	1.43***	0.24	–0.43***	–0.07
$\sigma_{LE} = \sigma_{EL}$	2.33***	1.12***	3.45***	1.31***	3.53***	2.61***	2.23***	3.31***
Morishima elasticities								
σ_{KL}	0.94***	1.05***	0.92***	1.07***	0.79***	1.04***	0.58***	0.95***
σ_{KE}	1.10***	0.80***	0.99**	0.91***	1.24***	0.96***	1.22***	1.03***
σ_{LE}	1.16***	0.84***	1.12***	0.93***	1.32***	1.06***	1.26**	1.15***
σ_{LK}	0.84***	0.94***	0.75***	0.95***	0.75***	0.79***	0.58***	0.85***
σ_{EK}	0.82***	0.77***	0.58***	0.83***	0.94***	0.66***	0.97***	0.70***
σ_{EL}	1.35***	1.00***	1.31***	1.09***	1.74***	1.67***	1.58***	2.01***

***, ** and * represent statistically significant at 0.1%, 1% and 5% level of significance. . Standard errors are calculated using the delta method.

Table 4.5 Own-and cross-price elasticities.

	Elasticities with iSUR estimates				Elasticities with multilevel model estimates			
	Whole	Primary	Manufacturing	Service	Whole	Primary	Manufacturing	Service
η_{KK}	–0.68***	–0.68***	–0.65***	–0.72***	–0.69***	–0.61***	–0.63***	–0.71***
η_{LL}	–0.65***	–0.59***	–0.73***	–0.62***	–0.67***	–0.72***	–0.67***	–0.68***
η_{EE}	–1.07***	–0.79***	–1.01***	–0.89***	–1.19***	–0.95***	–1.10***	–1.03***
η_{KL}	0.29***	0.45**	0.19**	0.45***	0.10***	0.31***	–0.11**	0.27**
η_{KE}	0.03***	0.02***	–0.03***	0.02**	0.05***	0.01***	0.11***	–0.00
η_{LE}	0.09***	0.05***	0.10***	0.04***	0.13***	0.11***	0.15***	0.11***
η_{LK}	0.16***	0.26***	0.09**	0.24***	0.06***	0.18***	–0.05***	0.14***
η_{EK}	0.14***	0.09***	–0.08***	0.12**	0.25***	0.05***	0.33***	–0.01
η_{EL}	0.69***	0.41***	0.58***	0.47***	1.05***	0.95***	0.89***	1.32***

***, ** and * represent statistically significant at 0.1%, 1% and 5% level of significance. Standard errors are calculated using the delta method.

4.4.2 Estimated decomposition results

To this point, we mainly focused on the pure substitution possibilities among factors if there is an absolute or relative change in input price without accounting for the output effect. We argued above that by estimating only the ES without considering the output effect may undermines the true nature of firm's behaviour, as firms are likely to adjust output accordingly not even only to changes in factor price, but also to technological change, shocks and market imperfections. Hence, we critically analyse this argument by estimating the output effect in addition to the substitution effect. In our empirical analysis, we explore the output effect of a change in energy input following the estimation of Eqs. (4.1 and 4.2) by decomposing the derived energy input into substitution and output effects with Slutsky equation as discussed in section 4.2.

The focus of this chapter is on own-price effect as expressed in Eq. (4.10) rather than the cross-price effect. To analyse the decomposition effects, we used the parameter estimates of the iSUR and multilevel models reported in Tables 4.1 and 4.2 to derive separate substitution and output effects from each of the techniques. The estimates of the substitution and output effects for whole sector and sector types are reported in Table 4.6[55]. For the multilevel modelling, we find the estimates of the substitution effects to be negative and statistically significant as expected. The results are in conformity with economic theory indicating that producer's consumption of energy input reduces as energy price increases. The reduction could be as a result of using cheaper substitutable inputs. On the other hand, we find a mix results for the iSUR technique, which is somehow questionable as substitution effect takes negative (whole

[55] The estimation of the output effect is not straightforward unlike the substitution effect, which is directly obtainable from the estimated translog model, therefore, generating the standard error is problematic. Moreover, since the output effect can either be positive or negative, the standard error is considered inconsequential here.

and manufacturing) and positive (primary and service) values and statistically significant. This result contradicts the theory as positive substitution effect indicates that producer increases the amount of energy use as energy price increases.

In general, it could be observed that the substitution effect from the multilevel modelling is bigger than that of the iSUR in absolute terms, but smaller than the estimates reported in Adetutu et al. (2016). One possible explanation to this difference could be the choice of analysis and sampled countries as they decomposed energy demand for individual BRIIC countries, while this study decomposes energy demand for a panel of industries across European countries.

Table 4.6: Decomposition effects of derived energy demand

	Based on iSUR estimates		Based on multilevel estimates	
	Substitution effect	Output effect	Substitution effect	Output effect
Whole	–0.004*	0.000	–0.008*	–0.001
Primary	0.007*	–0.000	0.000	–0.001
Manufacturing	–0.003*	0.000	–0.006*	–0.000
Service	0.002*	–0.000	–0.002*	0.000

* represent statistically significant at 5% level of significance

Arguably, industries in fast emerging economies such as BRIIC are likely to be more sensitive to changes in energy price as they exhibit a very strong substitution between energy and other inputs as demonstrated by Adetutu et al. (2016).

For the output effect, the results based on the estimates of the iSUR and the multilevel model differ by sign for the whole, manufacturing and service sectors. A positive output effect implies that energy input is an inferior factor, which suggests that a firm is not sensitive to a rise in energy price and therefore fails to reduce output accordingly. In contrast, a negative output effect indicates that energy is a normal factor input, therefore a rise in energy price is expected to increase the firm's production cost and consequently reduce the firm's output level. Intuitively, the latter case represents the true behaviour of a rational cost-minimizing firm, as we expect producer to reduce output to minimize loss when cost of production increases. Further, it is more logical to consider energy as a normal good given its historical essentiality in the production process. Again, we consider the multilevel modelling as a preferred method given the estimated negative output effects. The positive output effect for the service sector is justifiable given the nature of the service sector as they mainly provide services. This is because in the service sector, employers are unlikely to reduce the quality of their services or reduce the level of services by laying off workers, in response to an increase in energy price unlike in the manufacturing and primary sectors where energy input forms the major part of their production process.

However, notwithstanding the intuition behind the estimates of the output effect, the estimates are generally not different from zero, which allows the substitution effect to be a dominant factor in our case. With this outcome, it is logical to conclude that the output effect is likely not to have a significant implication on carbon reduction via reduction in energy use. Given this argument and in addition to the fact that the multilevel model is our preferred method of analysis as discussed above, we only analysed the relationship between carbon emissions and the output effects derived from the multilevel model in section 4.4.3. Therefore, it is in the context of these results we extend the literature by carrying out an exploratory investigation to analyse the relevance of the output and substitution effects (arising from increase in energy price) on carbon emissions.

4.4.3 Energy demand decomposition and CO_2 emissions

The exploratory analysis presented here is underpinned by the theoretical exposition discussed in chapter 3. Following the decomposition of derived energy demand into substitution and output effects, we now focus on the implications of these effects on CO_2 emissions. Given the hierarchical structure of our dataset and the necessity to control for heterogeneity at each level of the data as we did in chapter 1, we therefore employ a generalised 3-level multilevel modelling approach where country is level 3 and industry is level 2 number of observation is level 1[56]. Our generalised 3-level multilevel model is specified as follows:

$$co_{2,ijt} = X'_{ijt}\delta + CR'_{jt}\gamma + u_j^{(3)} + u_{ij}^{(2)} + \epsilon_{ijt} \tag{4.11}$$

where $t = 1, \ldots., T$, $i = 1, \ldots\ldots, I$ and $j = 1, \ldots\ldots, M$. The dependent variable $co_{2,ijt}$ denotes the CO_2 emissions for industry *i* in country *j* in time *t*. *X* denotes a vector of industry-level variables including estimated substitution and output effects, *CR* represents a vector of country-level variables and *t* indicates time dummies. The error terms assumed to be independently and identically distributed (*IID),* with zero mean and their respective variances:

$$u_j^{(3)} \sim N(0, \sigma_v^2); \qquad u_{i,j}^{(2)} \sim N(0, \sigma_u^2); \qquad \epsilon_{i,j,t} \sim N(0, \sigma_\epsilon^2)$$

where $u_j^{(3)}$ is the error term for the *j*th country, $u_{i,j}^{(2)}$ represents the nested effect of *i*th industry within the *j*th country, and $\epsilon_{i,j,t}$ is the remaining error term for *t*th response time of *i*th industry within the *j*th country.

[56] Given that the 3-level model had been explicitly defined in Chapter 2, we thus specified the general version in this chapter for simplicity.

We estimated Eq. (4.11) without and with the decomposition effects. The estimated results are reported in Tables 4.7 and 4.8 respectively. For analysis purposes, all estimated variables are in their natural logarithm and we centred the industry level variables on the log of their group means so that their estimated parameters can be interpreted as elasticities within country. The country level variables are the group means of the industry level variables and their coefficients can be interpret in form of between-country effect or contextual effect of a given variable[57]. As output is one of the variables estimated, we acknowledge that a strand in the literature (Halicioglu, 2009; Ghosh, 2010; Pao and Tsai, 2011) argues that output could mirror carbon emissions; as a result, Eq. (4.11) might suffer from endogeneity problem. However, another strand in the literature (Ang, 2007; Soyta and Sari, 2007; Zhang and Cheng, 2009; Chang, 2010) of emission-output nexus refutes this claim by arguing that there is a unidirectional causality running from output to carbon emissions. This implies there is no consensus in the existing literature regarding the direction of causality between output and emissions. We leverage on this inconclusive evidence in the literature of output-emissions nexus and estimated Eq. (4.11) on the assumption that only output drives emissions, but not the other way around in our case. Notwithstanding the strand in the literature we support, we advise readers to interpret our results with caution.

The results of the estimated model without decomposition are reported in Table 4.7. The results show that majority of the estimated variables for the whole, manufacturing and service sectors are statistically significant with expected sign. However, our results show the opposite for the primary sector as majority of the estimates are not statistically significant. Expectedly; energy, output and employees all have positive relationship

[57] Hox et al. (2010) and Steele (2008) provide explanation on using the means of lower level variables as higher level variables in multilevel model.

with carbon emissions. Generally, we find energy as the main driver of carbon emissions with relatively large within-country (0.24) and between-country elasticities (0.58). The larger value of the between-country elasticity compared to the within-country elasticity indicates that aggregate energy use has a stronger influence on carbon emissions than industry-level energy use.

Table 4.7: Estimated results for CO_2 emissions without decomposition effects

Fixed part:	Whole	Primary	Manufacturing	Service
Constant	–1.80***	–3.93***	–2.62***	–1.04**
	(0.30)	(0.86)	(0.39)	(0.49)
Industry-level variables				
Energy	0.24***	0.25***	0.29***	0.19***
	(0.01)	(0.04)	(0.01)	(0.01)
Output	0.11***	0.16	0.06***	0.21***
	(0.02)	(0.10)	(0.02)	(0.04)
Employee	0.11***	−0.06	0.01	0.17***
	(0.01)	(0.05)	(0.02)	(0.02)
Country-level variables				
Temperature	–0.12***	0.00	–0.28***	0.07
	(0.02)	(0.07)	(0.03)	(0.04)
Energy	0.58***	0.90	0.89***	0.21***
	(0.04)	(0.10)	(0.05)	(0.05)
Output	0.08***	−0.06	0.08***	0.15***
	(0.02)	(0.10)	(0.03)	(0.04)
Employee	0.47***	0.23	–0.00	1.03***
	(0.04)	(0.13)	(0.06)	(0.07)
Random part:				
σ_v^2	0.23**	0.22	0.27**	0.86***
	(0.09)	(0.19)	(0.12)	(0.26)
σ_u^2	2.36***	0.75**	2.32***	1.64***
	(0.11)	(0.21)	(0.16)	(0.12)
σ_ε^2	0.07***	0.04***	0.06***	0.08***
	(0.00)	(0.00)	(0.00)	(0.00)
Intra-class correlation	0.09**	0.21	0.10**	0.33
	(0.03)	(0.18)	(0.04)	(0.08)

***, ** and * represent statistically significant at 0.1%, 1% and 5% level of significance. Intra-class correlation coefficient $(ICC) = \frac{\sigma_v^2}{\sigma_v^2+\sigma_u^2+\sigma_\varepsilon^2}$.

The statistical significance of most of the estimated country-level variables demonstrates the importance for controlling for country-level effects while using industry level dataset. The results reinforce the fact that industries are not operating in isolation as their activities evidently tied to macroeconomic activities. Further, temperature is negatively related with industrial carbon emissions with estimated elasticities negatively statistically significant across the board as expected. The estimate of –0.12 suggests that a 10% increase in temperature is associated with about 1.2% reduction in carbon emissions. One possible explanation for the inverse relationship between carbon emissions and temperature is that industries are likely to reduce their energy consumption in warm weather period and subsequently reduce the amount of carbon emissions during this period.

The results of the random part explain the unobserved heterogeneity in our dataset. The results demonstrate the strengths of multilevel modelling in terms of its ability to account for and separate the unobserved heterogeneity at different levels of the data, which iSUR ignores. The coefficients on error terms σ_v^2 , σ_u^2 and σ_ε^2 represent unobserved variations in country, industry and time period respectively with most of the estimated coefficient being significant. To measure the extent of contextual unobserved heterogeneity in carbon emission, we employ the intra-class correlation coefficient (ICC). The coefficient of the ICC 0.09 suggests that just 9% of the unexplained variations in industrial carbon emission are traceable to country differences. In other words, 91% of unobserved heterogeneity in industrial carbon emissions is due to industry differences.

Table 4.8 presents the results of the decomposition effect derived from the estimated multilevel model having controlled for other competing factors. We find our control variables reliable as majority are statistically significant and demonstrate minimum or no variation compared to the estimates from model without decomposition. As expected, the substitution effect has a negative relationship with carbon emission across the board with estimated elasticities raging from –0.64 to –0.54. The estimated elasticity –0.64 indicates that a 10% increase in substitution effect arising from increase in energy price is associated with approximately 6.4% reduction in industrial CO_2 emissions. This result suggests that a rational producer will reduce energy use when energy price increases by consuming less energy, which could be in form of using more alternative sources of fuel, other substitutable inputs, more energy efficient or even the combination of the measures listed. The statistically significant and reasonable values of the substitution effects depict the degree of sensitivity of the producers to changes in price via the use of other inputs. However, the substitution effect for the primary sector is positive but not statistically significant. The result would have contradicted the theory if it was significant as it would imply that producers use more energy as energy price increases

As for the output effect, the estimates are negative across board, but only the estimates for the whole and service sectors are statistically significant. The negative output effect implies that energy is a normal good, which is logical given its historical importance in the production setting. The implication of the negative output effect is that producer is likely to adjust output accordingly following an increase in energy and this could result in higher production cost if substitution is hard as discussed in chapter 3. Subsequently, output level is reduced as well as CO_2 emissions. However, the values are generally smaller compared to the estimates of the substitution effect. For instance, the output effect –0.06 suggest that a 1% increase in output effect as a result of increase in price is associated with about 0.06% reduction in carbon emissions. In general, the impact of the output effect is relatively small compared to the impact of the substitution effect and that makes the substitution effect to be the dominant factor. The key implication of these results is that the output effect may not be as worthy to be considered as previous literature suggested when analysing the decomposition effect of an input. In overall, the impact of the decomposition effect arising from the increase in energy price is associated with reduction in carbon emissions given the negative combination of the substitution and output effects.

Table 4.8: Estimated results for CO_2 emissions with decomposition effects

Variable	Whole	Primary	Manufacturing	Service
Constant	–2.11***	–2.79***	–2.28***	–1.72***
	(0.31)	(0.89)	(0.40)	(0.49)
Industry-level variables:				
Substitution effect	–0.64***	0.28	–0.59***	–0.54***
	(0.06)	(0.36)	(0.11)	(0.07)
Output effect	–0.06***	–0.86	–0.00	–0.09***
	(0.02)	(1.43)	(0.03)	(0.03)
Output	0.27***	0.08	0.28***	0.29***
	(0.02)	(0.11)	(0.02)	(0.04)
Employee	0.17***	–0.06	0.08***	0.20***
	(0.01)	(0.05)	(0.02)	(0.02)
Country-level variables:				
Temperature	–0.13***	–0.10	–0.33***	0.09**
	(0.02)	(0.07)	(0.03)	(0.04)
Energy	0.48***	0.78***	0.74***	0.16***
	(0.04)	(0.11)	(0.05)	(0.05)
Output	0.17***	–0.20	0.20***	0.19***
	(0.02)	(0.11)	(0.03)	(0.04)
Employee	0.64***	0.40***	0.15***	1.18***
	(0.04)	(0.13)	(0.06)	(0.07)
Random part:				
σ_v^2	0.17**	0.25	0.27**	0.79**
	(0.07)	(0.23)	(0.13)	(0.25)
σ_u^2	3.10***	0.91**	3.39***	1.91***
	(0.15)	(0.26)	(0.22)	(0.13)
σ_ε^2	0.07***	0.04***	0.07***	0.08***
	(0.00)	(0.00)	(0.01)	(0.00)
Intra-class correlation	0.05**	0.21	0.07*	0.29***
	(0.02)	(0.18)	(0.03)	(0.07)

***, ** and * represent statistically significant at 0.1%, 1% and 5% level of significance. Intra-class correlation coefficient $(ICC) = \frac{\sigma_v^2}{\sigma_v^2+\sigma_u^2+\sigma_\varepsilon^2}$.

As for the results of the random part, the results reported in Table 4.8 show a decrease in the intra-class coefficients when allowing for the decomposition effect as compared to those reported in Table 4.7. The coefficient of the ICC 0.05 suggests that just 5% of the unexplained variations in industrial carbon emission are traceable to variations in country while allowing for decomposition effect. The insignificant of the primary sector's ICC (21%) indicates that country effect plays no role in the unexplained variations of the primary sector's CO_2 emissions.

4.5 Conclusion and policy implications

This chapter develops two-step procedure to analyse the decomposition effect of derived energy input on CO_2 emissions. Our empirical analysis makes significant contributions to the literature of inter-factor substitution and decomposition effect by comparing the estimates of the iSUR and the multilevel modelling techniques and then support in favour of the latter approach. To do so, we use hierarchical industry dataset across 29 European countries for the period 1995–2007. To analyse inter-factor substitution, we estimate a translog cost function with the popular iSUR and multilevel modelling. Unlike the iSUR, the multilevel model accounts for the cluster-level heterogeneity in our dataset and we further argue that failure to account for this heterogeneity may lead to unreliable estimates. Thereafter, we use the estimates of the estimated translog function from both techniques to decompose changes in energy demand resulting from changes in price into substitution and output effects. We conclude our analysis by investigating the impact of the substitution and output effects on CO_2 emissions having controlled for other competing forces.

Our empirical results reaffirm the importance of controlling for aggregate effects and cluster-level heterogeneity as majority of our country level variables as well as the estimates of the random part are statistically significant across board. We find some disparities in the magnitude of the elasticities of substitution derived from the iSUR and multilevel model, but the results of the AES and MES indicate strong substitutability between energy and other inputs. However, the estimates of the cross-price elasticity indicate weak substitutability between energy and other inputs. Specifically, we find energy as the most price responsive input and labour as the least price responsive.

Further, in asymmetric form, the substitutability between energy and labour demonstrates the strongest. These results are in line with existing literature.

The estimated decomposition results show that changes in derived energy input are largely dominated by substitution effects in absolute terms. In addition, our results reveal that, although both the substitution and the output effects arising from increase in energy price are inversely related to the carbon emissions, but the substitution effect is largely dominated. This result therefore suggests that the output effect may not be as worthy to be considered as previous literature suggested when analysing the decomposition effect of an input. In fairness, these results are in conformity with real life experience, as one would expect a cost minimising firm to adjust both output and inputs accordingly if an input price increases. Subsequently, one would expect carbon emissions to reduce as firms adjust output accordingly when marginal cost increases. Our findings are theoretically rooted as increase in input cost is expected to reduce output level and the amount of such input use in production. In addition, this study demonstrates the importance of using a more suitable modelling technique when analysing the decomposition effects of changes in production factor as failure to do so could lead to unreliable estimates.

The policy implications that can be drawn from our analysis are as follows. Firstly, the insignificant of the output effect suggests that producers are less likely to reduce the level of output as they can substitute other inputs for energy without any loss in production if energy price increases. Therefore, any energy policy targeted to increase energy/carbon taxes is less likely to be counterproductive. We hope this result will inform policy makers of European countries and other developed countries that policy targeted to increase energy/carbon taxes is not likely to retard business activities.

Secondly, we argue that there is a need to observe the substitution potential across sectors and the economy at large before formulating energy/carbon reduction related policy. This is because any emission reduction targeted policy being formulated without accounting for the substitution potential in a production setting is likely to be ineffective. In addition, although, we find that the overall effect of an increase in energy price will reduce carbon emissions, but moderately. Therefore, we argue that any attempt to reduce carbon emissions via an increase in energy/carbon taxes should be reinforced by other measures.

Chapter 5 Conclusions and Future Research

5.1 Summary

This thesis contains three essays aimed at examining the policy/environmental implications of econometric estimation of energy demand elasticities. More specifically, the main objective was to empirically analyse energy demand function with the primary purpose of generating reliable estimates, which could serve as policy tools in formulating macroeconomic policies related to energy security and carbon emissions. In doing so, the research undertaken in this thesis compare and contrast empirical results obtained from different model specifications and estimation techniques using a panel data analysis. Further, as tackling energy challenges such as climate change requires robust and effective energy policy actions, this research work observed the impact of energy demand elasticities and to what extent they are relevant in reducing to carbon emissions. The issues presented above were addressed via three papers/essays in Chapters 2, 3 and 4. The next section provides the main research findings of this thesis in terms of the research questions in Chapter 1.

5.2 Empirical findings and policy implications

Essay 1: To what extent would inappropriate econometric technique impacts energy demand elasticities?

- Is there a difference between industry-level and country-level energy demand estimates?
- Is heterogeneity in energy use more associated with between-industry or between-country differences?

Despite the huge existing literature on energy demand modelling, no previous study has extensively examined the implications of not account for the hierarchical nesting of industries within a system that also adequately allows for country specific determinants of energy demand. To fill this vacuum in the literature, chapter 3 therefore analyses energy demand for European industries over the period 1995-2007 using a dynamic multilevel model that accounts for this hierarchical data structure and the generalised method of moments (GMM). Among other things, findings from the first essay indicate that the European industrial energy consumption is significantly influenced by the country-level variables, as all country-level variables estimated are statistically significant. This is reinforced by the result of ICC in the DMM (0.44), suggesting that about 44% of the unexplained variations in industrial energy consumption are traceable to between-country differences.

The results of the dynamic multilevel model suggest that if industry income and the industry energy price increase by 10% respectively, long run energy demand will increase by 8.1% and fall by 6.8%, respectively. In contrast, the corresponding long run income and price elasticities are substantially larger in a standard dynamic model of energy demand which does not account for the hierarchical data structure. The results therefore suggest that not accounting for the hierarchical data structure results in unreliable estimates of energy demand elasticities. From a policy perspective this essay argues that it is imperative that future industry level energy demand studies account for the hierarchical structure of the data. This is to prevent energy policy making being based on industry level evidence that substantially inflates the responsiveness of long run energy demand to income and price changes. This finding has a serious implication that policy based on such wrong or inaccurate energy demand estimates is very likely to be misleading or inappropriate. More importantly, results of this essay indicate the need for modelling energy demand with appropriate econometric technique if we wish to make more appropriate predictions about future energy use and associated carbon emissions.

Essay 2: What is the relationship between estimated energy demand elasticities and carbon emissions?

- Are energy and non-energy inputs substitutes or complements?
- What are the main drivers of carbon intensity?

It is well established in the theoretical literature that energy demand estimation in terms of ES between energy and non-energy provides insightful information on the relevance of capital-energy substitution in reducing CO_2 emissions. Moreover, there are two positive implications associated with this practice. First, it removes over-reliance of continuing increase in energy prices as a way of stimulating improvement in energy efficiency. Second, it represents a way of relaxing the pressure of increasing global energy consumption and regarded as a natural way of reducing greenhouse gases. However, there is clearly a lack of empirical assessment of the effects of capital-energy substitution on carbon reduction. Hence, chapter 3 examined the relevance of factor substitution to carbon reduction by empirically analysing the impact of energy and non-energy substitution on carbon intensity for China. Another important issue that this study takes on is the potential role of export shocks in factor substitution. As far is known, this study is the first to consider the effect of structural change on energy substitution. To account for structural change, this study provides an empirical analysis for the period before and after China's accession to the World Trade Organisation.

Unlike most studies that estimate a single elasticity of substitution/complementarity, this study explicitly demonstrates how to compute a range of elasticities with each of the elasticities being identified with unique features. The empirical analysis is based on sectorial level data over the period of 1995–2009. Main findings reveal that energy and non-energy factors are substitutes while holding output constant but complements if output is free to adjust to changes in factor prices. Also, the results suggest that energy intensity is the major contributor to China's carbon intensity, which is in conformity with body of evidences. In contrast, technological progress and capital-energy substitution are inversely related to carbon intensity, though, their impacts are relatively weak. On the other hand, labour-material substitution displays a relative strong negative relationship with carbon intensity with an estimated elasticity of –0.90 before the structural change.

The main policy implications that emerge from chapter 3 are as follows. Firstly, it appears that China's accession to the WTO is a motivation for energy-savings and subsequently carbon reduction, given the strong ES between capital and energy after the structural break. One would expect this outcome given the international pressure China is facing to reduce its emissions level. This finding provides a blueprint for other emerging economies. Nonetheless, energy policy designs in these countries must consider that reduction in emissions cannot be achievable by only increasing energy and carbon taxes, but also by adopting a sound strategy that would encourage the use alternative fuels/inputs. In addition, our findings reveal that easy substitution between inputs in production setting will require a smaller carbon tax and will results in less loss of economic output. In this situation, any energy related policy design to reduce carbon emissions is less likely to affect production level. However, if substitution potential is different between sectors of the economy, which is more likely the case in practice, then the application of uniform tax to all sectors will hurt more sectors that deliver the greatest reduction in energy use. This curious result would likely strike most unfair. In addition, it may run counter to welfare maximization or cost minimisation for the energy efficient sector(s). Our results therefore reinforce the suggestion for a possible policy solution that would apply different levels of carbon taxes to different sectors.

Essay 3: What is the relationship between the decomposition of derived energy input and carbon emissions?

- What are the estimates of the substitution and output effects?
- Which of the two effects dominates?

Having argued in the literature that energy demand estimation in terms of energy substitution provides insightful information while making decisions related to energy security and carbon reduction, but this could have a serious policy implication as pure ES assumes of constant level of output. A representative producer would adjust output accordingly in response to changes in relative input prices. Hence, this renders the capital-energy substitution incomplete picture of inputs adjustment resulting from a relative change in inputs prices. A strand in the literature of energy economics argues in favour of the decomposition effects of changes in energy demand arising from an increase in energy prices. In this regard, the decomposition output effect depicts a more complex picture of inputs adjustments compared to the ES. This is because the output effect accounts for the flexibility of the producer to adjust output accordingly.

Chapter 4 builds on the above argument to provide more accurate/reliable information that could serve as policy tools by examining the impact of energy demand decomposition on carbon emissions. This study also picks on the importance of using suitable econometric technique while estimating energy demand. To achieve the objective, this study adopts a two-stage procedure using industry level data across Europe for the period 1995–2007. The first stage estimated a translog cost function using the iSUR and multilevel models, and decomposed derived energy input into substitution and output effects. The second stage carried out an exploratory investigation to examine the relationship between the decomposition effects and carbon emissions. The main findings show that, although both the substitution effect and the output effects have a negative relationship with carbon emissions, but the substitution effect largely dominates the output effect. This suggests that the estimation of the output effect while decomposing factor of production is less likely important as previous studies suggest. In fact, this is an indication as pointed out in chapter 3, that an easy substitution between inputs in a production setting will result in less loss of economic output. This is because, the insignificant of the output effect suggests that producers are less likely to reduce the level of output as they can substitute other inputs for energy without any loss in production if energy price increases.

From a policy perspective, our results argue for the need to observe the substitution potential across sectors and the economy at large before formulating energy/carbon reduction related policy. This is because any emission reduction targeted policy being formulated without accounting for the substitution potential in a production setting is likely to be ineffective. In addition, the overall implication of this chapter cuts across the relevance of both chapter 2: as it also reinforces the importance of using a more suitable modelling technique while estimating energy demand as failure to do so could lead to unreliable estimates, and chapter 3: argues that any attempt to reduce carbon emissions via increase in energy taxes should be reinforced by other measures.

In summary the main contributions of this thesis are three-fold. Firstly, this thesis argues that the application of inappropriate econometric modelling technique to energy demand could severely produce unreliable energy demand elasticities. Therefore, warns that future research should control for the hierarchical structure of energy data while using industry level data. Secondly, this thesis provides a blueprint on the extent in which energy demand elasticities in form of ES could act as a measure for carbon reduction by carrying out an exploratory investigation between ES and carbon emissions. Thirdly, this thesis extends the literature on decomposition analysis by carrying out an exploratory investigation on the impact of the decomposition effects of derived energy on carbon emissions. Therefore, argues that only the substitution effect, which arises from an increase in energy price, is relevant in policy making.

5.3 Limitations of the study

It is recognised that all research and analytical framework have limitations and this research work is not an exception in this respect. The limitations of this research are highlighted as follows. Firstly, this thesis was limited by the sample size across the three papers due to a lack of consistent data over the years for a good number of countries. For instance, the energy demand estimation in Chapter 2 relied on 29 countries for a period of 15 years (1995–2009). Given the global view associated with energy demand issues, it would have been more useful to have more years and countries to consider in this regard. This is also the case for Chapter 3 where inclusion of other countries would have provided a more informative finding on the relevance of structural change to energy demand elasticities and carbon emissions. Similarly, Chapter 4 is also limited by data sample size where by expanding the scope of the study would have permitted a much broader evaluation of energy demand decomposition.

Secondly, on a similar note, it is recognised that energy policies differ across countries and this research seriously considered this difference, but limited data and changing policy stance overtime made it difficult. The availability of consistent data on energy policy indicators for a number of years would have allowed for the inclusion of policy variables that could provide insightful information about the changes in energy policy across the sample countries. Energy policy is known to be changing overtime given the relative importance of energy issues. Hence, some policy measures were only implemented for a few years and discontinued thereafter. The use of dummy variables for instance, would amplify the impact of such discontinued policies overtime in respect to the relatively long-time frame of the dataset.

Finally, as it is often the case with most empirical research, the results of this thesis cannot establish a complete causality within all the estimated models, although, it is demonstrated with a high level of confidence that the major implications of applied energy econometrics have been analysed using well established modelling techniques.

5.4 Future research

This thesis comprises 3 essays/papers on the policy implications of applied energy econometrics. While these papers address important research questions, the insightful results provide useful avenues for further research. The first essay shows amongst others that energy demand estimates could be severely biased if inappropriate econometric technique is used to estimate energy demand. This indicates the importance of appropriate modelling technique if we wish to make accurate predictions about energy security and associated carbon emissions. Hence, it would be interesting to extend the analysis in Chapter 2 by re-visiting energy demand forecasts across the sampled countries with a view eliminating the biasedness in energy demand estimates. In a way, this would allow the assessment of actual future energy needs and related carbon emission. In addition, this paper highlights the need for more energy demand modelling techniques that can actually match up with the increasing stock of data.

Chapter 3 primarily focuses on the implications of energy demand elasticities on carbon emissions having adjusted for a structural change. Given the direction of the paper and data availability, the analysis is restricted to Chinese economy only. The main findings indicate that the relationship between energy substitution and carbon emissions after the structural break is more noticeable and negative. In this respect, a more rigorous study that accounts for structural change across countries is actually needed to solidify the findings of this essay. This would enable the evaluation of alternative policy options to achieve the long-term targets for sustainable energy consumption and climate change.

In Chapter 4, an implication of energy demand decomposition on carbon emissions across sectors in European countries is conducted. Having controlled for the hierarchical structure of the data, amongst others, although, the results indicate that the substitutability between energy and other inputs dominates changes in energy use, compared to the output effect. However, both effects have negative relationship with carbon emissions. These results motivate future research in terms of focusing on the decomposition analysis for different types of fuel rather than the approach adopted here. As such, analysis would not only show variations in substitution and output effects among fuel types, but also provides information about the fuel type that makes the economy better off in terms of sustainable environment.

All the above suggestions constitute the future research agenda.

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Appendix

A1: To show the importance of the response at first period let consider a simple dynamic multilevel model for simplicity.

$$E_{i,j} = \beta_1 + \delta E_{i-1,j} + \beta_2 x_{i,j} + u_j \epsilon_{i,j} \qquad (A.11)$$

Eq. (A.12) is only for time periods *i* > 1 because the value of the lagged response at period 1 is unknown. The model for the response at *i* = 2 is

$$E_{2,j} = \beta_1 + \delta E_{1,j} + \beta_2 x_{1,j} + u_j + \epsilon_{2,j} \qquad (A.12)$$

and by substituting Eq. (A.12) for the expression $E_{2,j}$ in model for the response at *i* = 3, we derive

$$E_{3,j} = \beta_1 + \delta E_{2,j} + \beta_2 x_{2,j} + u_j + \epsilon_{3,j}$$

$$= \beta_1 + \delta\big(\beta_1 + \delta e_{1,j} + \beta_2 x_{1,j} + u_j + \epsilon_{2,j}\big) + \beta_2 x_{2,j} + u_j + \epsilon_{3,j}$$

$$= (1+\delta)\beta_1 + \delta^2 E_{1,j} + \big(\delta x_{1,j} + x_{2,j}\big)\beta_2 + (1+\delta)u_j + \delta\epsilon_{2,j} + \epsilon_{3,j} \qquad (A.13)$$

Eq. (A.13) displays the importance of time period 1 as model $E_{3,j}$ can be re-specified in which it depends on $E_{1,j}$ with coefficient δ^2. Therefore, by continuing the substitution process it is straightforward to show that the response $E_{k,j}$ at any period *k* (*k* = 2,…,*T*) depends on $E_{1,j}$ with coefficient δ^{k-1}.

Table A. 3 List of ISIC Rev.4 (NACE Rev.2) Sectors

NACE Description	**Sector**
secAtB	Agriculture, Hunting, Forestry and Fishing
secC	Mining and Quarrying
sec15t16	Food, Beverages and Tobacco
sec17t18	Textiles and Textile Products
sec19	Leather, Leather and Footwear
sec20	Wood and Products of Wood and Cork
sec21t22	Pulp, Paper, Paper , Printing and Publishing
sec23	Coke, Refined Petroleum and Nuclear Fuel
sec24	Chemicals and Chemical Products
sec25	Rubber and Plastics
sec26	Other Non-Metallic Mineral
sec27t28	Basic Metals and Fabricated Metal
sec29	Machinery, Nec
sec30t33	Electrical and Optical Equipment
sec34t35	Transport Equipment
sec36t37	Manufacturing, Nec; Recycling
secE	Electricity, Gas and Water Supply
secF	Construction
sec50	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
sec51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
sec52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
secH	Hotels and Restaurants
sec60	Inland Transport
sec61	Water Transport
sec62	Air Transport
sec62	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
sec64	Post and Telecommunications
secJ	Financial Intermediation
sec70	Real Estate Activities
sec71t74	Renting of M&Eq and Other Business Activities
secL	Public Admin and Defence; Compulsory Social Security
secM	Education
secN	Health and Social Work
secO	Other Community, Social and Personal Services

Notes: based on the NACE classification, the industries could be classified into: primary sector which consists of S/N 1 to 2, manufacturing sector consists of S/N 3 to 18 and service sector consists of S/N 19 to 34.

A3: Assuming a standard multilevel model where only level 1 and level 2 variables are considered for simplicity is written as:

$$E_{i,j} = \beta_1 + \beta_2\, x_{i,j} + \beta_3\, x_{2,j} + u_j + \epsilon_{i,j} \qquad (A.21)$$

where level 1 variable is $x_{i,j}$ and level 2 variable is $x_{2,j}$. If the level 2 variable is the mean of level 1 variable (as the case of this study) that is also included in the model, Eq. (A.21) becomes

$$E_{i,j} = \beta_1 + \beta_2\, x_{i,j} + \beta_3\, \bar{x}_j + u_j + \epsilon_{i,j} \qquad (A.22)$$

where $\bar{x}$ is the mean of *x* in group *j*. In Eq. (A.22) β_2 is the within-group effect of *x* and $\beta_2 + \beta_3$ is the between-group effect of *x*. β_2 measures the relationship between an individual's *x* and *E* values within group while $\beta_2 + \beta_3$ captures the effect of the group mean of *x* on the group mean of *E*. β_2 measures the contextual effect of the group mean of *x* on an individual *e* that is over and above the effect of an individual *x* on *E*. The problem with Eq. (A.22) is that estimate of the between-group effect cannot be estimated directly. In order to get a direct estimate and standard error for the between-group effect of *x*, $x_{i,j}$ is transformed to $x_{ij} - \bar{x}_j$ which is called group mean centring, then Eq. (A.22) is therefore re-specified as:

$$E_{i,j} = \beta_1^* + \beta_2^*\left(x_{i,j} - \bar{x}_j\right) + \beta_3^*\, \bar{x}_j + u_j + \qquad (A.23)$$

where the within-group effect equals $\beta_2^* = \beta_2$, and $\beta_3^* = \beta_2 + \beta_3$ is the between-group effect.