Three Essays on Rebound Effects

by

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Dedication

To

Osas, Timi and Rotimi

Thank you for your unconditional love and sacrifice.

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Above all, I thank the Almighty God who is the source of all grace, inspiration and knowledge.

Abstract

This thesis investigates three major aspects of energy consumption rebound effects (RE) in three papers. More specifically, the issues addressed are (i) the magnitude of economy-wide rebound effect (ii) the role of energy policy instruments in mitigating it and (iii) its channels of impact. The research begins with the estimation of cross-country economy-wide rebound effects for a panel of 55 countries over the period 1980 to 2010. A two-stage approach is utilized in which energy efficiency is first estimated from a stochastic input distance frontier (SIDF). The estimated energy efficiency is then used in a second stage dynamic panel model to derive short-run and long-run RE for an array of developing and developed countries. The cross-country point estimates indicate substantial RE magnitudes across sampled countries during the period under consideration, although a positive and encouraging finding is the declining RE trend across most of the sampled countries during the study period.

The second paper contains an RE benchmark for 19 EU countries, as well as an investigation of the effects of two energy policy instruments (energy taxes and energy R&D) on RE performance over the period 1995 to 2010. The results indicate that RE performance improved over the sample period, reinforcing the results from paper one. In addition, there is also some evidence suggesting that binding market-based instruments such as energy taxes have been more effective in restricting RE than indirect instruments such as energy R&D during the period under consideration. This is consistent across both estimated model specifications.

An important observation from the first essay is the slightly larger average RE across the non-OECD countries. For this reason, the last empirical chapter evaluated the channels through which RE stimulated energy use across productive sectors of major developing/emerging economies, namely Brazil, Russia, India, Indonesia and China. To achieve this, the essay relied on duality theory to decompose changes in energy demand into substitution and output effects through the estimation of a translog cost function using data spanning 1995-2009. Findings reveal that energy use elasticities across sampled sectors/countries are dominated by substitution effects. One intriguing result that also emerges from this analysis is the role of economies of scale and factor accumulation, rather than technical progress, in giving rise to economic growth and energy consumption in these countries during the period under consideration.

Key words: energy efficiency, energy policy, duality, input distance function, panel data, rebound effect, stochastic frontier analysis, Slutsky decomposition.

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Chapter 1 Introduction

1.1 Background

Reducing greenhouse emissions arising from energy consumption is a principal concern for most governments and energy policymakers around the world. In this context, concerted efforts have been directed towards evolving sustainable energy use that is consistent with energy security and climate change mitigation. The most common policy approach towards achieving these objectives is the promotion of energy efficiency. This policy approach is based on the expectation that energy efficiency improvements will increase energy productivity in a way that a given energy service (consumer welfare or output) can be derived using less energy[1]. More importantly, energy efficiency improvement is generally regarded as a costless approach to conserving energy and curbing greenhouse emissions. However, despite the widespread implementation of policy measures to stimulate energy efficiency over the last two decades, energy consumption has grown rapidly and continuously (see Saunders, 2013; IAE, 2014).

In the energy economics literature, this phenomenon which is known as rebound effects (RE), is a situation where energy efficiency improvements stimulate energy demand via a reduction in the effective/implicit price of energy service. It

[1] An alternative view is to think of a situation where the same amount of energy yields greater welfare (e.g. miles driven) or greater output.

should be noted that the RE arising from energy efficiency improvements has technical/engineering and economic/behavioural dimensions. In other words, energy savsavings are derived from technical or thermodynamic efficiency improvements in the energy-using capital stock (appliances and equipment), which then triggers economic (lower effective price of energy services) and behavioural (ex-post increase in demand for energy services) responses.

For instance, when a household purchases an energy-efficient car, the cost of driving per mile falls even if the fuel price remains constant. This is because the car uses less fuel to travel for a given mile, such that the lower cost of driving could then induce greater driving, resulting in more fuel consumption- the rebound effect. A similar mechanism can be encountered on the production side, whereby energy efficient technologies lower the cost of energy services within the cost function, spurring producers to shift their production towards more energy-intensive processes.

Rebound effects arising from energy efficiency savings constitute severe challenges and problems in practical energy policy settings for a number of reasons. For instance, the contemporaneous increase in energy efficiency and energy consumption suggests that the predicted effectiveness of energy efficiency improvement in curbing energy consumption and greenhouse emissions may be limited in the face of substantial RE. In short, RE distorts the cost-benefit analysis of energy conservation measures. Secondly, notable global energy and climate change forecasts[2] are derived from projected energy efficiency savings without accounting for the 'take-back' arising from RE. Consequently, a strand of the literature (Saunders, 2005, 2008, 2013; Sorrell, 2010; Wei, 2010) argues that failure to account for RE in energy

[2] See for example http://www.roadmap2050.eu/attachments/files/EnergySavings2020-FullReport.pdf

and climate forecasts (especially when it is large in magnitude) may result in an understatement of future energy use, with the implication that we may have less time than predicted to tackle climate change.

The main argument in this thesis is that failure to account for RE in energy and climate forecasts is due to limited empirical assessment of the key rebound issues relating to its magnitude, appropriate estimation approach, channels of impact and the policy options towards mitigating it. This challenge is mirrored by the debates and uncertainty surrounding the magnitude of estimated RE from the few previous empirical studies. This debate about RE magnitude should be expected, given the incomparable and highly diverse range of rebound estimates arising from the inconsistent data and too many different methodologies employed by previous studies[3].

Additionally, the assessment of the channels through which RE impacts energy consumption remains grossly limited for any meaningful understanding of its nature. Furthermore, although the importance of policy instruments in managing RE is clear and well defined, this thesis is, as far as is known, the first attempt to quantitatively the impact of key energy policy instruments on RE mitigation. This apparent lack of clarity and consistent (reliable) estimates of RE magnitude, its channels and the potential role of energy policy are crucial gaps in the literature. Hence, these gaps constitute the motivation for this thesis, which aims to investigate the size, nature, policy options, composition and mechanisms of RE.

[3] As shown in Table 2.1, the literature on economy-wide RE estimation is dominated by computable general equilibrium (CGE) and econometric modelling which cover different time periods/data. Moreover, results from CGE simulations can be sensitive to parameter assumption about energy efficiency and factor substitution.

1.2 Overview and contributions of this research

This thesis contributes significantly to the literature on rebound effects and the wider energy economics literature. More specifically, the three main issues/contributions of this thesis are given as follows.

First, the RE literature has grown significantly over the last 2 decades, but there is an ongoing debate about the size of RE and the most appropriate approach to measuring it. The debate has been more intense regarding economy-wide RE given that it approximates the net effect of different mechanisms that are complex and interdependent, and whose effects may vary over time and across efficiency sources (Sorrell, 2007). Although there are several previous country-specific RE studies, they are incomparable, having employed different empirical and theoretical approaches; covering different time periods. Dimitropoulos (2007) argued that the lack of a widely accepted analytical framework arising from the diversity of methodologies has contributed to the controversies surrounding RE. This thesis therefore attempts to address the issues of RE magnitude and the appropriate modelling approach, by estimating economy-wide RE for several of countries using a consistent dataset and a two-stage econometric procedure.

Secondly, the mechanism/channels of RE remain crucial to understanding its nature. The theoretical RE literature (Saunders, 1992, 2000b, 2008; Sorrell and Dimitropoulos, 2008) suggests that the two main underlying direct RE mechanisms are substitution and income/output effects. Ceteris paribus, energy efficiency improvement lowers the effective price (marginal cost) of energy service, thus making it relatively cheaper than other goods/inputs; causing increased energy use (substitution towards energy). This mechanism is often referred to as substitution effects. On the other hand, lower effective energy prices arising from improved energy efficiency also reduces input costs which translate into lower output prices and higher output. The improved productivity or expansion in production possibility then requires or encourages more energy use. This second effect is the output effect. One key observation is that these effects (and the nature of RE) have not been adequately analysed empirically. Moreover, the theoretical demonstration of these effects in the literature differs from the standard economic ideas of both effects, and this constitutes a second motivation for this thesis.

Finally, efficiency and productivity analysis in the energy economics literature has focused on identifying the best-practice (most efficient) production technology which uses the minimum possible energy to produce a given level of output. However, with large RE, using only energy efficiency performance as a benchmark may provide incomplete and misleading information in policy settings. For instance, it is possible that a country with high energy efficiency might 're-spend' most of the energy savings derived from improved efficiency so that the ex-post net-efficiency gain may alter the actual position of a country in an energy benchmark. Therefore, by benchmarking RE, it is possible to identify countries with the minimum level of RE for a given level of output. This provides ex-post information on the success of countries in 'locking-in' energy efficiency.

1.3 Research questions

This thesis contains three essays exploring important aspects of RE using country and sector level data. To achieve the aims and objectives of this study, the following as-yet unanswered research questions are addressed:

Q1: What is the magnitude of economy-wide rebound effects?

Q2: What are the main channels through which RE impacts energy use?

Q3: Which countries have the minimum level of rebound for a given level of output?

1.4 Thesis plan

The thesis is devoted to answering the questions above in three different papers:

Q1 is addressed in Paper 1. Moreover, through the analysis undertaken in the chapter, the following sub-questions are answered:

Q1.1: Is there a difference between RE estimates for developed and developing countries?

Q1.2: What is the trend of RE across countries?

Therefore paper 1 addresses the issue of magnitude and appropriate model for analysing RE through a broad and extensive cross-country analysis of economy-wide RE for a panel of 55 countries[4]. Responding to climate change requires multilateral co-operation and co-ordination among different countries, thus there is need for a comparative top-down and consistent measurement of RE across several countries. This chapter proposes a two-stage econometric procedure where, first, energy efficiency is estimated using Stochastic Frontier Analysis (SFA). A dynamic panel framework is then employed to estimate short-run and long-run RE using the efficiency scores from the SFA model.

Paper 2 answers Q2 as well as other sub-questions:

Q2.1: What is the size/magnitude of substitution and output effects across productive sectors in major emerging economies?

Q2.2: What is the nature of productivity across the main emerging economies?

[4] Throughout this thesis, the choice of sampled countries and sample size is largely based on data availability.

More specifically, Paper 2 addresses the issue of RE channels/mechanism from two points of view in the literature. First, while the theoretical explanations underpinning the substitution and output effects are well established, the empirical evidence is limited. Secondly, few empirical analyses of these effects differ from their standard microeconomic definitions. Hence Paper 2 proposes a more appropriate assessment of substitution and income/output effects in energy demand. Using sector-level data for Brazil, Russia, India, Indonesia and Russia (BRIIC), a translog cost function is estimated using the seemingly unrelated regression equations (SUR) by iterative/feasible GLS. Duality theory is then explored to decompose changes in energy demand into substitution and output effects in order to evaluate RE channels for BRIIC countries. The sample choice is based on the consistently large average RE across these emerging economies, as well as data availability.

Q3 is addressed by Paper 3 which also attempts to answer a sub-question:

Q3.1: Why and how did the countries achieve their RE performance

Q3.2: What is the most effective energy policy instrument for addressing RE?

Paper 3 constructs a parametric RE frontier using an input distance function where RE is treated as an additional input (i.e. the production technology is modelled as the RE-minimizing combination of labour, capital and energy for a given level of output) using panel data for 19 EU countries over the period 1995-2010. The major determinant of the sample size is the availability of consistent quantitative variables on energy policy instruments of interest. Furthermore, this chapter estimates and decomposes TFP growth, while also exploring the role of energy policy instruments in mitigating RE, which has been largely overlooked in the RE literature. As shown by van den Bergh (2011), in order for energy policy makers to make well informed and effective decisions, it is important that rebound policies are incorporated into wider energy conservation policies.

The remainder of the thesis is organized as follows. Chapter 2 contains a review of the relevant RE literature, providing an overview of the RE literature and the recent methodological debates, with a view to motivating the research work undertaken in this thesis. The third, fourth and fifth chapters contain each of the essays/papers in this thesis. Chapter 6 summarises the main findings and offers remarks pertaining to the main research questions/objectives. The Chapter also offers suggestions for future research.

Chapter 2 Literature review

2.1 Introduction

This chapter contains a review of the literature and theoretical background for the three essays in this thesis. The chapter begins with a discussion on the current state of RE in the wider energy economics literature and practical energy policy settings. It then presents a theoretical background on RE by providing historical explanation of the RE theory. The emphasis then shifts to economy-wide RE and thereafter the theoretical framework underpinning RE channels (substitution and income/output effects) are discussed.

2.2 Background on Rebound Effect

The identification of rebound effect dates back to the seminal work of Jevons (1865) who argued that energy efficiency improvements tend to increase, rather than decrease the rate of consumption of a resource. Specifically, Jevon (*ibid*) suggested that the economy of coal use would eventually lead to its widespread use and ultimately, increase its consumption. However, Brookes (1978, 1979, 1990, 2000) and Khazzoom (1980, 1982, 1987, 1989) are generally credited with formalizing the intuition behind rebound phenomenon as an example of the *Jevons Paradox* in energy economics literature[5]. Their works provide a reference for the paradoxical relationship between energy efficiency improvement and energy consumption i.e. that energy

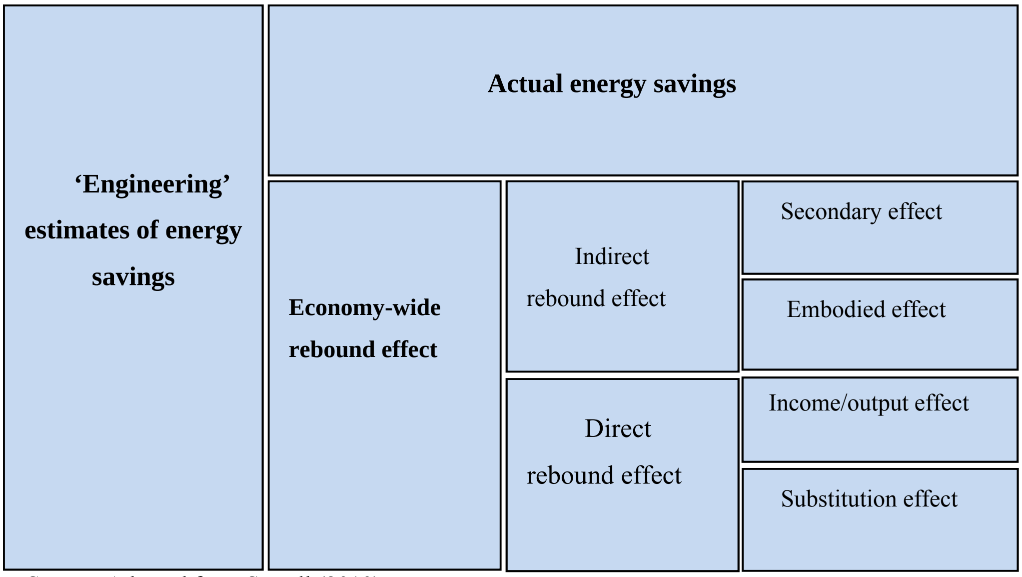
[5] The works of both authors are often considered under the banner of the *Khazzoom-Brookes postulate*. This phrase was first coined by Saunders (1992).

efficiency gains may not lead to proportional reductions in energy consumption, as predicted by conservationists. Saunders (1992) established the first known theoretical framework for assessing rebound effects by developing the hypothesis proposed by Brookes and Khazzoom using the neo-classical growth theory.

The underlying argument of rebound theorists is that energy efficiency improvement of an appliance reduces the effective price of the energy service and stimulates demand (*price effect*). Khazzoom further argued that such efficiency improvements do not only impact own end-use demand, but also the demand for other goods, given that all end use expenditures face given budget constraints. More specifically, lower effective price of energy alters relative prices and increases purchasing power, leading to an *income effect*. The foregoing implies that rebound effects may occur through direct or indirect channels and may be embodied or may occur simultaneously within an aggregate economy. Therefore, rebound effects can be categorized into direct effects, indirect effects and economy-wide effects (Greening et al. 2000; Sorrell, 2007).

2.2.1 Classification of Rebound Effect

This section presents a discussion on the different classifications of rebound effects, which are summarized in Figure 2.1 below. The predicted (engineering) savings arising from improved energy efficiency can be broadly decomposed into an 'actual saving' and economy-wide rebound. It is shown that the different components/channels/mechanisms of rebound effects all add up to economy-wide rebound effects. Each of these mechanisms is discussed in greater detail below.



Source: Adapted from Sorrell (2010)

Figure 2.1: Classification of Rebound Effect

2.2.1.1 Direct Rebound Effects

From Figure 2.1, it can be seen that economy-wide rebound can be broadly classified into direct and indirect effects. As stated above, energy efficiency improvements reduce the effective price or marginal cost of an energy service, such that, ceteris paribus, energy consumption increases. This is because the energy efficiency improvement decreases the amount of fuel required to produce a given level of comfort/satisfaction/output from an energy service, which effectively reduces the implicit price of energy. This mechanism is often referred to as the *price effect*, but more generally as direct rebound effect. Direct rebound effect can be decomposed into two major channels namely substitution and income/output effects (Schettkat, 2009; Sorrell, 2010).

2.2.1.1.1 Substitution Effect for Consumers

As shown in Figure 2.1, direct rebound effect has two components namely substitution and income/output effects. Both mechanisms can be observed for both households and firms, since economic theory prescribes that changes in commodity/input prices have implications for relative prices and purchasing power. As energy efficiency improvement lowers the relative price of energy, consumers move along their indifference curves substituting (the now relatively cheaper) energy services for other commodities while maintaining the same level of utility. As consumers substitute towards energy services, they use more energy which erodes some of the initial energy efficiency gains. For instance, if a fuel-efficient car is acquired, the owner's expenditure on fuel falls, holding income and travel distance constant. The driver may then choose to substitute the (now) cheaper driving (drive further or more frequently) for other commodities, thereby consuming more fuel and eroding some of the initial savings arising from the fuel-efficient car.

2.2.1.1.2 Income Effect for Consumers

Income effect on the other hand relates to the increase in energy consumption arising from higher purchasing power due to lower energy price (holding income and the prices of other commodities constant). Higher real income tends to boost purchasing power of consumers as their disposable income is augmented by the lower relative price of energy arising from energy efficiency improvements. In this case, consumers will increase their utility by consuming more goods and services in general, and energy is required to meet/produce this increased consumption of goods and services.

Consider a consumer who reduces his/her fuel expenditure by purchasing a fuel efficient car. This reduced energy expenditure boosts disposable income and s/he may choose to channel increase in purchasing power towards other energy services such as driving more, travelling more by air etc., thus using more energy and eroding some of the energy savings from the efficient car.

2.2.1.1.3 Substitution Effect for Firms

Energy savings may occur for a firm when it installs energy efficient equipment, such that the marginal cost of the energy input declines. In this case, the firm substitutes the cheaper energy for capital and/or labour in the production process to produce a given level of output. As the firm continues its substitution of energy for capital, energy consumption increases gradually, offsetting some of the initial energy savings.

2.2.1.1.4 Output Effect for Firms

This is the producers' version of income effect. As the cost of production falls due to lower energy prices, firms are generally able to produce more output i.e. the production possibility space expands (Saunders, 1992). This higher level of output requires the employment of inputs, including the energy input. Effectively, firms could simply re-invest the cost saving in output expansion, thereby using more factor inputs (energy inclusive). In this way, energy use rises in line with output expansion.

2.2.1.2 Indirect Rebound Effects

It is possible that improvements in energy efficiency do not directly impact energy consumption, but may do so through indirect channels. Indirect rebound effects can take a number of forms and can be broadly classified into embodied and secondary effects.

2.2.1.2.1 Embodied Energy Effects

To achieve energy efficiency, actions (such as installing a more efficient appliance) are required. These appliances (or actions) themselves require energy in their production, thus *embodied energy effects* refer to the energy consumption required to achieve energy efficiency improvement, through for instance, the design and manufacture of a more efficient appliance. For instance, the efficiency gain from producing a fuel-efficient car is partly offset upfront by its production and transportation, given that energy is consumed at each of these steps in its production and delivery. This indirect mechanism is referred to as *embodied energy effects*.

2.2.1.2.2 Secondary Effects

As consumers' (or indeed the whole economy's) purchasing power increases due to higher disposable income (resulting from lower energy prices), a higher level of utility can be achieved by increasing demand for other goods and services, including energy services. However, a shift in the demand for all goods and services means that a higher level of output is required, such that more factor inputs, including energy are needed. This effect is often termed *re-spend* effect in which savings from improved energy efficiency are re-spent on other goods and services. For instance, as household makes some savings from reduced fuel cost due to a fuel efficient car, it may re-spend these savings on other household gadgets, thereby shifting/increasing the aggregate demand. To meet this aggregate demand requires greater production and more input (energy) use.

2.2.1.3 Economy-wide Rebound Effects

The various mechanisms described above (both within direct and indirect effects) may be generalised to the aggregate economy as a whole. When these mechanisms are aggregated to the level of total consumption and production by households and firms respectively, the resulting effects are likely to be significant (Kydes, 1997). Widespread energy efficiency improvements reduce the price of intermediate and final goods throughout the economy, leading to a shift in aggregate demand which will require higher production (and more inputs, including energy). Another way to view this is to note that energy-efficiency improvements are likely to stimulate economic growth, which itself requires more energy consumption (Barker, et al. 2009). The economy-wide rebound effect is the most relevant to this study, given that this study aims to analyse macro-level or economy-wide rebound effects for various countries. Hence, subsequent discussions are focussed on economy-wide rebound effects.

2.3 Issues in Modelling Economy-wide Rebound Effects

There is no dispute in the literature about the existence of energy rebound effects. However, there is a controversy[6] about its magnitude, significance, sources and persistence (Chakravarty et al., 2013). Clearly, the debate has been more intense for economy-wide rebound effect which is the net effect of different mechanisms that are complex and interdependent, and whose effects may vary over time and across efficiency type/source; thus making its estimation difficult (Sorrell, 2010). This has been further compounded by the use of diverse models/methodologies, and the lack of a widely accepted rigorous theoretical framework (Sorrell and Dimitropoulos, 2007; van den Bergh, 2011). This explains the difficulty in reviewing and (or) comparing estimates of rebound effects from different studies, given the lack of consistent empirical estimates of economy-wide RE (Henly et al., 1987; Greening et al, 2000).

[6] This may have been supported by the variation in results of some studies on macroeconomic rebound effects.

Further, it is observed that the existing body of rebound literature is dominated by studies on direct RE which relates to the efficiency improvements in energy requirements for certain end-use energy services (Allan *et al*, 2007). Allan *et al*. (2007) have shown that drawing general inferences and conclusions from segmented studies such as household studies may be inadequate in the context of global climate change policy. For instance, the macroeconomic response to energy efficiency gains is likely to be different from segmented or specific energy end-uses. More specifically, households have relatively inelastic energy demand, compared to firms who are likely to respond to cheaper energy by adopting more energy intensive process in order to gain cost savings. Consequently, rebound possibilities might be substantially greater in production than consumption and are likely to have stronger indirect and economy-wide impacts. Hence this thesis addresses the issue of magnitude and model for economy-wide rebound effects. Addressing this gap is vitally important considering the relevance of economy-wide RE to the global climate agenda.

The second issue in rebound analysis relates to its channels/mechanisms (substitution and income/output effects). Saunders (2008) emphasized the importance of accounting for both effects in rebound analysis. A meaningful evaluation of rebound should not only be able to estimate rebound magnitudes, it should be possible to evaluate these two channels. For instance, it is often argued in the literature that the magnitude of rebound from improved energy efficiency depends on the ease of substitution between energy and other inputs such that greater substitution elasticity is expected to result in larger rebound (Saunders, 2000, 2013; Broadstock et al., 2007). Nonetheless, Sorrell (2008) showed that the relationship between substitution elasticities and rebound effect can be complex; and that large rebound effects are possible even where energy and capital are found to be complements. To provide some clarity on this issue of RE mechanisms, the second paper explores these channels, using the appropriate microeconomic duality principles, and a consistent dataset.

Finally, the role of energy policy instruments in managing rebound remains unclear. van den Bergh (2010) argued for a clear cut role for rebound effects policy within the wider energy policy framework for them to become more effective. While many rebound analysts and studies aim to quantify rebound magnitude or demonstrate the theory behind it, there is very little theoretical and empirical work on the implications of rebound mitigating policies with most studies focusing on the welfare implications of (mitigating) rebound (Hobbs, 1991; Gillingham et al., 2014; Borenstein, 2015). Consequently, the third paper in this thesis explores the effectiveness of some energy policy instruments in mitigating rebound. The paper also provides a benchmark analysis of country performance in RE management.

2.4 Literature review of empirical economy-wide rebound effects studies

The empirical literature on rebound effects is dominated by studies on direct rebound effects for energy services (such as travel, lighting, space heating). Most of these studies focus on household (house heating and cooling) and sectoral (transport and manufacturing) energy rebound effects. Bottom-up microeconomic studies are important for the explanation of underlying rebound effects behaviour, but economy-wide rebound effects arguably have greater implications than sectoral or direct rebound effects, given the global nature of related issues such as climate change.

It is argued here that rebound represents a major risk to global efforts to tackle climate change given that it represents a reduction in the savings arising from energy conservation, which is a key objective of the global climate change agenda. Hence, the issues of energy conservation and climate change require top-down macro-based analysis of rebound effects.

As stated in the introductory section above, this thesis is an attempt to analyse economy-wide rebound effects[7]across different countries of the world over a reasonably long period of time. In the energy economics literature, the number of studies dealing with rebound effects is growing but there is a relative dearth of economy-wide/macroeconomic rebound effects. Given this, the review of literature in this study is focused mainly on related studies on aggregate or economy-wide rebound effects.

Since the seminal works of Khazzoom (1980) and Brookes (1978), several studies have focused on discussing the theory and empirical evidence on rebound effects. One of the earliest theoretical explanations of rebound is Saunders (1992) who employed the neo-classical growth framework to demonstrate the possibility of the *Khazzoom-Brookes* postulate. Recent theoretical developments in the rebound theory have been undertaken by Hunt and Evans (2009); Sorrell (2010). Some of the earliest empirical studies of rebound effects can be found in Greene (1992; 1997); Jones (1993) and Greene et al. (1999) who all estimated transport or motor vehicle travel rebound effects.

Economy-wide rebound effects have been modelled in a number of ways, ranging from ordinary least squares techniques to computable general equilibrium (CGE) techniques. It is observed that some of these studies have modelled country-level rebound effects using aggregate national data while others have employed dis-

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[7] This may be used interchangeably with macroeconomic or aggregate or total rebound effects.

aggregated data to estimate sectoral/state/regional-level rebound effect. It is also noted that empirical studies of rebound effects have been dominated by Computable General Equilibrium (CGE) studies, with some of the earliest known macroeconomic rebound studies employing this approach.

For instance, Dufournaud et al. (1994) simulated the outcome of efficiency policies aimed at reducing firewood consumption in Sudan using the applied general equilibrium (AGE) model on data for 1982-84. They estimated economy-wide rebound effects in wood consumption arising from efficiency of stoves at 54-59%. Similarly, Semboja (1994) employed a CGE model to assess the effects of specific long-run energy conservation management policies in Kenya's production process. He projected rebound effects at 170-350% for a 1% improvement in economy-wide energy production efficiency and end-use efficiency. These two studies should be interpreted with caution, given the high levels of energy poverty across many African countries and the sensitivity of CGE analysis to parameter choices.

Grepperud and Rasmussen (2004) employed a multi-sector CGE model to analyse aggregate rebound effects from energy efficiency improvements in electricity and oil consumption across different sectors[8] in Norway using 1992 as a base year. Rebound effects were found to vary across the sectors of the economy and were quite significant in manufacturing sectors, but weak or insignificant in the other sectors. For instance, metals manufacturing industry recorded an 18% increase in electricity consumption and 87.5% increase in oil due to energy efficiency savings in the sector while the chemical and mineral products sector witnessed a 6% reduction in electricity demand and 1% fall in oil consumption.

[8] Pulp & Paper; Metals; Chemical & Mineral products; and Finance & insurance

Washida (2004) also applied a CGE model to 1995 data for Japan to estimate rebound effects from energy efficiency arising from environmental policies. The economy was disaggregated into 33 industrial sectors and the impact of energy efficiency improvements on total CO2 emissions was simulated for Japan. Rebound effect was estimated at 35-70%, and was found to be significantly influenced by the elasticity of substitution in industrial production technology and consumers' utility functions.

Allan et al. (2007) used an economy-energy-environment CGE (3E-CGE) model for all production sectors of the UK. They employed a Social Accounting Matrix (SAM) for the year 2000 to measure the impact of a 5% energy efficiency improvement across all productive sectors of the UK economy. They found rebound ranging between 30-50%. They also found results to be sensitive to a number of factors such as the assumed structure of the labour market, key production elasticities, the time period under consideration and the mechanism through which increased government revenues are recycled back to the economy.

Similarly, Hanley et al. (2009) conducted a CGE analysis to unravel the impact of energy efficiency improvements in Scotland using the 1999 SAM. They found that a general improvement in energy efficiency in the production sectors of the economy initially produced rebound effects that eventually grew into backfire, leading to a decline in the ratio of GDP to CO2 emissions. Specifically, they found that a 5% exogenous increase in energy efficiency in all production sectors results in only a 1% fall in total electricity and other energy consumption in the short to medium term. However, in the long run, their results indicate large rebound effects of over 63% and 54% for electricity and non-electricity energy consumption respectively.

Further, 'backfire' is observed in total energy consumption in the long-run (a rebound effect of 132% in electricity and 134% in other energy consumption) which they attributed to a concentration of competitiveness (and effectively export) in the most energy-intensive sectors of the economy.

However, Turner (2009) found contrary results in a CGE analysis of the response of UK energy consumption to energy efficiency improvements. The scenario simulation shows that a 5% increase in energy efficiency led to a 59.6% rebound in electricity consumption in the short run and 23.1% in the long run. Non-electricity rebound effects are estimated at 54.7% and 30.9% for the short-run and long-run respectively. However, negative rebound (super conservation) of -1.35% and -2.05% are estimated for the aggregate economy in the short-run and long-run respectively.

Guerra and Sancho (2010) estimated economy-wide rebound effects for Spain using 2004 data and a CGE framework. The CGE model had 16 representative firms, 4 factor inputs (capital, labour, energy and non-energy materials), a representative household, a government sector, an account for corporations, an external sector and a capital (savings/investment) account. Their results indicate that a 5% exogenous increase in energy efficiency will likely result in positive economy-wide rebound effect. Specifically, they also found that even when the elasticity of substitution is close to zero, the size of the economy-wide rebound effect still remained positive and close to 40%. More recently, Broberg, et al. (2014) employed a CGE model to estimate micro and macroeconomic rebound using 2012 Swedish industrial data and they found that a 5% energy efficiency improvement in the industrial sectors resulted in an economy-wide rebound of 40-70%.

There are other non-CGE econometric studies of economy-wide rebound effects, some of which have adopted disaggregated data or approach. For instance, Bentzen (2004) evaluated rebound effects in the US manufacturing sector by applying a DOLS version of the translog cost function to time series data for the period 1949-1999. In particular, he accounted for asymmetric price effects in his modelling framework which incorporated five factor inputs namely capital (K), labour (L), energy (E), non-energy materials (M) and business service inputs (S). Rebound effect for US manufacturing industry was estimated at 24%.

Brannlund et al. (2007) measured rebound effects in greenhouse emissions (carbon dioxide (CO2), sulphur dioxide (SO2) and nitrogen oxide (NOx)) using quarterly Swedish energy data for the period 1980-1997. Employing an Almost Ideal Demand model (AID model) with different scenarios, they showed that improvements in energy efficiency initially lowered energy consumption and emissions. Over time however, efficiency driven emissions rose, so that a 20% increase in energy efficiency increased CO2 emissions by approximately 5%. It is further shown that a 20% increase in energy efficiency in transport sector resulted in a 7.5%, 4.1% and 7.9% rebound effect in CO2, SO2 and NOx emissions, respectively. Additionally, they found that a 20% increase in energy efficiency for heating will lead to a rebound of 7.4%, 11.6% and 4.7% in CO2, SO2 and NOx respectively.

More recently, Barker et al (2009) estimated global macroeconomic rebound effect using the global "New Economics" model E3MG[9] containing 41 production sectors, 20 world regions, 12 energy carriers, 19 energy users, 28 energy technolo-

[9] E3MG is a sectoral macro-econometric non-equilibrium hybrid simulation model designed by the Cambridge Centre for Climate Change Mitigation Research (4CMR) and Cambridge Econometrics for assessing long-term energy and environment interactions within the global economy as well as short and long-term impacts of climate change policies. See (Barker et al. 2006) and http://www.camecon.com for details.

gies and 14 atmospheric emissions using data covering 1973-2002. Results from the study indicate that total global rebound effect will be 31% by 2020 rising to 52% by 2030. It is also found that global rebound effects will accumulate over time in line with higher real incomes from energy savings and investments.

However, Jenkins *et al*. (2011) pointed out some important issues in the global rebound analysis by Barker *et al*. (2009). First, unlike Saunders (2013) who estimated direct rebounds and also accounted for substitution and output effects, direct rebound effects are assumed to be exogenous to the model and assigned based on surveys of previous empirical studies. Also, and more importantly, the same rebound values are assumed for both OECD and non-OECD nations, despite the likelihood that direct rebound effects are likely to be higher in developing nations[10].

Freire-Gonzalez (2010) measured the rebound effect in household electricity consumption for a panel of 43 municipalities in Catalonia (Spain) over the period 1991-2002. They combined an Error Correction Mechanism Model (ECM) incorporating a partial adjustment mechanism with fixed effects model to obtain estimated short-run and long run rebound effects at 35% and 49% respectively.

Druckman *et al*. (2011) evaluated rebound effects for UK households' greenhouse emissions arising from three abatement actions[11]. Applying a Structural Time Series Model (STSM) to quarterly UK data (1964:q1 to 2009:q1) they estimated rebound effect for a combination of three abatement actions by UK households at approximately 34%.

[10] It is against this back-drop that it becomes more compelling to estimate country-specific economy-wide rebound effects over a significantly reasonable time-frame

[11] These actions are: reducing internal temperatures by 1^0C by lowering the thermostat; reducing food expenditure by one third by eliminating food waste; and walking or cycling

Li and Yonglei (2012) conducted an empirical investigation of energy rebound effect from energy efficiency saving for three Chinese industries using the Solow growth model and aggregate data for 1978-2007. GDP growth is estimated as a function of growth in Capital, Labour, Energy and Technological Progress. The estimated contribution of technological progress is then used to calculate the energy consumption embodied in the technological progress. Their results show that rebound effect was increasing slowly, peaking around 2005, after which it began to gradually decline for the sample period. The estimated rebound was found to be relatively small for the period before 2005, averaging 25% for 2000-2005 but rose significantly to an average of 133% for 2005-2009, which they attributed to the Chinese government's huge investments in industrial sectors and relaxed energy policy stance in the wake of the global financial crisis. The industrial rebound estimates show an average rebound effect of 30.36% for the secondary industry and 33% for the tertiary industry.

Similarly, Lin and Liu (2012) estimated macro-economic rebound effects for China for the period 1981-2009. By estimating total factor productivity using the Malmquist Index method, they obtained the contribution of various sources of technological progress to growth. A logarithmic mean weight Divisia index (LMDI) is then applied to measure the impact of technological improvement on the energy intensity. It is found that the average rebound effect for the study period is 53.2%; which falls within the estimated range (and is not too far from the median point of 78%) obtained by Lin and Yonglei (2012) for a quite similar sample period.

Kander and Stern (2014) applied a constant elasticity of substitution (CES) production function to Swedish data spanning 200 years using the Solow-growth framework. They found an average energy rebound effect of 76% during the sample period, arguing that the estimated size of rebound effect may be attributed to the connection between energy use and economic growth. They found that the expansion of energy services was a major factor in explaining economic growth in Sweden, especially before the second half of the 20th century after which labour-augmenting technological progress became dominant.

Saunders (2013) estimated the magnitudes of aggregate energy consumption rebound for the US economy and 30 different sectors using data covering 1960-2005. He estimated a four-factor translog unit cost function for each of the 30 sectors and found that the US economy recorded a huge rebound in energy consumption over the sample period, averaging 121% for 1980-85; 75% for 1985-90 and 60% for 1990-95. Although the results indicate that overall economy-wide rebound was declining over the entire period, mixed results were recorded at sectoral level, with some sectors experiencing increasing rebound while others decreased, possibly in line with trends in factor input prices. The mixed sectoral results have significant implications for carbon tax policies, such that a uniform national carbon tax policies will likely have different effects across the various sectors.

Antal and van den Bergh (2014) analyzed the "re-spend" effect in money saving arising from energy saving on energy intensive goods and services for over 90 countries using 2009 data. Rebound is calculated as the product of energy prices and the average energy intensity of goods and services on which money is re-spent. Further, by deriving savings and losses from marginal energy intensity, this study is susceptible to the criticisms that energy intensity is a weak proxy for energy efficiency/savings.

This section provides a review of the theoretical underpinnings of rebound effects, as well as the issues in its estimation. A review of empirical studies on aggregate/economy-wide rebound effects is also given in the section. A summary of these empirical studies are presented in Table 2.1 where it is shown to generally range from -2.05% to as high as 350%. An important observation from Table 2.1 is that none of the previous rebound studies used the stochastic frontier analysis (SFA) in this thesis. The SFA allows for an explicit treatment of energy efficiency which is an important contribution of this study, considering the importance of an appropriate measure of energy efficiency in any rebound analysis.

Table 2.1: Summary of economy-wide rebound studies

Reference	Data Type	Data	Methodology	Result
Barker et al. (2009)	Global Panel	1973-2002	Non-equilibrium Hybrid model	31-52%
Broberg, et al. (2014)	Industrial- Sweden	2012	CGE	40-70%
Saunders (2013)	Sectoral Panel/aggregate US	1960-2005	Translog Cost	60-121%
Li & Yonglei (2012)	Sectoral Panel/aggregate China	1978-2007	Solow model	25-133%
Guerra & Sancho (2010)	Aggregate Spain	2004	CGE	40%
Gonzalez (2010)	Household panel electricity- Spain	1991-2002	ECM	SR 35, LR49%
Grepperud & Rasmussen (2004)	Sectoral Cross Sections Norway	1992	CGE	(-36) -87.5%
Hanley et al. (2009)	Aggregate Scotland	1999	CGE	54-134%
Brannlund et al. (2007)	Aggregate Time series Sweden	1980-1997	AIDS model	5-11.6%
Turner (2009)	Sectoral and Aggregate UK	2000	CGE	SR -1.35%, LR -2.05%
Druckman et al. (2011)	Quarterly time series UK	1964- 2009	STSM	12-34%
Haas and Biermayr (2000)	Household Panel	1970-1995	DOLS	20-30%
Dufournaud et al. (1994)	Aggregate Sudan	1982-1984	AGE	54-59%
Bentzen (2004)	Time series US Manufacturing	1949-1999	DOLS	24%
Allan et al. (2007)	Aggregate UK	2000	CGE	30-50%
Washida (2004)	Sectoral and Aggregate Japan	1995	AGE	30-70%
Semboja (1994)	Aggregate Kenya	1976 base	CGE	170-350%

AIDS: almost ideal demand system; AGE: applied general equilibrium; CGE: computable general equilibrium; DOLS: dynamic ordinary least squares; ECM: error correction model; STSM: structural time series model

2.5 Review of Theoretical Framework

An important undertaking in this thesis is the appropriate evaluation of energy efficiency. This importance is underscored by the debates in the literature regarding the use of energy intensity as a proxy for energy efficiency (for instance Filippini and Hunt, 2011, 2012). Consequently, this section contains a review of literature on the theoretical underpinnings of efficiency and productivity measurement. It also provides a methodological review of frontier approaches employed in measuring efficiency using the production frontier framework. Ultimately, the primary objective of this section is to focus on the most common parametric approach which is the stochastic frontier analysis and its evolution over time.

2.5.1 Efficiency and Frontier Analysis

This section provides the theoretical and analytical background for the study of firm efficiency by offering definitions and measures of firm performance. A firm's performance over time may be attributed to efficiency change and technical change. Efficiency change is recorded when an observed firm moves closer to the production frontier, while technical change is related to a shift in the frontier over time. Technical efficiency can be defined as the ability of a productive unit or firm to minimize the use of a set of inputs in the production of a given level of output. Alternatively, it can be viewed as the ability to derive maximum possible output from a given input set[12].

[12] These two definitions indicate that technical efficiency can be output oriented or input oriented. Both concepts have the same underlying implications.

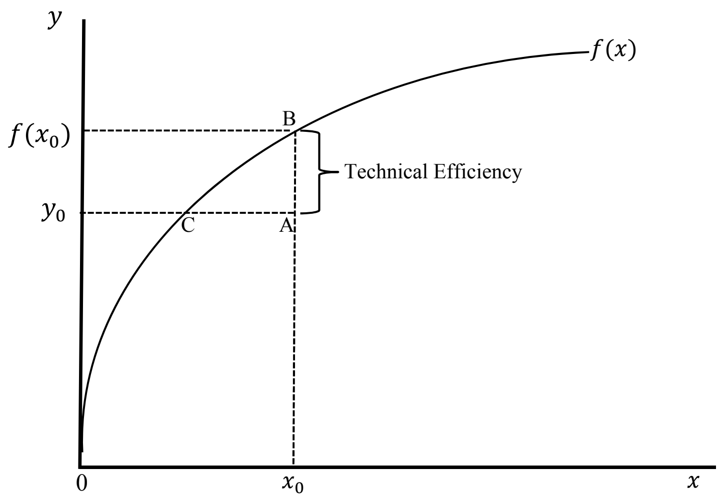

Figure 2.2: Efficiency of the firm

From the discussions above, it is clear that efficiency is a relative measure which compares a firm's input-output ratio to an optimal level. In Figure 2.1, the output oriented efficiency of the firm is given as x_0A/x_0B while input oriented efficiency is represented by y_0C/y_0A. In both cases, the efficiency measure ranges between 0 and 1, since actual output cannot exceed the maximum feasible output. The use of the frontier methodology builds on the underlying nature of the traditional production function which represents a boundary to all feasible output-input vectors. In essence, in terms of the frontier, a feasible output-input vector is technically efficient if, and only if, no increase in output or decrease in input is feasible. Therefore, frontier functions estimate relative firm performance with the theoretical notion that inefficiency is represented by the extent to which a firm deviates from the theoretical ideal (Greene 2008).

The study of productive efficiency dates back to Koopmans (1951), Debreu (1951) and Farrell (1957). The former was the first to define the concept of efficiency, while the latter two authors proposed a framework to measure it. Early efficiency studies adopted the OLS methodology by simply fitting a line to input-output observations. OLS production functions merely estimated average productivity of inputs, rather than optimal or maximum production (Murilio-Zamorano, 2004). Consequently, a major advantage of the frontier framework is that, while the least squares approach averages out the production technology of firms in an industry, the frontier identifies the firm with the best practice production technology in terms of this frontier and provides information on relative inefficiency of each firm (Schmidt, 1985).

2.6 Frontier Methodology

Frontier analysis of productive efficiency derives from the seminal work of Farrell (1957) who analysed technical efficiency as the deviations from a frontier (isoquant) in an input space. Given the firm's objective of output maximization or cost minimization, the idea of a frontier is more appealing and consistent with economic theory considering that frontier models are bounding functions (Coelli, 1995b). This bounding framework provides the border to the range of possible output/input observations, such that points below the production frontier, and the distance or magnitude by which such points lie below the production frontier (or above an isoquant) can be treated as a measure of inefficiency (Forsund etal, 1980). Farrell's (1957) input-oriented production process may be represented as:

$$y = f(x_1, x_2) \tag{2.1}$$

The production technology above employs inputs x_1, x_2 to produce output y with a given level of technology. Farrell identified that the overall efficiency (also called economic efficiency) of a firm can be decomposed into technical efficiency and allocative efficiency, where the former relates to the production of the maximum feasible output from a given input set while allocative efficiency refers to the employment of an appropriate input mix, given their prices. This process can be depicted by the isoquant SS’ in Figure 2.2 below which represents a constant-returns-to-scale production technology with a single output using two inputs.

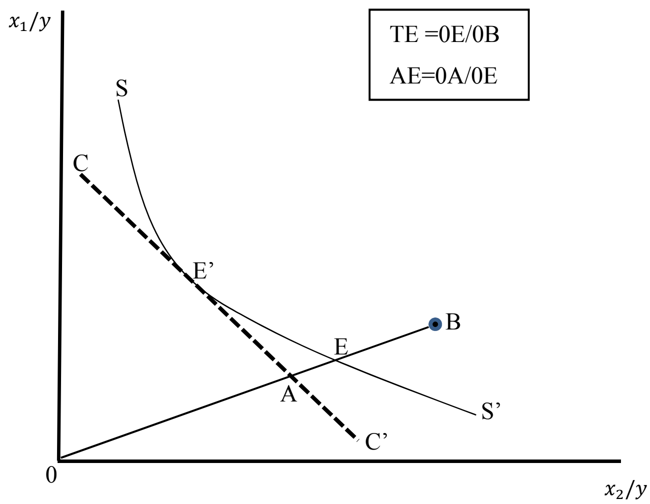

Figure 2.3: Technical efficiency of a firm

The production frontier is given by the unit isoquant SS’ which represents the locus of the minimum (technically efficient) input bundles available to the firm to produce a given level of output from a range of input combinations in the input-output space. The gap between any points above or to the right of the isoquant represents technical inefficiency, considering that input usage within such bundles can be contracted without any loss of output. On the other hand, line CC’ which is the iso-cost, depicts the minimum cost required to deliver the output level associated with isoquant SS’.

Using the firm operating at point B as a reference, it can be that it suffers both technical inefficiency and allocative inefficiency. The technical efficiency of the firm is given by 0E/0B, since moving from B to E contracts the input usage to produce the same level of output. Its allocative efficiency is given by 0A/0E, since moving from E to E’ ensures that the same level of output can be attained at lower cost; where point E' represents the firm equilibrium where the marginal product and input price ratios are equal. From the foregoing analysis, it is clear that TE ranges between zero and one, such that technical inefficiency is then measured as 1 – (0B/0A).

Frontier techniques attempt to quantify the ratios/gaps between actual and efficient production technologies as shown above. Various frontier methods for the analysis of productive efficiency abound, and these methods differ according to their assumptions about the production technology, firm behaviour and the data requirements. Generally, frontier methods can be broadly classified into parametric and non-parametric techniques, with Farrell's approach being largely non-parametric.

A key difference between both approaches relates to functional form[13] of the production technology. The parametric approach imposes a functional form on the efficient frontier and employs econometric/goal programming models for the estimation of the model parameters and efficiency. However, non-parametric frontier techniques stand out for their flexibility because they calculate efficiency from the sample observation, with no *a priori* (upfront) assumptions about the shape of the frontier. The parametric approach is adopted in this study due to considerations explained in the following sections. Notably, the most important consideration is that diagnostic tests revealed the presence of heteroscedastic error structure in the panel data set. It is known that panel SFA models are better able to address the problem arising from panel heteroscedasticity (see Kumbhakar and Lovell, 2003; Alvarez et al., 2006). Hence, the focus of this review is on parametric frontier methodology. Nonetheless, a brief description of the non-parametric frontier analysis is given in the next section.

[13] The most common functional form is the Cobb-Douglas model. More recently, more flexible functional forms such as the Translog (Christensen et al., 1971, 1973) and the Fourier flexible function (Gallant, 1981; 1982).

2.6.1 Non-Parametric Frontier Analysis

A major distinguishing feature of the non-parametric frontier modelling is the non-specification of a functional form for the frontier. Furthermore, it makes no up-front assumptions about the distribution of the random error term. By implication the production frontier is not influenced by random events, sampling and measurement errors, etc. The most common non-parametric frontier model is the Data Envelopment Analysis (DEA)[14] , which was first introduced by Charnes et al. (1978). DEA employs linear programming to fit a frontier to a data sample such that observations lie above the frontier[15]. In other words, the DEA procedure constructs a piecewise linear, quasi-convex hull around the data points in the input space (Greene, 2008).

Let us consider the CRS case of Figure 2.2 above by assuming that there are N firms with a technology employing K inputs to produce M, such that the i_{th} firm has inputs x_i and output y_i. A DEA frontier can be constructed over the $K \times N$ input matrix, X; and the $M \times N$ output matrix, Y. The N linear programs are given as:

$$\begin{aligned} &\min_{\theta,\lambda} \theta \\ s.t.\ \ & Y\lambda \geq y \\ & X\lambda \leq x\theta \\ & \lambda \geq 0 \end{aligned} \qquad (2.2)$$

θ is a scalar which represents the index of efficiency for the $\mathrm{i_{th}}$ firm and it ranges between 0 and 1. The closer it is to 1, the more efficient the observed firm is, imply-

[14] See Cooper et al. (2000) for a detailed review of DEA

[15] The pioneer DEA frontier by Charnes etal (1978) was constructed based on the assumptions of CRS and convexity of the firm's technology. One limitation of this approach is that the CRS restriction makes it difficult to analyze non-CRS technologies.

ing that 1- θ indicates the relative inefficiency of the firm, and the amount by which inputs can be contracted towards the isoquant without any loss in output.

A major advantage of the DEA is its simplicity and flexibility, which derives from the non-imposition of a functional form on the data. In effect, the DEA offers an array of choice in terms of specification. Its flexibility also makes it possible to incorporate the operating characteristics of the firms in a study sample. Moreover, it also lends itself to both cross sectional and time series data as well as panel data without concerns about sampling and error specification issues. Another advantage of the DEA is its ability to provide straightforward interpretation of return to scale, based on free disposability assumption, when in fact weak disposability better reflects firm inefficiency.

However, a major flaw of the DEA is that it is constructed from a subset of data observations, so it suffers from outlying observations and measurement error i.e. it is especially sensitive to efficient outliers (see Forsund *et al.*, 1980). In addition, due to the deterministic nature of DEA, it fails to differentiate between pure inefficiency and random disturbances (Murilio-Zamorano, 2004). Moreover, given their linear programming nature, it is difficult and often impossible to draw statistical inferences about the distribution of inefficiency from DEA frontiers. Further, the original DEA frontier by Charnes et al. (1978) was derived from a CRS technology, resulting in criticisms about its practical application considering the non-CRS imperfect market conditions which are obtainable in reality. In addition, the CRS assumption is only applicable when production levels are optimal such that suboptimal production technologies may bias estimates of technical efficiency via scale efficiency (Coelli et al, 2003).

As a result, Banker et al. (1984) constructed a DEA frontier which possesses the ability to account for variable returns to scale (VRS). More recent studies have addressed other areas of limitations of the DEA. For instance, it has been demonstrated that DEA models possessing statistical properties are possible through bootstrapping (see Simar and Wilson, 2000). Additionally, it has also been shown that stochastic DEA models can be implemented (Huang and Li, 2001; Shang et al, 2010). The stochastic DEA allows for variations in inputs and outputs such that the resulting efficiency measure derives from joint probabilistic comparisons of inputs and outputs with other firms by solving a chance constrained programming problem (Huang and Li, 2001). More recently, the Stochastic Nonparametric Envelopment of Data (StoNED) (Kuosmanen, 2008; Kuosmanen and Kuosmanen, 2009; Kuosmanen and Kortelainen, 2012) has been developed as a hybrid frontier framework incorporating the features of both DEA and SFA.

Nevertheless, the DEA remains susceptible to challenges emanating from outlying observations and its sensitivity to selection of inputs and outputs as well as the difficulty to test for the best specification (Berg 2010). Most of these limitations are addressed by the parametric frontier approach which is discussed in the next section.

2.6.2 Parametric Frontier Analysis

Parametric frontiers are constructed based on assumptions about the distribution of the error term and a clear cut functional form for the production technology. Unlike the DEA or other non-parametric models where the efficient frontier is calculated from data sample, the parametric frontier is econometrically estimated based on the notion that a functional mathematical relationship exists between inputs and output. Parametric frontiers can be broadly classified into deterministic and stochastic techniques.

2.6.2.1 Deterministic Frontier Approach

This section demonstrates the deterministic frontier approach in a cross-sectional context. This allows for the analysis of deterministic frontier approach while also building the tentative assumptions about cross-sectional models, which are relaxed later. Consider a production technology with N inputs employed by I producers to a single output, which can be written as $f(x_i; \beta)$. The production frontier is given by

$$y_i = f(x_i; \beta) \cdot TE_i \tag{2.3}$$

where y_i is the scalar output of producer i=1,…,I, x_i is the vector of the N inputs used by producer i, $f(x_i; \beta)$ is the production frontier, while β is a vector of technology parameters to be estimated. An efficient producer will operate or lie on the frontier since such a producer derives the maximum feasible output from the given input vector. In this case the producer's technical efficiency is equal to one. However, if a producer is observed to fall short of the maximum feasible output, then $TE_i < 1$ represents the degree of the shortfall of the firm.

Under deterministic frontier techniques, the slack between an observed level of output and the frontier is attributed solely to technical inefficiency, so that the output oriented technical efficiency can be defined as the ratio of the observed output to maximum feasible output:

$$TE_i = \frac{y_i}{f(x_i; \beta)} \tag{2.4}$$

Equation (2.3) above is deterministic, which means that (2.4) attributes all the entire shortfall of the observed output y_i from the frontier $f(x_i; \beta)$ to technical inefficiency. A deterministic frontier can be fitted by re-writing (2.3) as

$$y_i = f(x_i; \beta) \cdot \exp\{-u_i\} \tag{2.5}$$

where $TE_i = \exp\{-u_i\}$ and $u_i \geq 0$ ensure that $TE_i \leq 1$. By taking natural logarithms, (2.5) can be expressed as a deterministic frontier model:

$$\ln y_i = \ln f(x_i; \beta) - u_i \tag{2.6}$$

since $TE_i = \exp\{-u_i\}$, then $\ln TE_i = -u_i$ where $u_i \geq 0$ captures the firm's technical inefficiency by ensuring that $y_i \leq f(x_i; \beta)$. The notable deterministic frontier models are briefly discussed below.

2.6.2.1.1 Goal Programming

Goal programming was proposed by Aigner and Chu (1968) who estimated (2.6) using mathematical programming where the parameters in vector β are calculated using linear programming. The sum of the proportionate deviations of each observed level of output below the frontier is then minimized such that the programming goal is

$$\min \textstyle\sum_i u_i$$

$$\text{subject to } [\beta_o + \textstyle\sum_n \beta_n \ln x_{ni}] \geq \ln y_i. \tag{2.7}$$

One of the major limitations of goal programming is that the parameter estimates are calculated rather than estimated, leading to uncertainty about their statistical inferences since the estimates do not come with standard errors.

2.6.2.1.2 Corrected Ordinary Least Squares (COLS)

COLS was proposed by Winsten (1957) who estimated (2.6) in two steps. First ordinary least squares (OLS) is used to obtain consistent and unbiased estimates of the parameters in vector β, but with biased (though consistent) estimate of the intercept β_o. To address this, in the second stage the biased intercept term is shifted or corrected upwards so that the estimated frontier bounds the data from above. Hence, the consistently estimated intercept is given as

$$\hat{\beta}_o^* = \hat{\beta}_o + \max\{\hat{u}_i\} \quad (2.8)$$

$\hat{u}_i$ represent the OLS residuals which are corrected in the opposite direction so that

$$-\hat{u}_i^* = \hat{u}_i - \max\{\hat{u}_i\} \quad (2.9)$$

It is clear that the COLS residuals $\hat{u}_i^*$ are nonnegative, while at least one of them is zero, which is then used to estimate the technical efficiency of each firm via the mean of technical efficiency $TE_i = \exp\{-\hat{u}_i^*\}$. Although COLS is quite simple and straightforward approach, a major challenge with the technique is that it is parallel to the OLS production function, since it only shifts the OLS intercept. By implication, COLS simply implies that the best practice technology is a reflection of the "average technology" in the centre of the data (which reflects inefficient production).

2.6.2.1.3 Modified Ordinary Least Squares (MOLS)

MOLS is a modified version of COLS which was proposed by Afriat (1972) and Richmond (1974). Although it also employs a two-stage estimation procedure, it differs from COLS in two significant ways. First, the residuals are assumed to follow a one-sided distribution (e.g. half normal or exponential). Secondly, unlike COLS, the intercept is "modified" by the mean of the one-sided error distribution, so that (2.8) and (2.9) can be re-written as:

$$\hat{\beta}_o^{**} = \hat{\beta}_o + \mathrm{E}(\hat{u}_i) \tag{2.10}$$

and $$-\hat{u}_i^{**} = \hat{u}_i - \mathrm{E}(\hat{u}_i)$$

Although MOLS relies on the OLS residuals as in COLS, a limitation arises from the possibility that the modified intercept might not be shifted up adequately to ensure that all producers are bounded by the frontier from above. For instance, a producer with very large positive OLS residuals might record a situation where $[\hat{u}_i - \mathrm{E}(\hat{u}_i)] > 0$. The extreme opposite is also possible, where the intercept is modified to a great extent whereby no producer is found to be technically efficient. Finally, like COLS, MOLS is also parallel to OLS.

2.6.2.2 Stochastic Frontier Analysis (SFA)

As shown above, in the deterministic frontier set-up, a firm's position relative to the production frontier is attributed solely to its performance, without allowing for the impact of other significant stochastic exogenous influences such as weather and luck. Bundling these influences with the failings (inefficiency) of the firm and the normal random errors, and reporting all as inefficiency is a major source of criticism of the deterministic frontier approach.

The SFA is motivated by the idea that some part of the deviations from the production frontier are beyond the control of the firm, given that some exogenous factors such as bad weather, bad luck, government policies and regulations may have played a role. But these factors are usually captured and reported as observed inefficiency under the deterministic approach (Greene, 2008). Additionally, any error or mis-specification of the model may also influence estimated inefficiency measures. Consequently, a more appropriate approach is to make an observed firm face the production frontier which is randomly constructed by incorporating the whole collection of stochastic elements such as luck, sampling and mis-specification errors, which might be outside the firm's control (Førsund and Jansen, 1977; Greene, 2009).

The Stochastic Frontier Analysis (SFA) was introduced by Aigner et al. (1977) and Meeusen and Van den Broeck (1977). A major contribution of the SFA is the introduction of a composed error term consisting of the traditional disturbances and an inefficiency term. Another advantage of the SFA is the possibility to account for the effects of random unobserved heterogeneity. Moreover, it is also possible to make inferences about the parameters and the inefficiency term of the model. However, SFA requires a number of assumptions, which often make it less-flexible and restrictive.

For the SFA to be viable, it is important to ascertain the presence of inefficiency in the first place. It is possible to separate inefficiency from noise as it is possible to explicitly test for the presence of inefficiency and measure its contribution to the residuals. This is done by testing to see the degree of skewness of the residuals in order to determine the presence of inefficiency. If residuals are symmetric (no inefficiency), then $u_i = 0$ and $\varepsilon_i = v_i$, such that the model reverts to OLS. However, if $u_i \geq 0$ then ε_i is positively skewed above the cost frontier or negatively skewed below the production frontier. Table 2.3 below shows details of the test statistic.

Table 2.2: Test statistic for Presence of Inefficiency

Schmitdt and Lin (1984)	Coelli (1995)
$(b_1)^{1/2} = m_3/(m_2)^{3/2}$	$m_3/6m_2^3/I)^{1/2}$

m_2 and m_3 represent the second and third sample moments of the OLS residuals, respectively; where m_3 also represents the third sample moment of u_i, given that v_i is symmetric in its distribution. Under the Schmitdt and Lin (1984) approach, when $m_3 < 0$, it can be concluded that the OLS residuals are negatively skewed and vice versa. However, Kumbhaka and Lovell (2003) argued that the positive skewness of the OLS residuals ($m_3 > 0$) has little informational value other than indicating that the frontier model is a mis-specified model.

The second approach proposed by Coelli (1995) serves as an alternative which tests the hypothesis that $m_3 \geq 0$ under the null hypothesis of zero skewness in the errors. This test, which is asymptotically distributed as *N* (0, 1), may be more appropriate since the required skewness occurs when $m_3 < 0$. Both tests have the advantage they are based on OLS residuals which are easy to derive. However, they are based on asymptotic properties when in reality many samples are small in size.

Starting with a cross-sectional data set, consider the stochastic production frontier equation:

$$y_i = f\ (x_i)\ \exp\ (\varepsilon_i) \tag{2.11}$$

where y_i represents output and x_i denotes input, ε_i is a composed error term containing a traditional random term v_{i} and an inefficiency term u_{i} which measures frim inefficiency. Thus:

$$\varepsilon_i = v_i - u_i \tag{2.12}$$

Combining equations 2.11 and 2.12 it is possible to obtain a stochastic production frontier:

$$lny_i = \beta_0 + \sum_{i=1}^{n} \beta_i \, ln\, x_i + v_i - u_i \tag{2.13}$$

Given the frontier function in 2.13, technical efficiency may be represented as:

$$TE_i = \frac{y_i}{y_i^*} = \frac{y_i}{f\,(x_i)\exp(v_i)} = \exp(-u_i)\ ;\ 0 < TE_i \leq 1 \qquad (2.14)$$

The empirical estimation of technical efficiency following 2.12 to 2.14 requires assumptions about the distribution of the composed error term, as well as the functional form (and parameter estimates) of the production technology. In other words, distributional assumptions about the two error components are not required to obtain separate estimates of the random noise v_i and technical inefficiency u_i from ε_i for each firm. Under the assumption that the u_i in equation 2.13 are independently distributed of the x_i inputs, OLS yields consistent parameter estimates except for the intercept term. However, with additional assumptions and a different estimation approach such as the maximum likelihood method, it is possible to consistently estimate intercept term along with the other parameter estimates and the inefficiency term. In particular, under certain standard regularity conditions, the MLE is consistent, asymptotically normally distributed and asymptotically efficient (Kumbhakar and Lovell (2003). Hence, subsequent discussions are centred on maximum likelihood estimator (MLE).

The choice of an appropriate distribution[16] should depend largely on the careful consideration of the data and the features of the industry being investigated (Cullinane and Song, 2006). The truncated normal and the exponential distributions ensure relative flexibility of the model; however the problem of identification outweighs the potential gains from both distributions (Greene, 1997). Thus, the normal-half normal[17] distributional assumption remains the most common whereby:

[16] u_i can follow four different distributional assumptions namely the half-normal distribution (Aigner, 1977), the exponential distribution (Aigner, 1977; Meeusen and Van Den Broeck, 1977); the truncated normal (Stevenson, 1980) and the gamma distribution (Greene, W. 1990). These distributional assumptions and the density functions of the error components are presented in appendix 1.

[17] See Greene (2003) for further discussions on the half-normal distribution in SFA

(i) $v_i \sim$ iid $N(0, \sigma_v^2)$;

(ii) $u_i \sim$iid $N^+(0, \sigma_u^2)$, i.e. a non-negative half normal;

(iii) v_i and u_i are distributed independently of each other and of the regressors.

Two functions with these properties are most commonly adopted to describe the distribution of inefficiency across producers: the exponential and the half-normal. Both distributions have the added benefit that they are one-parameter distributions – all of the properties of the distribution can be expressed in terms of one parameter, and for these distributions this parameter is the standard deviation. These distributions are written out because they will be used many times in this study. Kumbhakar and Lovell (2003) wrote the density function of v and u in the normal-half normal model respectively as:

$$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot \exp\left\{-\frac{v^2}{2\sigma_v^2}\right\} \tag{2.15}$$

$$f(u) = \frac{2}{\sqrt{2\pi}\sigma_u} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2}\right\} \tag{2.16}$$

The independence assumption (iii) implies that their joint density is the product of their individual density functions:

$$f(u, v) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right\} \tag{2.17}$$

It is known that $\varepsilon_i = v_i - u_i$, so that the joint density function for u_i and ε_i can

$$f(u, \varepsilon) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon+u)^2}{2\sigma_v^2}\right\} \tag{2.18}$$

Finally, Aigner *et al.* (1977) derived the marginal density function of ε_i by integrating u out of $f(u, \varepsilon)$:

$$f(\varepsilon) = \frac{2}{\sigma} \cdot \phi\left(\frac{\varepsilon}{\sigma}\right) \cdot \left[1 - \Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \tag{2.19}$$

$where\ \sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$ and $\lambda = \sigma_u/\sigma_v$. In particular, λ gives an indication of the relative variation in the components of the composed error term. In other words, it shows the contribution of the inefficiency component to the composed error term such that as $\lambda^2 \to 0$ then $\sigma_v^2 \to \infty$ and $\sigma_u^2 \to 0$. In this case, it is possible to conclude that the traditional symmetric error dominates the one-sided inefficiency term in the composition of ε_i, hence the model collapses back to OLS without technical inefficiency. However, if the reverse is the case where $\lambda^2 \to \infty$, then the model becomes a deterministic frontier with no symmetric errors.

An important point to note from the foregoing discussion is that, when compared to the other parametric techniques, the SFA strikes a balance between both the OLS and deterministic techniques such as COLS. As Shown in Figure 2.4 below, the OLS production function fits a line through data observations by assuming that all firms are efficient. On the other hand, the deterministic production frontier approach constructs a production frontier by attributing all random errors to inefficiency, suggesting that firms have complete control over sources of inefficiency.

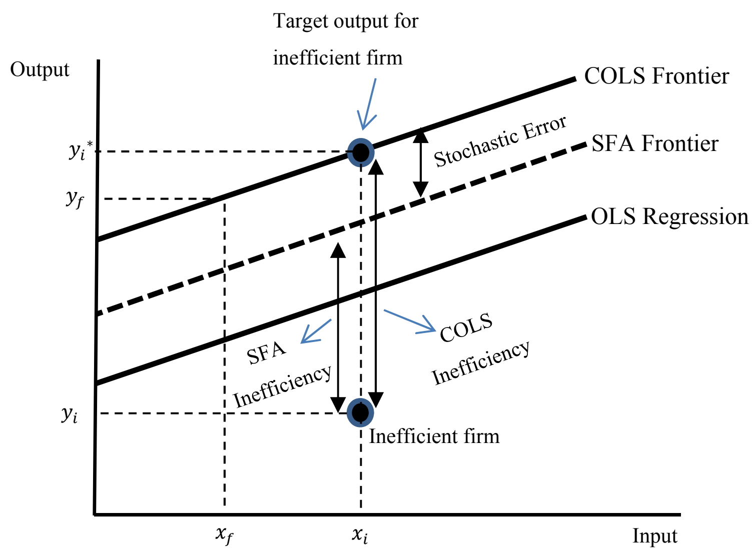

Figure 2.4: Comparison of production functions

As stated previously, the MLE may be combined with distributional assumption (usually normal-half normal) to obtain the model parameters including σ and λ, after which estimates of technical inefficiency can be derived from $\varepsilon_i = v_i - u_i$. It should be clear that when $\varepsilon_i > 0$, then u_i is relatively small, given that the mean of the random noise is zero, indicating that the firm is relatively efficient, and vice versa.

Extracting information on u_i from ε_i is possible by using the conditional distribution of u_i given ε_i. The two major approaches for doing this were proposed by Jondrow et al. (1982) and Battese and Coelli (1988). Given the model assumption (ii) above, Jondrow et al. (1982) (also named JLMS) derived the conditional distribution of u_i given ε_i as:

$$f(u|\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi}\sigma_*} \cdot \exp\left\{-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right\} \Big/ \left[1 - \Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right] \tag{2.20}$$

where $\mu_* = -\varepsilon\sigma_u^2/\sigma^2$ while $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$. Using the mean or mode of its conditional distribution, it is possible to obtain a point estimate of u_i since the conditional distribution of $(u_i|\varepsilon_i)$ is $N^+(\mu_*, \sigma_*^2)$. This mean or mode can be written as:

$$E(u_i|\varepsilon_i) = \mu_{*i} + \sigma_* \left[\frac{\phi(-\mu_{*i}/\sigma_*)}{1-\Phi(-\mu_{*i}/\sigma_*)}\right] = \sigma_* \left[\frac{\phi(\varepsilon_i\lambda/\sigma_*)}{1-\Phi(\varepsilon_i\lambda/\sigma_*)} - \left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right] \tag{2.21}$$

and

$$M(u_i|\varepsilon_i) = f(x) = \begin{cases} -\varepsilon_i\left(\frac{\sigma_u^2}{\sigma^2}\right) & if\ \varepsilon_i \leq 0 \\ 0 & Otherwise \end{cases} \tag{2.22}$$

Once point estimates of u_i are obtained, estimates of technical efficiency can be derived from $TE_i = \exp(-\hat{u}_i)$, where $\hat{u}_i$ is $E(u_i|\varepsilon_i)$ or $M(u_i|\varepsilon_i)$ as shown above. The alternative point estimator proposed by Battese and Coelli (1988) is given as:

$$TE_i = E(\exp\{-u_i\}\,|\varepsilon_i) = \left[\frac{1-\Phi(\sigma_*-\mu_*/\sigma_*)}{1-\Phi(-\mu_*/\sigma_*)}\right] \cdot \exp\left\{-\mu_* + \frac{1}{2}\sigma_*^2\right\} \tag{2.23}$$

Both approaches to obtaining technical efficiency above can result in different results, although Kumbhaka and Lovell (2003) argued that the B&C method is preferred (especially when u_i is close to zero) because it is an exact expression of the mean of the distribution of technical efficiency, while the JMLS approach is an exact expression of the central tendencies of a first order approximation to the technical efficiency distribution.

Having discussed different cross-sectional models in the context of different estimators of technical efficiency, it is important to note that the approaches above suffer from a number of limitations. Schmidt and Sickles (1984) showed that the cross-sectional stochastic production frontier models suffer from three notable problems:

(i) MLE estimation of the cross-sectional SFA production frontier and the resulting separation of technical inefficiency from the random white noise component both require strong distributional assumptions on each of the error components.

(ii) MLE also requires the independence assumption that the technical inefficiency component is independent of the regressors. This is a strong assumption in the face of potential correlation between technical inefficiency and the inputs.

(iii) Although both the JLMS and the B&C estimators are unbiased, they are inconsistent estimators of u_i, as the variance of the conditional mean/mode of estimated technical inefficiency does not go to zero as the size of the cross-sectional sample increases.

These limitations can be easily overcome with panel data techniques which are explored in the following sections.

2.6.2.3 Panel Data Models

Panel data techniques are common in empirical economic analyses due to the possibility of incorporating both cross sectional and time series observations into one framework. Therefore, panel data permit the observation of a cross-section of firms' efficiency over a period of interest. Clearly, this provides more information about firm performance compared to a snapshot of efficiency among firms in just a period of time.

For the traditional panel data models, it is not necessary to make certain strong distributional assumptions about the composed error term (especially the u) as is the case with the MLE estimation of cross-sectional SFA models. Amongst other important points or benefits, repeated observations on a set of firms can substitute for some strong assumptions. Moreover, repeated observations on firms yield additional information which cannot be derived from adding more firms to a cross-sectional sample (efficiency from larger sample). Hence, technical efficiency for each firm can be estimated consistently as $T \rightarrow +\infty$. To this end, panel data frontier models are likely to produce more consistent estimates of an individual firm's efficiency (Kumbhaka and Lovell, 2003).

Additionally, with panel data, it is possible to relax other standard model assumptions such as homoscedasticity (panel SFA models allow for the treatment of heteroscedasticity). Also, panel data allows for a richer range of models and yields greater testing power. Further, since the independence assumption is not necessary for panel data models, they are able to incorporate time-invariant regressors into some of the models (Murillo-Zamorano, 2004).

In some panel data SFA models, technical efficiency varies across firms but is assumed to be time-invariant for each firm. This assumption would appear unrealistic in this thesis given the relatively long time frame of the rebound analysis undertaken in this study. Consequently, the focus of the following sections is on panel data models that allow for time varying technical efficiency. I start with the traditional panel data techniques such as the fixed and random effects techniques.

2.6.2.3.1 Fixed-effects Model

The fixed effects (FE) model is generally more suitable when the symmetric noise component is independently distributed over time and across firms and uncorrelated with the regressors. In this case, there is no need to make distributional assumption about u_i and it can be correlated with the regressors or with v_{it}. v_{it} is assumed to be iid (0, σ_v^2). Since u_i varies across firms only, it can be treated as constant/fixed so it may be used as firm-specific intercept parameters in a fixed effects model, which can be estimated via OLS (or least squares with dummy variables (LSDV)):

$$\ln y_{it} = \beta_{o_i} + \sum_n \beta_n \ln x_{nit} + v_{it} \qquad (2.24)$$

where $\beta_{o_i} = (\beta_o - u_i)$ represents firm-specific intercept terms. The FE model can be estimated in three different ways: (i) by suppressing β_o and estimating *I* firm-specific intercepts (i.e. adding a dummy variable for each of the *I* firms; (ii) by keeping the intercept term β_o and estimating (I-1) firm-specific intercepts/dummies; or (iii) by employing the within transformation, in which all the data are expressed in terms of deviations from firm means (i.e. $y_{it} = y_{it} - \bar{y}_i$, etc.), such that the *I* intercepts are then recovered as means of firm residuals. Under this FE framework, the intercepts are derived following

$$\hat{\beta}_o = \max_i(\hat{\beta}_{oi}) \tag{2.25}$$

so that the technical inefficiency component of the residuals is estimated as:

$$\hat{u}_i = \hat{\beta}_o - \hat{\beta}_{oi} \tag{2.26}$$

which ensures that all $\hat{u}_i \geq 0$ so that firm-specific technical efficiency can be derived as:

$$TE_i = \exp\{-\hat{u}_i\} \tag{2.27}$$

As is the case with COLS, under the FE estimator, at least one firm is assumed to be 100% efficient against which all the other firms' relative efficiency is measured. However, in addition to the FE estimator not requiring the distributional or independence assumptions, when compared to the cross-sectional MLE models, it provides consistent estimates of β_n and technical efficiency as either $I \to +\infty$ or $T \to +\infty$, while consistent estimates of β_{o_i} only requires that $T \to +\infty$.

Notwithstanding the benefits of the FE estimator above, a number of major limitations exist. The fixed effects, u_i which capture firm-specific is likely to pick-up other time invariant factors across firms such as location, regulatory environment and sunk costs. This is especially true for the within transformation. This challenge could potentially result in the over-estimation of technical inefficiency. Moreover, even when such time-invariant factors are included in the model, there is the additional problem that they would be correlated with other regressors. Thus, a random-effects model may be adopted where it is possible to make assumptions that the fixed effects are uncorrelated with the other regressors, in addition to the random assumption about the distribution of the effects.

2.6.2.3.2 Random-effects model

Moreover, unlike the FE model, u_i is taken to be randomly distributed with constant mean and variance, but is uncorrelated with the regressors. This makes it possible to incorporate time-invariant factors since the inefficiency measure/effects and the regressors are independent of each other. However, just like with the FE estimator, the iid assumption about v_{it} is retaind so that a random effects (RE) model can be written as:

$$\ln y_{it} = [\beta_o - E(u_i)] + \sum_m \beta_m \ln x_{mit} + v_{it} - [u_i - E(u_i)]$$

$$= \beta_o^* + \sum_m \beta_m \ln x_{mit} + v_{it} - u_i^* \qquad (2.28)$$

Both components of the error term v_{it} and $u_i^* = \left(u_i - E(u_i)\right)$ have zero means and the RE model can be estimated using either the two-step generalised least squares (GLS) technique or MLE (when distributional assumptions about the error components are tenable such as the normal-half-normal distribution (Pitt and Lee, 1981); normal-truncated normal distribution (Kumbhakar, 1987; Battese and Coelli, 1988)). When distributional assumptions are not required on the composed error terms, the GLS approach is appropriate for estimating the model and technical efficiency. First, OLS is used to estimate the model parameter estimates and then in the second stage, β_o^* and β_m are reestimated using feasible GLS.

As shown by Kumbhaka and Lovell (2003), β_o^* does not depend on *i,* since $E(u_i)$ is a positive constant, such that only one intercept term is estimated. Once β_o^*

and β_m have been reestimated using feasible GLS, u_i^* can be derived by the means of the residuals:

$$\hat{u}_i^* = \frac{1}{T}\sum_t \left(\ln y_{it} - \hat{\beta}_o^* - \sum_n \hat{\beta}_n \ln x_{nit} \right) \tag{2.29}$$

Estimates of u_i can be obtained through means of the normalization:

$$\hat{u}_i = \max_i\{\hat{u}_i^*\} - \hat{u}_i^* \tag{2.30}$$

Or alternatively u_i can be estimated using the best linear unbiased predictor (BLUP). The BLUP of u_i^* is given as:

$$\tilde{u}_i^* = -\left[\frac{\hat{\sigma}_u^2}{T\hat{\sigma}_u^2 + \hat{\sigma}_v^2}\right] \cdot \sum_t \left(\ln y_{it} - \hat{\beta}_o^* - \sum_n \hat{\beta}_n \ln x_{nit} \right) \tag{2.31}$$

The RE model estimates above as consistent as both $I \rightarrow +\infty$ and $T \rightarrow +\infty$. The firm-specific technical efficiency estimates are derived by substituting $\hat{u}_i$ into (2.27) above. As with the FE estimator, the RE model also requires that at least one of the firms is 100% technically efficient, relative to the other inefficient firms. In general also, both the FE and RE models do not necessarily require distributional assumptions in the specification and estimation of a stochastic frontier (Murillo-Zamorano, 2004).

The RE estimator has the desirable possibility of permitting time invariant regressors in the model, which might yield lower technical inefficiency estimates. Notwithstanding the relative strengths of the RE model, it requires the extra (trade-off) assumption that the inefficiency term is not correlated with the regressors.

2.6.3 Distance Functions and Efficiency

In the preceding sections above, the different forms of frontier techniques have been reviewed. An important observation is that the approaches discussed above specify a production technology with one output and multiple inputs. In reality, however, a technology may incorporate a more complex input-output process, to the extent that it employs multiple inputs which produce multiple outputs[18]. The distance function is therefore a useful approach when modelling multiple output and multiple input production technologies.

The underlying objective of distance functions is the radial expansion or contraction of output or input respectively, towards their *ideal*. In particular, distance functions are useful for the analysis of multiple output technologies in which behavioural assumptions such as cost minimization or profit maximization are not applicable[19] (Coelli and Perelman, 2000). Thus, a key strength of distance functions is that they allow the estimation of productive efficiency when prices or cost information are not available.

Distance functions were first formulated by Malmquist (1953) and Shephard (1953). Thereafter, Shephard (1970) estimated a production technology for isoquants using the distance function. The two approaches to modelling distance functions are the output distance function and input distance function, which are discussed below.

2.6.3.1 Output Distance Function

The output distance function measures the distance between an observed level of output relative to the maximum attainable output (on the frontier), using a given

[18] For instance, in reality, most production processes yield desirable goods which satisfy/contribute towards utility, but sometimes yield undesirable outputs such as pollutants which are jointly produced with the goods.
[19] For instance, it might be important to benchmark performance of charity organizations or NGOs whose objective is neither profit maximization nor cost minimization.

input requirement set. This logic also applies to a multiple-output technology. Assuming a firm possesses a technology which is characterised by an output set $P(x)$ with output vectors $y \in R_{+}^{M}$ which are produced using input vectors $x \in R_{+}^{K}$ so that $P(x) = \{y \in R_{+}^{M}: x \text{ can produce } y\}$, then the output distance function can be represented by:

$$D_0(x, y) = \min\left\{\delta : \frac{y}{\delta} \in P(x), \delta > 0\right\}; \;\; D_o(x, y) \leq 1 \qquad (2.32)$$

The output distance function is the smallest positive scalar divisor δ of an output bundle y such that (y/δ) is within the output space in equation 2.32 above. $D_0(x, y)$ is non-decreasing and convex in outputs, homogeneous of degree +1 in outputs and decreasing in inputs (Khumbakar and Lovell, 2003). $D_o(x, y) \leq 1$, implying that the distance function takes the value of unity if y is on the boundary of the production possibility set. Furthermore, the distance may be interpreted as the multiple-output version of Farrell's (1957) technical efficiency, such that:

$$D_0(x, y) = TE \leq 1 \qquad (2.33)$$

If technical efficiency is measured by a negative exponential function of the non-negative inefficiency measure u which is independent across firms, then:

$$TE_i = \exp(-u_i) \text{ where } u_i \geq 0 \qquad (2.34)$$

u is inversely related to efficiency such that as it increases, technical efficiency falls. Consequently, since $\exp(-u_i)$ is the technical efficiency of a firm, then u_i is the observed firm's technical inefficiency. The log-log version of equation 2.34 yields:

$$u_i = -\ln TE_i \approx 1 - TE_i \qquad (2.35)$$

Combining 2.33 to 2.35 yields an output distance function:

$$\ln D_0(x, y)_i = -u_i \qquad (2.36)$$

When the property of homogeneity of degree +1 in outputs is introduced, as well as the traditional error term, then a stochastic output distance function (SODF) with time varying efficiency may be estimated as:

$$\ln y_{K_{it}} = \ln D_0\,(x_{it}, \tilde{y}_{it}) + v_{it} - u_{it} \tag{2.37}$$

where $TL(x_{it}, \tilde{y}_{it})$ represents the technology as the approximation of the log of the distance function while v_{it} is the traditional random error term and u_{it} denotes the inefficiency component of the composed error term. As shown in equation 2.32, the entire output set is given by P(X). The maximum output combination is denoted by y/δ. Producer operating at y is inefficient, and can reduce its inefficiency by minimizing δ. As δ tends towards zero, output radially expands towards the frontier at y/δ.

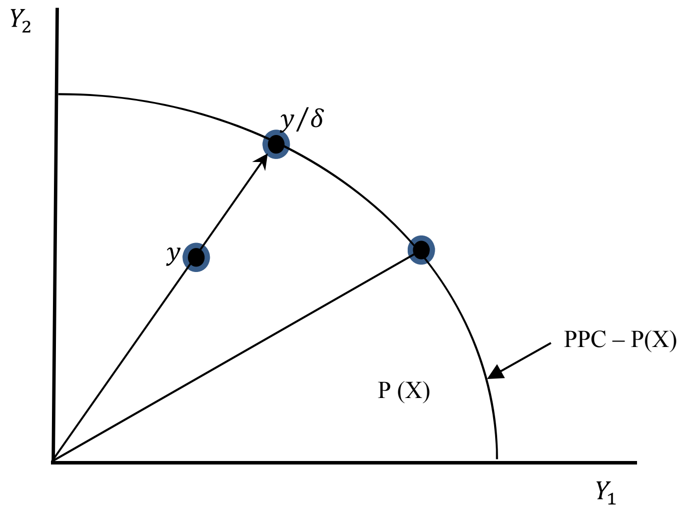

Figure 2.5: Output Distance Function with Two Outputs

2.6.3.2 Input Distance Function

The same theoretical reasoning discussed above may be applied to an input oriented technology. While the output distance function expands the output vector, holding the input vector constant, the input distance function considers the proportional contraction of the input vector, holding the output vector fixed. The input distance function is defined as:

$$D_I(x, y) = \max\left\{\rho : \frac{x}{\rho} \in I(y), \rho > 0\right\} \tag{2.38}$$

In this case, the input distance function is the largest scalar divisor ρ of the inputs bundle x such that x/ρ is still in the input requirements set. The objective here is to cause a radial contraction which pushes inputs down towards the isoquant, holding output constant. $D_I(x, y)$ is non-decreasing, homogenous of degree 1 and concave in inputs. $D_I(x, y) \geq 1$ if $x \in I(y)$.

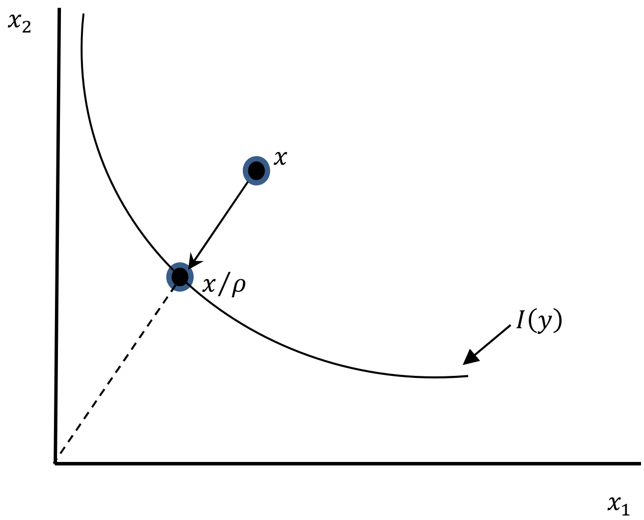

Figure 2.6: Input distance function with two inputs

With CRS, the input distance function is the inverse of the output distance function such that $D_0 = 1/D_I$ which is the measure of the Farrell input based efficiency. This inverse expression is defined as:

$$\theta(x, y) = \min\{\theta: \theta x \in I(y)\} \tag{2.39}$$

In this case, the smallest possible scalar factor which can contract the inputs towards the efficient input combination on the isoquant boundary of the input set is θ.

Here $\theta \in [0,1]$ and the inefficiency of the firm is $100(1-\theta)$. The stochastic input distance function (SIDF) with time varying efficiency can be written as:

$$-\ln x_{K_{it}} = \ln D_I\left(x_{it}/x_{K_{it}}, \tilde{y}_{it}\right) + v_{it} - u_{it} \tag{2.40}$$

2.7 Summary

This chapter reviews the concept, key issues and empirical analyses of rebound effect in economic literature. Although this review has focused mainly on macroeconomic rebound effect, an attempt is made to show its existence at microeconomic or disaggregated level. In particular, it is shown that a good number of studies have established the possibility of significant rebound effect magnitudes across a wide spectrum of end-use energy services. It is also shown that the controversies surrounding rebound effect may be due to the debate on the role of energy within the production function. This may have been further fuelled by the lack of a consistent benchmark study to clarify rebound effects across board. Arguably, rebound effects may pose significant risks to global energy and climate forecasts; and if found to be large in magnitude, it may indicate a need to revisit the assumptions underlying these forecasts with a view to incorporating RE. The next chapter delves into the data and first level economy-wide analysis of rebound effects across different countries of the world.

Chapter 3 Economy-wide Estimates of Rebound Effects: Evidence from Panel Data[20]

3.1 Introduction

There appears to be a consensus within the energy policy community about the contributions of energy efficiency improvements towards reducing global energy consumption and greenhouse emissions. Some protagonists of energy efficiency improvement often highlight its non-costly nature, arguing that the resulting decrease in energy use may not require higher energy prices or result in slower economic growth. For instance, the United Nations expert group on climate change in their 2007 report stated inter alia:

"World governments should exploit energy efficiency as their energy resource of first choice because it is the least expensive and most readily scalable option to support sustainable economic growth, enhance national security, and reduce further damage to the climate system. The need to provide adequate, sustainable, and environmentally sound supplies of energy to fuel global economic growth has created an imperative for increased energy efficiency. A strategy that emphasizes energy efficiency is the most economically and environmentally sensible way of meeting the

[20] A revised version of this chapter is published as: Adetutu, M., Glass, A. and T. Weyman-Jones (2016). "Economy-wide Estimates of Rebound Effects: Evidence from Panel Data". *The Energy Journal* 37 (3): 251-270.

twin objectives of providing energy for sustainable development and avoiding dangerous interference in the climate system"

To this end, some notable climate change forecasts[21] project future energy consumption based on (potential) energy efficiency gains[22]. However, a strand of literature starting with early works of Brookes (1979, 1990, 1992) and Khazzoom (1980, 1987, 1989) argues that the underlying assumption that energy efficiency improvements yield proportionate reduction in energy consumption is misleading. This view was recently elucidated by Saunders (2013) who argued that overtime rebound effects (RE) could potentially result in the partial or total erosion of energy savings derived from improved energy efficiency. Thus, failure to account for RE may imply that such energy forecasts may have overstated the actual benefits of energy efficiency improvements[23].

Since its inception, the RE literature has grown significantly, but controversies remain about its magnitude, mechanisms and the most appropriate approach to measuring it. Clearly, the debate has been more intense regarding macroeconomic RE since it approximates the net effect of different mechanisms that are complex and interdependent, and whose effects may vary over time and across efficiency sources. This possibly explains the scarcity of macroeconomic RE studies[24] as Chakravarty et al. (2013) show that most studies on economy-wide RE are few and they are country-

[21] For example, the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report, 2007 forecasts that energy efficiency will significantly address climate change by restricting global energy use to 30% below what it would naturally have been by 2030, thus countervailing the growth-inducing energy consumption.
[22] Some of the forecasts and projections appear to implicitly assume that energy efficiency improvements yield proportionate reduction in energy consumption.
[23] Rebound effect is not entirely bad on its own since the resulting increase in energy use contributes towards consumer welfare and expands the production possibility space. However, due to the urgency required in tackling dangerous climate change, failure to explicitly account for rebound effects in global energy forecasts may mean that energy forecasts might have understated future energy use to the extent that we actually have less time than predicted to address climate change.
[24] A detailed literature survey can be found in Sorrell (2007). More recent surveys include Jenkins et al. (2011) and Chakravarty et al. (2013).

specific. Moreover, the few available studies on macroeconomic RE use different empirical and theoretical approaches, with most of them covering different time periods. As expected, given the differences in methodological approaches and dataset, these studies are highly incomparable. In particular, Dimitropoulos (2007) and Sorrell (2010) have shown that the use of diverse models/methodologies and the lack of a widely accepted rigorous theoretical framework have contributed immensely to the controversies surrounding RE.

Understanding the nature and estimating macro RE is important for a number of reasons. First, the key issues associated with RE, especially global climate change, require top-down macroeconomic analyses of different economies over long time frames, which microeconomic or bottom-up analysis may be inappropriate to handle. This is because effective climate change policies require multilateral co-operation and co-ordination among different countries, thus there is need for a comparative and consistent measurement of RE across different countries. However, the available pool of studies[25] is inadequate to generate meaningful insight required to tackle climate change[26]. Moreover, drawing general inferences and conclusions from segmented studies such as household and other microeconomic studies may be inadequate in the context of global climate change (see Allan et al., 2007).

Secondly, this paper is an important step towards designing a sound methodological and consistent approach to assessing macroeconomic RE. This is expected to

[25] The dearth of macro RE studies for developing countries is more severe. Herring and Roy (2007) and Sorrell et al. (2009) argue that macroeconomic RE are likely to be significantly higher in developing countries because their economic growth and development increasingly burden the global environment as they lift millions of people from poverty (For instance see Goel and Korhonen, 2012)

[26] Although Antal and van den Bergh (2014) calculate the "re-spent" money saving arising from energy saving on energy intensive goods and services for over 90 countries in 2009, the limiting time-frame of the study and the simplistic approach employed makes it less suitable for the task in hand. Rebound is calculated as the product of energy prices and the average energy intensity of goods and services on which money is re-spent. Further, by deriving savings and losses from marginal energy intensity, this study is susceptible to the criticisms that energy intensity is a weak proxy for energy efficiency/savings.

yield a more beneficial and useful debate on RE. Given the discussions above, it is surprising that, as far as is known, no multi-country study of macroeconomic RE across several countries has been undertaken to provide greater clarity on the debate using a sound technique and consistent dataset. This is an important gap in literature given that RE arising from aggregate consumption and production by households and firms respectively are likely to be of great significance and implication (Kydes, 1999).

In this paper, the objective is to provide estimates aggregate RE for a panel of 55 countries between 1980 and 2010 using a two-stage procedure. First, energy efficiency was estimated using Stochastic Frontier Analysis (SFA). Secondly, by employing a dynamic panel framework, and using the efficiency scores from the SFA model, the short-run and long-run RE are estimated. The remainder of the paper proceeds as follows. Section 3.2 presents the methodology. Specifically, it presents a two-stage estimation exercise including the parametric SFA approach for estimating energy efficiency, and a GMM model for estimating the short-run and the long-run RE. In section 3.3, the dataset is described in detail. Section 3.4 presents the empirical results from both models and the resulting rebound effects. Concluding remarks and recommendations are offered in Section 3.5.

3.2 Modelling and theoretical approach

The aim of this chapter is to estimate RE within a macroeconomic production function by accounting for the increase in energy use arising from energy efficiency gain. This efficiency saving is expected to impact on energy consumption, resulting in energy conservation which is defined as:

$$\eta^E = \frac{\mathrm{d}\ln E}{\mathrm{d}\,Ef} \tag{3.1}$$

where E is energy consumption and Ef is energy efficiency. η^E is also referred to as efficiency elasticity of demand, which allows us to derive RE following Saunders (2000, 2008) and Wei (2007, 2010):

$$R = 1 + \eta^E \tag{3.2}$$

Intuitively, RE represents the size or percentage of the energy efficiency savings that is lost such that if energy consumption E falls by 40% due to a 40% increase in energy efficiency, then $\eta^E = -1$ and $\boldsymbol{R} = 0$. In the same vein, if a 100% increase in energy efficiency yields only a 40% fall in energy consumption, then $\boldsymbol{R} = 0.6$. Given these discussions above, it is easy to see that five rebound conditions are possible (Saunders, 2000; Wei, 2010):

- $\boldsymbol{R} > 1$ or $\eta^E > 0$: '**Backfire**' occurs as energy consumption increases due to improvements in energy efficiency;
- $\boldsymbol{R} = 1$ or $\eta^E = 0$: **Full rebound** as energy demand remains unchanged in the face of energy efficiency gains;
- $\boldsymbol{0} < \boldsymbol{R} < 1$ or $-1 < \eta^E < 0$: **Partial rebound** as energy consumption falls by a less-than-proportionate rate to efficiency improvements;
- $\boldsymbol{R} = 0$ or $\eta^E = -1$: **Zero rebound** implies a one-to-one or unit relationship between energy consumption and efficiency improvements;
- $\boldsymbol{R} < 0$ or $\eta^E < -1$: **Super conservation** as energy consumption falls by a more-than-proportionate rate with respect to efficiency gains.

Turning now to the multi-stage approach to estimating RE, the key objective is the econometric estimation of the efficiency elasticity η^E. The need for an econometric estimation is underscored by criticisms and inappropriateness of using energy intensity as a proxy for energy efficiency (see Filippini and Hunt, 2011; Saunders, 2013). To this end, this study estimate energy efficiency using the stochastic frontier analysis (SFA).

3.2.1 Energy Efficiency Estimation

Given the discussions above, this study must start by estimating energy efficiency (Ef) using the stochastic frontier analysis (SFA) which was introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977). The SFA allows for a composed error term which contains a one-sided error term to measure inefficiency in addition to the traditional two-sided error term which captures random noise. The objective of the first stage is to estimate energy inefficiency by constructing a best-practice stochastic frontier to unravel the degree to which a country could potentially reduce its energy consumption, relative to the other countries for a given level of national output.

SFA has been applied in energy and environmental economics literature. Specifically, a number of studies have estimated efficiency in aggregate energy consumption[27]. One of such is Filippini and Hunt (2011) who estimated aggregate energy efficiency for 29 OECD countries using an energy demand SFA. Moreover, considering that they employ an energy demand function, it can be argued that they estimated an input requirement function (IRF) in which case other factor inputs are implicitly assumed to be constant. Similarly, Zhou et al (2012) estimated a stochastic energy input requirement function for a sample of 21 OECD countries. More recent-

[27] Other studies such as Jamasb and Pollitt (2003) have estimated efficiency performance of disaggregated economic units such as electricity utilities.

ly, Filippini and Hunt (2012) also estimated energy efficiency in residential energy demand for a panel data of 48 US states using an IRF.

Stern (2012) estimated efficiency trends in energy intensity for 85 countries using a Stochastic input distance approach for the period 1971-2007. Energy efficiency was modelled as the extent to which a country minimizes energy intensity. However, the use of energy intensity in energy efficiency analysis has come under great criticisms in energy economics literature[28]. The criticism has centered on the inappropriateness of declining energy intensity as an indication of energy efficiency improvements. The critics of this approach argue that declining energy intensity is too simplistic a proxy to describe energy efficiency gains, given that, in addition to energy efficiency, it embodies (and is influenced by) numerous factors such as relative factor prices, factor substitution elasticities, technological progress, changing economic structures, capital deepening and so forth[29].

This study differs from the studies mentioned above by estimating a production technology using an input distance function (IDF), rather than an energy demand or input requirement function (IRF). With an IRF, the objective is to radially contract energy use in an input vector for a given level of output, conditional on energy prices and other exogenous factors. By implication, other factor inputs are implicitly assumed to be fixed or held constant; hence studies relying on an IRF have arguably estimated short-run energy efficiency. However, an IDF seeks to radially contract energy and the other factor inputs in the input vector for a given level of output. This

[28] The estimated parameter values were either found to have the wrong signs (i.e. theoretically inconsistent) or statistically insignificant or only slightly significant. Moreover, Stern adopted a Cobb–Douglas functional form which may be unsuitable for the purpose of rebound analysis. Saunders (2008) demonstrated the importance of adopting a “rebound-flexible” functional form, such as the Translog function. Further, it is shown in footnote 10 and Figure 1 below the advantages of the Translog over the Cobb-Douglas form.

[29] For instance see Filippini and Hunt (2011) and Saunders (2013) for discussions and empirical evidence on the inappropriateness of declining energy intensity as a proxy for energy efficiency.

approach is consistent with long term energy efficiency estimation, which is arguably more suitable for practical energy and climate change policies. In reality one would expect efficiency gains to alter relative/effective prices of factor inputs, resulting in factor substitution as firms adjust input combinations to take advantage of energy efficiency improvements[30].

The production technology can be represented by the input requirement set $I(y)$ represents the set of K inputs $x \in \mathbb{R}^+$ which can produce a set of R outputs $y \in \mathbb{R}^+$ i.e. $I(y) = \{x \in \mathbb{R}^+ : x\ can\ produce\ y\}$.The inputs and output are assumed to be weakly disposable, so that $(x', y') \in T\ if\ \ x' = \lambda x\ for\ some\ but\ not\ all\ \lambda > 0$. This technology (which is shown in Figure 3.1) can be represented in time *t* by the input distance function, $D_I(\boldsymbol{y}', \boldsymbol{x}', t)$ which takes a value of 1 if a country is efficient (i.e. on the frontier) but is greater than 1 when a country is energy inefficient $D_I \geq 1$ so that:

$$\ln D_I\,(\boldsymbol{y}, \boldsymbol{x}, t) - u = 0 \qquad (3.3)$$

where $u \geq 0$

As shown in Figure 3.1, weak disposability allows for the possibility of having an "uneconomic" (inefficient) region of the function/graph, where for some input combinations, the isoquants are upward sloping implying that one of the inputs erodes output, since its marginal product is negative. In reality, the questions relating to energy and environmental inefficiency border on the "uneconomic" use of resources, such that invoking weak disposability is both theoretically and empirically sound. Moreover, weak disposability, rather than strong disposability reinforces the need for a translog functional form which unlike the Cobb-Douglas function, allows for the

[30] Comparable considerations apply to households who may alter their consumption bundles in response to changing relative prices.

possibility of negative marginal products on any quasi-fixed inputs. In this specific case, as shown later, $D_I(\boldsymbol{y}, \boldsymbol{x}, t) \equiv D_I(Y, K, L, E, M, t)$, where *Y* is output; *K* is capital; *L* is labour; *E* is energy; *M* is materials and *t* represents time.

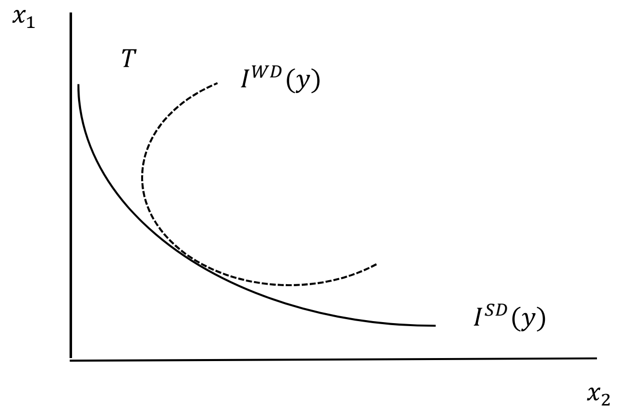

Figure 3.1: Strongly and weakly disposable input sets

The IDF denotes the maximum magnitude λ by which a country's input vector can be radially contracted, while the initial level of output remains feasible. The non-negative variable u is a measure of the distance or slack in input use, relative to the most efficient country (ies) on the frontier i.e. it is the feasible contraction of inputs required to project an inefficient producer on to the efficient frontier of the input requirement set. In the parametric approach to inefficiency measurement, u_{it} is treated as a random variable distributed across producers with a known asymmetrical probability density function. Economic theory requires that the IDF exhibit certain properties[31] (McFadden, 1978):

(i) non-decreasing in inputs, x': $\partial \ln \mathrm{D_I} / \partial \ln x_\mathrm{k} \equiv ex_\mathrm{k} \geq 0$ for $\mathrm{k} = 1, \dots, \mathrm{K}$, where ex_k is the kth input elasticity;

[31] The estimated production function is tested to ascertain these economic properties at the sample mean, assuming that the sample mean falls within the monotonic/economic region of Figure 1. Further, it is also test across the entire sample points to verify if the properties are verified or violated at each sample point.

(ii) homogeneity of degree one in x': $D_I(y', x'/x_k, t) = D_I(y', x', t)/x_k$;

(iii) concave in x ;

(iv) non-increasing in outputs, y': $\partial \ln D_I / \partial \ln y_r \equiv ey_r \leq 0$ for $r = 1, \ldots, R$, where ey_r is the rth output elasticity;

(v) the scale elasticity of the technology at time t is

$$E^t = -\left(\sum_{r=1}^{r=R} \partial \, ln \, D_I / \partial \, ln \, y_r\right)^{-1} \equiv -\left(\sum_{r=1}^{r=R} ey_r\right)^{-1}$$

By imposing property (ii), and using the IDF definition with a normalizing input as the left hand side (LHS) variable, an equation can be obtain as follows:

$$-\ln x_K = \ln D_I(\boldsymbol{y}, \boldsymbol{x}/x_K, t) - u \quad (3.4)$$

By adopting a translog functional form in conjunction with the elements, $i = 1, \ldots, N; t = 1, \ldots, T$), equation 3.4 can be written in panel context[32]:

$$-\ln x_{Kit} \approx TL(\boldsymbol{y}, \boldsymbol{x}/x_K, t)_{it} + \boldsymbol{\pi}'\boldsymbol{z}_{it} + v_{it} - u_{it} \quad (3.5)$$

where $TL(y, x/x_K, t)_{it}$ represents the technology as the translog approximation to the log of the distance function; $\boldsymbol{\pi}'\boldsymbol{z}_{it}$ captures country specific heterogeneity which is distinct from inefficiency while $\boldsymbol{z}_{it}$ represents observable exogenous characteristics across countries that shift the production function. v_{it} is the traditional symmetric error term representing sampling, specification and measurement errors, while u_{it} represents the non-negative inefficiency component of the composed error term.

Using the notations $\tilde{x}_K \equiv x_k/x_K$, $ly' = (\ln y_1, \ldots, \ln y_R)$ and $l\tilde{x}' = \ln \tilde{x}_1, \ldots, \ln \tilde{x}_{K-1})$, a translog input distance function $TL(\boldsymbol{y}, \tilde{\boldsymbol{x}}, t)$ may be specified:

$$TL(\boldsymbol{y}, \tilde{\boldsymbol{x}}, t) = \alpha_0 + \boldsymbol{\alpha}'\boldsymbol{ly} + \boldsymbol{\beta}'\boldsymbol{l\tilde{x}} + \frac{1}{2}\boldsymbol{ly}'\boldsymbol{A}\boldsymbol{ly} + \frac{1}{2}\boldsymbol{l\tilde{x}}'\mathbf{B}\boldsymbol{l\tilde{x}} + \boldsymbol{ly}'\boldsymbol{\Gamma}\boldsymbol{l\tilde{x}} +$$

[32] A panel data framework with time-varying inefficiency is employed, given the reasonably long timeframe of this study. It is unlikely that energy efficiency will be constant or time-invariant over a long time period of time such as the one for this study.

$$\delta_1 t + \frac{1}{2}\delta_2 t^2 + \boldsymbol{\mu}'\boldsymbol{ly}t + \boldsymbol{\eta}'\boldsymbol{l\tilde{x}}t \tag{3.6}$$

where α', β', δ, μ', η', ζ', **A** and **B** are estimated parameter vectors/matrices. To ensure continuity of the IDF, symmetry restrictions are imposed on the elements of matrices **A** and **B** so that $\alpha_{rs} = \alpha_{sr}$ and $\beta_{kj} = \beta_{jk}$. The energy efficiency of each country in each period is then estimated as the conditional expectation of the one-sided error term, $\exp(u)$, given the composed error, $v - u$. So that the energy inefficiency of each country i in period t is given by:

$$TE_{it} = E[exp(-u_{it})|\varepsilon_{it}] \tag{3.7}$$

$$\text{where } \varepsilon_{it} = v_{it} - u_{it} \tag{3.8}$$

3.2.1.1 Exogenous Variables and Energy Efficiency

The typical production frontier function assumes homogeneity of producers and homoscedasticity of the errors. However, some practical empirical works have relaxed these assumptions by introducing exogenous variables which are different from factor inputs but affect or influence the technical inefficiency of firms/countries into the different parts of the SFA model. It is desirable to evaluate the impact of observable country-specific exogenous factors on inefficiency because, in reality; such factors reflect the operating environment and are likely to be partly responsible for energy efficiency performance across countries (Kumbhakar and Lovell, 2003 pp261). Moreover, with this approach, it is possible to address the problem of conditional heteroscedasticity in the energy inefficiency term. Kumbhakar and Lovell (2003) also argue that failure to control for observable heterogeneity in the components of the composed error term may affect inferences derived from SFA models[33].

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[33] Specifically, Caudill and Ford (1993) and Caudill et al. (1995) have shown that MLE estimates of the production technology in the presence of heteroscedasticity results in overestimated intercept, underestimated slope

There are two broad approaches to introducing exogenous variables into the inefficiency term. Under the first approach, the exogenous variables are introduced into the location of the distribution of inefficiency so that the inefficiency term u_i is assumed to follow the truncated normal distribution, but the constant mean assumption is relaxed so that the mean of the pre-truncated inefficiency distribution is parameterized (i.e. the inefficiency is a function of the exogenous variables). Models under this first approach include Kumbhakar et al. (1991); Huang and Liu (1994); Battese and Coelli (1995) and the three models are jointly classed as KGMHLBC where:

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_{it}^2) \tag{3.9}$$

Here the mean of the inefficiency term is given by $\mu_{it} = \boldsymbol{\varphi}' \boldsymbol{z}_{it}$.

Under the second approach, the exogenous effects are introduced into the inefficiency term by scaling its distribution so that the assumption about constant variance of the truncated normal distribution is relaxed. In this case the variance is a function of the exogenous variables[34] and it permits heteroscedasticity in u_{it}. A number of notable papers jointly referred to as RSCFGH including Reifschneider and Stevenson (1991), Caudill and Ford (1993), Caudill et al. (1995) and Hadri (1999) parameterize the variance of the pre-truncated inefficiency distribution as follows:

$$u_{it} \sim \mathcal{N}^{+}(0, \sigma_{u_{it}}^2) \tag{3.10}$$

$$\sigma_{u_{it}}^2 = \exp(\boldsymbol{\gamma}' \boldsymbol{z}_{it}) \tag{3.11}$$

moreover, the scaling property of this approach is desirable when evaluating the impact of exogenous variables on inefficiency. Alvarez et al. (2006) provide a technical

coefficients and ultimately bias estimates. See Galán and Pollitt (2014) for an application on the role of heterogeneity on efficiency in Colombian electricity industry.

[34] The impact of exogenous variables on the variance of inefficiency is particularly crucial since the variance parameters of the model are the key devices in the estimation of inefficiencies.

explanation of the practical advantages and the desirability of the scaling property. Notably, they show that the property implies that changes in the exogenous variables affect/determine the scale and not the shape of the distribution of u_i, unlike under the previous approach where the z's enter the mean efficiency and alter the shape of its distribution[35]. Amongst other advantages, Alvarez et al. (2006) also show that scaling offers an intuitive economic interpretation in that u_{it} is taken as a unit's base efficiency level which captures natural abilities within the unit, which is assumed to be random, so that the extent to which these natural abilities or skills are exploited depends on the operating environment which is captured by exogenous influences, z_{it}.

Further, and more importantly, the scaling property allows for a straightforward interpretation of the parameter $\boldsymbol{\gamma}$. Scaling functions, such as the exponential function yield coefficients that are derivatives of the log of inefficiency w.r.t the exogenous variables: $\gamma = \partial \ln (u_{it})/\partial z_{it}$ for $u_{it} = \exp(z_{it}, \boldsymbol{\gamma}) \cdot u_{it}{}^{*}$. This is a highly desirable property, as it permits the interpretation of the coefficients as the quantitative effects of changes in exogenous variables on inefficiency. This is not the case with the KGMHLBC specification.

Hadri (1999) extends the RSCFGH specification to the case where the variance of the two-sided error term is also assumed to be heteroscedastic in which case the exogenous variables also enter the variance of the two-sided error term:

$$v_{it} \sim \mathcal{N}(0, \sigma^2_{v_{it}}) \tag{3.12}$$

$$\sigma^2_{v_{it}} = \exp(\boldsymbol{\delta}' \boldsymbol{z}_{it}) \tag{3.13}$$

Hence, given the discussions above and the advantages of a scaling model, this study introduced different exogenous variables into the variance of the inefficiency term to

[35] The shape of the conditional distribution is determined by the density function of the inefficiency component of the error, u_{it}.

capture the impact of structure of economy, demography, geography, climate on energy inefficiency. These variables were included because they play an important role in shaping the operating environment (and by implication the level of energy efficiency) across the different countries. For instance, extreme climatic conditions (i.e. hot temperature and cool temperature) may result in different practices with respect to energy use and this may affect efficiency levels. Similarly, population and area size directly influence the energy required to deliver given levels of output or consumer satisfaction. Finally, the structure of a country's economy (industrial or non-industrial) which is proxied by industrial share of value added, determines the nature of the production technology in terms of energy required to deliver a unit of national output. Thus, the 'double-heteroscedasticity' extension of Hadri (1999) is also explored to see if it is supported or accepted by the data. Finally, for the purpose of comparison, the KGMHLBC model is also estimated[36].

3.2.2 Stage Two: Estimation of Rebound Effects

After estimating energy efficiency using SFA above, short-run and long-run RE are then computed for each country following Saunders (2000, 2008) and Wei (2007, 2010). RE is derived as:

$$R = 1 + \eta^E \tag{3.14}$$

where η^E is the elasticity of energy consumption with respect to energy efficiency $\frac{d \ln E}{d\, Ef}$; E is energy consumption and Ef is energy efficiency. The task in this second stage is the econometric estimation of η_τ^E. Short run and long run efficiency elasticity

[36] To arrive at a preferred model, model performance is checked econometrically and theoretically. First, robustness checks are conduct using diagnostics tests such as the likelihood ratio (LR) and Wald tests. In addition, the theoretical appropriateness of the models are assessed by observing the curvature properties of the different models.

are estimated in order to compute SR and LR rebound effects *a la* equation (3.14). To achieve this, this study utilized the Arellano-Bond (1991) autoregressive dynamic-panel energy consumption model estimated by generalized method of moments, GMM, where the estimated energy efficiency in the first stage is included as a regressor, alongside energy price and national output. The GMM autoregressive dynamic panel model is written as:

$$\ln E_{it} = \beta_i + \delta \ln E_{it-1} + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} + \beta_3 Ef_{it} + \beta_4 t + \beta_5 P_{it} * Ef_{it} + \beta_6 Y_{it} * Ef_{it} + \beta_7 P_{it} * Y_{it} + (\alpha_i + v_{it}) \quad (3.15)$$

where E_{it} is energy consumption, treated as the long-run equilibrium level of energy use by a country in time t. E_{it-1} is the lagged energy consumption while P_{it} is the corresponding real price of energy in time t, Y_{it} represents a country's real GDP at time t; Ef_{it} denotes each country's estimated efficiency from the IDF above in time t. The panel data error term consists of an unobserved country-specific component α_i and an idiosyncratic disturbance term which is assumed to be identically and independently distributed $v_{it} \sim (0, \sigma^2)$. The $\beta's$ are all parameter estimates of the model[37]. ε_{it} is an error term consisting of an unobserved country-specific component α_i and the traditional disturbance term which is assumed to be identically and independently distributed $v_{it} \sim (0, \sigma^2)$ i.e. $\varepsilon_{it} = \alpha_i + v_{it}$. From the parameter estimates of equation 3.15 above, short-run and long-run efficiency elasticity can be derived as follows:

$$\text{Short-run } \eta^E_{SR} \equiv \frac{d \ln E}{dEf} = \beta_3 + \beta_5 P_{it} + \beta_6 Y_{it} \quad (3.16)$$

[37] In addition, the data are also mean-adjusted, so that the estimated parameters can be interpreted as elasticities evaluated at sample mean. Specifically, efficiency is not logged since it is expressed in percentages. Nonetheless, its coefficient can still be interpreted as a measure of elasticity so that $\eta^E \equiv \frac{d \ln E}{dEf}$. However, because the study explored a non-linear specification with interaction terms between efficiency and the other regressors, the efficiency elasticity cannot be captured by β_3 alone, but by assessing the derivative of the energy function at each given level of price and income.

The short run efficiency elasticity is derived as the partial derivative of energy use with respect to energy use. The values of energy prices and national output at the sample mean are used to calculate this short run efficiency. The long run efficiency elasticity is derived by collecting like terms (the dependent variable and its lagged values) in order to find a long run expression.

$$\text{Long-run } \eta_{LR}^{E} = \frac{\beta_3+\beta_5 P_{it}+\beta_6 Y_{it}}{1-\delta} \qquad (3.17)$$

Ceteris paribus, it can be expected that both SR and LR efficiency elasticities to be negative since improved energy efficiency will most likely reduce the fuel required to achieve a given level of energy service. Therefore, the question of RE centers on the extent to which efficiency gain lowers energy use, so that the magnitude of RE depends on the size of η^{E} (i.e. the larger η^{E}, the smaller the RE magnitude).

Dynamic models are common in energy demand studies[38] in estimating short-run and long-run elasticities. This is because the response of energy consumption to changes in exogenous influences such as price and income are gradual in nature[39]. Furthermore, the use of partial adjustment models (PAM) stems partly from their simplicity considering that they do not require imposition of any specification on the model structure (Prosser, 1985). However, the dynamic modelling approach can be generally complicated by issues such as the correlation between lagged values of the dependent variable and the error term, especially the country-specific heterogeneity component[40] (Nickell 1981). This is because E_{it} is a function of the unobserved

[38] For example see Dahl and Sterner (1991); Gately and Huntington (2002).

[39] For instance, due to appliance stock and psychological reasons, households do not immediately change their energy use habits in response to a price increase as such changes may result in some disutility, hence the need for a partial adjustment approach in energy demand modeling.

[40] This is often referred to as the Nickel bias.

country-specific heterogeneity v_i which is time invariant, it then follows that E_{it-1} which is one of the regressors is correlated with ε_{it}. Moreover, v_i may also be correlated with the other regressors. Furthermore, the presence of the lagged dependent variable as one of the regressors may result in the problem of autocorrelation. Under these circumstances, parameter estimates are biased and inconsistent, particularly for OLS[41].

Thus, the generalized method of moments (GMM) procedure (Holtz-Eakin et al., 1988; Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond 1998) is employed in this study. In the first place, by using the GMM estimator, it is possible to control for cross-country heterogeneity, which is practically impossible to achieve with country dummies due to the PAM specification. Secondly, the GMM estimator addresses the issues arising from the possibility of endogenous regressors by exploring the orthogonality between E_{it-1} and v_{it} as N and/or T approach infinity.

Arellano and Bond (1991) derived two GMM estimators namely one-step and two-step estimators. In the one step estimator, weighting matrices independent of parameter estimates are used. For the two-step estimator, the moment conditions are weighted by their covariance matrix often regarded as optimal weighting matrices. Thus the two-step estimator yields asymptotic efficiency over the one-step estimator, especially in large samples. In this case, the estimator can handle numerous instruments and it uses the consistent variance co-variance matrix from first step GMM which is robust to panel-specific autocorrelation and heteroskedasticity (See Roodman, 2009a). However, its standard errors may be biased and therefore unreliable. Also, the proliferation of numerous instruments in the two-step GMM context may

[41] See Roodman (2009 a, b) for detailed discussions on the benefits of the GMM estimator, especially over other estimators such as the FE and 2SLS estimators

also yield misleading over identification test (see Windmeijer, 2005; Bowsher, 2002). The problem of downward bias in the standard errors can be rectified using the factor introduced by Windmeijer (2005), while Roodman (2009b) proposed a parsimonious instrumental variable matrix to handle the latter. Given the large sample property of the data sample in this study and the resulting efficiency gain, the two-step GMM estimator is employed.

To ascertain the consistency and validity of the model, two diagnostic tests are conducted namely the Hansen test of over-identifying restrictions under the null hypothesis of correct model specification and valid over-identifying restrictions, i.e. the hypothesis being tested is that the instrumental variables are valid (independent or uncorrelated with the random errors). This statistic is distributed as χ^2 with degree of freedom equal to the degree of over-identification. The second test is the AR test for serial correlation, under the null hypothesis that disturbances of the differenced equation are not serially correlated, especially at the second order. For the system-GMM to be reliable and consistent, it is required that the study fails to reject both null hypotheses.

3.3 Data and descriptive statistics

The dataset is an unbalanced panel of annual data for 55 countries (including OECD and non-OECD, as listed in the results section) over the period 1980-2010. The number of countries and the length of time are largely determined by the availability of data for different countries[42], as countries with too many missing observations were eliminated. As stated before, the variables employed in this study are Y, K, L, E, M and z-variables. Y, K and L are all extracted from the Penn World

[42] In particular, energy price data.

Table (PWT) Version 8.0. Y is represented by “Real GDP at constant 2005 national prices (in mil. 2005US$)”. K is given by “Capital stock at constant 2005 national prices (in mil. 2005US$)”. (L), the labour input is “Number of persons engaged (in millions)”. E is given by “Total Final Energy Consumption” in thousand tonnes of oil equivalent (ktoe), obtained from the International Energy Agency (IEA) database. M, the Material variable is taken from the Sustainable Europe Research Institute (SERI) materials flow database. It is represented by “used material extraction” in tonnes.

As stated previously, exogenous variables capturing observable cross-country heterogeneity are also included in this study. Previous studies (Filippini and Hunt, 2011, 2012; Stern, 2012) have established the impact of some exogenous factors/variables on energy use and energy efficiency. These variables are industrial share of value add, trade openness, population, area size and temperature. Population and trade openness are taken from the Penn World Tables (PWT); Industrial sector shares of value added is downloaded from the World Development Indicators (WDI) database. A time invariant factor, land area in square km. is also taken from the WDI. Finally, annual average temperature data are taken from the Tyndall Centre for Climate Change Research database and the UNDP climate change database. These are then spliced with regional temperature data from the UK Met Office for 2007-2010.

Finally, in the second stage where an energy consumption function is estimated, the study used energy prices P_{it} which is taken from the IEA Energy Prices and Taxes database (Indices of End-use Prices for industry and households in the case of OECD countries, 2005=100) and energy price index taken from the International Labor Organization (ILO) database for the non-OECD countries. These are normalized to 2005 base year for consistency. Data for Libya, Nigeria and Saudi are from the

Organization of the Petroleum Exporting Countries (OPEC) database, while those for Argentina, Brazil and Qatar are obtained from Thomson Datastream.

Table 3.1: Descriptive statistics

1631 Observations	Variable	Mean	SD	Min	Max
Variables minimized i.e. inputs					
Capital (million US2005$)	K	2884690.73	6755249	43697.65	75301295.05
Labour (million people)	L	36.77	103.11	0.067	781.38
Energy (ktoe)	E	102473.8	228512.7	1742.55	1581622
Materials (tons)	M	347359.5	989507.7	1603.44	16176128
Variable held constant i.e. output					
GDP (million US2005$)	Y	727134.7	1553914	13361.71	13144400
Environmental variables					
Population (million people)	z_1	82.94	204.41	0.94	1330.14
Area size (km^2)	z_2	1552501	2966275	670	16389950
Industrial sector share (% of GDP)	z_3	33.66	8.99	9.19	78.66
Temperature (degree Celsius)	z_4	15.67	8.45	-8.74	28.88
Trade Openness	z_5	65.32	48.07	6.69	433.05
Variables used in 2nd stage					
Energy price index (2005=100)	p_E	79.59	30.76	0.02	192.06

The descriptive statistics of all the variables defined above are presented in Table 3.1 above. The resulting data set is an unbalanced panel data set containing 55 countries banks with a total of 1631 observations.

3.4 Empirical results

3.4.1 Estimates from SFA Model

This study estimated four different models namely the time-decay (BC92), the pooled conditional mean model (KGMHLBC), the pooled conditional variance model (RSCFGH) and the conditional variances/double heteroskedatic model (Hadri99). The output and inputs data are in logarithms, and where possible, the logarithms of some of the environmental variables are also taken (area size and population)[43]. To estimate[44] the model, all logged data for each variable are mean-adjusted, so that the first order coefficients in the model can be interpreted as elasticities at the sample mean. Also, energy is the normalizing input and is therefore the dependent variable in the model, represented by the negative of its logged values. Estimates of the first-order coefficients[45] and the inefficiency effects from the different models are presented in Table 3.2.

The BC92 model clearly shows that energy efficiency was time varying (and increasing) over the sample period, shown by the statistically significant η value of 0.004. This verifies one of the critical requirements of this study of obtaining time-varying energy efficiency in order to conduct the second-stage rebound estimation. The estimated λ of 94.13 also shows the presence of inefficiency in the model, providing compelling evidence that the production frontier estimation is appropriate.

However, the time-decay model only permits monotonically increasing or decreasing efficiency scores by parameterizing inefficiency as a function of time, which in reality, is not likely to be the case. Arguably, inefficiency is likely to vary in a non-constant/non-monotonic fashion. Moreover, given the need to allow for exogenous efficiency effects and the desirability of the scaling property, the RSCFGH model is estimated.

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[43] The other variables are included in their levels because they are ratios that add-up to 1 (or 100%). Finally, the natural log of temperature is not taken, given that a good number of countries have negative temperature values in degrees Celsius.
[44] Maximum-likelihood estimations of the model were obtained using STATA 12.
[45] The entire estimation results are provided in the appendix.

Table 3.2: First stage SFA results

Variable	Parameter	Model 1 BC92	Model 2 KGMHLBC	Model 3 RSCFGH	Model 4 Hadri99
Constant	α_0	1.069***	2.142***	0.230***	0.344***
		(0.04)	(0.05)	(0.02)	(0.01)
$ln\, y$	α_Y	-0.657***	-0.383***	-0.954***	-0.849***
		(0.02)	(0.01)	(0.01)	(0.01)
$ln\, x_2$	β_K	0.418***	0.0742***	0.443***	0.428***
		(0.01)	(0.01)	(0.01)	(0.01)
$ln\, x_3$	β_L	0.437***	0.639***	0.0423***	0.202***
		(0.02)	(0.01)	(0.01)	(0.01)
$ln\, x_4$	β_M	0.0525***	0.0378***	0.114***	0.0640***
		(0.01)	(0.01)	(0.01)	(0.01)
t	δ_1	-0.008***	-0.001	0.00173	-0.001
		(0.00)	(0.00)	(0.00)	(0.00)
Parameters in μ or σ_u					
z_1	π_{pop}		0.618***	0.363**	0.787***
			(0.01)	(0.1)	(0.1)
z_2	π_{area}		0.022***	0.755***	0.435***
			(0.00)	(0.1)	(0.04)
z_3	π_{ind}		0.409***	8.405***	4.113***
			(0.04)	(1.38)	(0.55)
z_4	π_{temp}		-0.009***	-0.005	0.031***
			(0.00)	(0.01)	(0.01)
z_5	π_{open}		0.101***	1.319***	0.750***
			(0.01)	(0.3)	(0.2)
t			-0.001	-0.025	-0.028***
			(0.00)	(0.02)	(0.01)
t^2			-0.003***	-0.003	-0.0003
			(0.00)	(0.00)	(0.00)
LLF		1970.172	1175.153	334.747	479.916
η		0.004***			
μ		0.931***			
γ		0.989***	1.00***		
LR Stat				312.47	290.34
Wald				112.03	735.70

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

The RSCFGH model is tested against a pooled model with no exogenous effects using the LR and Wald tests under the null hypothesis of homoscedaticity[46] in the variance of the one-sided error term (i.e. that the exogenous variables in the variance of the error term are jointly zero) against the alternative that at least one of their parameters is different from zero. The null is rejected, given that a likelihood ratio statistic of 312.47 is obtained, which exceeds 18.48, the value of the chi-square distribution for 7d.f. at 1%. This is strongly supported by the Wald test statistic of 112.03 which again exceeds 15.09, the chi-square distribution for 5d.f. at 1%. These tests results indicate that the dataset favours a heteroskedastic one-sided error term.

The analysis then proceeds to the Hadri99 double-heteroskedastic model, which an extension of the RSCFGH model. The Hadri99 is tested as an unrestricted version of RSCFGH model with the null that the parameters in the variance of the two-sided error are jointly zero. This test returns an LR-stat value of 290.34, which again exceeds the chi-square distribution value for 7 d.f. given above. Therefore, based on these diagnostics, it is concluded that the dataset favours the Hadri99 model where exogenous variables influence both the inefficiency term and the two-sided error term. Thus, all the subsequent analysis is based on the preferred model, the Hadri99.

All the estimated first-order coefficients on inputs and outputs have the appropriate signs and they are all statistically significant, implying that the model is generally consistent with the underlying assumption of a *KLEM*-type production technology. This conclusion is supported by regularity tests for economic properties

[46] Moreover, in order to avoid arbitrary assumption of heteroscedastic error structure across the panel data set, further robustness checks are conducted using the LR test procedure recommended by Poi and Wiggins (2001). The LR test approximately follows a chi-square distribution by nesting the homoscedastic model in the heteroscedastic model under the null hypothesis of homoscedasticity. The LR chi2(54) = 1629.37 clearly indicates the presence of heteroscedasticity in the model.

(see next section below) which indicate that the preferred model largely satisfies the curvature properties. For the inefficiency effects, all the coefficients on the environmental variables are found to be statistically significant and they all have a positive effect on the estimated inefficiency.

3.4.1.1 Results of Regularity Tests

The regularity conditions are checked to ascertain that the model has the required economic properties such as monotonicity and concavity. Scale elasticity of the production technology is also evaluated. The results of these regularity checks are given in Table 3.3. The monotonicity property is also verified at the sample mean by checking the first-order input and output coefficients of the estimated input distance function. Given their appropriate signs (positive for inputs and negative for output) and high statistical significance, it is concluded that the underlying production technology is monotonic at the sample mean i.e. non-decreasing in input and non-increasing in output. Furthermore, tests are conducted to confirm that the model satisfies the monotonicity conditions at each data point of the data sample. This is confirmed at 100% for (y); 97% for (x_2); 96% for (x_3); 83% for (x_4). Scale elasticity is estimated at 1.178, suggesting that scale economies are fully exploited at the sample mean. Also, the number of data points with increasing returns to scale (IRS) are checked and it is found that 1418 (87%) of the data points exhibit IRS. This reflects the nature of countries' distribution, implying that most countries are in the range of increasing returns.

Table 3.3: Results of regularity tests

Monotonicity	Elasticity	Parameter	Std. errors	Outside sample mean
y at sample mean	ey_1	-0.849	0.01	100%
x_2 at sample mean	ex_2	0.428	0.01	97%
x_3 at sample mean	ex_3	0.202	0.01	96%
x_4 at sample mean	ex_4	0.064	0.01	83%

Scale Elasticity	Parameter	Std. Errors	t-ratio	IRS over sample
E. at sample mean	1.178	0.01	17.8	87%
			Reject	
			$H_0: E = 1$	

Concavity	Function	Principal minors	Values	Outside sample mean
H at sample mean	$\mathbf{H}(\mathbf{w})$	First order	-0.498	1442 points
			-0.256	(88%)
			-0.093	
		Second order	0.127	
			0.046	
			0.023	
		Third order	- 0.012	

To ensure that the IDF is concave in inputs, it is required that the Hessian is negative semidefinite. This can be confirmed by checking the sign pattern of the principal minors of the Hessian. The necessary and sufficient condition for the IDF's concavity is that all the odd-numbered principal minors of the Hessian matrix must be non-positive and the even-numbered principal minors must be non-negative[47]. At the sample mean with mean corrected data, the Hessian can be written as

$$H(\bar{x}) = \mathbf{B} - \hat{\hat{\beta}} + \beta\beta' \tag{3.18}$$

[47] Specifically the first order principal minors must be negative and second order principle minors must be positive.

where $\hat{\hat{\beta}}$ is a diagonal matrix with estimated input elasticities, β_K for $k = 1, \dots, K - 1$ on the leading diagonal and zeros elsewhere, and β is a vector of estimated input elasticities β_K. Given the alternating sign pattern of the principle minors in Table 3.3 above, the concavity condition is satisfied at the sample mean, and at 88% of the data points. The satisfaction of monotonicity and concavity properties indicates that the fitted IDF is a true production function and that the efficiency estimates are reliable.

3.4.1.2 Estimates of Energy Efficiency

After estimating the frontier, the residuals of the model are retrieved following Jondrow et al. (1982). The descriptive statistics of estimated energy efficiency across the whole sample are given in Table 3.4 below. It is shown that the estimated mean efficiency of the preferred model is about 82% with a degree of variation around it, as shown by the standard deviation of 0.17 and a minimum efficiency of 18%.

Table 3.4: Summary of estimated energy efficiency

	RSCFGH	Hadri99
Min	0.431	0.181
Mean	0.908	0.819
Max	0.992	0.998
Std. dev.	0.094	0.171

3.4.2 GMM Results

The results[48] of the estimated two-step GMM model[49] are given in Table 3.5. Overall, most of the parameter estimates have the expected signs and are within cred-

[48] The xtabond2 in STATA12 is used. Although *T* is fairly large (31 years), the set of lags is restricted to 2-3 lags given that more lags will result in a huge number of instruments and the attendant weakening of the instruments validity tests (see Roodman, 2009b).

ible range in terms of magnitude, with the exception of the coefficient on income elasticity which is statistically insignificant.

Also, non-linearity[50] is explored within the model by interacting energy efficiency with energy prices and income. This is an important aspect of energy technical progress modelling, which could be price-induced, endogenous or exogenous; hence, models should be correctly specified accordingly (see Adeyemi and Hunt, 2014). The non-linearity assumption is accepted by the data, as shown by the statistical significance of their coefficients. This permits an assessment of the effect of energy efficiency on energy demand arising from a unit change in energy price or income. *Ceteris paribus*, higher energy prices stimulate energy-augmenting technological progress so that a higher energy price results in a greater energy efficiency effect[51] (more negative or reducing effect) on energy consumption. Moreover, by accounting for the interaction between price and efficiency, it is possible to disentangle price effects from other exogenous efficiency effects thereby reducing the problem of overestimating the efficiency elasticity[52].

For the system-GMM to be reliable, it necessary to fail to reject both null hypotheses on the Hansen and AR tests. In Table 3.5, notice that the p-values on the AR

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[49] Given that energy efficiency gains could be exogenous or endogenous as shown by effects of energy prices, regulations and policies, tastes etc. on energy efficiency, a model with interaction between energy efficiency and the other regressors is explored. Results show that these assumptions are accepted by the data.

[50] This derives from the likelihood that the relationship between energy efficiency improvement and energy consumption is non-linear. The same could be said of its relationship with the other regressors (price and income). Moreover, the non-linearity assumption allows us to evaluate efficiency elasticity and rebound effects at each given data point. Hence, the coefficient on energy efficiency alone cannot be interpreted as measuring efficiency elasticity. To obtain the efficiency elasticity, it is important to take the coefficients on the interaction terms into account, so that the computation typically evaluates efficiency elasticity at the sample mean using the averages of the other regressors. The same procedure is adopted in generating the elasticity at each data point.

[51] This has been partly demonstrated by asymmetric price responses of energy demand where reductions in energy consumption via technical progress due to higher prices are not fully reversed in the face of lower prices (see Dargay, 1992; Adeyemi and Hunt, 2007)

[52] The coefficients on the interaction terms may therefore be interpreted as price-induced and growth induced energy technological progress.

tests indicate first-order serial correlation, but no serial correlation at the second-order[53].

Table 3.5: GMM estimation results

	Dep. variable Energy Consumption (E)
Lagged E	0.923***
	(0.06)
p_E	-0.0751*
	(0.04)
y	0.0780
	(0.06)
ef	-0.474**
	(0.22)
t	0.000709
	(0.00)
$p_E * ef$	-0.353**
	(0.15)
$y * ef$	0.148**
	(0.07)
$p_E * y$	-0.0323**
	(0.02)
constant	0.0551***
	(0.02)
N	1631
Number of instruments	63
Hansen Test (p-value)	0.606
Ar(1) (p-value)	0.003
Ar(2) (p-value)	0.448

*Windmeijer corrected standard errors in parentheses. *, ** and *** represents significant level at 10%, 5% and 1% respectively*

[53] This is consistent with a priori expectation since the differenced error term is probably serially correlated, hence the presence of first-order serial correlation. This is why the AR (2) is the more appropriate test of autocorrelation, since it detects autocorrelation in the levels equation.

The Hansen test statistic indicates that the study is unable to reject the null hypothesis that the instruments used in the GMM estimation are valid. Both specification tests imply that the moment conditions underlying the GMM model are strongly supported.

3.4.2.1 Rebound Effects Estimates

The estimated efficiency elasticities[54] from the results in Table 3.5 above are -0.10 in the short run and -1.36 in the long run. These yield short run and long run rebound effects of 90% and -36% respectively, at the sample mean. The long run rebound estimate suggests that energy efficiency gain is likely to generate a more than proportionate reduction in energy use (a 1% energy efficiency gain will result in a 1.36% reduction in energy consumption)[55], a situation referred to as *super conservation* in the RE literature. To compute rebound outside the sample mean (i.e. for each country and time period), point efficiency elasticity are calculated for each year across the entire sample. In particular, the estimates indicate that the modeling approach demonstrates the entire rebound possibilities, ranging from super-conservation to backfire[56].

The computed RE magnitudes are quite substantial, ranging from an average of 18% for Dominican Republic to 117% for Russia. The results also show some variation in rebound estimates overtime and across the sample countries. Average rebound estimates over 3 decades across the different countries are reported in Table

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[54] Given the interaction terms, elasticity is drive as the derivative of the function w.r.t energy efficiency and the mean values of the regressors are plugged into the resulting derivative.

[55] While this result indicates the potential for energy efficiency to reduce energy use, it should be noted that the LR is an unobservable optimum or steady-state equilibrium which reflects the desired level of energy use. While this result indicates the remarkable potential for energy efficiency, it is highly likely that a 'business as usual' approach to energy policy designs may not achieve this target, hence, a great range of policy measures and instruments are required to reach this LR target.

[56] See Saunders (2008) for a discussion on the rebound taxonomy, and the importance of a modelling framework that permits all rebound possibilities.

3.6, while the long run estimates are presented in Table 3.7. Interestingly, overall, results indicate slightly different RE magnitudes and patterns between OECD and non-OECD countries. For instance, it is observed that RE magnitudes for non-OECD countries (with an average of 56%) are on average, slightly bigger those for OECD countries (with average 49%)[57] while for the 7 OPEC countries in the sample, average RE is estimated at 60%.

Also, the estimates indicate an inverted U-shaped trend for most OECD countries, with generally increasing rebound trends in the 1980s which stabilized in the 90s before declining in the 2000s. A spike in rebound levels around 2008/09 for most of the OECD countries is also observed, which may be partly due to the recession which might have curbed RE around that period. It is also noteworthy that the emissions targets from the Kyoto agreement come into effect around 2008.

[57] Slightly lower average rebound levels are observed for EU-OECD countries.

Table 3.6: Average rebound effects by decades

OECD Countries	1980-89	1990-99	2000-10
Australia	49%	54%	54%
Austria	30%	40%	39%
Belgium	38%	47%	43%
Canada	61%	66%	63%
Chile	73%	45%	35%
Czech Rep.	-	36%	35%
Denmark	31%	38%	33%
Finland	32%	36%	32%
France	59%	69%	67%
Germany	71%	80%	73%
Greece	27%	35%	38%
Hungary	42%	32%	29%
Ireland	14%	29%	34%
Israel	82%	36%	33%
Italy	68%	69%	66%
Japan	65%	78%	79%
Mexico	65%	67%	63%
Netherlands	50%	56%	51%
New Zealand	16%	27%	27%
Norway	39%	40%	39%
Poland	63%	56%	49%
Portugal	20%	32%	36%
Slovak Rep.	-	28%	23%
Spain	48%	57%	61%
Sweden	49%	47%	40%
Switzerland	34%	43%	40%
Turkey	66%	58%	53%
UK	61%	69%	66%
US	88%	101%	98%

BRICS Countries	1980-89	1990-99	2000-10
Brazil	89%	82%	66%
China	84%	67%	88%
India	85%	97%	75%
Russia	-	184%	69%
South Africa	99%	63%	42%

OPEC Countries	1980-89	1990-99	2000-10
Iran	74%	113%	58%
Kuwait	26%	25%	29%
Libya	18%	30%	28%
Nigeria	64%	63%	43%
Saudi Arabia	63%	63%	58%
UAE	29%	38%	40%
Venezuela	190%	103%	37%

Other Non-OECD Countries	1980-89	1990-99	2000-10
Argentina	35%	66%	46%
Dominican Republic	20%	15%	19%
Egypt	93%	53%	39%
Indonesia	85%	92%	57%
Malaysia	25%	33%	37%
Morocco	25%	26%	22%
Pakistan	80%	59%	39%
Philippines	96%	62%	40%
Singapore	16%	32%	29%
Sri Lanka	74%	47%	16%
Syria	71%	30%	17%

cont'd	1980-89	1990-99	2000-10
Tanzania	130%	49%	10%
Thailand	60%	59%	50%
Tunisia	20%	24%	16%

Interestingly, for the US, the estimates are consistent with results in Saunders (2013) who adopted a sectoral approach to estimating economy-wide RE for the US over 1960-2005. Saunders estimated aggregated short run and long run RE at 126% and 62% respectively, providing a band for the average US RE of 96% over the sample period. Further, average RE for Spain is estimated at 55%, in line with Gonzalez (2010) who estimated SR and LR RE at 35% and 49% respectively for household energy services in Catalonia (Spain) over the period 1999-2006.

In general, this study finds evidence of backfire[58] in mostly non-OECD countries (Iran, Russia, Tanzania, India, Indonesia, Philippines, South Africa and Venezuela) with the US being the only OECD country where backfire is observed. Overall, a very encouraging sign from the analysis is the generally declining RE trend[59] across most countries in in this study, to the extent that *super conservation* was observed for Sri Lanka and Syria towards the end of the sample period 2009-10.

It is not immediately clear why non-OECD and OPEC RE estimates are slightly higher on average, although it is known that higher growth effect and the prevalence of energy subsidies could be responsible for these higher estimates. A closer look at the results in Table 3.6 will also reveal significant variation across OECD countries despite their relatively similar energy policy environments. These variations might be reflective of the differences in energy prices, structure of the economy and nature of energy policy instruments. So I briefly revisit these issues in order to better understand the RE estimates in Table 3.6.

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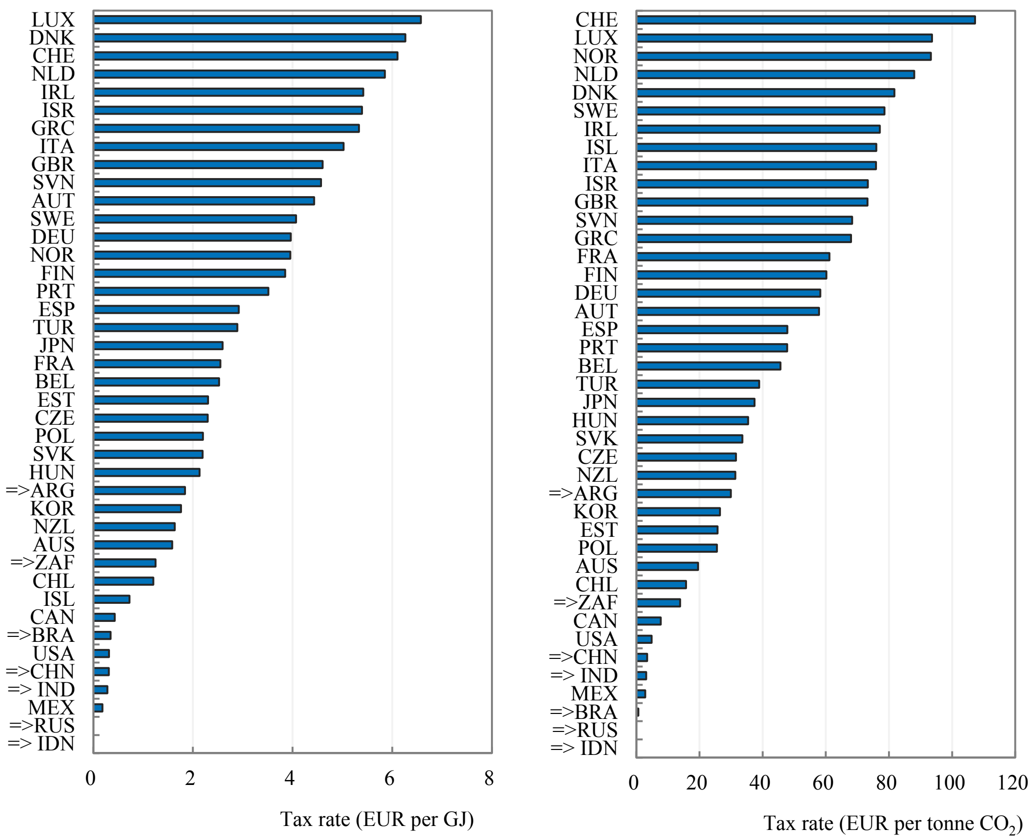
[58] A situation where energy efficiency leads to a more-than-proportionate increase in energy consumption, in which case RE exceeds 100%.

[59] Although the declining RE trend is an encouraging sign for the future, current RE levels are still significantly high to pose serious challenges to energy and climate policy plans.

Figure 3.2 is a plot of economy-wide levels of energy and carbon taxation across the 41 countries. The first general observation is that the emerging/non-OECD countries (Brazil, China, India, Russia and Indonesia) in the graph have relatively lower energy and carbon taxes which are almost €0 per gigajoule (GJ) and per tonne of CO2. The average rebound for these countries was 87% over the study period. It is also worth mentioning that the structure of these emerging economies might have played a role in the RE estimates, as shown by their relatively high industrial share of GDP (Brazil 33%, Russia 39%, India 27%, Indonesia 42% and China 45%).

Figure 3.2: Energy taxes across the world



Source: OECD Taxing Energy Use: A Graphical Analysis, 2015

Conversely, some OECD countries (such as Switzerland, Denmark, Finland, Norway, Ireland) with relatively lower RE estimates are found to have some of the highest energy taxation rates, although some other OECD countries (US, Canada, and Mexico) with relatively high RE estimates also have quite low energy and carbon tax rates. Furthermore, as shown by both Table 3.6 and Figure 3.2, it can be argued that some OECD countries such as Japan, UK and Germany have both high tax rates and high RE estimates. Conversely, other countries (New Zealand, Austria and Czech Republic) have low tax rates but relatively lower RE estimates. For this reason, it might be appropriate to consider case studies of energy policies across some of the OECD countries, since these policies are likely to differ in terms of primary focus and target. For instance some economies might have more energy policy interventions for residential energy use because this dominates their end-use energy mix.

In order to identify the energy policy environment of OECD countries, a close look at the IEA energy policy databases on energy efficiency and climate change policies is undertaken. Using a country with relatively low RE estimates (Denmark) and another with a relatively high estimate (US).

For Denmark, the end-use energy is dominated by the residential sector (32%), compared to the transport sector (27%) and industry (20%). However, for the US, energy consumption is dominated by the transport sector (37%) compared to the residential energy use (17%) and industry (22%). This provides some intuition on why both countries would have different RE estimates. Moreover, it is also shown that these differences in energy use appeared to have shaped the energy policy focus and targets across both countries. For instance, for Denmark, a total of 37 energy policies where introduced over the study period 1980-2010, compared to 126 for the US. Given the dominance of the residential sector in Demark, it is not surprising that 18

(49%) of these policy interventions where targeted at the residential sector. In the same vein, for the US 30 (24%) of the policies were targeted at the transport sector.

Furthermore, some differences are observed in the nature of energy policies across both countries. In Denmark, the energy policy instruments are dominated by energy regulations (such as building codes) and energy policy support (such as strengthening institutions/regulators) whereas in the US economic instruments (e.g. fiscal instruments, infrastructure investments) and voluntary/informational policies dominate energy policy interventions. These developments also point to the differences in energy policy stance and objectives. It is under these different energy policy regimes that the variations in RE estimates are obtained.

Table 3.7: Long run rebound estimates

	Long run RE		Long run RE
Argentina	-71%	Morocco	-98%
Australia	-69%	Netherlands	-67%
Austria	-89%	New Zealand	-101%
Belgium	-81%	Nigeria	-56%
Brazil	-25%	Norway	-84%
Canada	-52%	Pakistan	-54%
Chile	-62%	Philippines	-42%
China	-23%	Poland	-61%
Czech Republic	-90%	Portugal	-99%
Denmark	-90%	Russia	46%
Dominican Republic	-102%	Saudi Arabia	-52%
Egypt	-49%	Singapore	-99%
Finland	-90%	Slovak Republic	-98%
France	-51%	South Africa	-40%
Germany	-34%	Spain	-66%
Greece	-94%	Sri Lanka	-65%
Hungary	-88%	Sweden	-76%
India	-14%	Switzerland	-86%
Indonesia	-26%	Syria	-73%
Iran	-14%	Tanzania	-39%
Ireland	-99%	Thailand	-59%
Israel	-61%	Tunisia	-100%
Italy	-46%	Turkey	-57%
Japan	-37%	UAE	-86%
Kuwait	-97%	United Kingdom	-50%
Libya	-96%	US	7%
Malaysia	-94%	Venezuela	26%
Mexico	-49%		

Turning now to the long run RE estimates, the estimated partial adjustment model shows the desired or targeted level of rebound across sampled countries. In line with the negative long run rebound (super conservation) obtained at the sample mean, the country-specific long run estimates in Table 3.7 reflect widespread super-conservation across most of the sampled countries. In general, the long-run estimates indicate that energy efficiency could potentially lead to more-than-proportionate declines in energy consumption. However, for two countries, US and Venezuela, the long run estimates show positive but smaller RE estimates at 7% and 26% respectively.

3.5 Summary and conclusions

RE is one of the most debated issues in energy economics literature. A great deal of this debate derives from the lack of clarity on its nature and a consistent range for its estimate. These challenges are more severe for economy-wide RE, which is arguably the most relevant to the global climate change. This paper has attempted to estimate economy-wide RE for 55 countries, and as far as is known, it is the first attempt to evaluate RE for several countries over a reasonably long timeframe, using an econometric approach and a consistent dataset.

First energy efficiency is estimated by adopting a specification that allows for estimation of inefficiency across different heterogeneous economies within the panel SFA framework. Secondly, the study estimates aggregate SR and LR efficiency elasticity of energy using a GMM energy consumption model. Rebound effects from these efficiency elasticities are then computed using the approach proposed by Saunders (2005, 2013) and Wei (2010). Amongst many other insights, the study estimated SR and LR rebound effect across sample countries and sample period at 90% and -

36% respectively. While the short run estimate shows significant RE, the long run indicates the potential for energy efficiency to significantly lower energy consumption in the future[60].

In particular, on average, the country-wise RE estimates are slightly larger for developing countries. Also, most importantly, given the evidence presented here, it can be argued that the energy forecasts derived from potential energy efficiency savings may have underestimated future energy consumption by failing to account for ex-post RE. Thus, overall, the evidence presented here provides some constructive justification for the consideration of RE in the wider climate change agenda, particularly in the context of developing countries.

In terms of the policy implications of the findings in this study, it can be argued that the slightly higher average RE estimates for non-OECD countries is consistent with the reasoning that developing countries are on a growth trajectory that requires greater energy consumption, to the extent that energy savings are easily "re-spent" to fuel further growth. This result should alert policy makers that RE in developing countries might represent one of the most challenging energy and climate policy issues in the future. For instance, Wolfram et al. (2012) show that as households come out of poverty and join the middle class, they boost their welfare by purchasing goods and services that require energy to use and produce. They argue that energy demand forecasts for developing countries may be understated by their failure to capture this poverty-reducing effect, a part of which may be embodied or manifested in RE.

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[60] Based on the LR estimate it is clear that energy efficiency improvement will remain an important policy measure, but the estimated rebound magnitudes suggest a need for an array of policy instruments to "lock-in" such efficiency gains and prevent their erosion by rebound effects.

Another important insight derivable from the analysis here is the relatively higher average RE for some major oil exporting countries[61], possibly reflecting a *subsidy effect* arising from artificially low end-use energy prices. This should also indicate to policy makers that measures aimed at curbing energy use and mitigating RE need to internalize environmental/pollution cost so that energy prices reflect the implicit pollution/environmental cost of energy use.

Finally, this study does not in any way attempt to downplay the role of energy efficiency measures and policies, but rather calls for a more inclusive and comprehensive approach via incorporation of RE. As shown by van den Bergh (2010), energy policy in general is likely to be more effective with the incorporation of RE. Thus, unless this study is undertaken, it might be impossible to precisely evaluate the benefits of energy efficiency measures, failing which, we may actually have less time to devise adequate solutions to climate change than is previously thought.

[61] All of which are OPEC countries.

Chapter 4 Benchmarking rebound effects across 19 EU countries[62]

4.1 Introduction

In the past two decades, efficiency and productivity analysis in the energy economics literature has focused on identifying the best-practice production technology using the minimum possible energy to produce a given level of output[63]. This research pattern is possibly due to the important role of energy efficiency improvements as a vital energy policy objective towards attaining energy conservation and reducing greenhouse emissions. The perceived importance of efficiency improvement derives from the notion that efficiency gains deliver proportional or comparable reductions in energy consumption. However, as shown in the previous chapter, *ex-post* rebound effects (RE) after energy efficiency improvements can be substantial, thereby reducing the actual energy saving from increased energy efficiency.

Although energy efficiency improvement is necessary to conserve energy and reduce greenhouse emissions; large RE estimates would imply that it is not a sufficient condition. Birol and Keppler (2000) provide a theoretical exposition that since

[62] This chapter was presented at the 14th IAEE European Energy Conference (28th-31st October 2014, Rome, Italy).

[63] From an environmental point of view, studies also aim to identify productive units with the minimum greenhouse emissions from a production process, given a set of inputs

energy efficiency reduces the effective price of energy i.e. energy services become cheaper, even if physical energy prices are unchanged. This implies that the global climate agenda of reducing physical energy consumption[64] in the face of high economic growth is extremely difficult with falling effective energy prices arising from energy efficiency improvement. This hypothesis appears to be supported by the illustration in Figure 5.1 below where the average estimated energy efficiency of EU countries from the previous chapter is plotted against average energy consumption. It can be seen that energy consumption rose steadily over the sample period, despite the consistently high average energy efficiency which was generally greater than 90%.

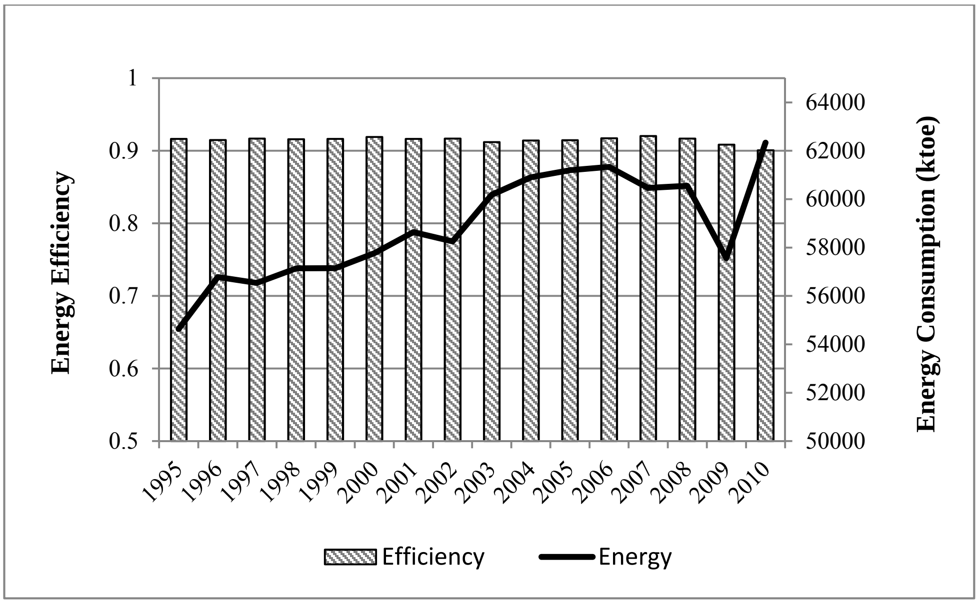

Figure 4.1: Average EU Energy Consumption vs Energy Efficiency

Birol and Keppler (2000) argue that, for high economic growth to be compatible with stable energy prices and low greenhouse emissions through efficiency improvement, one would expect annual energy efficiency to increase at the rate of $\frac{g}{1-R}$, where g is the annual GDP growth rate and R is rebound effect. In this case,

[64] And by implication, greenhouse emissions.

with 4% economic growth, a rebound effect of 0.6 (or 60%) would require an annual energy efficiency gain of 10%.

As shown in the Chapter 3, the magnitude of macroeconomic RE is slightly larger on average, reaching 'back-fire' in some developing countries. It is easy to see that the global climate change agenda of compatible energy technical progress and economic growth requires careful consideration of RE[65]. This chapter attempts to explore the issue of RE performance quantitatively, using an efficiency and productivity approach.

In line with the paucity of research on macroeconomic RE, studies that evaluate or benchmark countries with the minimum RE magnitudes for their given levels of output or prosperity are limited. This is an important gap because, in the presence of RE, using only energy efficiency performance as a benchmark may provide incomplete and misleading information in policy settings. For instance, it is possible that a country with high energy efficiency might 're-spend' most of the energy savings derived from improved energy efficiency so that the *ex-post* net-efficiency[66] gain may alter the actual position of the country in an energy benchmark. Therefore, unless a rebound effects frontier is estimated[67], it may be impossible to benchmark the 'net-efficiency' in energy use. More specifically, a country with a high level of energy efficiency, but also high RE magnitude should be designing policies to secure or 'lock-in' such efficiency gains by mitigating RE.

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65 In spite of the on-going debates on the magnitudes and relevance of RE to energy and climate policy designs, the need for its careful consideration appears to be gaining attention within the international policy arena. For instance see
http://www.unido.org/fileadmin/user_media/Services/Research_and_Statistics/WP122011_Ebook.pdf
66 Net efficiency is employed throughout this study to refer to the efficiency gain less rebound effects.
67 In this study therefore, the aim is to minimize both energy use and rebound effects, alongside other factor inputs for a given level of output.

Another important issue which this study takes on is the potential role of energy policy instruments in mitigating RE. Most previous studies have focused on describing or attempting to estimate RE. While a few studies such as van den Bergh (2010) offer descriptions of potential rebound policies, there is a dearth of studies precisely evaluating the impact of such policy instruments[68] on RE in a quantitative context. Policy makers require reliable information and estimates on the precise impact of energy policy instruments on RE in order to make informed and effective decisions to tackle RE[69]. Specifically, Birol and Keppler (2000) argue that addressing the issue of RE requires a balance between economic and technology-based policy instruments. Consequently, this chapter also estimates the impact/effectiveness of two energy policy instruments in mitigating RE. Given the discussions above, this chapter has three primary objectives:

- To benchmark EU countries[70] in order to evaluate countries that minimize rebound effects and other factor inputs for a given level of output;
- To precisely estimate the impact and extent of energy policy instruments in minimizing/addressing the RE problem.
- To estimate total factor productivity change (TFPC) and to further decompose it into the different components: technical change, efficiency change and scale change

[68] Discussions on the taxonomy of energy policy instruments can be found in Jaffe et al. (1995). Vollebergh (2007) presents a detailed review and discussion on the impact of different environmental policy instruments on technological change.
[69] van den Bergh (2010) argued that energy policy in general is likely to be more effective with some rebound effects policies.
[70] The choice of EU countries derives largely from the availability of data on energy policy instruments, which are scarce for non-EU countries.

Specifically, this chapter effectively combines two important aspects of energy economics literature namely RE and efficiency analysis. On top of this, because the stochastic frontier analysis (SFA) framework is adopted, it is possible to explore the total factor productivity (TFP) for the estimated RE frontier.

4.2 Brief Review of Energy Policy Instruments

As discussed in the introductory section above, RE benchmarking for different countries has not been undertaken previously, as far as is known[71]. A comprehensive review of RE literature and the SFA technique has been undertaken in Chapter 3. Thus, since this chapter also explores the possible role of energy policy instruments in mitigating RE, this chapter only undertakes a brief review of literature on energy policy instruments.

Some of the earliest studies on energy and climate policy instruments include Orr (1979) and Bohm and Russell (1985). While the former discussed the US energy policy, the latter provides a comparative theoretical discussion of different energy policy instruments. Similarly, Fullerton (2001) provides a comparative discussion of the taxonomy and effectiveness/distributional impacts of various environmental policy instruments.

While the aforementioned studies above provide theoretical discussions on energy policy instruments, other studies attempted to quantitatively measure their impacts. For instance, Jorgenson and Wilcoxen (1993) evaluated the impact of carbon taxes on CO_2 emissions, in comparison to two other fiscal instruments namely VAT on fuel use and tax on energy content of fossil fuels (i.e. a British thermal unit

[71] Chapter 3 is the first multi-country panel study of economy-wide RE covering over 50 countries. Hence this chapter builds on the previous chapter in this benchmarking exercise.

(BTU) tax). By simulating an intertemporal general equilibrium model of US growth, based on econometric estimates using data from 1947-85, they find that for a given amount of emissions reduction, carbon taxes have the smallest impact on the macro economy, albeit with a large effect on the coal mining sector. VAT and BTU taxes show greater macroeconomic effects.

Jaffe and Stavins (1995) explored the impact of energy taxes, technology adoption subsidies and technology standards (such as building codes) on the US building sector across 48 lower US states over the period 1979-1988. They found that energy taxes had significantly quicker effect on energy efficiency improvement, although adoption subsidies had greater effects on efficiency. They found that building codes had no significant impact. Their finding on building codes contrasts other studies such as Saussay et al. (2012) who found building energy codes to have a significant effect on the improvement in energy efficiency of residential space heating in the selected EU countries. Filippini et al. (2014) also found some evidence that performance standards of buildings, heating systems and appliances stimulated efficiency improvements for the residential building across the EU-27.

Baranzini et al. (2000) investigated the competitiveness and impacts of carbon taxes in selected OECD countries. They show that carbon taxes may be an effective environmental policy instrument whose negative impact may be offset by re-distribution of the derived revenue from such taxes. Berkhout et al. (2004) estimated the ex-post effect of an energy tax introduced in 1996 on Dutch household energy consumption, using two-stage budgeting model and panel data for 2500 households over 1992-1999. They found modest short-run impact of the taxes on energy use (8% for electricity and 4.4% for gas).

More recently, given the increasing relevance of the global climate agenda, Otto et al. (2008) examined the cost effectiveness of Dutch climate policy options by estimating a KLEM-type production function in CGE context using 1999 data. They find that the most cost effective climate policy mix is a combination of R&D subsidies and carbon tax.

Similarly, Oikonomou and Jepma (2008) analyzed the interaction between different energy and climate policy instruments with a view to developing a qualitative framework for reaching an appropriate policy mix which allows for policy overlaps and complementarities.

All of the studies mentioned above have focused on the impact of energy policy instruments on energy consumption and (or) greenhouse emissions. Even studies on the impact of energy policy instruments on energy efficiency are few. One of such few studies include Bigano et al. (2011) who evaluated the impact of energy policies on EU energy and carbon intensity using panel data econometrics by estimating energy intensity as a function of price, income and dummy policy variables[72].

Similarly, studies attempting to estimate the impact of energy policy instruments on the level of energy efficiency using the SFA framework are also very few. Although, Buck & Young (2007) employ the Battese & Coelli (1995) conditional mean SFA model in estimating energy efficiency for the Canadian commercial buildings, permitting exogenous inefficiency effects via building-specific characteristics such as building ownership and building segment, they did not analyze the impact of policy instruments on inefficiency. However, Saussay et al. (2012) explicitly modelled the impact of energy policy instruments (building energy codes) on energy

[72] The criticisms of the use of energy intensity as a proxy for energy efficiency are well documented in literature (See Filippini and Hunt, 2010; Saunders, 2013).

efficiency in residential space heating of seven European countries over the period 1990-2008, using the BC92 and BC95. Similarly, Fillipini et al (2013) employed SFA models (True Random Effects (TRE) and BC95) in estimating energy efficiency for the EU residential sector over the period 1996-2009, allowing a series of policy measures to influence the level of energy inefficiency.

Given the discussions above, and the need to unravel the possible policy options to tackle RE, this study adopts a modelling approach that permits this in the RE frontier modelling exercise. Thus, the analyses in this study builds on Chapter three and explicitly account for the impact of the energy policy across EU countries on RE efficiency.

The remainder of this study is organized as follows. Section 4.3 sets out the methodology, specifying a production technology with rebound effects as an input. In addition, the TFP change derivations are also presented in this section. In Section 4.4 the dataset is described, with emphasis on the decomposition of energy into 'net energy' and the rebound component using the estimated rebound magnitude in the previous chapter. This is followed by Section 4.5 where the estimated results from the SFA model are presented and the main findings are discussed. The TFP growth results are also presented and analysed in Section 4.5, while Section 4.6 provides concluding remarks and policy insight on handling the RE issue.

4.3 Methodology and Data

This study is interested in benchmarking RE for EU countries, and to estimate the impact of some energy policy instruments on the level of 'rebound inefficiency'. Therefore the focus is on constructing a rebound effect frontier and to estimate the impact magnitude of two energy policy instruments[73] on rebound inefficiency. To achieve this, an input distance approach is employed where RE is treated as an input in the production technology. This is because RE represents a gain or addition to the energy input usage, arising from technological progress via the reduction in effective and/or relative price of energy[74]. Hence, rebound is treated as one of the inputs to be minimized for a given level of output within the production technology. This approach is consistent with the global emissions reduction efforts of the climate agenda, since the ultimate goal is to lower energy use (part of which is the unintended and embodied RE).

4.3.1 Model Specification

Given the discussions above, it is assumed that each EU country in the sample possesses a technology which can be represented by a requirement set $I(y) = \{x \in \mathbb{R}^{+}: x\ can\ produce\ y\}$. The non-zero positive inputs vector $\mathbf{x}' = (K, L, E, R)$ and the vector of outputs is $\mathbf{y}' \equiv (Y)$. K stands for capital, L represents labor, E denotes energy, R denotes rebound effect and Y is national output, given by GDP. The overriding objective is to model a best practice frontier using SFA to benchmark the degree or magnitude by which a country minimizes RE (and other factor inputs), relative to other countries in the sample for a given level of national output. Further, the impact of policy instruments on rebound is evaluated by accounting for heteroscedasticity in u as proposed by Kumbhakar *et al.* (1991) and Battese and Coelli (1995) on

[73] Energy/Environmental taxes and energy R&D. While the former is a direct/binding instrument, the latter is an indirect instrument. It is should be noted that the choice of the two instruments derives largely from the limited availability of data on energy policy instruments.

[74] In other words, RE is treated as the portion of energy consumption attributable to technical energy efficiency, which boosts energy use by reducing effective prices.

the one hand, and by Reifschneider and Stevenson (1991), Caudill and Ford (1993), Caudill et al. (1995), Hadri (1999) on the other hand.

Accounting for heteroscedasticity is important for a number of reasons. For instance, the estimation of traditional production frontier functions is based on the assumptions that producers are homogenous and errors are homoscedastic. However, in reality this may not be the case given the possibility that different producers may operate under uniquely different circumstances or possess distinguishing characteristics. Moreover, it is also possible to have heteroscedastic errors[75]. Thus, some practical empirical works have relaxed these assumptions by introducing exogenous variables which are different from factor inputs but affect or influence the technical inefficiency of firms/countries into the different parts of the SFA model. These factors reflect the operating environment and are likely to be partly responsible for the firm efficiency performance (Kumbhakar and Lovell, 2003 pp261). Further, this approach allows for the correction of the problem of conditional heteroscedasticity in the inefficiency term.

Next is to proceed to discuss the input distance function (IDF) and its economic properties as follows. The fitted IDF is given by $D_I(y,x) = \max\left\{\lambda: \frac{x}{\lambda} \in I(y)\right\}$; $\lambda > 0$. This is the maximum magnitude λ by which a country's input vector can be radially contracted, while the initial level of output remains feasible for the *N* countries in the sample over *T* periods can be written as:

$$-\ln r_{it} = D_I(y,x,t) = TL\left(y, \frac{k}{r}, \frac{l}{r}, \frac{e}{r}\right)_{it} + v_{it} - u_{it} \tag{4.1}$$

[75] To confirm this, it is possible to test for panel heteroscedasticity using the GLS Likelihood Ratio (LR) test procedure recommended by Wiggins and Poi (2001).

where the normalizing input is derived as $-\ln r_{it}$ which is the negative of rebound effect of country i in time t. y_{it} is a vector of output in logarithms; k, l, e are the logarithms of capital, labour and energy respectively. The TL function presents the production technology as the translog approximation to the log of the distance function. v_{it} is the traditional symmetric error term representing sampling and measurement errors, while u_{it} represents the inefficiency component of the composed error term. Given the study objective of allowing for the energy policy environment to influence the level of rebound efficiency, u_{it} is assumed to follow a truncated normal distribution with mean μ_{it} which is specific to each observation. This assumption is vitally important, considering that, in reality; the rebound conditions (operating environment) across sampled countries are likely to vary, in line with the regulatory environment. Thus, for the purpose of this study, this assumption is more flexible than the well-known half-normal assumption (Stevenson, 1980). Hence, μ_{it} is parameterized as a function of energy policy instruments (π) and is simultaneously estimated in a one-step fashion, so that the mean of u_{it} is given as:

$$\mu_{it} = \delta_0 + \delta' \pi_{it} + \varepsilon_{it} \qquad (4.2)$$

An alternative specification proposed by Reifschneider and Stevenson (1991), Caudill and Ford (1993), Caudill et al. (1995) and Hadri (1999) is also explored, where the distribution of the inefficiency distribution is scaled by parameterizing the variance of the inefficiency distribution as function of the energy policy instruments:

$$u_{it} \sim \left| N^{+}(0, \sigma_{u_{it}}^2) \right| \qquad (4.3)$$

$$\text{where } \sigma_{u_{it}}^2 = \exp(\pi_{it} \delta) \qquad (4.4)$$

4.3.2 Parametric Total Factor Productivity

The economic growth literature often emphasizes the growth in total factor productivity growth (TFP) as an important objective for every economy which embodies advancement in knowledge, know-how and technical progress (see Solow, 1958). Consequently, one of the issues often explored in the parametric efficiency literature is the source of economic growth. Usually, in many modelling exercises such as the one undertaken here, the focus is on evaluating the contribution of factor inputs and technological progress to output growth. This leads to the concept of productivity growth which is the part of output growth not attributed to the use of factor inputs, but to technical change i.e. it is the growth of output minus the growth of input. Therefore, Total factor productivity growth (TFPG) is the rate of growth in a multiple input quantity index minus the rate of growth in a multiple input quantity index. Orea (2002) states that a TFP index generalized from a single input-single output technology should satisfy four properties namely:

1. Identity
2. Monotonicity
3. Seperability
4. Proportionality

Identity requires that if inputs and outputs do not change, the TFP index is unity, while monotonicity requires that the weighted input and output growth rates are chosen so that higher output and lower input unambiguously inprove TFP. Seperability is a property of the chosen technology set which allows us to extend or generalize to the multiple-input and multiple-output case. Finally, proportionality requires that the weights in the input and output growth indices add up to unity. Coelli et al. (2003)

show that a TFP index satisfying the above properties can be derived from the translog approximation to the input distance function. Considering that the negative log of the input distance is the input based technical efficiency, $-\ln D_I(t) = \ln TE_I(t)$, then by employing the quadratic identity lemma (Caves et al., 1982) the following expression can be derived:

$$\ln TFPC = [\ln TE_I(t+1) - \ln TE_I(t)] + \frac{1}{2}[(\partial \ln D_I(t+1)/\partial t) + (\partial \ln D_I(t)/\partial t)]$$

$$+ \left[\frac{1}{2}\sum_{r=1}^{r=R}((ey_{rt+1}SF_{t+1}^{I}) + (ey_{rt}SF_{t}^{I}))\,(\ln(y_{rt+1}/y_{rt}))\right] \tag{4.5}$$

where *TFPC* is TFP change; ey_{rt} is the column vector of output elasticities in period t. SF_t^I is the input scale factor as in Saal et al. (2007) and it is given as:

$$SF_t^I = \left(\left(\sum_{r=1}^{r=R} ey_{rt} + 1\right) / \sum_{r=1}^{r=R} ey_{rt}\right) = 1 - E^t \tag{4.6}$$

The three terms in square brackets in the $\ln TFPC$ expression above represent the well-known decomposition of *TFPC* into efficiency change, *EC*; technical change, *TC* and scale change, *SC*; so that:

$$TFPC = EC + TC + SC \tag{4.7}$$

The first order and second order elasticity and scale parameter from the estimated IDF are used to calculate *EC*, *TC* and *SC* which are then summed up to compute *TFPC*.

4.4 Data

This study is based on an unbalanced annual panel data set constructed for a sample of 19 EU countries ($i = 1, \dots, 19$) over the period 1995 to 2010 ($t = 1, \dots, 16$). The descriptive statistics of the dataset are given in Table 4.1 below. The number of countries and the length of time are largely determined by the availability of data, as countries with too many missing observations were eliminated[76]. The data for the inputs and output and the energy instruments are extracted as follows. Output (Y), capital (K) and labour (L) are all extracted from the Penn World Table (PWT) Version 8.0. Y is represented by "Real GDP at constant 2005 national prices (in mil. 2005US$)". K represents the stock of capital, given by "Capital stock at constant 2005 national prices (in mil. 2005US$)". (L), the labour input is "Number of persons engaged (in millions)".

Energy is decomposed into components: the rebound effect component (REC) and the non-rebound component (NRC). The decomposition is as follows, "Total Final Energy Consumption" is downloaded from "World Energy Balances (2013 Edition)" found on the International Energy Agency (IEA) database and is presented in thousand tonnes of oil equivalent (ktoe). This total energy is assumed to be composed of REC arising from energy efficiency savings or gains. REC is separated out of total energy in two steps. First, energy efficiency gain data[77] from the ODYSSEE-MURE project database is applied to derive energy saving across sample countries. REC is then derived by multiplying the estimated RE from the first chapter

[76] The most problematic data issues arose from the missing or completely unavailable data on energy policy instruments.
[77] Because this dataset is only available from 2000-2010, the change in efficiency trends from the first chapter is used to derive efficiency gains for 1995-1999.

and the calculated efficiency saving in the first step. NRC is then calculated as total energy consumption less REC.

Table 4.1: Summary statistics

303 Obs.	Variable	Mean	SD	Min	Max
Capital (million US2005$)	K	1998830	2332970	116940.8	8757859
Labour (million people)	L	10.47	10.76	1.28	40.80
Energy (ktoe)	E	60726.30	62115.81	7927.62	245242.90
Energy saving (%)	S	5.21	5.58	0.01	32.40
Rebound Effect (%)	R	46.10	15.04	19.66	83.28
GDP (million US2005$)	Y	642426.90	720695.40	54866.16	2830250
Energy Policy variables					
Energy Taxes (US2005$ pet ktoe)	z_1	225.61	96.53	64.45	635.30
Energy R&D (million US2005$)	z_2	123.54	203.32	0.14	1128.87

Finally, data on two energy policy instruments is included in the estimations. Notwithstanding the taxonomy of energy policy instruments, they can be broadly classified into binding/direct and voluntary/non-binding/indirect instruments. A good example of a binding instrument is energy taxes since such taxes are included in end-use energy prices, and are imposed on every unit of energy consumed. Conversely, an indirect or non-binding instrument is research and development (R&D), which is not mandatory or conditional on end-use energy consumed, but requires voluntary adoption by end-users. To capture the impact of energy taxes, “total environmental taxes” which is taken from EUROSTAT database is used. Total environmental taxes include energy taxes, taxes on pollution, natural resources and transport taxes. Since this is given in million Euros/ECU, the series are converted using constant 2005 PPP$ taken from the OECD stat extracts. The implicit tax per ktoe is then derived by dividing these taxes by total energy consumed. The second instrument is energy R&D which is represented by total government R&D expenditure on production, distribution and rational utilization of energy, also taken from the Eurostat database. This is also in million Euros, so is converted to US PPP terms using the procedure above for energy taxes.

4.5 Empirical Results and Analysis

This section presents the main results of the analysis undertaken. First the estimation results for the two SFA models are presented. Secondly, the efficiency results are set out and discussed in detail, and finally the TFP growth results are analysed.

4.5.1 SFA Model Results

All results are based on the estimation of Equation 4.1. In order to evaluate the impact of energy policy instruments, the BC95 (Model 1) and RSCFGH (Model 2)[78] are estimated. Both models are based on the assumption of heteroscedasticity in the inefficiency term. However, before proceeding it is important to check for the presence of heteroscedasticity in the panel data using the LR test procedure recommended by Wiggins and Poi (2001). The LR test approximately follows a chi-square distribution by nesting the homoscedastic model in the heteroscedastic model under the null hypothesis of homoscedasticity. This yields an LR chi2 (18) = 761.49,

[78] The BC92 time-varying decay model and the Hadri99 extension are also explored, but both models strongly violated the concavity condition across the whole (100% of the) sample. The estimation results of the rebound frontier using the different SFA models are given in the appendix.

clearly indicating the presence of heteroscedasticity in the dataset. The models are then estimated.

Table 4.2: SFA estimation results

		Model 1- BC95		Model 2- RSCFGH	
Variable	**Parameter**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**
Constant	α_0	0.605***	0.08	0.269	0.03
$ln\, y$	α_Y	-0.878***	0.02	-1.024***	0.02
$ln\, x_2$	β_K	0.087*	0.05	0.169***	0.04
$ln\, x_3$	β_L	0.086*	0.05	0.369***	0.05
$ln\, x_4$	β_E	0.793***	0.06	0.403***	0.05
t	δ_1	-0.002	0.003	-0.010***	0.00
Parameters in					
$\boldsymbol{\mu\ or\ \sigma_u}$					
tax	π_{tax}	-0.478***	0.04	-4.612***	0.54
$R\&D$	π_{RD}	0.072***	0.010	-0.008	0.13
Υ		0.678	0.452		
LLF		236.367		172.392	

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

The input and output elasticities for both fitted functions have the expected signs and are all significant[79], implying that the monotonicity conditions are satisfied at the sample mean. Across the whole data sample, Model 1 fairly satisfies the monotonicity condition (100% for output, 51% for capital, 58% for labour and 95% for energy) whereas, for Model 2 this condition is confirmed at 100% for output, 65% for capital, 66% for labour and 57% for energy (see Table 4.3 and 4.4).

Table 4.3: Summary of regularity tests for BC-95 model

Monotonicity	**Elasticity**	**Parameter**	**Std. errors**	**Outside sample mean**
y at sample mean	ey_1	-0.878	0.02	100%
x_2 at sample mean	ex_2	0.087	0.05	51%
x_3 at sample mean	ex_3	0.086	0.05	58%
x_4 at sample mean	ex_4	0.793	0.06	95%
Scale Elasticity	**Parameter**	**Std. Errors**	**t-ratio**	**IRS over sample**
$E.$ at sample mean	1.139	0.02	-6.95	72%
			Reject	
			$H_0: E = 1$	
Concavity	**Function**	**Principal minors**	**Values**	**Outside sample mean**
$\mathbf{H}$ at sample mean	$\mathbf{H}(\mathbf{w})$	First order	-2.648	179 points
			-2.095	(59%)
			-2.260	
		Second order	4.227	
			4.415	
			3.571	
		Third order	- 0.081	

[79] It is noted, however, that the capital and labour elasticities for Model 1 are only significant at 10% level.

The returns to scale estimates at the sample mean are 1.14 and 0.98 for models 1 and 2, respectively. In particular, both model estimates suggest that the scale elasticities are not so far apart. Increasing returns to scale (IRS) is confirmed across 72% and 46% of the entire sample for Model 1 and 2 respectively. Both models are also found to be concave at the sample mean and across 59% and 46% respectively.

Table 4.4: Summary of regularity tests for UHET model

Monotonicity	**Elasticity**	**Parameter**	**Std. errors**	**Outside sample mean**
y at sample mean	ey_1	-1.024	0.02	100%
x_2 at sample mean	ex_2	0.169	0.04	65%
x_3 at sample mean	ex_3	0.369	0.05	66%
x_4 at sample mean	ex_4	0.403	0.05	57%

Scale Elasticity	**Parameter**	**Std. Errors**	**t-ratio**	**IRS over sample**
$E.$ at sample mean	0.977	0.02	-1.15	46%
			Fail to reject	
			$H_0: E = 1$	

Concavity	**Function**	**Principal minors**	**Values**	**Outside sample mean**
H at sample mean	$\mathbf{H(w)}$	First order	-1.455	143 points
			-2.893	(47%)
			-2.551	
		Second order	3.405	
			3.638	
			2.330	
		Third order	- 0.032	

Turning back to the inefficiency effects, i.e. the impact of energy policy instruments on estimated efficiency levels; some interesting results are discussed as follows. For both models, energy taxes are shown to have a statistically significant negative (reducing) effect on estimated inefficiency. This is not surprising, given that energy taxes appear to better internalize or capture the negative externalities arising from energy use (see Baranzini *et al.*, 2000 for some discussions).

However, for the energy R&D variable, a negative but insignificant coefficient is found for Model 1, while Model 2 yields a positive, albeit significant coefficient. These results indicate that energy R&D might have had little or no impact on rebound effects over the sample period. In general, the overall implication of the estimated inefficiency effects is that binding market-based energy policy instruments such as energy taxes have been more effective in tackling rebound effects, compared to indirect instrument such as R&D expenses or subsidies.

Greenstone and Allcott (2012) identified energy use externalities[80] as a major factor/distortion responsible for deviations from the social optimum (a situation where energy consumption falls, along with its associated externalities while maintaining or increasing social welfare). The economic intuition behind the argument for energy taxes is that the cost of energy use externalities such as climate change and environmental damage are usually not (fully) borne by polluters. Pigouvian taxes can better convey the full social cost of environmental pollution to polluters, hence, internalising the externality arising from such pollution. It can also generate socially optimal outcomes and improve social welfare.

[80]For example harm to human health, climate change.

On the other hand, energy subsidies are more appropriate in the presence of investment gaps/inefficiencies arising from imperfect information such that consumers and firms refuse to undertake profitable investments in energy efficient technologies. It is possible to increase social welfare by showing/informing consumers and firms about the investment gap while also subsidizing efficient technologies. Hence, the main economic idea is that the benefits of corrective policy interventions such as energy taxes are likely to outweigh their costs in the presence of negative externalities, while the same could be the case when shifts are required for shifts to correct informational and investment gaps. Similarly, Yuan et al. (2011) showed that taxes were more effective for reducing energy use and carbon emissions for the US, relative to policy interventions such as mandated efficiency standards.

4.5.2 Benchmarking results

The average efficiency estimates for the rebound effect frontier for EU countries between 1995 and 2010 are plotted in Figure 4.2. The plot suggests considerable difference between the average efficiencies from models 1 and 2, although both models indicate significantly higher average efficiency scores at the end of the sample period, compared to the start of the sample. The average RE efficiency score across the 19 EU countries ranged from 61% in 1995 to 66% in 2010 for Model 1. For model 2, it is found to range from 84% in 1995 to 94% in 2010.

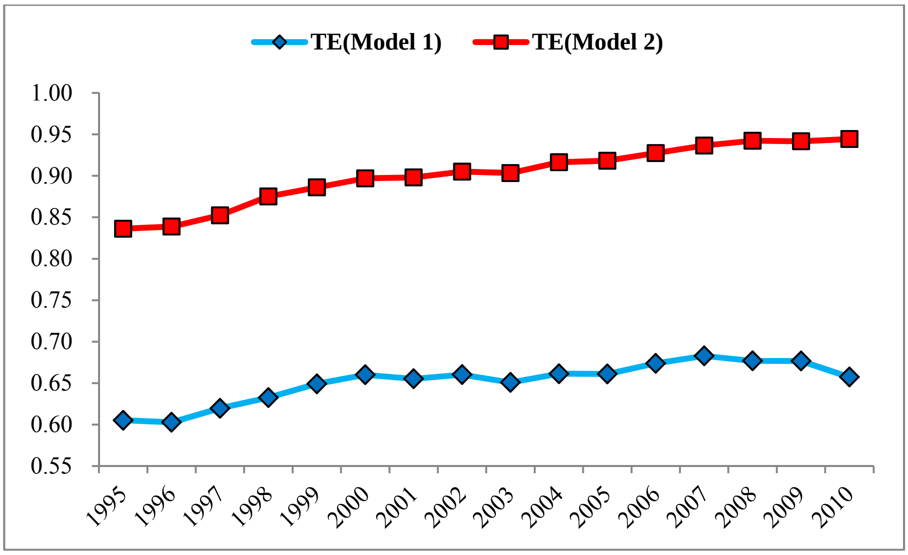

Figure 4.2: Average estimated rebound efficiency

Intuitively, for Model 1, one could say that the average EU country in the sample could potentially reduce RE by around 30% for a given level of output. For Model 2, it shows scope for around 10% reduction in RE for a given level of output. In particular, it is important to note that both models indicate an encouraging sign of rising RE efficiency over the sample period. This may be indicative of the progress that EU countries have made in "locking-in" energy efficiency gains.

Table 4.5 shows rebound performance rankings of the sampled countries across both models. These rankings give an indication of the relative rebound performance of a country relative to other countries in the sample. It can be seen that some countries (Denmark, Ireland, Portugal and UK) are consistently close to the frontier whereas other countries such as Czech Republic, Belgium, Finland, and Slovak Republic are found to be far away from the frontier, for both models. Both Czech Republic and Slovak Republic are some of the most recent EU memberships who joined as part of the EU accession countries in 2004. Their distance to the frontier might be reflecting the 'catching-up' required for the accession countries in terms technology and energy policy alignment.

It is important to place the RE performance results in the context of domestic energy policies across the EU. Filippini et al. (2014) investigated the effectiveness of energy policy instruments designed to increase the level of energy efficiency. Following the oil price shocks of the 1970s, many EU countries have attempted to reduce import dependency and improve security of supply through a range of energy policy instruments. Over the last three decades, such policy instruments have included performance standards in buildings, heating systems and electrical appliances, monetary such as subsidies.

Filippini et al. (2014) further showed that country-level policy efforts and instruments towards attaining improved energy performance have recorded varied levels of success due to falling effective energy prices and variation in priorities/commitments across member states. For instance, the findings in this study about energy taxes being more effective improving rebound performance is consistent with their finding that fiscal &financial instruments, as well as performance standards of buildings played important roles in reducing energy inefficiency across the residential sector in the EU member states.

Table 4.5: Rebound efficiency rankings and energy policy

Country	Model 1	Model 2	Number of policy measures by type					
			Performance standards	Informative-Labelling	Information/ Education	Financial/ Fiscal	Other	Total
Austria	7	11	**7**	2	6	**7**	1	23
Belgium	15	14	**9**	6	6	**16**	0	37
Czech Republic	19	19	**10**	3	4	**7**	0	24
Denmark	2	1	**9**	8	8	**6**	1	32
Finland	17	16	**8**	6	**10**	7	1	32
France	18	9	**15**	8	5	**24**	1	53
Germany	16	10	**18**	**12**	4	7	4	45
Greece	4	6	**11**	6	3	**13**	2	35
Hungary	9	15	**10**	7	8	**25**	0	50
Ireland	1	3	**13**	2	6	**8**	0	29
Italy	10	2	**17**	**10**	2	5	0	34
Netherlands	12	8	4	2	4	**8**	8	26
Norway	5	7	2	2	6	13	7	30
Poland	8	17	**4**	2	0	**4**	0	10
Portugal	3	4	**8**	**3**	2	0	0	13
Slovak Republic	14	18	**11**	**4**	0	3	0	18
Spain	13	13	**42**	9	6	**25**	3	85
Sweden	11	12	4	**7**	4	**6**	2	23
United Kingdom	6	5	**25**	3	10	**15**	2	55

Source: Author's calculation, Filippini et al. (2014)

Aligning the performance results in this study to country-specific energy policies is a difficult task; nevertheless, Table 4.5 presents the performance ranking in this study alongside the adopted energy-efficiency policy measures across sampled countries from 1974 to 2015. One observation, as shown by the bold and coloured text in Table 5.5 is that the energy policy environment across most of the sampled countries is dominated by performance standards and financial/fiscal instruments. While this does not give much information about the variation in performance across countries, a deeper look at the policy targets/approach does.

For instance, given that Danish end-use energy is dominated residential energy demand (32%), the IEA energy policy database shows that most (49%) of its policies are targeted at residential energy demand. Similarly, for the UK where end-use energy is almost evenly split among the end users (residential energy 29%, Transport 27% and Industry 23%); most of its energy policies (35%) are multi-sectoral in nature. This is also the case in Ireland where most energy policies (35%) are multi-sectoral in nature, given the energy mix of residential use 27%, industry 25% and transport 28%.

These findings at least indicate that variation in energy use conditions might have played a role in shaping the observed energy policy approach across sampled countries. This can therefore be expected to result in different energy use and rebound performance across the sampled countries.

4.5.3 TFP Growth Results

TFPG comprises three components namely efficiency change (*EC)* which captures the ‘catching-up’ to the RE frontier; technical change (*TC*) reflects the shifts in the estimated frontier, while scale change, (*SC*) is the returns to scale component reflecting the movement along the estimated frontier. Of course *SC* may also be viewed as representing the effect of changes in inputs on output. When it is positive (negative), the countries are said to experience an increasing (decreasing) returns to scale production technology.

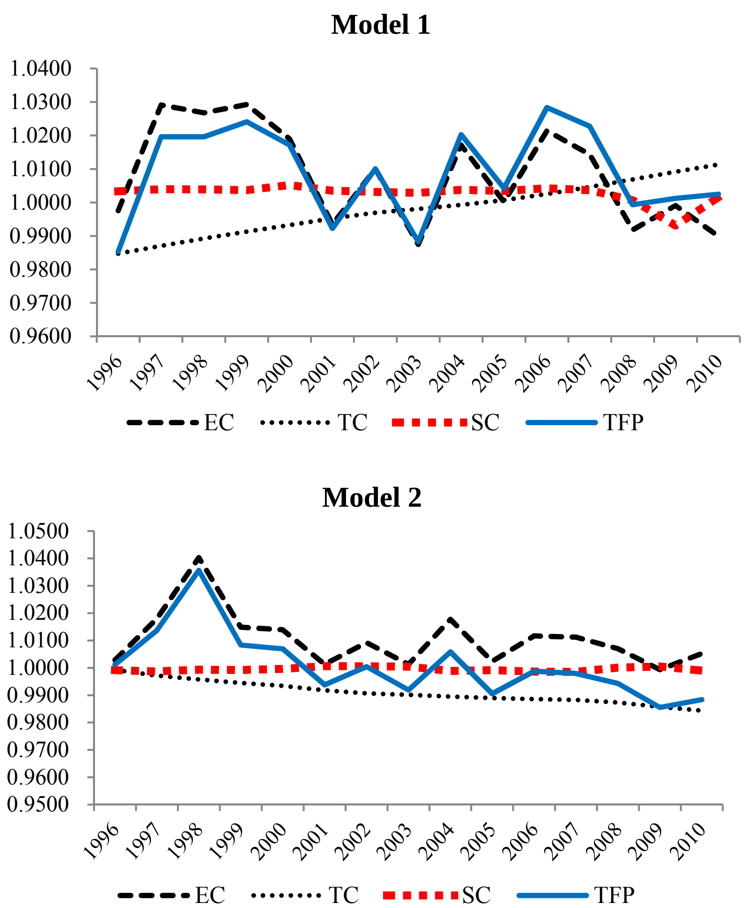

Figure 4.3: Average TFP growth 1996-2010

Estimates of TFP growth for EU countries during the period 1996-2010 are derived from the estimated frontier using equations 4.5-4.7 above, and the results are presented in Figure 4.3. Both models show generally declining TFPG over the sampling period, with that of model 2 being the more obvious. Evidently, the decomposition shows that, for both models, TFP change was largely driven by efficiency gain, which also demonstrated overall decline over the sample period. Efficiency varied quite reasonably and appears to mirror the path of TFP change. Scale change is shown to have been generally stable across both models, although model 1 appears to indicate a spike around 2008/09, possibly reflecting the global recession. Also, the plotted scale changes in the diagrams above appear consistent with the estimated returns to scale of 1.14 and 0.98 for models 1 and 2. For technological change, contrasting trends are observed across both models as model 1 suggests that technological change increased significantly over the sampling period, whereas the converse is found for model 2. Nonetheless, both models show similar TFP evolution over the first decade of the sample period.

4.6 Conclusion

This paper is a benchmarking exercise to estimate a rebound effects frontier using a production technology for EU countries during period 1995-2010. In the spirit of the climate change agenda which aims to promote economic prosperity while pursuing a cleaner environment, EU countries' production technology is modelled to produce national output, choosing the input-minimizing combination of factor inputs, including RE. This study also accounts for the impact of energy policy instruments on the level of RE efficiency (which is theoretically the degree to which countries minimize RE, for their given levels of output).

Results of this study indicate that energy taxes had a significant reducing effect on RE inefficiency, while energy R&D is found to have either a positive or insignificant effect. This is consistent with the notion that the most effective way of internalizing the environmental impact of energy use is through the use of fiscal/economic instruments such as energy taxes. Although, a huge strand of literature indicate that energy/carbon taxes have disruptive influences on economic growth[81], however, it can be argued that the extent of such disruption will depend largely on the factor substitutability or complementarity between energy and other factors (especially capital)[82].

Notwithstanding the disruption that fiscal instruments may pose, the results show the potential scope for RE reduction via energy taxes. The ideal energy policy strategy would be to recycle the revenue raised from such taxes towards subsidizing other factor inputs. This may well help to lock-in the benefits of energy efficiency gains, reduce RE and minimize welfare losses arising from the energy taxes (see Nordhaus, 1993; Saboohi, 2001; Saunders, 2013). But the ability or ease of doing this depends, amongst others, on the elasticity of substitution between factor inputs[83].

On average, RE efficiency estimates imply some scope for RE reduction across sampled EU countries. In terms of global climate talks, results from the TFPG decomposition show that TFP is dominated by efficiency change, with scale economies also contributing reasonably.

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[81] For instance Feng et al. (2010) and Kerkhof et al. (2008).

[82] See Berndt and Wood (1975), Saunders (2000) for theoretical discussions on the implications of factor substitution and complementarity.

[83] Since the seminal works of Berndt and Wood (1975, 1979), a good number of studies have contributed to the analysis of factor substitutability. Recently, Broadstock (2010) and Stern (2011) brought this issue back to the front burner by evaluating the energy-capital substitutability. Other studies such as Sorrell (2008) and Saunders (2013) place their analysis in the rebound context. To shed some light on the relationship between RE and substitution elasticities, the next chapter explores the empirical relationship between substitution elasticities and RE.

Chapter 5 Decomposing Energy Demand to Identify the Channels of Rebound Effects[84]

5.1 Introduction

Large RE constitutes a major challenge to global efforts towards curbing energy use and the associated greenhouse gases, since such RE will erode part of the savings arising from energy efficiency improvements. The previous chapter established significant economy-wide RE for several countries over the 1980 to 2010 period using a panel of 55 countries. More specifically, the estimated average RE for developing countries is found to be slightly larger in magnitude (average of 56%) than those for OECD countries (49% average). Given these results, this chapter aims to unravel the channels through which RE impacts energy demand in fast emerging economies.

The energy consumption rebound arising from an energy efficiency improvement occurs via two major mechanisms which can be easily assessed within the microeconomic theory of duality. Of course an energy efficiency improvement will reduce the effective price of energy which is tantamount to a fall in the relative price of energy. A key implication then is that change (fall) in relative prices stimulates

[84] A revised version of this chapter was submitted for publication as: Adetutu, M., Glass, A. and T. Weyman-Jones (2015). "Decomposing Energy Demand to Identify the Channels of Rebound Effects." *Energy Economics*. Further revisions have been submitted to the journal.

increased consumption of energy, holding output and prices of other inputs constant. In short, this mechanism stimulates substitution towards energy. The second mechanism is the output effect which, ceteris paribus, captures the realization that an efficiency improvement reduces total production cost via lower energy expenditure, thereby expanding the production possibility space which then requires further energy use. An understanding of these channels is required in order for policy makers to better devise strategies towards managing the impact of RE.

These two effects are well grounded in microeconomic theory, yet the limited empirical evaluation of these RE channels is noted in the literature. The closest relatives to this paper are Saunders (2008) and Borenstein (2015)[85]. While both studies offer useful schemes for decomposing changes in energy demand, they differ from the original theoretical idea of substitution and income effects. For instance, Saunders (2008) relied on quantitative examples to demonstrate energy use decomposition whereby parameter values (on elasticities and factor shares) were assumed rather than estimated. On the other hand, although Borenstein's (2015) analysis derives from a microeconomic framework, he treats the effective price of energy as a discrete or non-marginal variable. The discrete price assumption is at variance with the role of lower effective price of energy as the important device/driver of changes in energy demand[86]. Hence his analysis also differs from the standard microeconomic decomposition of substitution and income effects.

In this paper, however, a more appropriate scheme for decomposing changes in energy demand into substitution and output effects based on duality theory and the

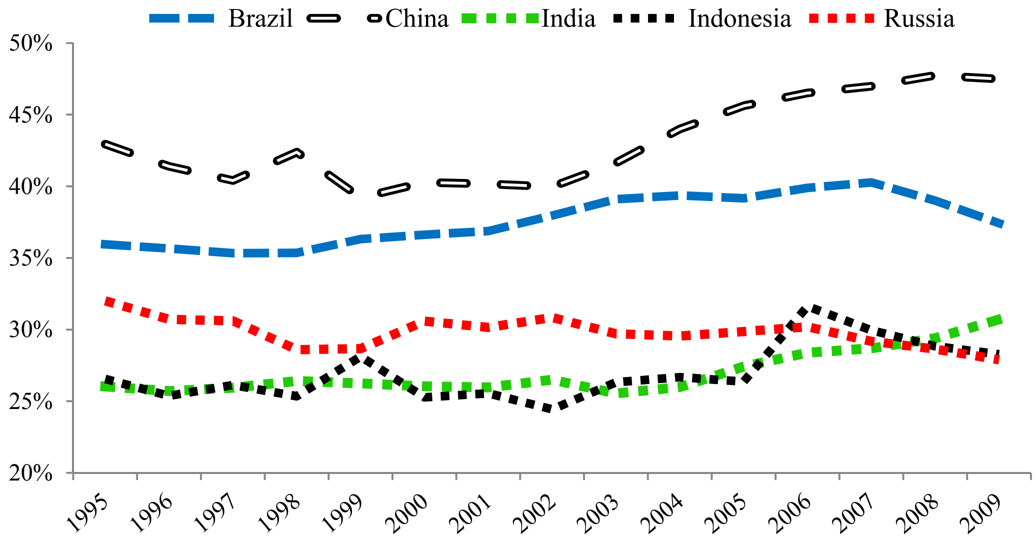
[85] In a detailed review of literature, Sorrell (2010) described a decomposition frame based on the Slutsky equation, although the limited empirical demonstration of this scheme is noted in the literature.
[86] This is made all the more crucial given that energy efficiency enters into the production function via lower effective price of energy.

Slutsky equation is presented. In contrast to previous studies, this study also allows for non-neutral technical progress and output adjusting behaviour. These two assumptions are crucial for the following reasons. The typical assumption of Hick-neutral technical change in the presence of biased technical progress could be misleading and may result in biased parameter estimates (Kim, 1987). Moreover the Hicks-neutral assumption of constant and identical rate of technical progress for each factor input can be overly restrictive given the wide-ranging innovative (R&D) activities of firms. Further, the assumption of flexible output behavior is consistent with the reality that firms are likely to continuously adjust output in response to changes in input prices and other wide-ranging market conditions.

In the application of the decomposition analysis, a translog cost function with biased technical progress[87] is estimated. Given the possibility with the translog specification, the study examines substitution elasticities between energy and other factor inputs. It then decomposes changes in energy demand into substitution and output effects.

[87] The translog specification also allows relaxation of the standard assumption of strong (free) disposability of inputs, so that the existence of uneconomic regions of the production function is permitted.

Figure 5.1: Industrial Share of Total Energy Consumption (%)



Source: *IAE*, 2014

The estimations are based on sector-level production data for Brazil, Russia, India, Indonesia and China (BRIIC). The choice of sampled countries hinges on a number of crucial considerations. First, these countries are important (dominant) high-population and high-growth emerging economies that increasingly burden the global environment as they lift millions of people from poverty. Secondly, they have large manufacturing and energy/emissions-intensive sectors compared with other major and emerging economies as shown in Figure 4.1 which illustrates industrial energy as share of total energy consumption to be greater than 25% across sampled countries. Thirdly, as shown by Sorrell et al. (2009), rebound effects are likely to be higher in developing countries because they are likely to re-spend energy efficiency savings to fuel their rapid economic growth and development.

Further, analyzing energy consumption of the productive sectors of these economies is vitally important given that a great deal of energy use is "embedded energy" contained in the creation of goods and services (Saunders, 2013). Hence, this study is crucial in providing deeper insight and understanding of rebound effects channels and mechanisms on the production side. This is because policymakers will be more concerned about the components of energy demand change in order to target their industrial policy interventions precisely. In particular, a further investigation of factor demand provides a clearer and more complete picture of these channels, and gives them valuable information on the likely impact of policy measures on the production technology (see Dimitropoulos (2007)) for discussions about the need for clarity on RE mechanisms). Moreover, given the huge resources committed by governments and international agencies towards stimulating energy efficiency, a clear understanding of RE allows for a more realistic cost-benefit analysis of such policy measures.

To give an insight into the key empirical findings, it is found that both substitution and output effects matter, although energy demand is dominated by substitution effects. One intriguing result that emerges from the analysis is the role of economies of scale and factor accumulation, as opposed to technical progress, in giving rise to economic growth in these countries over the period under consideration. The analysis in this paper is the first attempt to evaluate RE channels in this way by considering and addressing a range of issues and assumptions; and the idea behind this decomposition analysis can easily be applied to consumer demand analysis.

The remainder of this paper proceeds as follows. Section 5.2 presents the empirical methodology used in this paper. The data set is described in Section 5.3, focusing on how the input prices and cost data are computed. Section 5.4 presents the empirical results of this paper and is divided into 3 subsections, comprising the discussion of the estimates of the estimated cost function, substitution elasticities estimates and the decomposition of energy demand. Section 5.5 offers the study's conclusions and recommendations by using the estimation results to provide key insight on RE channels.

5.2 Empirical Framework

In this analysis, four input types are identified: capital, labour, energy and materials (the familiar KLEM), together with the input prices: w_K, w_L, w_E, w_M.

5.2.1 *Translog Cost Function*

This study proceeds by invoking the microeconomic assumption that firms minimize input costs $(w_K K + w_L L + w_E E + w_M M)$ subject to the production of a given level of output (y) as determined by a standard production function $F(x)$ so that:

$$C(y, w_K, w_L, w_E, w_M) = \min_{K,L,E,M} (w_K K + w_L L + w_E E + w_M M)$$

$$s.t. \qquad y = F(x) \tag{5.1}$$

where: $\sum_k w_k x_k$ and x_k is the typical input K,L,E,M

y: Output

w_K: Price of Capital

w_L: Price of Labour

w_E: Price of Energy

w_M: Price of Material

K: Capital

L: Labour

E: Energy

M: Material (5.2)

In the empirical economics literature, studies have relied on different functional forms such as the Cobb-Douglas, Leontief and the CES in estimating (5.1). However, these functions impose a-priori restrictions on the model in terms of scale economies and the substitution possibilities among the factor inputs. Consequently, the translog cost function (Christensen et al., 1973) is used due to its flexibility which allows for the calculation of second order effects and non-constant elasticities and shares, without placing a-priori restrictions on the production technology. The translog cost function for sector i in period t using k inputs in this study can be written in the context of panel data as:

$$\ln C_{it} = \alpha_0 + \alpha_y \ln y_{rt} + \sum_{k=1}^{4} \beta_k \ln w_{kit} + \frac{1}{2}\alpha_{yy} \ln {y_{rt}}^2 + \frac{1}{2}\sum_{k=1}^{4}\sum_{l=1}^{4} \gamma_{kl} \ln w_{kit} \ln w_{lit}$$

$$+ \frac{1}{2}\sum_{l=1}^{4} \delta_{kr} \ln w_{kit} \ln y_{rt} + \theta_1 t + \theta_2 t^2 + \varphi_t \ln y_{rt}\, t + \sum_{k=1}^{4} \xi_t \ln w_{kit}\, t + v_{it} \tag{5.3}$$

where all variables remain as defined above and $\alpha_y, \beta_k, \alpha_{yy}, \gamma_{kl}, \delta_{kr}, \theta_1, \theta_2, \varphi_t, \xi_t$ are all parameters to be estimated. Duality theory requires that fundamental restrictions of symmetry and linear homogeneity in the input prices are imposed, so that:

$$\beta_{ij} = \beta_{ji}, \forall ij$$

$$\textstyle\sum_i \beta_i = 1$$

$$\sum_i \delta_{kr} = 0, \forall r$$

$$\sum_j \gamma_{kl} = 0, \forall kl$$

$$\sum_i \xi_t = 0$$

(5.4)

Moreover, as suggested by Kumbhakar and Lovell (2003), for a cost function $c(y,w)$ to be well behaved, some economic properties should be satisfied:

(i) non-decreasing in outputs, y, $\partial \ln\ c(y,w)\,/\partial \ln y_j \equiv ey_j \geq 0, j = 1, \dots, J$;

(ii) non-decreasing in input prices, w, $\partial \ln\ c(y,w)\,/\partial \ln w_m \equiv ew_m \geq 0$, $m = 1, \dots, M$;

(iii) homogeneity of degree one in input prices, w, $c(y, w/w_m) = c(y,w)/w_m$

(iv) a concave and continuous function in inputs prices w;

Finally the scale elasticity of the cost function can be measured as:

$$E = \sum_{j=1}^{J} \partial \ln c(y,w)\,/\partial \ln y_j = \sum_{j=1}^{J} ey_j$$

(5.5)

Given the foregoing, the symmetry condition is imposed implicitly in the model specification, while homogeneity (condition iii above) is imposed by normalizing[88] the input prices and total cost by w_m so that the estimated cost function can be written as:

$$\ln\frac{C_{it}}{w_m} = \alpha_0 + \alpha_y \ln y_{rt} + \sum_{k=1}^{3} \beta_k \ln\frac{w_{kit}}{w_m} + \frac{1}{2}\alpha_{yy} \ln {y_{rt}}^2 + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} \gamma_{kl} \ln\frac{w_{kit}}{w_m} \ln\frac{w_{lit}}{w_m}$$
$$+ \frac{1}{2}\sum_{l=1}^{3} \delta_{kr} \ln\frac{w_{kit}}{w_m} \ln y_{rt} + \theta_1 t + \theta_2 t^2 + \varphi_t \ln y_{rt}\, t + \sum_{l=1}^{3} \xi_t \ln\frac{w_{kit}}{w_m} t + v_{it}$$

(5.6)

For a given level of output, the cost minimizing input demand functions can be derived via Shephard's lemma by differentiating the equation 5.5 above with respect

[88] In this study, the normalizing input price is the material input price

to each input price so that $S_{kit} = \frac{\partial \ln C_{it}}{\partial \ln w_{kit}} = x_{kit}$; $k = (K, L, E, M)$ and the input demand equations in terms of cost shares can therefore be obtained as:

$$S_{kit} = \beta_k + \gamma_{kk} w_{kit} + \gamma_{kl} w_{lit} + \delta_{kr} \ln y_{rt} + \xi_t t \tag{5.7}$$

where S_k is the cost share[89] of the kth input. Equations 5.6 and 5.7[90] are jointly estimated using seemingly unrelated regression equations (SUR) by iterative/feasible GLS which is known to converge on the maximum likelihood estimation (MLE). The joint estimation of the share equations allows us to increase the degrees of freedom and efficiency of the parameter estimates by exploiting correlations between the errors of the share equations.

Turning now to the economic properties discussed previously, it is important that the estimated cost function exhibits the economic properties of monotonicity and concavity. The monotonicity conditions (i) and (ii) can be checked by obtaining the output and input price elasticities, $ey_j = \partial \ln\ c(y, w) / \partial \ln y_j$ and $ew_m = \partial \ln\ c(y, w) / \partial \ln w_m$. The concavity condition (iv) is satisfied when the Hessian of the cost function with respect to input prices w is negative semi-definite[91]. The Hessian of the cost function can be written as:

$$H(w) = \boldsymbol{\delta} - \hat{\mathbf{s}} + \boldsymbol{s}\boldsymbol{s}^T \tag{5.8}$$

where $\boldsymbol{\delta}$ is the matrix of second-order coefficients on the input prices. By Shepherd's lemma, the share equations can be expressed as $s_m = \partial \ln\ c(y, w) / \partial \ln w_m = ew_m$

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[89] Given that the study employs four factor inputs, the model includes only three share equations as the sum of the shares is one, so that only three of the factor shares are independent, hence one share equation (for materials) is omitted.

[90] The Seemingly Unrelated Regression (SUR) System estimation is conducted using the Zellner's iterative method for SUR models by imposing the restrictions in (5.4) using STATA 12.

[91] The negative semi-definiteness of the Hessian can be confirmed from the alternating sign pattern of its principal minors. The necessary and sufficient condition for concavity is that all the odd-numbered principal minors of the Hessian must be non-positive and all the even-numbered principal minors must be non-negative.

in which case $\boldsymbol{s}$ is a column matrix of share equations, so that $\boldsymbol{s}' = [s_1, \dots, s_m]'$ and $\hat{\boldsymbol{s}}$ is the diagonal matrix with share s_m on the main diagonal.

5.2.2 *Substitution Elasticities*

It is possible to compute substitution elasticities between energy and non-energy inputs from (5.6). For a cost function, the most common elasticity of substitution (ES) used in empirical studies is the Allen Elasticity of Substitution (AES)[92]. For the translog cost function, the ES can be written as:

$$\sigma_{kl}^{AES} = \frac{\gamma_{kl}+S_k S_l}{S_k S_l}\,; \quad \sigma_{kk}^{AES} = \frac{\gamma_{kk}+S_k^2-S_k}{S_k^2} \tag{5.9}$$

where S_k and S_l are the factor shares of inputs k and l respectively. γ_{kl} and γ_{kk} are estimated coefficients from the cost function where γ_{kl} is the cross-price coefficient between inputs *k* and *l*, whereas γ_{kk} is the second-order coefficient for input *k*.

Blackorby and Russell (1981) demonstrated that the AES is a limited measure of ES as it ignores information on relative factor shares. Consequently, they argued that the AES cannot be interpreted as an indicator of the curvature of a production technology. To this end, they proposed the Morishima (1967) elasticity of substitution (MES) as a more appropriate measure of the ES since it allows for the evaluation of the elasticity of change in input ratios with respect to price ratios for a given level of output, while allowing for input adjustments, holding prices constant (see Stern, 2011). Furthermore, unlike the AES, the MES is asymmetric in nature, hence $MES_{kl} \neq MES_{lk}$. Stern (2011) argues that a measure such as the MES which allows for optimal input changes is more appropriate for capturing changes in factor

[92] This is also known as the Allen-Uzawa Elasticity of Substitution (Allen, 1938; Uzawa, 1962)

shares when all inputs are variable within a cost-minimizing production technology. The MES is given as:

$$\sigma_{kl}^{MES} = S_l(\gamma_{kl} - \gamma_{ll}) \tag{5.10}$$

The MES measures the percentage change in the ratio *k*/*l* due changes in the price of *l* so that if $\sigma_{kl}^{MES} > 0$ then an increase in the price of *l* stimulates an increase in the optimal use of input *k* relative to the optimal use of *l* (in other words, input *k* substitutes for *l*). However, it is concluded that there is complementarity between the two inputs when $\sigma_{kl}^{MES} < 0$.Because the MES is asymmetric in nature, confirming substitutability or complementarity depends on which input price changes[93].

5.2.3 Decomposing Changes in Energy Demand

The primary focus in this study is to demonstrate producers' response to changing relative input prices arising from energy efficiency. This response can be decomposed into substitution and output effects using the Slutsky equation. Changes in input demand can be decomposed using the uncompensated Marshallian demand analysis where it is assumed that a firm maximizes output subject to a budget constraint on input costs:

$$y(w', c) = \max_{\boldsymbol{x}}\{f(\boldsymbol{x}'): \boldsymbol{w}'\boldsymbol{x} = C\} \tag{5.11}$$

The input demand functions are Marshallian[94] in form:

$$x_k = m_k(\boldsymbol{w}', C) \tag{5.12}$$

---

[93] It is realistic to assume that producers aim to optimally adjust all factor inputs in response to changes in their relative prices. It is also consistent with reality to assume that factor inputs adjust to changing relative prices in an asymmetric fashion, rather than in a symmetric manner as suggested by the AES. Further, unlike the AES , the MES allows for variable factor inputs within the production technology, rather than holding some factors fixed. For these reasons, the MES is also explored in this study.

[94] By the envelope theorem this satisfies Roy's identity: $x_k = m_k(\boldsymbol{w}', C) = -\frac{\partial y(w',C)}{\partial w_k} \Big/ \frac{\partial y(w',C)}{\partial C}$

where x_k is the cost minimizing input demand, $\boldsymbol{w}$ is a vector of input prices and C is the target level of input expenditure. Dual to this decision is the firm's cost function:

$$c(\boldsymbol{w}', y) = \min_{\boldsymbol{x}'}\{\boldsymbol{w}'\boldsymbol{x}: y = f(\boldsymbol{x}')\} \tag{5.13}$$

This has input demand functions that are Hicksian in form[95]:

$$x_k = h_k(\boldsymbol{w}', y) \tag{5.14}$$

Given the implicit relationship between the cost function and the indirect production function at the equilibrium point, the Marshallian input demand at cost C is equal to Hicksian input demand at production y:

$$m_k(\boldsymbol{w}', C) = h_k(\boldsymbol{w}', y(w', C)) \tag{5.15}$$

Hicksian demand at production y is equal to Marshallian demand at cost C:

$$h_k(\boldsymbol{w}', y) = m_k(\boldsymbol{w}', c(\boldsymbol{w}', y)) \tag{5.16}$$

These properties are brought together in the Slutsky equation to decompose the total effect of change in an input price into substitution and income effect. By taking the derivative of (5.16) w.r.t $\boldsymbol{w}_k$ using the composite rule yields:

$$\frac{\partial h_k(\boldsymbol{w}',y)}{\partial \boldsymbol{w}_k} = \frac{\partial m_k(\boldsymbol{w}',C)}{\partial c} \cdot \frac{\partial c(\boldsymbol{w}',y)}{\partial \boldsymbol{w}_k} + \frac{\partial m_k(\boldsymbol{w}',C)}{\partial \boldsymbol{w}_k} \tag{5.17}$$

Using $x_k = h_k(w', y) = \partial c(\boldsymbol{w}', y)/\partial w_k$, the equation can be re-arranged to formulate a Slutsky relation:

$$\frac{\partial m_k(\boldsymbol{w}',C)}{\partial \boldsymbol{w}_k} = \frac{\partial h_k(\boldsymbol{w}',y)}{\partial \boldsymbol{w}_k} - \frac{\partial m_k(\boldsymbol{w}',C)}{\partial c} m_k \tag{5.18}$$

For the two-input case (i and j), (5.18) can be written in a more parsimonious (uncompensated and compensated) elasticity form following Mundlak (1968):

$$\eta_{kl} = \eta_{kl}^{c} - \eta_{kC} S_l \tag{5.19}$$

[95] Again by the envelope theorem, these satisfy Shephard's lemma: $x_k = h_k(w', y) = \partial c(\boldsymbol{w}', y)/\partial w_k$

From the estimated cost function, it is possible to derive substitution and output effects as follows. The first term on the RHS of the equation $\eta_{kl}^{c} = \frac{\partial \boldsymbol{h}_k(\boldsymbol{w}',y)}{\partial \boldsymbol{w}_l}$ captures the substitution effect, which can be derived from the cross-partial derivative of the estimated cost function as: $\eta_{kl}^{c} = \frac{\partial^2 c}{\partial w_k \partial w_l} = \frac{\partial x_k}{\partial w_l}$. The second RHS term is the output effect which has two components: S_l is the cost/expenditure share of input *l* which is computed as the ratio of input expenditure to total cost. The other component $\eta_{kC} = \frac{\partial m_k(c,\boldsymbol{w})}{\partial c}$ is the expenditure elasticity of input demand, which can be derived from the equilibrium relationship between the Marshallian and Hicksian demands in (5.15 and 5.16), so that $\eta_{iC} = \frac{\partial x_k}{\partial c} = (\partial x_k/\partial y)(\partial y/\partial c)$. Given the estimated share equations and cost function, $\partial x_k/\partial y$ is the elasticity of input w.r.t output which can be retrieved from the share equation, while $\partial y/\partial c$ can be derived as the inverse of the cost elasticity of output, $\left(\frac{\partial lnC}{\partial lnY}\right)^{-1}$.

5.3 Data

The model estimations are based on the panel data of 33 sectors at two- and three-digit level using International Standard of Industrial Classification (ISIC) Rev. 2[96] for Brazil, China, India, Indonesia and Russia over the period 1995-2009. The raw data series are mainly taken from the World Input-Output Database (Timmer et al., 2015). The measure of output is value added (y) which is expressed in millions of national currency. All monetary variables are measured in local currency at current prices. In particular, for each of the four input sectors (capital, labour, energy and materials) the

[96] The sectors and their Industrial Classification are listed in the appendix.

producer price indices in each country in current prices are also obtained from the World Input-Output Database. These are then deflated to constant (1995=100) prices in each country by applying the implicit price deflator for that sector in each country from the same database. These constant price series are then converted to international prices using the purchasing power parity exchange rates from the Penn World Table (PWT7.1). The measure of output is value added (y) which is expressed in millions of national currency.

The input prices and total cost are computed as follows. The price of capital (pk) is computed as the ratio between capital compensation and Real fixed capital stock; the price of labour (pl) is derived as the ratio of labour compensation to the Number of persons engaged, while the price of energy (pe) is calculated as the ratio of intermediate energy input expenditure at current purchasers' prices to Gross energy use in terajoule (TJ). The price of material (pm) is constructed as the ratio of value of intermediate material input expenditure at current purchasers' prices to intermediate material volume which is expressed as volume indices (1995 = 100). The total cost is the sum of capital, labour, energy and material expenditure. Finally, the cost, output and input price data are in logarithms. For the estimations, all logged data for each variable are mean-adjusted, so that the first order coefficients in the model can be interpreted as elasticities at the sample mean. As shown in equation (5.6), the material price is the normalizing input.

5.4 Estimation Results and Analysis

This section presents the main results of the analysis undertaken in this study. It consists of three sub-sections. In the section ‘Model results’ the fitted cost functions is presented with comment on the curvature properties of the estimated models.

In the section 'Substitution elasticities' the computed factor substitution between energy and the other factor inputs are discussed. In the final section 'Decomposition results' the substitution and output effects of change in energy demand across the sampled countries are presented.

5.4.1 Model results

In Table 5.1, the parameter estimates of the fitted cost function are presented with standard errors in parentheses. It can be seen from the results that the input price and output elasticities across the five models have the expected signs and they are all statistically significant at the 0.1% level. These parameters are all positive which indicates that the monotonicity of the cost function is satisfied at the sample mean. In particular, the elasticity of cost with respect to output gives an important measure of scale economies, such that an output elasticity smaller (larger) than one indicates scale economies (diseconomies)[97]. The output elasticities across all the models indicate strong economies of scale ranging from 1.8 in Brazil to 3.5 in China. The scale economies are sensible and consistent with the strong growth and output expansion across the BRIIC countries over the last two decades.

One intriguing result that emerges from this analysis is the role of economies of scale and factor accumulation as opposed to technical progress[98] in giving rise to economic growth in these countries over this period. This mirrors a debate that featured strongly in the research on growth performance during the years of the so-called Asian miracle and tiger economies. Liao et al (2007) identified two sides of

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[97] Of course, economies of scale is given by $1/ey = \frac{1}{\partial \ln\, c(y,w)/\partial \ln y}$

[98] Technical progress is evaluated as the derivative of the cost (or input demand in the case of biased technical progress) function with respect to time, to derive panel-varying functional estimates.

the debate. Accumulationists believed that the increased use and accumulation of inputs (especially the investment) rather than the increases in productivity explains all growth; this was represented by Young (1992, 1994a, 1994b, 1995), Krugman (1994), Collins & Bosworth (1996), Drysdale & Huang (1997), Crafts (1999a, 1999b). Assimilationists argued that the answer to growth lies in the use of more efficient technology, represented by World Bank (1993), Sarel (1996, 1997), Nelson & Pack (1999). Liao et al (2007) concluded that Krugman's (1994) hypothesis that the fast growth of East Asian economies had little to do with TFP growth was invalid, but could not dispute Young's (1995) 's conclusion that these economies' growth had been mainly input-driven.

This study finds an almost identical issue arising in this sample of the BRIIC countries over the period 1995-2009. The results show strong economies of scale but are unable to identify positive technical progress (compare the output elasticity of the estimated cost functions with the elasticity of cost with respect to time, which is consistently positive at the sample mean and over most of the individual panel sample points). The robustness of this finding is investigated in two ways. In addition to the original iterative SURE estimation, all the models are re-estimated using one-way fixed and random effects panel methods. The importance of input accumulation over technical progress remained. Secondly, the models were re-estimated after imposing constant returns to scale on the technology: this should have the effect of eliminating any spurious scale effects and allowing positive technical progress to be discovered if it is present. The basic finding however is unchanged: technical progress is not estimated as being positive for these economies in this period. This means that the BRIIC economies have demonstrated the same experience as the Asian economies a decade earlier in that the principal engine of their growth has been factor accumulation rather than technical progress[99]. It is in the context of this additional intriguing finding that this study has been able to investigate output effect components of energy rebound effects.

[99] Interestingly, a recent (Oct. 11, 2014) edition of *The Economist* magazine highlighted this same issue that the Chinese economy's productivity growth between 1997 and 2012 had decelerated; and the TFP growth itself has been dominated by scale effects arising from huge accumulation of capital and capacity, rather than the efficiency within firm production technologies.

Table 5.1:Estimated translog cost models

Variable	Brazil	China	India	Indonesia	Russia
Constant	-0.071**	0.028	0.252***	0.025	0.079**
	(0.033)	(0.038)	(0.037)	(0.056)	(0.037)
Output	0.546***	0.284***	0.484***	0.449***	0.369***
	(0.017)	(0.022)	(0.014)	(0.027)	(0.015)
Capital Price	0.274***	0.212***	0.236***	0.190***	0.144***
	(0.006)	(0.005)	(0.005)	(0.007)	(0.004)
Labour Price	0.249***	0.172***	0.220***	0.269***	0.231***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)
Energy Price	0.045***	0.048***	0.056***	0.033***	0.096***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Output Squared	0.043***	-0.011	-0.017*	0.050***	0.038***
	(0.009)	(0.017)	(0.009)	(0.015)	(0.007)
Output*Capital Price	0.086***	0.066***	0.057***	0.047***	0.019***
	(0.005)	(0.008)	(0.003)	(0.007)	(0.004)
Output*Labour Price	0.062***	0.083***	0.045***	0.039***	0.068***
	(0.005)	(0.007)	(0.004)	(0.006)	(0.004)
Output*Energy Price	0.001	-0.007***	-0.004*	-0.007***	-0.008***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Capital Price Squared	0.063***	0.040***	0.040***	-0.007***	0.043***
	(0.003)	(0.006)	(0.005)	(0.003)	(0.005)
Capital Price*Labour Price	0.017***	0.030***	0.036***	0.009***	-0.013***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Capital Price*Energy Price	0.008***	0.015***	-0.014***	0.001	-0.013***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Labour Price Squared	0.023***	0.015***	0.000	0.008*	0.025***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)

Labour Price*Energy Price	0.015***	0.011***	0.019***	0.009***	0.026***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Energy Price Sqaured	-0.020***	-0.018***	-0.014***	-0.007***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time	0.045***	0.068***	0.039***	0.074***	0.112***
	(0.004)	(0.004)	(0.003)	(0.006)	(0.004)
Time Squared	0.003***	0.004***	0.001	-0.002*	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Output*Time	0.013***	-0.011**	0.001	0.021***	0.006**
	(0.002)	(0.005)	(0.003)	(0.005)	(0.003)
Capital*Time	0.006***	-0.010***	0.000	0.002	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Labour*Time	0.004***	-0.015***	-0.002*	0.004***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Energy*Time	0.000	0.002***	-0.001	0.001***	0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)

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

Notwithstanding the Hicksian-neutral result above, this study re-visited the issue raised by Hunt (1986) about the importance of testing for non-neutrality (bias) in the measure of technological progress. This is made more important by the nature of the Hicksian-neutral result above, which is more likely to be biased in the face of technological regress. This is explored by estimating restricted versions of equations (5.6) and (5.7) by restricting ξ_j to zero and then applying a likelihood ratio (LR) test statistic to test this restriction against the unrestricted model. The LR test statistic is given by $LR = 2(\ln L_U - \ln L_R)$ where L_U is the maximized value of the log likelihood of the unrestricted model and L_R is the maximized log likelihood of the restricted model. The LR test statistic is asymptotically distributed as a chi-square distribution χ_p^2, where p represents the number of restrictions (three in this case).

The LR statistics in Table 5.2 show that the assumption or specification of neutral technical progress is clearly rejected across board with the LR statistics for all the models exceeding 7.81, the critical value for chi-square distribution with 3 degrees of freedom at the 5% level. With the exception of India, technical progress is generally found to be biased towards using energy across the sampled countries. These non-neutrality tests indicate that the assumption of Hicksian neutral technical progress should only be imposed when accepted by data, given that, in reality, technical progress may be biased towards using a particular input[100].

[100] Kim (1987) shows that the assumption of Hicks-neutral technical progress is unrealistic in the face of firm's innovative activities. Fisher-Vanden and Jefferson (2008) found firm-level factor bias as an important channel of technical change in a large panel of Chinese industrial enterprises.

Table 5.2: LR test statistics for non-neutral technical progress

LR Statistic	**Brazil**	**China**	**India**	**Indonesia**	**Russia**
H_0:*neutral technological progress* ($\xi_j = 0$)	**107.673**	**167.149**	**7.851**	**35.016**	**20.434**
Decision					
Capital	Capital-using	Capital-saving	Capital-saving	Capital-using	Capital-saving
Labour	Labour-using	Labour-saving	Labour-saving	Labour-using	Labour-saving
Energy	Energy-using	Energy-using	Energy-saving	Energy-using	Energy-using

Now turning to the economic properties of the estimated models, it is important to briefly discuss the results on the monotonicity and concavity conditions of the fitted translog cost function which are presented in Table 5.3. Monotonicity and concavity are evaluated ex post, both for the sample mean and for every sample point. As discussed above, the monotonicity condition was strongly satisfied at the sample mean, based on the statistically significant positive input price and output elasticities. Further, monotonicity is strongly satisfied outside the sample mean for all countries, with results indicating that for each of the five countries, a large proportion (at least 83%) of the data points are monotonic. The results on monotonicity suggest that the estimated cost functions are non-decreasing in outputs and input prices,

For concavity, the sign pattern of the principal minors of the Hessian are checked. As shown in Table 5.3, concavity is confirmed at the sample mean across all fitted cost functions. In addition, concavity is established at varying levels across the entire data points for the models, ranging from 29% concavity for Brazil to 97% in Indonesia. The concavity condition (apart from Brazil) indicates that the cost function is concave in input prices i.e. firms are taking advantage of substitution opportunities to the extent that costs have grown slower than linearly in response to changing relative factor prices. This appears to be supported by the significant scale economies observed across all the estimated cost functions.

Table 5.3: Curvature properties of estimated cost functions

Variable		Brazil	China	India	Indonesia	Russia
Elasticity at sample mean						
Capital		0.274	0.212	0.236	0.189	0.144
Labour		0.249	0.172	0.220	0.269	0.231
Energy		0.045	0.048	0.056	0.033	0.096
Economies of Scale		1.832	3.521	2.066	2.227	2.710
Monotonicity (% of sample)						
Capital		96.162	98.990	96.667	100	98.788
Labour		100	100	100	100	100
Energy		83.434	88.687	85.417	91.313	100
Concavity at sample mean						
1^{st} order principal minors	h11	-0.073	-0.086	-0.100	-0.169	-0.038
	h22	-0.142	-0.113	-0.171	-0.180	-0.127
	h33	-0.083	-0.080	-0.080	-0.046	-0.112
2^{nd} order principal minors	pm1	0.003	0.005	0.009	0.027	0.004
	pm2	0.006	0.006	0.008	0.008	0.004
	pm3	0.011	0.009	0.013	0.008	0.012
3^{rd} order principal minor	pm11	-0.0001	-0.0003	-0.001	-0.001	-0.0004
Concavity (% of sample)		29.495	65.859	56.875	96.566	69.091

5.4.2 Substitution Elasticities

Substitution elasticities are derived following equations 5.9-5.10 using the cross-price parameters from the estimated translog model and the computed factor shares[101]. Empirical elasticity results at the sample mean are presented in Table 5.4.

Table 5.4:Elasticity of substitution

		K-L	L-K	K-E	E-K	L-E	E-L
Brazil							
	AES	1.238***		1.619***		2.352***	
		(0.050)		(0.082)		(0.104)	
	MES	0.964***	0.848***	1.473***	0.957***	1.505***	1.234***
		(0.012)	(0.009)	(0.016)	(0.024)	(0.016)	(0.006)
China							
	AES	1.813***		2.372***		2.346***	
		(0.107)		(0.169)		(0.163)	
	MES	1.049***	0.998***	1.434***	1.123***	1.433***	1.139***
		(0.016)	(0.016)	(0.019)	(0.042)	(0.019)	(0.002)
India							
	AES	1.673***		0.008		2.445***	
		(0.066)		(0.135)		(0.123)	
	MES	1.148***	0.996***	1.172***	0.594***	1.316***	1.319***
		(0.009)	(0.011)	(0.021)	(0.034)	(0.021)	(0.013)
Indonesia							
	AES	1.162***		1.180***		2.331***	
		(0.049)		(0.130)		(0.176)	
	MES	1.005***	1.070***	1.253***	1.074***	1.287***	1.288***
		(0.011)	(0.007)	(0.028)	(0.030)	(0.028)	(0.025)
Russia							
	AES	0.654***		0.103		2.112***	
		(0.106)		(0.108)		(0.070)	
	MES	0.8112***	0.6693***	1.0447***	0.5842***	1.2402***	1.1573***
		(0.015)	(0.019)	(0.013)	(0.031)	(0.011)	(0.001)

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

The standard errors of the estimated substitution elasticities are computed using the delta method (Binswanger, 1974; Koetse, et al., 2008). As shown in Table 5.4,

[101] The cross-price coefficients are taken from the fitted cost functions in Table 4.1 while the factor shares are computed as the ratio between expenditure on an input and total cost.

the estimates at the sample mean generally indicate strong substitution possibilities across the board for energy-non energy input combinations for both the AES and the MES. However, it is observed that the AES values are generally larger than the MES values in absolute terms. This might be due to the substantial asymmetries observed for the input combinations under the MES. This flexible substitution pattern under the MES, which is limited under the AES, possibly explains why the latter is likely to overstate the elasticity of substitution (see Stiroh, 1999).

Briefly, the estimates indicate that energy is strongly substitutable for capital and labour, with estimated elasticity of substitution (ES) greater than 1 in most cases, and across both the AES and MES. The implication of this result is that firms/sectors across BRIIC countries strongly substituted energy for capital and labour with relative ease, in response to changing relative energy prices. Sector-specific elasticities are also computed across the sampled countries to give a disaggregated view of energy substitutability. Generally, strong substitutability is found between energy and the other two inputs[102] as shown in the appendix. In particular, certain sectors are observed to have high substitution elasticities (in terms of the magnitude of the ES) such as Brazil (real estate, leather & footwear and transport equipment); China (electrical & optical equipment, leather &footwear, rubber & plastic, transport equipment, textiles, wood & cork and paper & pulp). Also for India the main sectors are education, food & beverage, leather & footwear, manufacturing and real estate; Indonesia (food & beverage and machinery, NEC) and Russia (food & beverage & transport equipment).

[102] It is noted, however, capital and energy are complements for some sectors in India and Russia (see appendix).

5.4.3 Decomposition Results

So far, only pure substitution elasticities have been measured without accounting for output effects. As shown by Chambers (1982), the implicit assumption in this case is that output held constant (i.e. these elasticties derived from cost functions restrict the producer to a given level of output). However, this assumption constitutes a serious limitation in the analysis of firm behavior because in reality, producers are likely to respond to changing relative prices, technological progress, external shocks and so forth, by adjusting output accordingly. Therefore, the output effect captures this adjustment process and gives a better and complete view of factor input adjustments within a production technology. For instance, previous oil price shocks have been shown to reduce output and productivity across firms and countries, to the extent that ignoring output effects in empirical studies of firm behavior results in the loss of valuable information (Kim, 1987; Frondel, 2011).

Having estimated the input demand function in equation (5.6), change in energy demand is decomposed into substitution and output effects following equation (5.15). The focus is on the own-price of effect of energy, which is relevant for rebound analysis. Table 5.5 presents the results of the decomposition of energy demand.

Table 5.5: Decomposition of changes in energy demand

	Elasticity with respect to price of Energy	
	Substitution Effect	**Output Effect**
Brazil	-0.020	0.000
China	-0.018	0.001
India	-0.014	0.001
Indonesia	-0.007	0.001
Russia	-0.013	0.002

Expectedly, the own substitution effects arising from increase in energy price are negative across all the countries, confirming the theoretical expectation that own-price substitution effects are negative (i.e. rising energy prices curbed energy demand). This also confirms that the Marshallian demands slope downwards. Further, this is also consistent with the widespread energy-non energy input substitutability across most sectors/countries since the negative own-price substitution effect indicates that higher energy prices caused productive units to substitute away towards other inputs.

The output effects are positive across board, although they are strictly smaller than the substitution effects in terms of magnitude. As expected, this clearly shows that the substitution effects dominate the changes in energy demand arising from changing relative price of energy. This finding is also consistent with other previous studies (e.g. Saunders, 2013; Borenstein, 2015; Sorrell, 2014) where the results are dominated by substitution effects[103]. Further, the positive sign on the output effects suggests that energy may not be a normal factor input for these sectors because if firms are free to adjust output, a rise in input price will raise total cost as well as marginal cost of production, making them produce less output overall. However, in the case of this study, it would appear that although rising energy prices restricted energy demand, the expected fall in output arising from higher total cost (negative output effect) has been countervailed by the significant economies of scale.

Notwithstanding opposing directions of both effects, the total effect is consistent with economic theory, to the extent that higher energy prices led to a reduction in energy consumption via substitution effects. Therefore, the key implica-

[103] The ease of substitution between energy and the other inputs is a major determinant of the size of rebound effects such that easier substitution results in larger rebounds (see Saunders, 1992)

tion is that RE arising from improved energy efficiency is likely to enter energy use of productive units of BRIIC countries through substitution effects.

5.5 Concluding Remarks and Further Work

This study has attempted to present an approach for evaluating the channels through which RE entered energy demand of productive sectors of fast emerging economies in order to better understand their significantly higher economy-wide RE estimates in Chapter 3. Given that industrial energy consumption constitutes the bulk of energy use across these countries, this study addressed a number of crucial structural, technological and modelling issues which are crucial to understanding energy consumption of these economies in the context of their production technology.

To unravel the energy use channels, this study adopted a decomposition scheme that is consistent with the standard economic idea behind substitution and output effects, which is applied to the production data of BRIIC countries covering the period 1995-2009. This approach is based on the premise that energy efficiency improvements impact energy demand by acting to lower the relative price of energy, leading to substitution and output mechanisms (which constitute RE).

The substitution elasticity estimates indicate strong substitutability between energy and other inputs. Further, the decomposition of changes in sectoral energy demand across BRIIC countries indicates that changes in energy demand are strongly dominated by substitution effects. In addition, the analysis revealed that economies of scale and factor accumulation, as opposed to technical progress have been the major drivers of firm performance in these countries over the period under consideration. This finding is consistent with the body of evidence on the nature of economic growth of emerging economies. This finding is underscored by the positive output effects which implied that the effects of higher energy prices were countervailed by these scale effects.

The main idea behind this paper is particularly appealing because it is not limited to the analysis of firm behavior. Its application to consumer demand is straightforward and grounded in the same economic intuition. It is hoped that future research work will be conducted with focus on consumer demand. However, the challenge is the lack of income and multi-product price data on developing countries.

Chapter 6 Conclusions and future research

6.1 Summary

This thesis contains three essays aimed at investigating three major issues on rebound effects. More specifically, the main objective was to empirically evaluate the size of economy-wide rebound effects for a broad array of countries and to propose a two-stage econometric procedure for assessing it. The issue of RE mechanisms/channels were investigated for high energy-using emerging economies such as Brazil, Russia, India, Indonesia and China. Further, as tackling energy challenges such as rebound effects requires robust and effective energy policy actions, this thesis aimed to analyse the impact of two energy policy instruments and to what extent they have been effective in restricting rebound effects. These three main issues were addressed via three papers/essays in Chapters 3, 4 and 5. The next section details the main research findings of this thesis in terms of the research questions in Chapter 1.

6.2 Empirical Findings and Policy Implications

Essay 1: What are the estimates of economy-wide rebound effects?

- Is there a clear difference between RE estimates for developed and developing countries?
- What is the trend of RE across countries?

Despite the remarkable growth of the RE literature, there is no single broad and extensive study of economy-wide RE covering several countries. To fill this literature gap, cross-country estimates of RE are derived for 55 countries using a two-stage econometric approach with data covering 1980-2010. In the first stage stochastic frontier analysis is employed to estimate energy efficiency, and in the second stage, efficiency elasticity of energy demand is estimated using a dynamic panel model. Economy-wide RE is then computed from the efficiency elasticities.

Findings from this first essay indicate that cross-country heterogeneity explains the level of energy efficiency across sampled countries. Further, the main RE estimates show significant RE of 90% at the sample mean in the short-run. However, the LR estimate suggests super conservation (1.36% decrease in energy consumption for 1% efficiency improvement). However, an encouraging sign is that although the point estimates across the different countries over the period 1980-2010 indicate significant RE magnitudes, they are generally decreasing across most of the countries in the sample. In the same vein, the long run RE estimates indicate super conservation across sampled countries, although it is noted that the long run for partial adjustment models indicate the desired or targeted or appropriate level of the dependent variable which is unobservable[104].

Given the estimated magnitudes of cross-country RE, the overall implication of Chapter 3 is that energy forecasts derived from potential energy efficiency savings may have underestimated future energy consumption by failing to account for ex-post RE. Energy policy makers should note that RE distorts the cost-benefit analysis of energy conservation measures with the implication that future global energy con-

[104] In this model, actual energy demand is assumed to adjust towards its desired/targeted level.

sumption has been underestimated, and we may have less time than predicted to address global warming. Given the huge resources committed by governments and international agencies towards stimulating energy efficiency, a clear understanding of RE allows for a more precise and realistic cost-benefit analysis of such energy efficiency measures. By incorporating RE into such policy agendas, climate change mitigation efforts are likely to become more effective and transparent. Hence, the message is that RE should now be on the energy policy agenda.

Essay 2: Which countries have the minimum level of rebound for a given level of output?

- Which energy policy instrument is more appropriate in mitigating rebound effects?
- What drives total factor productivity (TFP)?

Efficiency and productivity analysis in the energy economics literature has focused on identifying the best-practice production technology using the minimum possible energy to produce a given level of output. However, ex-post rebound effects (RE) after energy efficiency improvements could be substantial, thereby reducing the actual energy saving from increased energy efficiency. Hence, in addition to improving energy efficiency, countries should also aim to reduce or minimize RE in order to realize as much energy efficiency savings as possible. This study is, as far as is known, the first to benchmark RE (i.e. countries with the minimum RE magnitudes for their levels of output). Another important issue which this study takes on is the potential role of energy policy in curbing RE, given the dearth of studies precisely evaluating the impact of such policy instruments on RE in a quantitative context.

Therefore Chapter 4 constructs a rebound effects frontier for EU countries during period 1995-2010. Using an input distance approach, EU countries' production technology is modelled to produce national output, choosing the input-minimizing combination of RE and other factor inputs (which is theoretically the degree to which countries minimize RE, for their given levels of output). Results and findings show increasing efficiency in RE minimization across sampled countries over the period under consideration, with Ireland, Denmark and Portugal consistently being efficient in minimizing RE whereas Czech Republic, Slovak Republic and Finland were consistently the farthest away from the frontier.

The main policy implications that emerge from Chapter 4 are as follows. It appears that binding energy policy instruments such as taxes are more appropriate for tackling RE than indirect instruments such as energy R&D investments. One would expect greater impact elasticity from energy taxes than from energy subsidies due to its direct impact on income. Nonetheless, loss aversion implies that results might not be identical across countries or economic agents. Some economic agents might be more sensitive to the loss of income (resulting from taxes) whereas others might be more concerned that someone else gains more (due to subsidies).

Secondly, given that some of the farthest countries from the RE frontier such as Czech Republic and Slovak Republic are 2004 accession countries, the results might indicate that 'catching-up' is required by these countries. For this reason, energy policy designs in these countries must consider the country-specific level of development. Adopting identical policies with more developed EU countries might be more harmful to economic growth.

Essay 3: What are the main rebound effects channels? /What drives rebound effects?

- What is the size of substitution elasticity between energy and non-energy inputs across sectors?
- What is the role of energy in productivity growth?

It is well-established in the theoretical literature that the two-main channels of energy RE are the substitution and output effects. Nonetheless, there is clearly a lack of empirical assessment of these two effects. Moreover, from a theoretical point of view, it is noted that the few available decomposition studies differ from the original microeconomic idea of these effects. Hence, Chapter 5 investigated the channels of RE for Brazil, Russia, India, Indonesia and China (BRIIC) through the estimation of a translog cost function by applying the iterative seemingly unrelated regression equations (SUR)/feasible GLS model to production data covering 1995-2009. Amongst others, changes in energy demand are decomposed into substitution and output effects; the economic properties of these productive sectors are evaluated; nature of technological progress is evaluated.

Findings from this chapter revealed that the RE mechanism towards changes in energy demand was dominated by substitution effects which ranged from -0.007 in Indonesia to -0.020 in Brazil, over the period under consideration. It is a well-established notion in the literature that easier substitution (larger substitution elasticity) leads to larger rebounds. Therefore, policymakers will be concerned about the components/mechanisms of ex-post energy demand change arising from energy conservation in order to target their policy interventions more precisely.

Previous studies such as Saunders (1992, 2008), Stern and Kander (2012) and Sorrell (2014) have demonstrated the link between the energy elasticity of substitution and the magnitude of rebound effects. The main energy policy implication from the findings in Chapter 5 suggests that, given the size of the elasticties, most productive sectors across the BRIIC countries are more vulnerable to RE, as reflected in the economy-wide estimates from Chapter 3. This argument is supported by the large energy-intensive industrial sectors across these economies.

Policy makers should also note that sectors with easier substitution away from energy-intensive processes are less likely to be affected by rising energy prices. For instance, the asymmetric Morishima elasticties indicate great substitutability between energy and the other factor inputs. This implies that rising energy prices are likely to have limited effects on the production technology across sampled countries and sectors, since the firms are able to substitute capital and labour for energy.

It can be argued therefore that the use of fiscal instruments such as energy taxes to internalize the cost of environmental pollution arising from energy use can possibly reduce energy use, RE and emission over time, without significant effects on long term growth. The highly flexible production technologies across these countries, whereby factor inputs easily adjusted to changing relative factor prices (and other exogenous or policy shocks) during the period under consideration. These conclusions have important policy implications relating to energy use within productive sectors of emerging economies.

Overall, it must be noted that Rebound effect is not entirely bad on its own since the resulting increase in energy use contributes towards consumer welfare and expands the production possibility space. Hence, this study does not advocate for the elimination of RE, but argues for its inclusion in wider energy policy and forecasting design. One possible approach to coping with RE will be for policymakers to substitute cleaner energy RE for ‘dirty’ energy RE by mitigating fossil-related RE while supporting renewable energy RE.

6.3 Limitations of the Study

It is recognized that all research and analytical frameworks have limitations and this study is not different in that respect. The limitations of this thesis are highlighted as follows. First, this research was limited by the sample size across the three papers due to a lack of consistent data for a good number of countries. For instance, the economy-wide estimations in Chapter 3 relied on data for 55 countries. Given the global nature of the problems associated with RE, it would have been more useful to have more (if not all) countries in the sample. This is also the case for Chapter 5 where the inclusion of other developing countries would have permitted a broader data sample to evaluate substitution elasticties across their productive sectors.

Secondly, on a related note, energy policies differ across countries and this research (especially Chapters 3 and 4) seriously considered these energy policy differences, but limited data and changing policy stance overtime made this difficult. For instance the most comprehensive subsidy database “OECD-IEA Fossil Fuel Subsidies and Other Support” database covers only 39 countries and spans a period of 5 years (2007-2011). Further, even when some descriptive energy policy information was available for OECD countries, it is found that energy policy stance changed over a period of time, where for instance some policy measures were only implemented for a few years and discontinued thereafter. The use of dummy variables, for instance, would overstate the impact of such discontinued policies overtime in the light of the relatively long-time frame of the dataset. For both of these points, however, it is the case that the country fixed effects included in the DPD instrumental variables estimation will pick up additional country specific effects including inter-country differences in energy policies.

Finally, as with most econometric analyses, the results here cannot establish complete causality within all the estimated models, although it is demonstrated, with a high degree of confidence, that the major dimensions of the rebound effect have been captured using well-established modelling procedures.

6.4 Directions for future research

This thesis contains 3 essays on major issues bothering on rebound effects. While these essays/papers address key research questions, the ensuing results give useful indications of several areas for further research. The first essay shows amongst others that rebound magnitudes are quite substantial; hence, it would be interesting to extend the analysis in Chapter 3 by re-visiting energy consumption forecasts across sampled countries with a view capturing the impact rebound on energy consumption. In a way, this would also allow for an assessment of the actual contribution of energy efficiency measures to curbing energy use and greenhouse emissions. Furthermore, given the significant magnitudes of the estimated RE across sampled countries, it would also be useful to investigate which sectors (whether households, transport, industrial, electricity) are rebounding the most. A greater understanding of RE drivers is required to further assist policy makers. Ideally a sectoral analysis of aggregate residential, industrial and electricity sector RE across different countries should follow, to decompose macro RE into its underlying sources. Such an investigation would be interesting and would represent a step in the right direction.

From Chapter 4, it is found that a binding energy policy instrument, energy taxes, had a significant (reducing) effect on rebound performance relative to a non-binding instrument, energy R&D expenditure. Because the papers tests the impact of only two energy policy instruments on rebound, it is necessary to explore a range of other energy policy instruments for a more comprehensive assessment of their impact on rebound performance. This would enable the evaluation of alternative policy options to achieve the long-term targets of sustainable energy consumption and climate security.

In Chapter 5, a decomposition of energy demand by productive sectors for Brazil, Russia, India, Indonesia and China is conducted towards identifying the channels/mechanisms of rebound. The results indicate that substitutability between energy and other inputs dominated changes in energy demand, compared with output effects. While this finding provides key insight on RE channels in BRIIC countries, further decomposition studies across more developing countries are needed to build the body of evidence on the underlying sources of rebound across these countries. Additionally, because the proposed Slutsky decomposition is more appropriate and consistent with the original microeconomic intuition of substitution and output effects, further application of this scheme will help to test its reliability and consistency.

All these issues constitute the future research agenda.

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Appendix 1: SFA distributional assumptions

SFA Model	Normal-Half Normal	Normal-Exponential	Normal-Truncated Normal	Normal-Gamma
Distribution of v_i	$v_i \sim$ iid $N(0, \sigma_v^2)$	$v_i \sim$ iid $N(0, \sigma_v^2)$	$v_i \sim$ iid $N(0, \sigma_v^2)$	$v_i \sim$ iid $N(0, \sigma_v^2)$
Distribution of u_i	$u_i \sim$iid $N^+(0, \sigma_u^2)$	$u_i \sim$iid exponential	$u_i \sim$iid $N^+(\mu, \sigma_u^2)$	$u_i \sim$iid gamma
Density function of v	$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot \exp\left\{-\frac{v^2}{2\sigma_v^2}\right\}$	$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot \exp\left\{-\frac{v^2}{2\sigma_v^2}\right\}$	$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot \exp\left\{-\frac{v^2}{2\sigma_v^2}\right\}$	$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot \exp\left\{-\frac{v^2}{2\sigma_v^2}\right\}$
Density function of u	$f(u) = \frac{2}{\sqrt{2\pi}\sigma_u} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2}\right\}$	$f(u) = \frac{1}{\sigma_u} \cdot \exp\left\{-\frac{u}{\sigma_u}\right\}$	$f(u) = \frac{1}{\sqrt{2\pi}\sigma_u \Phi(\mu/\sigma_u)} \cdot \exp\left\{-\frac{(u-\mu)^2}{2\sigma_u^2}\right\}$	$f(u) = \frac{u^m}{\Gamma(m+1)\sigma_u^{m+1}} \cdot \exp\left\{-\frac{u}{\sigma_u}\right\}$
Joint density u and v	$f(u,v) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right\}$	$f(u,v) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} \cdot \exp\left\{-\frac{u}{\sigma_u} - \frac{v^2}{2\sigma_v^2}\right\}$	$f(u,v) = \frac{1}{2\pi\sigma_u\sigma_v\Phi(\mu/\sigma_u)} \cdot \exp\left\{-\frac{(u-\mu)^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right\}$	$f(u,v) = \frac{u^m}{\Gamma(m+1)\sigma_u^{m+1}\sqrt{2\pi}\sigma_v} \cdot \exp\left\{-\frac{u}{\sigma_u} - \frac{v^2}{2\sigma_v^2}\right\}$
Joint density v and ε	$f(u,\varepsilon) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon+u)^2}{2\sigma_v^2}\right\}$	$f(u,\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v} \cdot \exp\left\{-\frac{u}{\sigma_u} - \frac{1}{2\sigma_v^2}(u+\varepsilon)^2\right\}$	$f(u,\varepsilon) = \frac{1}{2\pi\sigma_u\sigma_v\Phi(\mu/\sigma_u)} \cdot \exp\left\{-\frac{(u-\mu)^2}{2\sigma_u^2} - \frac{(\varepsilon+u)^2}{2\sigma_v^2}\right\}$	$f(u,\varepsilon) = \frac{u^m}{\Gamma(m+1)\sigma_u^{m+1}\sqrt{2\pi}\sigma_v} \cdot \exp\left\{-\frac{u}{\sigma_u} - \frac{(\varepsilon+u)^2}{2\sigma_v^2}\right\}$

Appendix 2: Envelope theorems applied to the primal and dual problems.

Envelope theorem I: primal constrained output maximisation

$$\max_{\boldsymbol{x}}\{f(\boldsymbol{x}'): \boldsymbol{w}'\boldsymbol{x} = C\}$$

Lagrangean:

$$L = f(\boldsymbol{x}') + \mu(C - \boldsymbol{w}'\boldsymbol{x})$$

FOC:

$$\partial L/\partial x_i = f_i - \mu w_i = 0$$

$$\partial L/\partial \mu = C - \boldsymbol{w}'x = 0$$

These solve for input demand functions (Marshallian in form):

$$x_i = m_i(\boldsymbol{w}', C)$$

Envelope result:

$$\partial L/\partial w_i = -\mu x_i = -\mu m_i(\boldsymbol{w}', C) = \partial y(\boldsymbol{w}', C)/\partial w_i$$

And

$$\partial L/\partial C = \mu = \partial y(\boldsymbol{w}', C)/\partial C$$

Envelope theorem II dual cost minimisation

$$\min_{\boldsymbol{x}'}\{\boldsymbol{w}'\boldsymbol{x}: y = f(\boldsymbol{x}')\}$$

Lagrangean:

$$L = \boldsymbol{w}'\boldsymbol{x} + \lambda\big(y - f(\boldsymbol{x}')\big)$$

FOC:

$$\partial L/\partial x_i = w_i - \lambda f_i = 0$$

$$\partial L/\partial \lambda = y - f(\boldsymbol{x}') = 0$$

These solve for input demand functions (Hicksian in form):

$$x_i = h_i(\boldsymbol{w}', y)$$

Envelope results

$$\partial L/\partial w_i = x_i = h_i(\boldsymbol{w}', y) = \partial c(\boldsymbol{w}', y)/\partial w_i$$

And

$$\partial L/\partial y = \lambda = \lambda(\boldsymbol{w}', y) = \partial c(\boldsymbol{w}', y)/\partial y$$

Appendix 3: List of NACE rev 1 (ISIC rev 2) Sectors

Code	NACE Description	Sector
1	AtB	Agriculture, Hunting, Forestry and Fishing
2	C	Mining and Quarrying
3	15t16	Food, Beverages and Tobacco
4	17t18	Textiles and Textile Products
5	19	Leather, Leather and Footwear
6	20	Wood and Products of Wood and Cork
7	21t22	Pulp, Paper, Paper , Printing and Publishing
8	23	Coke, Refined Petroleum and Nuclear Fuel
9	24	Chemicals and Chemical Products
10	25	Rubber and Plastics
11	26	Other Non-Metallic Mineral
12	27t28	Basic Metals and Fabricated Metal
13	29	Machinery, Nec
14	30t33	Electrical and Optical Equipment
15	34t35	Transport Equipment
16	36t37	Manufacturing, Nec; Recycling
17	E	Electricity, Gas and Water Supply
18	F	Construction
20	51	Wholesale Trade and Commission Trade, Except of Motor Vehicles
21	52	Retail Trade, Except of Motor Vehicles ; Repair of Household Goods
22	H	Hotels and Restaurants
23	60	Inland Transport
24	61	Water Transport
25	62	Air Transport
26	63	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
27	64	Post and Telecommunications
28	J	Financial Intermediation
29	70	Real Estate Activities
30	71t74	Renting of M&Eq and Other Business Activities
32	M	Education
33	N	Health and Social Work
34	O	Other Community, Social and Personal Services
35		Financial intermediation services indirectly measured (FISIM)