Energy Efficiency and the Rebound Effect in Developing Countries

Paraskevas I. Kipouros

Surrey Energy Economics Centre

Faculty of Arts and Social Science

School of Economics

University of Surrey

This dissertation is submitted for the degree of
Doctor of Philosophy (Ph.D.)

2017

Declaration

I herewith declare that this thesis and the work to which it refers are the results of my own efforts. Any ideas, data, images or text resulting from the work of others (whether published or unpublished) are fully identified as such within the work and attributed to their originator in the text, bibliography or in footnotes. This thesis has not been submitted in whole or in part for any other academic degree or professional qualification. I agree that the University has the right to submit my work to the plagiarism detection service TurnitinUK for originality checks. Whether or not drafts have been so-assessed, the University reserves the right to require an electronic version of the final document (as submitted) for assessment as above.

The thesis work was conducted from October 2014 to September 2017 under the supervision of Professor Lester C. Hunt at University of Surrey.

Guildford, United Kingdom.

Signature:

Date:

Acknowledgments

'If I have seen further, it is by standing on the shoulders of giants'

Completion of this thesis was possible with the support of several people. I will be eternally grateful to my teachers and mentors from my childhood till now. First and foremost, I offer my sincerely gratitude to my principal supervisor Professor Lester C. Hunt, who has supported me throughout my thesis with patient whilst allowing me the room to work in my own way. I am also thankful to the co-supervisor Dr. Mona Chitnis as well as to all my colleagues in the School of economics for their support and contibutions.

I am particularly grateful to the School of Economics for the three years scholarship they offer me. Thorough this journey several people supported me with their experience and knowledge contributing to my deeper understanding of the investigated field. I would like to express my special appreciation to Professor Williams H. Greene and Professor Massimo Filippini for the priceless advices. I am also hugely appreciative to Dr. Aristeidis Dadoukis and Dr. Morakinyo O. Adetutu.

Furthermore, I would like to acknowledge all my friends from all over the world for their great support. I also owe special thanks to Miss Valentina Dedi for her unconditional love and support. Finally, special thanks to my friend Dr. Evangelos Paradas for all our conversations and Miss Stavroula Ioakeimidou for her valuable assistance. Last but not least, I am very much indebted to my family. My parents, Ioannis and Despoina, my brother, Konstantinos and my grandmother, Paraskevi.

Abstract

This thesis investigates relative aggregate energy efficiency for a panel of 39 developing countries using two stochastic frontier analysis (SFA) approaches over the period 1989 to 2008. The first adopts an energy demand function (EDF) approach and the second an input distance function (IDF) approach.

The EDF approach attempts to estimate a measure of the 'true' aggregate energy efficiency across the panel of countries over the investigated time. Estimates of the 'true' energy efficiency from this approach approximates the economically efficient use of energy, thus capturing both technical and allocative efficiency. The results from the analysis confirm that energy intensity should not be considered as a de facto standard indicator of energy efficiency. While, by controlling for a range of socio-economic factors, the measurements of energy efficiency obtained by the analysis are deemed more appropriate and hence it is argued that this analysis should be undertaken to avoid potentially misleading advice to policy makers. The energy efficiency results from this first approach are also used to estimate potential reductions in CO_2 emissions that might be achieved if countries were to move towards the estimated efficient frontier.

Using IDF and two-stage dynamic panel data approach both relative energy efficiency and the so-called rebound effect (RE) for each country in the panel is estimated. Benefits from better technologies evoke behavioural responses by economic agents that can cause that the full benefit of the technological energy efficiency improvements can not be realised. Hence, failing to consider the magnitude of the RE may undermine the emissions reductions designed by policy makers. Especially in the case of developing countries, these effects are expected to be higher because of the unmet energy demand.

This is, as far as is known, the first attempt to model energy demand and energy efficiency in a panel of developing countries using both approaches. Moreover, the results from such analysis is arguably particularly relevant in a world dominated by environmental concerns, especially in the aftermath of the Paris agreement in December 2015. the thesis concludes by comparing the different methodologies adopted and the policy messages that come from the analysis.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

EIA	Energy Information Administration
GDP	Gross domestic product
GHG	Greenhouse gases
IEA	International Energy Agency
INDC	Intended Nationally Determined Contributions
Mtoe	Millions tonnes of oil equivalent
PPP	Purchase Power Parity
SFA	Stochastic Frontier Analysis
TFC	Total final consumption
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change

For every good and perfect gift is from above, coming down from You, the Father of lights.

Chapter 1

Introduction

1.1 Background and motivation

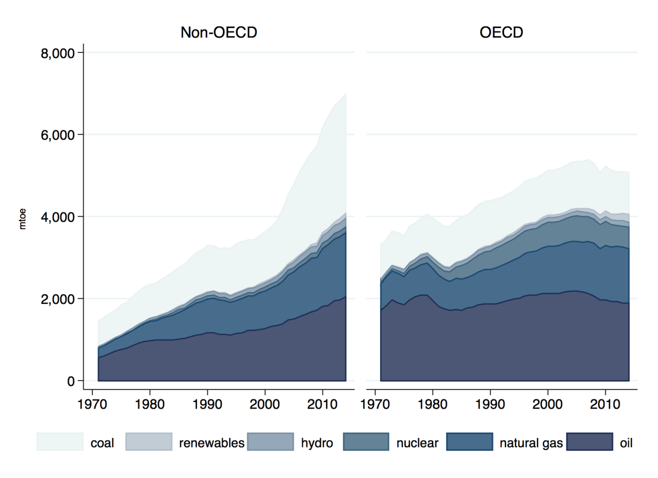
Since the dawn of civilisation, the ability to harness and store different forms of energy has far improved living conditions of people, endowing them with the privilege to indulge in a certain level of comfort. In the aftermath of the Industrial Revolution, increased energy use has fuelled economic development (Fouquet, 2008). However, since the first oil crisis in 1973, governments around the world have found themselves confronting an enormous energy challenge. According to United Nations Framework Convention on Climate Change (UNFCCC), the current patterns of energy supply and use is deemed to be environmentally unsustainable and the hyperbolic reliance on fossil fuels to produce energy threatens the security of the energy system causing catastrophic effects on the Earth's climate (UNFCCC, 2017). Amid growing concerns over volatility in energy prices and the global attention towards limiting CO_2 emissions, the environmental agenda is under the spotlight as never before. This unprecedented challenge to combat the alarming climate change, has put an impetus for urgent, concerted action from both developed and developing countries.

The effects of the climate change are inherently global in nature and require collective decisions. Thus environmental concerns came to the forefront and became an integral aspect of political agendas. The first World Climate Conference in 1979 (UNFCCC, 2017) was the first attempt to foresee and prevent potential changes in climate, caused by human activities and might be adverse to the well-being of humanity. The UNFCCC, adopted in 1992 with the ultimate objective to stabilise greenhouse gases (GHG) concentrations and prevent dangerous anthropogenic interference with the climate system. The Kyoto protocol in 1997 was the first international agreement, linked to the UNFCCC, which commits its Parties to reduce GHG emissions, recognising however that developed countries were historically the principal responsible, as a result of their industrial activity (UNFCCC, 2017) . Governments, in Cancun 2010, as an attempt to address the challenges of climate change comprehensively, agreed to reduce the level of anthropogenic emissions in order to hold the increase in global average temperature below two degrees Celsius, compared with the pre-industrial levels, in accordance with each country's responsibilities and capabilities (UNFCCC, 2017). Two years later, in Doha 2012, a deadline was set for a global climate agreement to be adopted by 2015 and implemented by 2020 (UNFCCC, 2012). Precursory discussions and eulogies regarding environmental issues turned into the first ever universal, legally binding climate deal, in December 2015 in Paris. The Paris Agreement was a major milestone capping more than two decades of global negotiations meant to avert hazards of climate change. As the Paris Agreement comes into force, more than 190 countries have submitted their national GHG reductions pledges (UNFCCC, 2017), known as Intended Nationally Determined Contributions (INDCs), setting clear targets and developing appropriate plans to supervise and achieve these targets.

Despite the concerted efforts, the International Energy Agency (IEA) highlights that global energy-related CO_2 emissions have risen by more than 50% since 1992, from 20.56 Giga tonnes (Gt) to the historic high of 32.38 Gt in 2014, driven mainly by economic growth and increasing share of fossil-energy use especially in non-Organisation for Economic Cooperation and Development (OECD) regions IEA (2016a). Figure 1.1 illustrates the persistent predominance of fossil fuels in energy mix with increasing trends in the case of developing countries.

Additionally, developed countries traditionally emit the vast majority of anthropogenic GHGs. However, according to IEA (2016a), the relative share of developing

Figure 1.1: Primary energy supply by fuel and region



Data source: IEA (2017b)

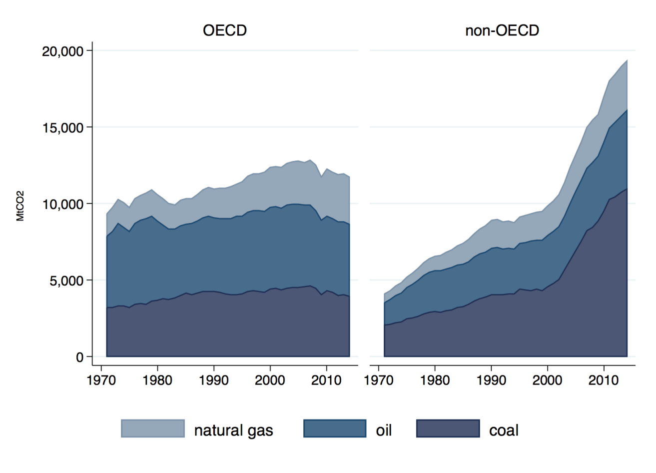
countries'[1] CO_2 emissions surpassed those of industrialised countries in 2005 and have kept rising very rapidly due to increased use on non renewables sources of energy such as coal and oil, as illustrated in Figure 1.2. Furthermore, as Figure 1.3 indicates, emissions from emerging economies accounted for the majority of global emissions (62.06%) in 2014, up from only 30.38% in 1971 IEA (2016a). Besides, IEA (2016a) highlights the role of growing world energy demand in the upward trend in CO_2 emissions, accounting for approximately two-thirds of global GHGs emissions. Additionally, IEA (2016a) suggests that economic activity and demographic developments are the two principal drivers of energy demand, determining the energy requirements and structure of energy systems. Energy use in developing countries has risen more than threefold over the past three decades and according to IEA (2014) is expected to continue increasing rapidly in the future.

Several historic shifts have altered the global energy map. In particular, Figure 1.4 illustrates historical trends of some basic socio-economic indicators for both developed and developing countries while figure 1.5 shows the relative shares of those indicators in developed and developing world in 1971 and 2014.[2] Firstly, energy demand has

[1]The terms of developed, OECD and industrialised counties are used interchangeable to denote the group of high income counties following the classification of International Monetary Fund (IMF) while the terms developing, emerging, non-OECD denote the group of middle and low income countries.

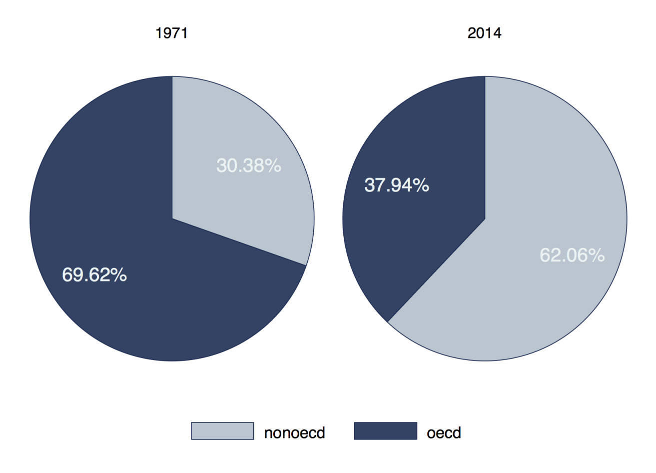
[2]The time selection was determined by data availability from IEA database (IEA, 2017*b*).

Figure 1.2: CO_2 emissions by fuel and region



*Data source: IEA (2017*b*)*

Figure 1.3: Shares of CO_2 emissions by region in 1971 and 2014

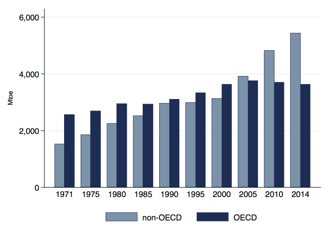


*Data source: IEA (2017*b*)*

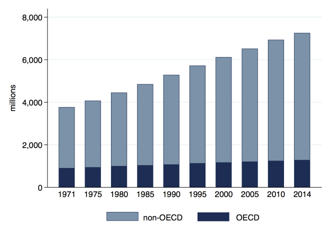
been propelled to increasing levels. In particular, between 1971 and 2014, total final consumption of energy more than doubled (IEA, 2014) while almost all of the growth in energy demand comes from non-OECD countries in recent years. Figure 1.4a depicts the increasing predominance of developing world in global energy demand, as economies move from poverty to relative affluence. Energy demand in non-OECD countries overtook that of OECD in 2005, and continues its rise accounting for approximately 80% globally, thus shifting the centre of energy use to developing counties (IEA, 2014).

Secondly, the level of population would appear to be an important driver of the overall demand for energy services. Historically, according to Population Reference Bureau (2017), from the beginning of the Industrial Revolution through 1950, a cascade of health and safety improvements and advances in technology, radically ameliorate living conditions. Thus swelling global population in an unprecedented scale over little more than a century. More recently, world population growth accelerated after World War II, when the population reside in less developing countries began to increase dramatically, accounting for more than over 90 percent of world population growth (Population Reference Bureau, 2017).

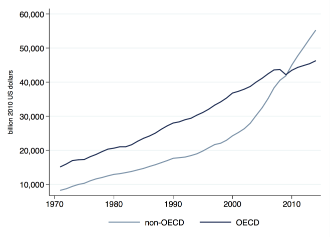
Figure 1.4: Historical trends of basic socio-economic indicators



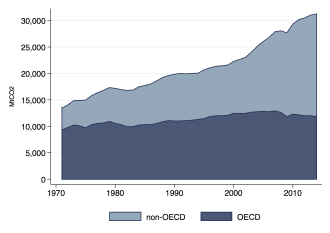
(a) Total final energy consumption



(b) Population



(c) GDP

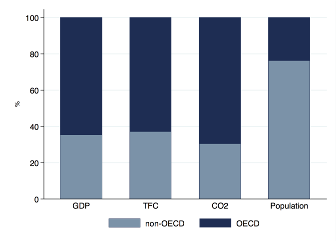


(d) CO_2 emissions

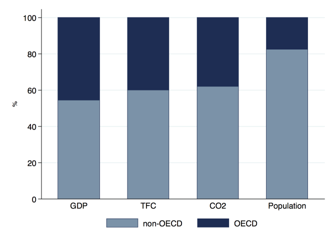
Data source: IEA (2017b)

Finally, as economic growth goes hand in hand with increased access to modern energy services, the economic prosperity of the world's population is rapidly increasing as well, especially in emerging countries. As figure 1.4 illustrates, in recent years the balance of the world economy is shifting away from the developed world towards the emerging economies. In particular, in 1971, developed countries contribute less than 40% in global GDP while, since 2005, emerging economies outperform developed ones, accounting for more than 50% of global GDP in 2014.

Figure 1.5: Relative shares of basic socio-economic indicators by region in 1971 and 2014



(a) 1971



(b) 2014

*Data source: IEA (2017*b*)*

As economies develop, energy needs and priorities change. Many developing countries transitioned from agricultural to the more energy intensive phase of industrial development with concomitant growth in demand for ‘modern’ energy intensive goods and services such as cars, household appliances, heating and cooling systems, etc. Furthermore, according to IEA (2014), increasing energy demand, particularly in developing counties, has been further augmented by demographic pressure and the increased urbanisation rate. Therefore, in the years to come, constant high rates of economic growth will be required in developing countries to provide their rapidly growing populations with improved living standards.

Additionally, IEA (2016d) highlights the fact that approximately 2 billion people of the world population lack access to electricity while nearly 2.7 billion people still rely on the traditional use of solid biomass for cooking, vast majority of them inhabit in developing countries. At the same time, many areas in the world have no reliable and secure energy supplies. Overall, one-third of the world’s population is unable to take advantage of the fundamental amenities and contentment made feasible by modern forms of energy. This lack of access to ‘modern’ energy services severely limits socioeconomic development. Consequently, it is not only crucial for developing countries to meet their growing appetite for energy needs, in order to maintain robust socio-economic development and increase living standards, but the most immediate energy priority is to expand access and increase the reliability of energy systems. In this context, the United Nations for Industrial Development Organisation (UNIDO) highlights that access to clean, reliable and affordable energy services is indispensable for prosperity of a country (UNIDO, 2010) and in case of failure to harness the increasing demand, sustained development may be put in jeopardy.

The judicious use of available resources, adaptation of new technology, provision of appropriate economic incentives as well as the design and implementation of energy policy at national and international levels are prerequisites for achieving sustainable economic development on a global scale. The IEA (2016d) argues that improved energy efficiency is a critical response to the pressing climate change, economic development and energy security challenges facing the world today. The IEA (2015) states that energy efficiency can deliver multiple benefits beyond GHG emission reductions. Improvements in energy efficiency lead in reduced demand for energy services that can improve the security of energy system. Furthermore, energy efficiency improvements can lower the cost of energy system as well as fuel import expenditures creating financial benefits for consumers as well increasing energy security of a country by decreasing the level of reliance by external sources. Besides, the IEA (2015) suggest that improved energy efficiency is one of the most cost-effective and readily available means to mitigate the volatility in energy prices, tackling the potential environmental risk and bolstering sustainable development.

Therefore, energy efficiency is taking its place as a major energy resource in the context of national and international efforts to achieve sustainability targets and according to IEA (2016d) can be proved to be the real protagonist for the remedy of climate change accounting for a substantial part (nearly 40%) of global CO2 emissions reductions by 2050. As revealed by the submitted INDCs the majority of the countries have already designed appropriate energy efficiency policies to achieve their national energy efficiency targets. Hence, researchers along with policy makers, are seeking ways to improve energy efficiency and espouse the benefits that it offers in pursuit of their national policy goals. Besides, for the effectiveness of any energy efficiency policy, it is important to be able to measure country's development and to monitor its progress or lack of progress towards its specific national goals. To this end, it is crucial to develop and maintain well-founded indicators and measurements to better inform policymaking and assist decisions makers to formulate policies that are best suited to national objectives, especially when developing countries are concerned.

However, despite the fact that energy efficiency is in trite use, it is arguably difficult to define or even conceptualise. Energy efficiency seems to be an engineering concept at the most fundamental level. However, it is used by many people in many different ways depending on the focus of analysis since as a contextual concept, it meets various definitions in the literature. In energy economics, energy efficiency is broadly referred to the relationship between the output produced by an economy and the amount of energy consumed to produce it (Bhattacharyya, 2011). Hence, energy efficiency can be broadly defined by the following ratio:

$$\frac{\text{Useful output of a process}}{\text{Energy input into a process}} \tag{1.1}$$

Also, Patterson (1996) proposes a range of energy efficiency indicators allowing the input and the output of this ratio to be quantified by different ways. Hence, Patterson (1996) proposes the following four categories of indicators namely Thermodynamic, Physical-thermodynamic, Economic-thermodynamic and Economic indicators where the numerator and/or the denominator of the ratio in equation 1.1 can be expressed in thermodynamic, physical or monetary units. Besides, energy intensity, which is defined as the ratio of energy consumption to GDP, and in practise is the inverse ratio of economic-thermodynamic indicator proposed by Patterson (1996), is the most often used energy efficiency indicator in macroeconomics analysis.

Furthermore, the concepts of energy intensity and energy efficiency are often used interchangeably, although this is not entirely accurate since trends in energy intensity can be influenced by factors other than energy efficiency. Such factors can be the structure of an economy, the level of industrialisation, affordability of energy services, climate, demographic as well as policy implemented and lifestyle. Besides, according to IEA (2009), energy intensity measures are at best a rough surrogate for energy efficiency. Additionally, IEA (2009) highlights the problem of using energy intensity as a proxy of energy efficiency and notes that "*Energy intensity is often taken as a proxy for energy efficiency, although this is not entirely accurate*". Thus, efficiency impact can be masked by variations in those non-energy related factors and it is impossible to remove or even consider all of the behavioural or structural factors that would be necessary to obtain a 'true' measurement of energy efficiency (IEA, 2009).

This clearly unveils the weakness of using energy intensity as energy efficiency measurement and highlights the need to control the influence of the non-energy related factors in order to get a 'true' measurement of energy efficiency. Moreover, IEA (2009) goes as far to suggest that "*in the absence of reliable, unequivocally calculated and commonly accepted definition, energy efficiency is a vague, subjective concept that engenders confusion rather than insightful analysis*". Therefore, policymakers are likely to have a misleading picture of the real energy efficiency resulting in disguised decisions.

Given the problems discussed above, the first objective of this study is to estimate an aggregate energy demand function in a panel of developing countries using Stochastic Frontier Analysis (SFA) and after controlling for a series of important economic and non-economic factors, to get a 'true' measurement of energy efficiency, consistent with economic theory of production.[3] Thus generating a more reliable energy efficiency indicator for developing countries and providing valuable information to policy makers to address national and international energy, economic and environmental issues.

Achieving the emission reduction goals and targets of the INDCs is a significant challenge for every country and the universe. Managing energy demand is a vital tool to eliminate GHG emissions, notably through energy efficiency improvements which reduce the amount of energy needed to support continued and sustainable economic growth. However, according to IEA (2015), one of the most persistent challenge in designing energy efficiency policy is accounting for the phenomenon called 'rebound effect'. Benefits from the technologies evoke behavioural responses by economic agents that can cause that the full profit of energy conservation can not be cashed. This rebounding energy consumption imposes an important problem when energy efficiency

[3]Filippini and Hunt (2011) as an attempt to distinguish the estimated efficiency scores that gathered from the estimation of a stochastic frontier energy demand function, from the energy intensity uses the term 'underlying energy efficiency'.

policies, which have been implemented on the basis of an expected amount of energy demand and GHG emissions reduction, do not deliver the expected results. As policies to stimulate energy efficiency improvements become a key part of national and international policies to tackle climate change, the magnitude of the potential rebound effect is of vital importance to assessing the effectiveness of those policies. Hence, policy makers need to fully assess and account for any potential rebound effects when planning energy efficiency strategies to ensure that they pose pragmatic targets.

However, analysts and policymakers tend to ignore those so-called rebound effects, despite the fact that a growing body of academic research suggests that they could be significant. A possible reason could be that even though there is no dispute in the literature about the existence of energy rebound effects, as it is rooted in neoclassical economic theory and has been entrenched by behavioural economics,[4] the magnitude and even the definition of rebound effects have been the subject of intense debate. This thesis therefore attempts to address the issue relating with the magnitude of the RE and the appropriate modelling approach, by estimating economy-wide RE for a panel of countries using data for developing countries for the period 1989-2008 and a two-stage econometric procedure.

This chapter introduces the direction of this research, the motivation that has driven this study, and the main research aims and contributions of this thesis. In particular, Section 1.2 presents main research objectives and contributions of the study followed by the Section 1.3 that presents the research questions underpinning this study while Section 1.4 outlines the main structure of the thesis.

[4]Economic dynamics such as substitution and income effects are not the only argument inducing individuals to value energy efficiency improvements. Socio-psychological research has also pointed to several factors such as personal norms, beliefs and attitudes as determinants of human behaviour which could also lead to an increased usage of energy services after an efficiency improvement and thus the existence of the rebound effect. According to Peters et al. (2012), psychological action theories as well as lifestyle approaches can be useful in explaining various behaviours as they capture the social aspects of consumption. Furthermore, Hastings and Shapiro (2013) examine the category budgeting model where individuals keep track of category-specific budgets and try to maintain category spending at a target level in order to explain consumption behaviours in price changing

1.2 Research objectives and contributions

This thesis contributes trifold to the energy economics literature. More specifically, the three main issues considered in the rest of the analysis are:

First, measuring and monitoring energy efficiency indicators has become an important component of energy strategy in many countries around the world. Thus energy efficiency came to the forefront of the scientific research and some approaches have been proposed in the academic literature in order to circumvent the fundamental conceptual difficulties of defining and measuring energy efficiency. This study builds upon the methodology developed by Filippini and Hunt (2011) to estimate the level of the 'true' energy efficiency using SFA in a panel of developing countries using data for the period from 1989 to 2008. Filippini and Hunt (2011, 2012, 2015b) argue that estimates of the 'true' energy efficiency from this approach approximates the economically efficient use of energy, that captures both technical and allocative efficiency. They also highlight that energy intensity should not be considered as a de facto standard indicator of energy efficiency. While, by controlling for a range of socio-economic factors, the measurements of energy efficiency obtained by this analysis are deemed more appropriate and hence it is argued that this analysis should be undertaken to avoid potentially misleading advice to policy makers. Additionally, the use of different econometric specification allows for the estimation of the persistent and the transient energy efficiency of each country and hence allow policy makers to design the appropriate short or long term policies.

Second, even though the RE literature has considerably grown over the last decades, there is no consensus about the magnitude of RE and the apt econometric approach to measuring it. Sorrell and Dimitropoulos (2007) argue that the lack of a widely accepted analytical framework arising from the diversity of methodologies has contributed to the controversies surrounding RE. Therefore, this thesis attempts to address the issues of RE magnitude and the appropriate modelling approach, by estimating economy-wide RE for a panel of countries using data from 1989 to 2018 and a two-stage econometric procedure. In the first stage energy oriented technical efficiency scores are estimated for the panel of developing countries using SFA and input distance function approach while in the second step those measurements are used to estimate the short and long run RE. Literature indicates that there is inadequate empirical evidence to support the magnitude of the RE in the content of developing countries where it is expected to be higher than that of the developed world, since the demand for energy services such as lighting, heating, cooling etc. have yet to be met, (Chakravarty et al., 2013). Hence, as Paris agreement entered into force and countries have started to implement their policies to achieve their respective national goals it is of crucial importance to develop and maintain indicators to proper evaluate the progress of such policies. In this context, this study could offer a useful instrument to policy makers so that the rebound effect is netted out.

Finally, the ultimate goal of any energy policy is the reduction of the anthropogenic GHG emissions. Taking into account how efficient are the countries in the use of energy, policy makers could have a clear picture of the potentials to improve energy efficiency and espouse the benefits of energy efficiency policies. Furthermore, as IEA (2015) argues, policy makers should consider the potential RE when design the appropriate effective strategies. Taking both into consideration this study compute the potential contributions of energy efficiency improvements toward limiting CO_2.

1.3 Research questions

This thesis investigates contentious aspects of energy efficiency and rebound effect using aggregate data in a panel of 39 developing countries from 1989 to 2008. To achieve the objectives as described in section 1.2 , this study addressess the following research questions:

Question 1: What is the 'true' energy efficiency in developing countries?

Question 2: What is the magnitude of the economy-wide rebound effect in developing countries and how that change over time?

Question 3: What is the contribution of energy efficiency improvements towards eliminating CO_2 emissions in developing countries? Does the rebound effect matter?

1.4 Thesis outline

The remainder of this thesis is organised as follows. Chapter 2 presents an overview of the state of the art in the relevant research fields. This chapter provides the theoretical framework that this study has built upon, presents a detailed literature review of the examined topics and concludes by identifying potential contributions. In Chapter 3 the energy demand function approach is adopted in an attempt to estimate a measure of the 'true' aggregate energy efficiency over time and across the 39 developing countries while in Chapter 4 the RE is estimated having previously estimate the energy oriented technical efficiency of the countries using input distance function approach. Chapter 5 concludes this thesis summarising our findings and highlighting our main contributions with respect to the thesis' objectives. Research limitations and the main avenues for future work in the field are also deduced.

Chapter 2

Theoretical framework and Literature Review

As the Paris agreement came into force, the implementation of the designed national energy policies requires accurate measurements of energy efficiency and appropriate indicators to evaluate progress over time. Thus energy efficiency came to the forefront of the scientific research and some approaches have been proposed in the academic literature in order to circumvent the fundamental conceptual difficulties of defining and measuring energy efficiency as well as problems arising from the use of simple ratio indicators, such as the energy intensity, as a proxy of energy efficiency. Based on frontier analysis, this thesis investigates contentious aspects of energy efficiency and rebound effect. Section 2.1 presents the theoretical background developed for measuring efficiency and productivity within the production frontier framework while section 2.2 provides the appropriate literature review on energy efficiency. Additionally, section 2.3 describes the theoretical underpinnings on the concept of rebound effect followed by section 2.4 that provides the literature review on the economy-wide rebound effect.

2.1 Theoretical framework on efficiency and frontier analysis

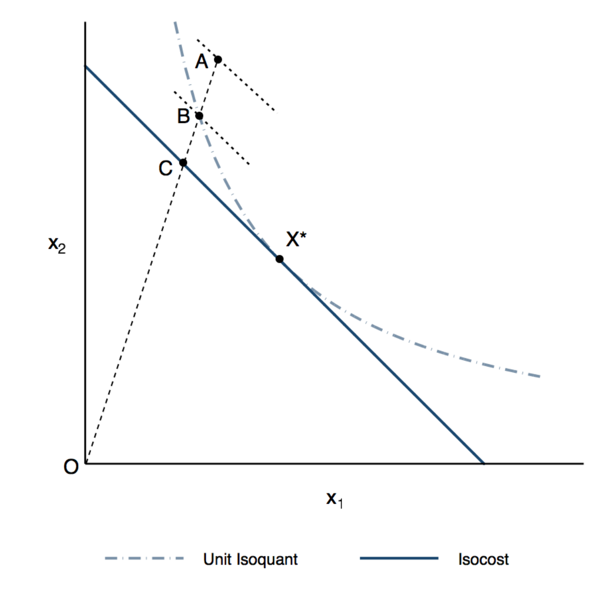
As a measurement of performance, frontier analysis has been widely applied in many economic areas such as energy, environmental, health and education studies and has also found implications in an aggregate as well as a disaggregate level. For instance, Dong et al. (2016) use parametric Frontier Analysis, to estimate the cost and profit efficiency of four Chinese commercial banks using data for the period 2002-2013. Hamidi and Akinci (2016) examine the technical efficiency of health systems in the Middle East and North Africa region using also Frontier Analysis and panel data for 20 countries for the period 1995-2012. Finally, a recent example of the use of non-parametric Frontier Analysis is Toma et al. (2017) who assess and compare the agricultural efficiency of European countries, using appropriate data for the period 1993 to 2013.

According to standard economic theory, decision makers, households and firms, are assumed to be rational. Thus, their actions are often modelled as solutions to optimisation problems. From an economic standpoint, producers' objective is to produce output in an efficient way, that refers to the ability to maximise the output given the technology in place and input resources at their disposal or combine inputs in optimal proportions in light of the prevailing prices and technology available so that to minimise the production cost or finally to maximise the profit given the existing technology and the prices of both inputs and outputs.

However, in practice, not all producers are able or willing to obtain the optimal. Hicks (1935) was the first to challenge the viewpoint of optimisation. Consequently, inefficiency comes to the fore and frontier techniques have been developed to deal with performance measurement of producers who fail to meet the optimising assumption. Historic discussion concerning measurement of productivity and efficiency in the economic literature started with two contemporaneous papers by Debreu (1951) and Koopmans (1951) who make the first systematic efforts in the investigation of efficiency and its measurement. However, it has only been since the pioneering work of Farrell (1957) that serious consideration has been given to the estimation of a frontier production function. The frontier describes the optimum result that producers can produce given the technology and efficiency is defined as the distance between the frontier and the observed results that producers actually get. Reifschneider and Stevenson (1991) claim that it is unlikely that all economic agents operate at the frontier. Hypothetical failure to attain the frontier implies the existence of technical and/or allocative inefficiency.

Farrell (1957) was the first to introduce how to measure cost efficiency and how to decompose cost efficiency into its technical and allocative components. Farrell (1957) sheds light on the different ways in which a firm can be inefficient either by producing less than the maximal achievable output given the level of inputs (technically inefficient) or by not employing the optimum combination of inputs given their prices and marginal productivities (allocatively inefficient). Figure 2.1 explains the analysis of efficiency carried out by Farrell (1957) in a simple example where firms can use combinations of two inputs (x_1, x_2) in order to produce a single output (y) assuming that the production technology described by constant returns to scale. This assumption allows the production frontier to be illustrated by the use of a unit isoquant in the graph. Hence, the unit isoquant describes all the technical efficient combinations of inputs (x_1, x_2). Additionally, given the relative price of the inputs, isocost line indicates the minimum cost required to produce the output level associated with the isoquant.

Figure 2.1: Technical and allocative efficiency measures



Source: Own elaboration, based on Farrell (1957)

The cost-minimising input combination is described at point x^* where the isocost line is tangent to the isoquant. If an economic agent produces the same level of output at point A, which lies above the isoquant, suffers from technical and allocative inefficiencies. In particular, using an input oriented radial measurement of technical, allocative and overall productive efficiency, the technical efficiency (TE) is given by the ratio between the distance from the origin to the technical efficient input combination B and the distance from the origin to the input combination A, $\left(\text{or } TE = \dfrac{OB}{OA}\right)$. Economic agent can produce the same level of output by contracting the use of inputs from A to B. Additionally, the level of allocative efficiency (AE) is given by the ratio between the the distance from the origin to allocative efficient input combination C and the distance from the origin to technical efficient input combination B, $\left(\text{or } AE = \dfrac{OC}{OB}\right)$. Economic agent can produce the same level of output with lower cost by moving from B to C. Finally the overall or cost efficiency (OE) is can be calculated as the product of TE and AE and will be given as the ratio between the distance from the origin to the input combination C and the distance from the origin to input combination A, $\left(\text{or } OE = TE \cdot AE = \dfrac{OB}{OA} \cdot \dfrac{OC}{OB} = \dfrac{OC}{OA}\right)$.

Literature on the Frontier Analysis proposes two basic approaches to measure technical efficiency. The first one is the non-parametric, Data Envelopment Analysis (DEA) and the second is the parametric, Stochastic frontier Analysis (SFA).[1] Each technique has merits as well as demerits. For instance, SFA accounts for statistical noise and can be used to conduct conventional hypothesis tests while it requires to specify a distributional form for the inefficiency term and the specification of a functional form for the production, cost of profit function. On the other hand, the danger of imposing the wrong functional form is avoided by using DEA. Additionally, DEA can easily touch upon multiple inputs and outputs contrary to SFA, which is restricted to the single output case when estimating a production technology. However, any statistical noise, measurement errors, omitted variables and other misspecification are counted as inefficiency in DEA analysis. Building upon Farrell's linear programming technique, Charnes et al. (1978) develop DEA, a non-parametric method that has gained great popularity in the literature. However, DEA does not consider measurement errors and other sources that can affect the statistical noise and are beyond the control of the

[1] There is also the linear programming technique used by Farrell (1957).

firms, such as regulation, weather conditions, structure of the economy etc. As a result, any deviation from the frontier is assumed to have originated due to the existence of technical inefficiency (Coelli et al., 2005). In this sense, DEA is known as a deterministic frontier analysis which seems to suggest the lack of statistical underpinnings. To overcome this limitation, Simar and Wilson (2000) and others attempt to provide a statistical foundation for DEA models using a bootstrapping procedure. However, Coelli et al. (2005), point out that these DEA bootstrapping methods are designed to deal with sampling variability rather than to account for random noise. Additionally, the technique produces a deterministic frontier that is generated by the observed data, so by construction, some individuals are efficient that it is not indispensably correct in particular when outliers are considered. On the other hand, SFA pioneered by Meeusen and van den Broeck (1977) and Aigner et al. (1977) takes into consideration the effect of noise by disentangling the error term into two parts, namely the classical standard error and the inefficiency. Murillo-Zamorano (2004) highlight that the use of both parametric and non-parametric approaches entails advantages and disadvantages. However, neither approach appear to have dominant advantage above the other. This study focuses on parametric, SFA and will be examined in more details in the rest of the chapter.

2.1.1 Stochastic Frontier Analysis

Parametric frontiers, by construction, require assumptions about the distribution of the error term as well a specification of the frontier production function. Given the assumption about the specification of the error term, the literature proposes two main approaches for the estimation of a frontier function, namely deterministic and stochastic econometric approaches. The former accommodates efficiency as an explicative factor for output variations, but still the analysis of random shocks is lacking while the latter separates the effect of noise from the inefficiency allowing for hypothesis testing. In the general, cross-sectional form, a production frontier function can be written as:

$$y_i = f(x_i; \beta)e^{-u} \tag{2.1}$$

where y_i is the level of output produced by individual i using inputs x_i. $f(x_i)$ denotes the production frontier and β are parameters to be estimated. Assuming a Cobb-Douglas logarithmic form, the deterministic production frontier is given by:

$$\ln y_i = \alpha + \sum_{i=1}^{n} \beta_i \ln x_i - u_i \tag{2.2}$$

Three methods have been proposed for the estimation of the parameters of the equation 2.2, namely Goal programming, Corrected Ordinary Least Square (COLS) and Modified Ordinary Least Squared (MOLS). Aigner and Chu (1968) introduced goal programming where the technical efficiency is computed, using mathematical programming techniques, rather than estimated. Thus statistical inference concerning of the calculated parameters becomes complicated and any hypothesis testing is precluded. Additionally, COLS model proposed by Winsten (1957) and MOLS model proposed by Afriat (1972) as well as Richmond (1974). Both COLS and MOLS use OLS in the first step to estimate the parameters of the model and in a second step the intercept parameters are adjusted. In particular, in COLS procedure the intercept parameters are shifted up in order to bound all the data while in the MOLS the error term is assumed to be one-sided and the intercept of the parameter is shifted up by the mean of the assumed distribution. Following deterministic approach and OLS, the estimation of all the parameters of equation 2.2 but the intercept are consistent and unbiased. However, the intercept parameter is still consistent but biased. Hence, distributional assumption of the error and alternative estimation technique such as the Maximum likelihood (ML) is required.[2]

Meeusen and van den Broeck (1977) and Aigner et al. (1977) propose the use of the stochastic production frontier approach to measure the level of productive efficiency of an individual.[3] The error term now consists of two parts. The first part is a random error term v_i account for the statistical noise such as measurement error and mis-specification of the model while the second part, u_i is a non-negative inefficiency component that

[2]Coelli et al. (2005) highlight that ML estimator is asymptotically more efficient than COLS especially when the contribution of technical efficiency effect on the error is relatively large.

[3]Regarding the level and the concept of the analysis the term 'individual' is possible to refer to households, firms or countries

captures the individuals' specific inefficiency. Thus equation 2.1 under the the stochastic production frontier is given by:

$$y_i = f(x_i;\beta)e^{(v_i-u_i)} \tag{2.3}$$

Assuming also a Cobb-Douglas logarithmic form the cross-sectional stochastic production frontier can be re-written as:

$$lny_i = \alpha + \sum_{i=1}^{n} \beta_n \ln x_i + \varepsilon_i \tag{2.4}$$

where the error term $\varepsilon_i = v_i - u_i$. Empirical estimation of technical efficiency requires some distribution assumption for the components of the error term. While v_i is invariably assumed to follow the normal distribution with zero mean and constant variance several distribution assumptions can be applied for the inefficiency term. Most frequently distributions used are the half-normal as well as the exponential distribution, proposed by Aigner et al. (1977), the truncated normal distribution initially introduced by Stevenson (1980) and the gamma distribution proposed by Greene (1980).The most common distribution assumption of the components of the error term in equation 2.4 is the Normal - Half normal[4] whereby:

$$v_i \sim iid\, N(0, \sigma_v^2) \tag{2.5}$$

$$u_i \sim iid\, N^+(0, \sigma_u^2) \tag{2.6}$$

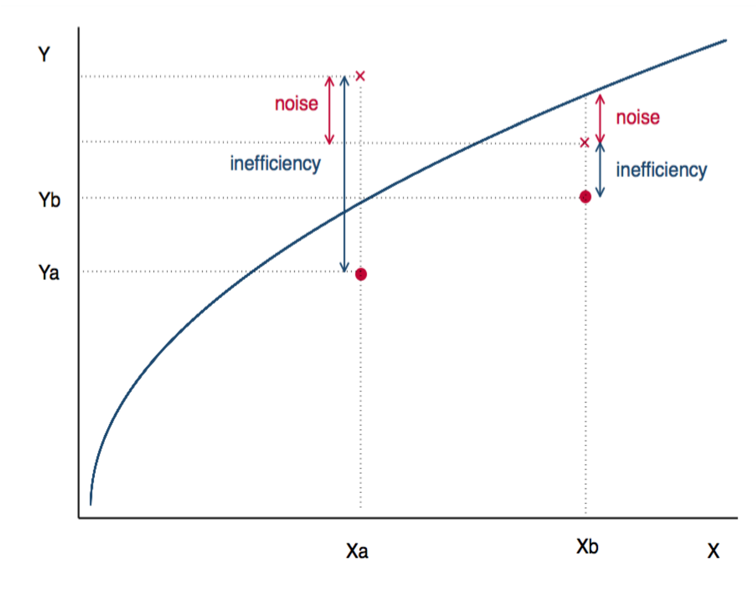
Assumption 2.5 contends that the random error, v_i is identically and independently distributed, following the normal distribution, with zero mean and constant variance. Random error can be either positive or negative. Furthermore, assumption 2.6 says that the inefficiency component of the error term u_i is a non-negative, identically and independently distributed normal random variable with zero mean and constant variance. Additionally, both counterparts of the error term assumed to be distributed

[4]Table A.2 in appendix A illustrates the assumptions for the cases where the inefficiency component of the error term follows the exponential, truncated normal and gamma distribution.

independently of each other and of the regressors.

A stochastic production frontier of two firms a and b is depicted in figure 2.2, where firms utilises inputs X (horizontal axis) in order to produce outputs Y (vertical axis). In particular, firm a uses input x_a to produce output y_a while firm b uses input x_b to produce output y_b. In the absence of inefficiency effects the so-called frontier output of the firm a would lie above the deterministic frontier due to the presence of positive disturbance term while the frontier output of the firm b would lie below the deterministic frontier due to the presence of negative disturbance term. Finally, observed output for both cases always lies below the frontier as $v_i - u_i < 0$. If $v_i - u_i$ is close to zero, then there is significant inefficiency while in the case where $v_i - u_i > 0$ it is possible that the function is mis-specified.

Figure 2.2: The stochastic production frontier



Source: Own elaboration, based on Coelli et al. (2005)

The density function of v_i and u_i respectively is given by:

$$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot exp\left\{-\frac{v^2}{2\sigma_v^2}\right\} \tag{2.7}$$

$$f(u) = \frac{2}{\sqrt{2\pi}\sigma_u} \cdot exp\left\{-\frac{u^2}{2{\sigma_u}^2}\right\} \tag{2.8}$$

As v_i and u_i assumed to be independent, the joint density function will be product of the equations 2.7 and 2.8:

$$f(u,v) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2{\sigma_v}^2}\right\} \tag{2.9}$$

Since $\varepsilon = v_i - u_i$,the joint density function of u_i ad ε_i is described by:

$$f(u,\varepsilon) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon+u)^2}{2\sigma_v^2}\right\} \tag{2.10}$$

Finally, the marginal density function of ε is derived by integrating u_i out of (u,ε) and is given by:

$$f(\varepsilon) = \int_0^\infty f(u,\varepsilon)\,du = \frac{2}{\sigma}\phi\left(\frac{\varepsilon}{\sigma}\right) \cdot \Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right) \tag{2.11}$$

where $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$ and $\lambda = \dfrac{\sigma_u}{\sigma_v}$. As $\lambda \to 0$, either $\sigma_v \to +\infty$ and/or $\sigma_u \to 0$ while when $\lambda \to +\infty$, either $\sigma_v \to 0$ and/or $\sigma_u \to +\infty$. In the first case the standard error dominates the inefficiency component in ε. All deviation from the frontier is due to the noise and the model collapse back to OLS with no technical inefficiency. In the latter case the there is no symmetric error in the model and any deviation from the frontier is due to technical inefficiency. Hence the model becomes deterministic. Overall, λ indicates the relative contribution of the inefficiency component to the composed error term. Finally, $\Phi(\cdot)$ as well as $\phi(\cdot)$ denote the standard normal cumulative distribution and density function accordingly.

Using parametrisation of the equation 2.11 the Log-Likelihood function of n firms is given by:

$$\ln L = -\frac{n}{2}\ln\left(\frac{\pi\sigma^2}{2}\right) + \sum_i^n \ln\phi\left(-\frac{\varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_i^n \varepsilon_i^2 \tag{2.12}$$

Then, by maximising equation 2.12 with respect to the parameters in the model, ML estimates of the respective parameters are obtained. However, the ultimate goal of the Stochastic frontier analysis is not only to estimates the coefficient of the parameters but predict [5] the inefficiency component of the error term.

Having already estimated $\varepsilon = v_i - u_i$ it is possible to derive information on u_i using the conditional distribution of u_i given ε_i. Jondrow et al. (1982) derive the conditional distribution of u_i given ε_i, if $u_i \sim N^+(0, \sigma_u^2)$ as:

$$f(u|\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi\sigma^*}} \cdot exp\left\{-\frac{(u-\mu^*)^2}{2\sigma^{*2}}\right\} / \left[1 - \Phi\left(-\frac{\mu^*}{\sigma^*}\right)\right] \tag{2.13}$$

where $\mu^* = -\varepsilon \cdot \sigma_u^2/\sigma^2$ and $\sigma^{*2} = \sigma_u^2 \cdot \sigma_v^2/\sigma^2$. As $f(u|\varepsilon)$ is distributed as $N^+(\mu^*, \sigma^{*2})$, using either the mean or the mode of $f(u|\varepsilon)$ point estimators of the u_i will be given by:

$$E(u_i|\varepsilon_i) = \mu_i^* + \sigma^*\left[\frac{\phi(-\mu_i^*/\sigma^*)}{1-\Phi(-\mu_i^*/\sigma^*)}\right] = \sigma^*\left[\frac{\phi(\varepsilon\lambda/\sigma^*)}{1-\Phi(\varepsilon\lambda/\sigma^*)} - \left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \tag{2.14}$$

and

$$M(u_i|\varepsilon_i) = \begin{cases} -\varepsilon\left(\dfrac{\sigma_u^2}{\sigma^2}\right) & if \varepsilon_i \leq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.15}$$

accordingly. Having estimated point estimator of u_i, Jondrow et al. (1982) argue that the technical efficiency (also called JLMS estimator) of each firm can be derived by:

$$TE_i = exp\{-\hat{u}_i\}, \tag{2.16}$$

where $\hat{u}_i$ is either $E(u_i|\varepsilon_i)$ or $M(u_i|\varepsilon_i)$.

However, Schmidt and Sickles (1984) note that cross-sectional models appear three decisive drawbacks. In particular:

(i) Firm specific TE can not be consistently estimated using JLMS estimator. ML approach provides consistent estimation for the composed error term that includes information about the inefficiency term and statistical noise. However the variance of the conditional distribution of technical inefficiency remains unchanged as the sample size increases and extra information is included.

[5]Coelli et al. (2005) use the term predict instead of estimate since TE is a random variable and not a parameter of the model

(ii) ML estimation of equation 2.4 requires strong distributional assumptions for both components of the error term in order to disentangle the effects of noise and inefficiency.

(iii) The assumption that inefficiency term is independent of the regressors may be improper since if knowing their relative technical efficiency, firm may affect input choices.

However, Kumbhakar and Lovell (2000) as well as Schmidt and Sickles (1984) state that each of the above mentioned limitations is avoidable by the the use of panel data techniques. Hence, great potential advantages can be derived by modifying cross-section frontier models to allow the use of panel by incorporating time-series observations.

2.1.2 Panel data production frontier models

Pitt and Lee (1981) and Schmidt and Sickles (1984) propose the use of panel data to overcome obstacles of cross-section estimations. Panel data models provide information on firm specific behaviour, both across individuals ($i = 1, ..., N$) and over time ($t = 1, ..., T$) and are favourable in frontier analysis since they allow researchers to avoid the limitations that the use of cross-section imposes. First, panel data contain more information about firm specific performance over time. Hence, the variance of the JLMS estimator should decrease and as $T \to \infty$ and TE estimates tend to be consistent. Furthermore, strong distributional or independence assumptions of the inefficiency component can be relaxed. For instance panel data techniques allow for heteroscedasticity.[6] Several structures have been proposed according whether the inefficiency term change over time or not.

2.1.2.1 Time-invariant inefficiency

Pitt and Lee (1981) and Schmidt and Sickles (1984) initially apply panel data techniques into the frontier framework assuming that the technical inefficiency is time-invariant.

[6]Models with heteroscedastity are discussed in more detail in chapter 4.

In that context, both Fixed Effect Model (FEM) and Random Effect Model (REM) are applicable by using Least Square with Dummy Variables (LSDV) and Feasible Generalised Least Squares (FGLS) estimation techniques accordingly.

- **Fixed Effect Models**

The panel fixed effect, time invariant version of equation 2.4 can be written as:

$$\ln y_{it} = \alpha_i + \sum_n \beta_n \ln x_{nit} + v_{it} \tag{2.17}$$

where $\alpha_i = \alpha - u_i$, denotes the individual specific intercept. It that case no special assumptions about the distribution of u_i is required and is allowed to be correlated with the regressors and with the v_{it}, while v_{it} are assumed to be *iid* $(0, \sigma_v^2)$. There are three techniques to estimate equation 2.17. First by removing α and introducing N dummy variables instead, one for each individual. Equivalently, by keeping α and introducing N-1 dummy variables, to avoid perfect collinearity and finally by applying the within transformation where all data are expressed as deviations from individual means. In the later case the individual specific intercepts are given by:

$$\hat{\alpha} = \max_i(\hat{\alpha}_i) \tag{2.18}$$

and u_i are estimated as:

$$\hat{u}_i = \hat{\alpha} - \hat{\alpha}_i \tag{2.19}$$

which actually ensures that $\hat{u}_i \geq 0, \ \forall i$. Then, individual specific estimates of technical efficiency can be derived by:

$$TE_i = exp\{-\hat{u}_i\} \tag{2.20}$$

Worth noting that this technique, as in the case with COLS, measures the TE relative to the most efficient individual and hence there is at least one individual who appears to be 100% efficient, which is, to a large extent, unrealistic. Besides, Kumbhakar and Lovell

(2000) argue that LSDV provide consistent estimates of β_n as either $I \to \infty$ or $T \to \infty$. Consistency property is regardless of the assumption that u_i is uncorrelated to the regressors. This technique also provides consistent estimates of α_i as $T \to \infty$. Neither consistency property requires normality of the standard error. Notwithstanding the nice consistency properties of the FE estimator, FE model appear a potentially important disadvantage. Namely, any factor that can vary across individuals but is time invariant is captured as technical inefficiency. Hence estimations of TE with LSDV tend to overestimate the level of TE. This drawback intrigues researchers to develop random effect panel data models.

- **Random Effect Models**

In the Random Effect context, unlike FE, u_i is assumed to be uncorrelated with the regressors and v_{it} are randomly distributed with constant mean and variance as $u_i \sim iid(\mu, \sigma_u^2)$. No special distributional assumption is required but as in the case of FE , it is assumed that $u_{it} \geqq 0$ and $v_{it} \sim iid\ (0, \sigma_v^2)$. This modification allows to incorporate time-invariant regressor in the model. The panel, time invariant, random effect specification of equation 2.4 can be written as:

$$\begin{aligned} \ln y_{it} &= [\alpha_0 - E(u_i)] + \sum_n \beta_n \ln x_{nit} + v_{it} - [u_i - E(u_i)] \\ &= \alpha^* + \sum_n \beta_n \ln x_{nit} + v_{it} - u_i^* \end{aligned} \tag{2.21}$$

Using this modification both components of the error term v_{it} and u_i^* have zero means and can be estimated using either or ML technique or two steps GLS. ML approach requires additional distributional assumption for u_i.[7] Adopting the case where $u_i \sim iid\ N^+(0, \sigma_u^2)$ the ML framework for the estimation of the stochastic production frontier within the panel data context with time-invariant TE will be structurally similar with the framework described in the cross-sectional section above, incorporating the time dimension and individual technical efficiencies are generalisations of the formulas used

[7] Pitt and Lee (1981) assume that u_i follow the half normal distribution while Battese and Coelli (1988) use the truncated-normal distribution.

in cross-sectional case[8] in section 2.1.1.

Two-stages GLS on the other hand, does not require any distributional assumptions for u_i. In the first step all parameters are estimated by OLS while in the second step α^* and β_n re-estimated using FGLS. α^* is independent of individual characteristics[9] since $E(u_i)$ is a positive constant. Hence, only one intercept needs to be estimated. Having estimated α^* and β_n, u_i^* is estimated from either the residuals or the Best Linear Predictor (BLUP). In the former case u_i^* can be derived by:

$$\hat{u}_i^* = \frac{1}{T} \sum_T \left(\ln y_{it} - \hat{\alpha}^* - \sum_n \hat{\beta}_n \ln x_{nit} \right) \tag{2.22}$$

and then estimates of u_i can be obtained by means of normalisation:

$$\hat{u}_i = \max_i \left\{ \hat{u}_i^* \right\} - \hat{u}_i^* \tag{2.23}$$

Alternatively, the BLUP of $u_i^*$is will be:

$$\tilde{u}_i^* = -\left[\frac{\hat{\sigma}_u^2}{T \cdot \hat{\sigma}_u^2 + \hat{\sigma}_u^2} \right] \cdot \sum_t \left(\ln y_{it} - \hat{\alpha}^* - \sum_n \hat{\beta}_n \ln x_{nit} \right) \tag{2.24}$$

and then similarly, the estimates of u_i will be given by:

$$\tilde{u}_i = \max_i \left\{ \tilde{u}_i^* \right\} - \tilde{u}_i^* \tag{2.25}$$

Finally, individual specific TE estimations are derived by substituting $\hat{u}_i$ from equation 2.20 with $\hat{u}_i$ and $\tilde{u}_i$ from equations 2.23 and 2.25 respectively. Kumbhakar and Lovell (2000) argue that with large time dimension estimators in 2.23 and 2.25 are equivalent. Additionally, both estimators are consistent as $T \to +\infty$ and $N \to +\infty$ while exactly as the case with FE model COLS, TE is measured relatively to the most efficient individual or in other word at least one of the individuals act entirely efficient. However, including time-invariant regressors in the model it is possible to derive lower TE estimates.

Generally, the three estimators discussed in the context of time-invariant efficiency,

[8]For further details you can see Kumbhakar and Lovell (2000).
[9]and time, as time-invariant models are considered.

namely the fixed effect LSDV estimator, the random effect FGLS or BLUP estimator and the Maximum likelihood estimator appear different properties and imposes different assumptions. Hence, given specific circumstances one estimator may be preferable to other two. For instance, in the case when the sample include large cross-section information and small time horizon, or in the case when time-invariant regressors included in the model, FGLS is preffered to LSDV estimator, while when independence assumptions of effects and regressors are tenable, ML estimator is generally more efficient than FGLS or LSDV, since incorporates distributional information.

2.1.2.2 Time-varying inefficiency

The assumption that technical efficiency remains unchanged over time is quite unrealistic. It is generally expected that managers and policy makers learn form experience and can improve the efficiency levels over time. Cornwell et al. (1990), Kumbhakar (1990) and Battese and Coelli (1992) are among the first to propose the use of stochastic production frontier model with time-varying technical efficiencies.

The Cobb-Douglas production frontier with time-varying inefficiency model is as follows:

$$\begin{aligned} y_{it} &= \alpha_t + \sum_n \beta_n \ln x_{nit} + v_{it} - u_{it} \\ &= \alpha_{it} + \sum_n \beta_n \ln x_{nit} + v_{it} \end{aligned} \tag{2.26}$$

where α_t denotes the common intercept for all individuals at time t and $\alpha_{it} = \alpha_t - u_{it}$ is the individual specific intercept for individual i at time t. Cornwell et al. (1990) modelled the intercept parameters as a quadratic function of time so that individual specific efficiency could be changed from time to time according to the following specification:

$$\alpha_{it} = \theta_{0i} + \theta_{1i} t + \theta_{2i} t^2 \tag{2.27}$$

and TE of each individual at period t is estimated by:

$$TE_{it} = \exp\{-\hat{u}_{it}\} \tag{2.28}$$

where $\hat{u}_{it} = \max(\hat{\alpha}_{it}) - \alpha_t$ and thus, in every period, there is at least one 100% technical efficient individual.

Lee and Schmidt (1993) propose a different form for the time varying efficiencies in which the technical inefficiency effects for each individual at a different time period are defined by:

$$u_{it} = \delta_t u_i \tag{2.29}$$

where δ_ts denote the time effects represented by time dummies while u_i can be either fixed or random individual-specific effects.

If distributional and independence assumptions are tenable, ML techniques could also be applied for the estimation of the stochastic production frontier where technical inefficiency varies over time. Kumbhakar (1990) suggests a model in which the technical inefficiency component of the error term assumed to follow the half-normal distribution, and depend on time according to the following expression:

$$u_{it} = \delta(t)u_i = \left[1 + \exp(\gamma t + \rho t^2\right]^{-1} u_i \tag{2.30}$$

where both ρ and γ are unknown parameters to be estimated. Battese and Coelli (1992) suggest an alternative formulation of time varying efficiencies where the function of u_{it} is given by:

$$u_{it} = \delta(t)u_i = \exp\left\{-\eta(t-T)\right\} u_i \tag{2.31}$$

where u_i assumed to be *iid* that follows a truncated-normal distribution. Finally[10], Battese and Coelli (1995) propose:

$$u_{it} = \exp\left\{g(t, T, \zeta_i t)\right\} u_i \tag{2.32}$$

[10]Literature provides more alternative stochastic frontier models that allow the estimation of time-varying inefficiency. Only few, selective models are presented in this section. For further investigation see Greene (2008).

2.1.3 Persistent and transient inefficiency

In general productive inefficiency can be decomposed into persistent and transient part (Greene, 2005; Filippini and Greene, 2016). These two components are result of different shortfall and completely different policies are required to improve the level of efficiency in each case. In particular, persistent inefficiencies stem from the presence of structural problems related to the organisation of the production process of a firm, any factor misallocations that are hard to change over time and/or the presence of systematic deficiency of managerial skills, in other words organisations do not learn from experience. Transient inefficiencies on the other hand, exist as a presence of non-systematic managerial misconceptions that can be solved within a short period of time.

As described previously, several approaches proposed in the stochastic frontier framework for panel data, that recognise that efficiency can either vary over time and therefore express, to some extent, the transient part of inefficiency or can be time invariant and thus being closer to the persistent part of inefficiency. However, these studies do not address the possibility that the efficiency can be split into two separate parts. In particular, those models that estimate a time-varying TE are generally variants of the random or fixed effects models where inefficiency component includes also the persistent part a_i. Therefore those models are not able to completely isolate the transient part of inefficiency. Additionally, in those models inefficiency term captures any unobserved, time-invariant, individual-specific heterogeneity.

Greene (2005), transforms the original panel data version introduced by Aigner et al. (1977), and proposes two variants, namely the 'True' Fixed Effects (TFEM) by adding firm specific time-invariant effects and the 'True' Random effects (TREM) by including a term for time invariant unobserved heterogeneity and a firm-specific time varying inefficiency term. These models separate unobserved time-invariant effects from time-varying efficiency estimates and therefore, the efficiency estimates obtained with these models provide information on the transient component of productive efficiency. Cobb-Douglas log-linear formulations of the models are:

- **True Fixed Effect Model**

$$\ln y_{it} = (\alpha_i) + \sum_n \beta_n \ln x_{nit} + v_{it} - u_{it} \tag{2.33}$$

where a_i represents time invariant heterogeneity that might be correlated with the other regressors. Then the estimator is a pooled SFA with firm dummy variables added to the stochastic frontier model.

- **True Random Effect Model**

$$\ln y_{it} = \alpha_i + \sum_n \beta_n \ln x_{nit} + v_{it} - u_{it} \tag{2.34}$$

where $\alpha_i = \alpha + w_i$ and $w_i \sim iid\ N(0, \sigma_w^2)$, u_{it} is a time varying inefficiency component, while any unobserved, time-invariant, individual specific heterogeneity are captured by the term w_i. This is a main difference compared with the random effect model as proposed by Pitt and Lee (1981) where the inefficiency component of the error term contains all other time invariant unobserved heterogeneity. Therefore it is expected that REM underestimates efficiency scores. Maximum Simulated Likelihood method is used for the estimation of equation 2.34.

- **Generalised True Random Effect Model**

The Generalised True Random Effects comes as an extension of the TREM, where Greene (2005) adds a time persistent counterpart to the inefficiency term so that both persistent and transient efficiencies can be estimated by the same model simultaneously. The general form of this model is given by:

$$\ln y_{it} = \alpha + (w_i - h_i) + \sum_n \beta_n \ln x_{nit} + v_{it} - u_{it} \tag{2.35}$$

where $h_i \sim\ iid`N^+(0, \sigma_h^2)$. As a result the disturbance term consists of two parts and each part is characterised by a skewed normally distribution.

2.1.4 Input Distance Function

Given that the input set is described by $L(y) = \{x \mid x \text{ can produce y}\}$ and assuming that $L(y)$ satisfies the regularity conditions namely closedness, convexity and monotonicity, Kumbhakar and Lovell (2000) provides the definition of the Input Distance Function (IDF) as follows:

$$D^I(x, y) = \max\{\lambda : x/\lambda \in L(y)\},\ \lambda \geqslant 1 \tag{2.36}$$

It can be show that the IDF satisfies the following properties:

(i) is non-decreasing in inputs x and non-increasing in outputs y

(ii) is linearly homogeneous in inputs x

(iii) is concave in inputs and quasi-concave in outputs

(iv) is equal to unity if x belongs to the frontier of the input set (on the isoquant)

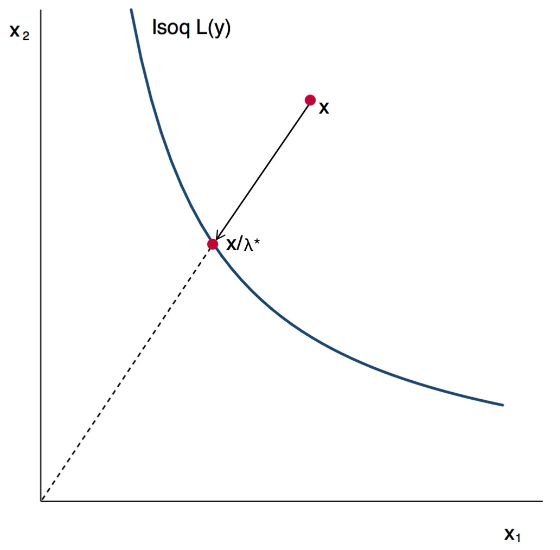
For a given level of output IDF gives the maximum amount by which the input vector can be radially contracted and still remain feasible for the output vector it produces. In figure 2.3, all the minimum combination of inputs x_1, x_2 that can produce a given level of output are described by the input isoquant $L(y)$. Additionally, the input vector x is feasible for output y but y can be produced with the radically contracted input vector x/λ^* and so $D_I(x, y) = \lambda^* \geqslant 1$. Also $D_I(x, y) = 1$ only if individual is technically efficient.

Assuming panel data set IDF for individual i, where $1 = 1, ..., I$, who uses inputs n, where $n = 1, ..., N$ to produce output m, where $m = 1, ..., M$ the IDF can be defined as:

$$D^I_{it} = D^I_{it}(x_{nit}, y_{mit}) \tag{2.37}$$

where x_{ni} denotes the the n-th input of individual i and y_{mi} refers to the m-th output of individual i. Econometric estimation of an input distance function requires specification of the of a functional form for 2.37. Cobb-Douglas and Translog transformation are

Figure 2.3: Input Distance Function (two inputs, one output)



Source: Own elaboration, based on Kumbhakar and Lovell (2000)

among the most common functions used in the literature. Assuming log linear Cobb-Douglas transformation and time-varying inefficiency term, then equation 2.37 can be rewritten as:

$$\ln D^I_{it}(x_{nit}, y_{mit}) = \alpha + \sum_{m=1}^{M} \beta_m \ln y_{mit} + \sum_{n=1}^{N} \beta_n \ln x_{nit} + v_{it} \tag{2.38}$$

The function in equation 2.38 is non-decreasing, homogeneous of degree one and concave in inputs if $\beta_n \geqq 0 \forall n$ and

$$\sum_{n=1}^{N} \beta_n = 1 \tag{2.39}$$

Homogeneity of degree one can be expressed by:

$$\frac{D^I_{it}(x_{nit}, y_{mit})}{x_{Ni}} = D^I_{it}\left(\frac{x_{nit}}{x_{Ni}}, y_{mit}\right) \tag{2.40}$$

where x_{Ni} denotes one of the inputs in the input set as described above. Substituting into 2.38 can be rearranged as:

$$
\begin{aligned}
\ln\left(\frac{D^I_{it}(x_{nit}, y_{mit})}{x_N}\right) &= \alpha + \sum_{n=1}^{N-1} \beta_n \ln x^*_{nit} + \sum_{m=1}^{M} \gamma_n \ln y_{mit} + v_{it} \\
\ln D^I_{it}(x_{nit}, y_{mit}) - \ln x_N &= \alpha + \sum_{n=1}^{N-1} \beta_n \ln x^*_{nit} + \sum_{m=1}^{M} \gamma_n \ln y_{mit} + v_{it} \\
- \ln x_N &= \alpha + \sum_{n=1}^{N-1} \beta_n \ln x^*_{nit} + \sum_{m=1}^{M} \gamma_n \ln y_{mit} + v_{it} - u_{it}
\end{aligned}
\tag{2.41}
$$

where $x^*_{nit} = x_{nit}/x_N$ and $u_{it} = \ln D^I_{it}(x_{nit}, y_{mit})$. Assuming also that $v_{it} \sim\ iidN(0, \sigma^2_v)$ and $u_{it} \sim\ iidN^+(0, \sigma^2_u)$, using ML estimation is is possible to get the radial input-oriented estimation of TE as:

$$
TE_{it} = \exp\{-u_{it}\} \tag{2.42}
$$

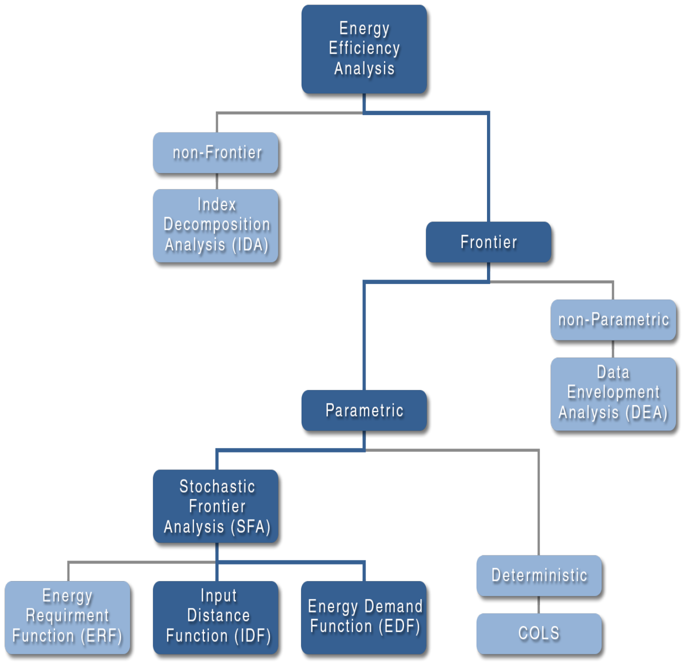
2.1.5 Energy efficiency analysis

Measuring and monitoring energy efficiency indicators has become an important component of energy strategy in many countries around the world. Thus energy efficiency came to the forefront of the scientific research and some approaches have been proposed in the academic literature in order to circumvent the fundamental conceptual difficulties of defining and measuring energy efficiency as well as problems arising from the use of simple ratio indicators, such as the energy intensity, as a proxy of energy efficiency. Such approaches include non-Frontier approach, such as the Index Decomposition Analysis (IDA) and the Frontier Analysis. Figure 2.4 represents the approaches have been used in the literature for the analysis of energy efficiency.

IDA is a non-Frontier, bottom-up framework, used to create energy efficiency indicators that disentangles energy intensity into changes in energy efficiency and non-efficiency factors, such as the structure of economy and fuel mix. Various decomposition techniques have been formulated to quantify the impacts of changes of those factors[11]. IDA was initially proposed by Myers and Nakamura (1978) and since then has been widely used in both energy and environmental economics. However, it should be

[11]For a more general discussion on decomposition methods see Ang (2006).

Figure 2.4: Energy efficiency approaches



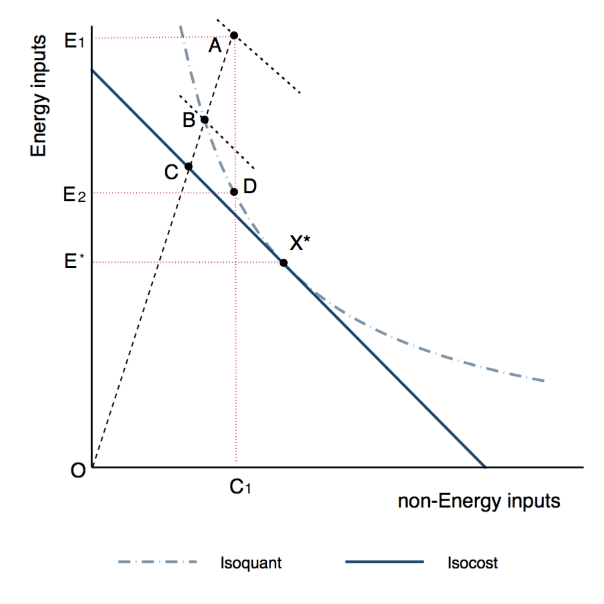
Source: Own elaboration, based on Filippini and Hunt (2015b)

noted that this approach is not directly related to microeconomic theory of production as Frontier Analysis does and for that reason is out of the scope of this study.

On the other hand, there is a substantial growth in the empirical literature discussing various dimensions of efficiency since Aigner et al. (1977) first introduced SFA. Energy economic literature picked up the concept of best practice frontier analysis as a tool to quantify how efficient is the use of energy, considering energy as an input within the process of production. To understand that process it is first necessary to highlight that the demand for energy is a derived demand for products, services or energy services such as heating, cooling, lighting, motion etc. Hence, energy along with labour and capital can be regarded as inputs in the production of several outputs. Following the neoclassical production theory and building upon Farrell's representation as described previously, Huntington (1994) illustrates the case where an economic agent uses energy and non-energy inputs (i.e. capital) in order to produce a given level of output (i.e.

energy services). Figure 2.5 depicts this example by making use of isoquant and isocost lines.

Figure 2.5: Productive efficiency



Source: Own elaboration, based on Huntington (1994) and Kopp (1981)

The cost-minimising input combination is described at point x^* where the isocost line is tangent to the isoquant. If an economic agent produces the same level of energy services at any other combination (i.e. at point A which lies above the isoquant) then it is technical and/or allocative inefficient. Changes in the quantity and combination of inputs it is possible to improve the level of technical and/or allocative efficiency. For instance, by reducing both inputs it is possible that agent produces now the given level of energy services using the combination described at point B. Such a combination is technical efficient, as it lies on the isoquant line, however, is allocative inefficient since it is produced with higher cost. By increasing the use of the non-energy inputs, such as capital and decreasing the use of energy, economic agent is able to reach the optimal combination x^*. This can be the case where a household or a firm decides to replace electric appliances with energy efficient ones or improves the insulation of a building. It is note worthy, that any improvement at the level of technical efficiency, proposed by Farrell (1957) and discussed by Huntington (1994) in the above example, requires proportional reduction of all inputs as technical inefficiency is a result of equiproportionate over utilisation of all inputs. However, having as main objective to estimate the input (energy) specific efficiency the analysis should be based on a non-radial notion of efficiency as proposed by Kopp (1981). Thus, following, Kopp (1981) energy specific technical efficiency in the above example can be expressed as the ratio of the technical efficient use of energy (E_2) and the observed used of energy E_1[12].

Several applications have attempted to use frontier analysis in applied production theory in order to measure the level of the energy efficiency. Zhou and Ang (2008) is an example of a non-parametric frontier analysis approach. They use DEA to measure economy-wide energy efficiency performance of 21 OECD countries using data from 1997 to 2001. DEA as described in previous section is a non-parametric technique and since this study focuses on parametric approaches, stochastic frontier analysis in the concept of energy efficiency and will be examined hereafter[13]. As illustrated in figure 2.4 above, Filippini and Hunt (2015b) suggest three different parametric approaches that can be used in order to estimate the level of energy efficiency, namely the Input Distance function (IDF), the Energy Requirement Function (ERF) and the Energy Demand Function (EDF).

2.1.5.1 (Shephard Energy)Input Distance Function

Following the neoclassical production theory, energy (E) can be combined with other inputs (x) to produce output (y). Conceptually, the production technology can be described by $T(E, x, y) = \{(E, x, y) : (E, x) \text{ can produce y}\}$. Then, the input requirement set will be given by $L(y) = \{E, x : (E, x) \in T(E, x, y) \text{ given y}\}$ and assuming that $L(y)$ satisfies the regularity conditions namely closedness, convexity and monotonicity, Kumbhakar and Lovell (2000) provides the definition of the Input Distance Function (IDF) as follows:

$$D_I(E, x, y) = \max\{\lambda : \frac{1}{\lambda}E, \frac{1}{\lambda}x \in L(y)\},\ \lambda \geqslant 1 \tag{2.43}$$

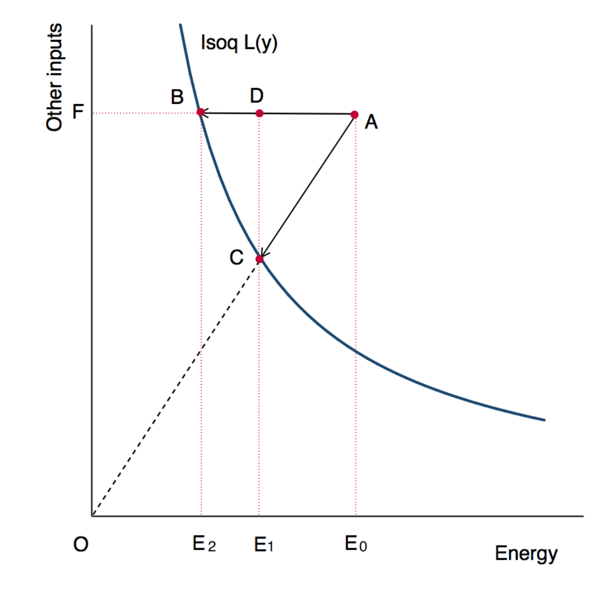
[12]Filippini and Hunt (2011) propose a measurement what they called 'underlying' energy efficiency which is equal to the ratio of the cost minimising level energy (E^*) to the observed use of energy (E_1).

[13]Mardani et al. (2017)provide a comprehensive review on the DEA regarding energy efficiency

Considering all the input factors, but energy, as exogenous, the energy requirement set is described by $L_E(y) = \{E, \bar{x} \in L(y), \text{ given } \bar{x}, y\}$ and the Shephard energy distance function (SEDF) is given by:

$$D_I^E(E, \bar{x}, y) = \max\{\rho : \frac{1}{\rho}E \in L_E(y), \text{given } \bar{x}, y\},\ \rho \geqslant 1 \tag{2.44}$$

Figure 2.6: Shephard Energy Distance Function



Source: Own elaboration, based on Lin and Du (2013)

Figure 2.6 illustrates the case of SEDF as well as the difference between the conventional Shephard distance function and the Shephard energy distance function. Production isoquant L(y) is presented by the curve. Unlike the radial definition of technical efficiency in the context of input distance function, the SEDF does not require all inputs to be radially contracted. Individuals can adjust only the level of energy used to meet the production frontier while keeping other inputs unaffected. Therefore, the Shephard energy distance function is the ratio of FA/FB while the Shephard distance function as described in section 2.1.4 is the ratio of OA/OC which is equal to FA/FD.

Equation 2.44 suggests that $D_I^E(E, \bar{x}, y) \geq 1$. Hence, $\ln D_I^E(E, \bar{x}, y) \geq 0$ and then:

$$\ln D_I^E(E, \bar{x}, y) - u = 0, \qquad u \geq 0 \tag{2.45}$$

If an individual (country, firm etc) is efficient $D_I^E(E, \bar{x}, y) = 1$ but is greater to one when an individual is energy inefficient so that u in a non-negative term that refers to inefficiency. Additionally, as described in section 2.1.4, Input Distance Function is homogeneous of degree 1 in E and x and hence:

$$\kappa D_I^E(E, \bar{x}, y) = D_I^E(\kappa E, \kappa\bar{x}, y) \qquad \forall\kappa > 0$$

so, for $\kappa = \frac{1}{E}$ the above equation becomes:

$$\frac{1}{E} D_I^E(E, \bar{x}, y) = D_I^E(\frac{1}{E}\bar{x}, y)$$

and taking the natural logarithms in both sides derives:

$$\begin{aligned} -\ln E + \ln D_I^E(E, \bar{x}, y) &= \ln D_I^E(\frac{1}{E}\bar{x}, y) \\ -\ln E &= \ln D_I^E(\frac{1}{E}\bar{x}, y) - \ln D_I^E(E, \bar{x}, y) \end{aligned} \tag{2.46}$$

Now, the first part in the right hand side of equation 2.46 can take any log function form such as Cobb-Douglas or the Translog, while the second part denotes the random non-negative inefficiency term u as described in equation 2.45. Assuming Cobb-Douglas transformation and panel data framework, equation 2.46 can be described by:

$$-\ln E = \alpha + \sum_{n=1}^{N-1} \beta_n \ln x_{nit}^* + \sum_{m=1}^{M} \gamma_n \ln y_{mit} + v_{it} - u_{it} \tag{2.47}$$

where $x_{nit}^* = x_{nit}/E$ and $u_{it} = \ln D_{it}^E(E, \bar{x}_{nit}, y_{mit})$. Assuming also that $v_{it} \sim iid\, N(0, \sigma_v^2)$ and $u_{it} \sim iid\, N^+(0, \sigma_u^2)$, the non-radial input-oriented estimation of TE is given by:

$$TE_{it} = \exp\{-u_{it}\} \tag{2.48}$$

2.1.5.2 Energy Requirement Function

Within the context of the neoclassical production theory, energy (E) can be combined with other inputs (x) to produce output (y). Then the input specific (i.e. energy) production frontier function as proposed by Kumbhakar and Hjalmarsson (1995) can be derived by solving equation 2.3 for the input of interest[14] (i.e. energy):

$$E_i = f(\mathbf{x}_i, y_i, z_i)e^{v_i+u_i} \tag{2.49}$$

where z_i denotes a set of time varying or invariant additional covariates other than inputs and outputs including any time dummy or trend in order to capture the impact of technology. where $u_i \geq 0$. In particular, if $u_i = 0$ then individual i is operating on the frontier while if $u_i > 0$ individual waste energy since it uses more than the minimum amount energy for the production of y. The minimal energy requirements function combined with other, non-energy inputs to produce output y can be defined as:

$$E_i^* = f(\mathbf{x}_i, y_i)e^{v_i} = E_i e^{-u_i} \tag{2.50}$$

Then, the excess use of energy (waste energy) for individual i will be equal:

$$E_i - E_i^* = E_i - E_i e^{-u_i} = E_i(1 - e^{-u_i}) \tag{2.51}$$

Boyd (2008) proves that ERF is equal SDEF evaluated at $E = 1$ by defining the SEDF or sub-vector energy input distance function as:

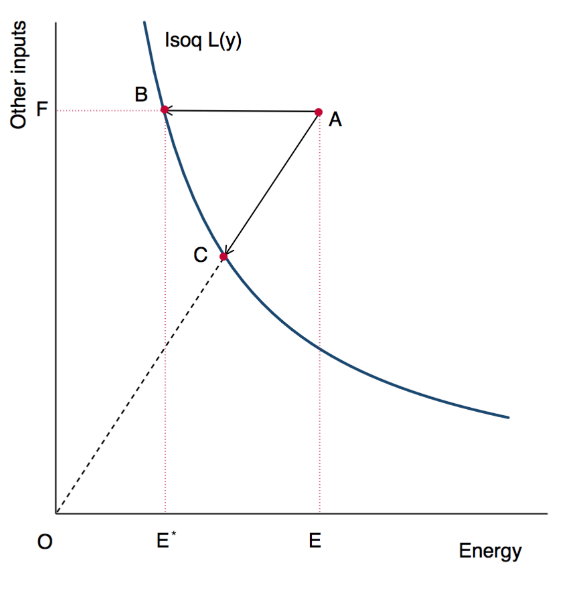
$$D_{SI}(y, x; E) = \frac{E^*}{E} = \frac{f_E(\mathbf{x}_i, y)}{E} \tag{2.52}$$

and imposing the homogeneity property.

Figure 2.7 where L(y) denotes a production isoquant for given level of output y and fixed non-energy inputs. The conversional Input Distance Function then is given by the ratio OA/OC while the sub-vector energy distance function is equal the ratio OA/OB.

[14]Equation 2.49 called Energy Requirement Function (ERF) and gives the minimum amount of energy used to produce a given level of output.

Figure 2.7: Energy Requirement Function



Source: Own elaboration, based on Boyd (2008)

2.1.5.3 Energy Demand Function

Filippini and Hunt (2011) propose an alternative way to provide measurements of energy efficiency based on the estimation of a conditional stochastic energy demand function[15] as follows:

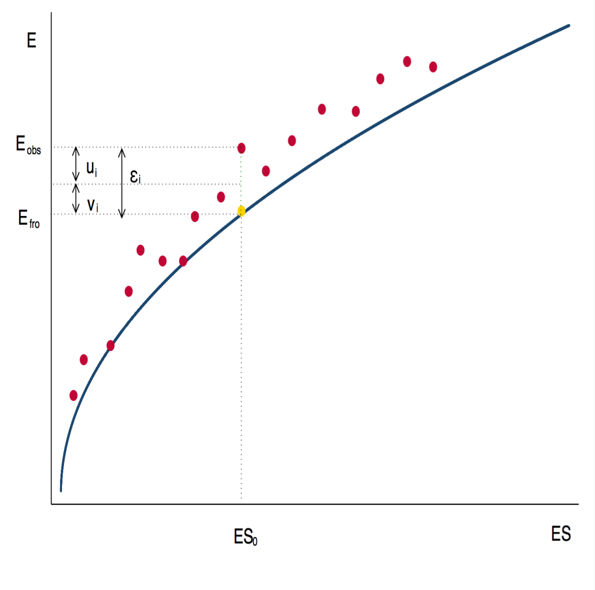
$$E = f(X_i)\, e_i^{\varepsilon} \tag{2.53}$$

where $\varepsilon_i = u_i + u_i$ and X_i includes input prices, output and a set of additional time-

[15]Using a self-duality of the Cobb-Douglas production function, Schmidt and Lovell (1979) derive a system of stochastic input factor demand frontiers and from them a stochastic cost frontier. The estimation of that system satisfies the theoretical restrictions imposed by neoclassical production theory, considering the same time that estimation each of the input demand frontiers could lead to different allocative efficiency from each input. Hence, Filippini and Hunt (2011) approach is an approximation of energy efficiency since estimating only one input demand function theoretical restriction of production theory are not fully satisfied. However, in principle the approach proposed by Filippini and Hunt (2011) indicate the difference between the observed level of energy use of individual i and the optimal use of energy that corresponds to the cost minimising level of energy by estimating the conditional energy demand frontier function. In appendix A is illustrated how the conditional energy demand function is the outcome of a cost minimisation process by energy consumers.

varying or invariant covariates that capture individual specific observed heterogeneity as well as time dummies or time trend that captures exogenous technological effects.

Figure 2.8: Energy Demand Function



Source: Own elaboration, based on Filippini and Hunt (2011)

Figure 2.8 graphically illustrates equation 2.53 that gives the minimum amount of energy required to produce a given level of output given input prices, technology and other individual specific factors. Then any deviation from the frontier indicates inefficiency use of energy (waste energy). In particular, as in Kopp (1981), observed energy demand for individual i differs from the frontier due to the presence of both technical and allocative inefficiency. Finally, a log linear panel data Cobb-Douglas transformation of equation 2.8 will be given by:

$$\ln E_{it} = \alpha + \sum_{n} \beta_n X_{it} + \varepsilon_{it} \tag{2.54}$$

2.1.6 Summary

Section 2.1.5 describes three approaches within the context of SFA, that energy economic literature proposes to effectively estimate energy efficiency. In particular, the estimation of an Energy Requirement Function, a Shephard Energy Demand Function and a conditional stochastic Energy Demand Function. The differences between the SEDF and the ERF is the dependent variable and the sign of the inefficiency component of the composed error term while the differences between both the SEDF and the ERF and the EDF is that the later requires information about input prices as well as output quantities, since conditional stochastic energy demand is the outcome of a cost minimising process and prices are basic component of a cost function, while both SEDF and ERF require information about input and output quantities. Additionally, the estimation of conditional energy demand function derives information about the overall economic efficiency, that is both technical and allocative efficiencies, while estimation of both SEDF and ERF will provide information about the level of energy oriented technical efficiency.

In parametric frontier analysis framework one crucial decision is the selection of an appropriate functional form. Coelli and Perelman (1996) propose that this selection should satisfy three criteria. In particular, the functional form should (i) allow some flexibility, (ii) should be easy to calculate and (iii) in the case of a distance function it is important to choose a functional form that the homogeneity condition can be imposed[16]. Broadly the selection can be made between traditional functional forms such as Cobb-Douglas and functional forms that allow flexibility, in terms that it is not necessary to impose a priori restriction on the values of the first and second partial derivatives of the production function Filippini (2012).

Econometric estimation also requires additional distribution assumptions about the components of the error term while several econometric specifications can be applied both in cross-section and panel data analysis. Finally, in the case of ERF and the SEDF as energy regressed on other inputs and outputs, can potentially bring endogeneity into the model Guan et al. (2009) deal with this problem and propose an two-step approach to estimate an input requirement function even in the presence of endogeneity.

[16]Chambers (1988) provides a comprehensive overview of the use of traditional and flexible functional forms in production theory

2.2 Empirical evidence on energy efficiency

Stochastic Frontier Analysis is a parametric approach that disentangles inefficiency from random noise providing researchers with strong analytical capabilities in estimating efficiency scores. Energy economic literature picked up the concept of best practice frontier analysis to provide accurate estimates of energy efficiency. According to Filippini and Hunt (2015b) Existing literature can be divided in three basic approaches, namely the Shephard Energy Distance function (SEDF), the Energy Requirement Function (IRF) and the Energy Demand Function (EDF).

2.2.1 Energy Requirement Function

Boyd (2008) is an example of using ERF to estimate efficiency in the use of energy in the manufacturing sector. A non-public micro-dataset of wet corn milling plants is used over the period 1992-1997 to analyse the use of energy. Lin and Wang (2014) also use an ERF [17] approach to measure the total factor energy efficiency of China's iron and steel industry using panel data over the period 2005 to 2011 concluding that the particular industry appears to have a great potential for energy reduction via improving energy efficiency. In particular, they estimate an average energy efficiency of almost 70%.

2.2.2 Energy Distance Function

Zhou et al. (2012) use parametric frontier analysis as well but they make use of the Shephard Energy Distance Function (SEDF) to estimate economy-wide energy efficiency performance using cross-section data for 21 OECD countries. Their estimations suggest that energy efficiency varies significantly among the investigated countries indicating some quite low efficient countries such as Canada and Norway (33% and 47% accordingly) as well as fully efficient countries like Italy. They also use a non-parametric approach to compute the level of energy efficiency and compare those measurements with the estimations from parametric approach. They suggest that the choice between SEDF and DEA affects both energy efficiency scores and the relative rank of the coun-

[17] Lin and Wang (2014) start by specifying an input distance function. However, their estimated equation is consistent with an input requirement specification.

ties. Lin and Du (2013) is another example of using SEDF to estimate the level of energy efficiency across several regions in China over the period 1997 to 2010. Results suggest important differences in the level of energy efficiency among the regions studied. In particular there are groups of region that appear to be very inefficient in the use of energy (less than 20% efficiency score) while some other regions are remarkably efficient.

Input distance function also used by Adetutu et al. (2016). However, unlike Zhou et al. (2012), they allow for radially contraction in energy and other inputs in the set of input vector for a given level of output. The main objective of their study however, is to estimate an economy-wide rebound effect using SFA and two stage procedure. In the first stage they estimate energy efficiency scores for a panel of 55 countries, both developed and developing. Using data from 1980 to 2010 their results suggest Switzerland and Denmark to be the most efficient countries in the panel while on the contrary China and Russia the least efficient ones. This is a significant result in the light of their respective contributions to global CO_2 emissions (IEA, 2016a). Additionally, Lin and Long (2015) employ SEDF, utilising provincial data from 2005 to 2011 to estimate the energy efficiency of Chinese chemical industry. They suggest that chemical industry in China appears great potentials for energy savings in years to come, being on average 70% efficient on the way it uses energy. Finally, Shen and Lin (2017) estimate total factor energy efficiency by using SEDF and a panel data for 30 sub-industries over the period 2002-2014. Results show that most of the sub-industries perform very inefficient. However, on average, energy efficiency in Chinese industry increased over the period at an annual rate of 3.63%.

2.2.3 Energy Demand Function

Filippini and Hunt (2015b) highlight that two approaches above give estimates only for the technical efficiency in the use of energy, as an input in the production process. However, from an economic point point of view it is quite important to have information on the level of overall or cost efficiency (i.e. technical and allocative efficiency). Hence, Filippini and Hunt (2011) and Evans et al. (2013) built upon the theoretical framework introduced by Huntington (1994) and motivated by the notion of non-radial input specific efficiency introduced by Kopp (1981), propose a way to measure energy efficiency by estimating a single conditional input demand frontier function, namely the demand function for energy. Then the waste use of energy (energy inefficiency) is defined as the distance between the optimal use of energy that corresponds to the cost minimising input combination to produce any given level of energy services and the observed use of energy. Estimated inefficiency in that case represents both technically and allocative inefficiency.

In particular, Filippini and Hunt (2011) use data from 1978 to 2006 to estimate what they call 'underling' energy efficiency for a panel of 29 OECD countries. They provide empirical evidence that energy intensity, at least for some of the countries, is very poor proxy for energy efficiency according to their measures while they argue that efficiency measurements from the estimation of an energy demand function after controlling for several socio-economic factors is more appropriate measurement of energy efficiency. Filippini and Hunt (2012) use a stochastic aggregate energy demand frontier as well to estimate residential energy efficiency using data for 48 US 'states' over the period 1995 to 2007. This approach estimates the efficient level of residential energy use for each state and measures the relative energy efficiency across the states suggesting that energy intensity should not be considered as an informative proxy of energy efficiency. Furthermore, Filippini et al. (2014) estimate residential energy efficiency in EU 27 member states over the period 1996 to 2009. They also assess the impact of various energy efficiency policies on the efficiency. Their estimates confirm that there is significant potential for energy savings while they also find that financial incentives and energy performance standards as policy instruments have indeed promoted energy efficiency improvements. Otsuka and Goto (2015), following Filippini and Hunt (2011), apply EDF to derive estimates of energy efficiency using data from 47 Japanese prefectures over the period between 1991 and 2007. Authors suggest that the correlation of the ranking between energy intensity and estimated energy efficiency scores is quite high.

Unlike previous empirical work that did not consider the distinction between persistent and transient inefficiency, Alberini and Filippini (2015) estimate the persistent and transient aggregate energy efficiency in US 49 'states'. Based upon Filippini and Greene (2016) they simultaneously estimate both the persistent and the transient components of energy efficiency using household data set of 40,246 observations over the period 1997-2009. In the same vein, Filippini and Hunt (2016) estimate the persistent and transient aggregate energy efficiency in 49 US 'states' over the period 1995-2009 but unlike Alberini and Filippini (2015) they make use of two separate estimation techniques. In particular, they argue that the Mundlak version of the REM approximates persistent notion of energy efficiency while the TRE model gives estimates about transient energy efficiency. Following Filippini and Hunt (2016), Filippini and Zhang (2016) also estimate the persistent and transient energy efficiency of Chinese provinces using data on 29 provinces observed over the period 2003 to 2012.

Lundgren et al. (2016) estimate energy demand and energy efficiency for 14 sectors in Swedish manufacturing at a firm level, during 2000-2008, making use of stochastic frontier analysis (SFA). In line with Filippini and Hunt (2011) they argue that energy intensity is not an accurate proxy of energy efficiency. Broadstock et al. (2016) estimate electricity consumption efficiency at a household level, using cross-section set of data for more than 7,000 Chinese households in 2012. They extend Filippini's and Hunt (2011) framework analysis, making also use of a metafrontier analysis which envelopes subgroup frontiers differentiated by cities, towns and villages. Finally, Marin and Palma (2017) apply EDF and stochastic frontier analysis to investigate the energy efficiency in 10 EU countries. They use household data for the period 1995-2013.

Even though stochastic frontier analysis has gained popularity in recent years, literature that attempts to monitor and analyse energy efficiency performance in developing countries at an aggregate level is extremely scarce and limited only for the case of China. Therefore, despite the fact that this study focuses on the parametric frontier analysis, some non parametric and/or non-frontier studies that deal with the concept of energy efficiency in developing counties, are selectively presented at the rest of this section. In particular, in the content of non-parametric Frontier analysis, Zhang et al. (2011) use a total-factor framework to investigate energy efficiency performance in 23 developing countries for the period 1980-2005 applying DEA. They argue that Botswana, Mexico and Panama are the most efficient counties on average while among the panel Asian developing counties (i.e. China, India, Thailand, Sri Lanka and Zambia) that appear to have an increasing trend in their total factor energy efficiency scores over the research period, 11 countries (i.e. Dominican, Ecuador, Guatemala, Honduras, Iran, Morocco, Paraguay, Peru, Syria and Venezuela) show a decline in their total factor energy efficiency scores and finally, Argentina, Bolivia, Botswana, Chile, Kenya, Mexico and Panama present significant fluctuations.

Unlike frontier analysis, non-frontier analysis to measure energy efficiency in developing counties appears more often in the literature. Cantore (2011) assess the role of energy efficiency and economic structural components in determining the energy intensity by using the non-frontier, Fisher Ideal Index energy intensity decomposition technique in a panel of 20 developing countries. His results suggest that the majority of the counties present a negative trend in their energy intensity and that energy efficiency dominant the structural effects. He also argues that there appears to be a great heterogeneity across countries since some countries show significant fluctuations in their energy efficiency effects. Jimenez and Mercado (2014) use IDA approach to decompose the energy intensity into the relative contributions of energy efficiency and economic structure in a panel of 75 countries. They suggest that the overall downward sloping of energy intensity is mainly attributable to efficiency improvements, while the structural effect does not represent a clear source of change. They also highlight the case of Latin America countries where results show that energy intensity has decreased on average by 17% during the period 1970-2010 but presenting a great valuation and slightly increased for the period 1990-2000. Finally, Voigt et al. (2014) use IDA in several sectors of 40 major economies, including some developing economies. The decomposition analysis highlights that the decline in aggregate energy intensity over the period 1995-2007 is driven mainly by an increase in the efficiency of production through the use of better technology. Table 2.1 ppresent a summary of the the empirical studies reviewed in this chapter.

Table 2.1: Summary of SFA studies on energy efficiency

Author(s)	Country	Analysis level	Period	Methodology	Econometric techniques
Developed counties					
Boyd (2008)	US	manufacturing	1992-1997	ERF	–
Filippini and Hunt (2011)	OECD	aggregate	1978-2006	EDF	POOLED, TRE
Filippini and Hunt (2012)	US	residential	1995-2007	EDF	POOLED, REM, MREM
Zhou et al. (2012)	OECD	aggregate	1992	SEDF	–
Filippini et al. (2014)	EU-27	residential	1996-2009	EDF	BC95, MBC95, TFEM
Alberini and Filippini (2015)	US	households	1997-2009	EDF	REM, TREM, GTREM
Adetutu et al. (2016)	OECD/non-OECD	aggregate	1980-2010	SEDF	BC92, POOLED, RSCFGH, Hadri99
Otsuka and Goto (2015)	Japan	regional	1991-2007	SEDF	POOLED
Filippini and Hunt (2016)	US	aggregate	1995-2009	EDF	MREM, TREM
Lundgren et al. (2016)	Sweden	multi-sectors	2000-2008	EDF	BC95
Marin and Palma (2017)	EU-10	aggregate	1995-2013	SEDF	TREM, TFEM
Developing counties					
Lin and Du (2013)	China	regional	1997-2010	SEDF	BC92
Lin and Wang (2014)	China	multi-industries	2005-2011	ERF	BC95
Lin and Long (2015)	China	chemical industry	2005-2011	SEDF	BC92
Broadstock et al. (2016)	China	household	2012	EDF	BC95
Filippini and Zhang (2016)	China	regional	2003-2012	EDF	REM, MREM, TREM, MTREM
Shen and Lin (2017)	China	sub-industies	2002-2014	SEDF	BC92

*Note:**TREM:** True Effect Model, **REM:**Random Effect Model, **MREM:** Mundlak Random Effect Model, **GTREM:** Generalised True Effect Model, **BC:**Battesse Coelli, **TFEM:** True Fixed Effect Model, **MTREM:** Mundlak True Effect Model*

2.2.4 Summary and contributions

In general, some recent studies analyse the level of energy efficiency using stochastic or non-stochastic techniques. However, the substantial body of the energy economic literature focuses on industrialised countries while as for the developing world, China has attracted the main attention of the researchers. Besides, there are studies that estimate or compute the level of energy efficiency in a specific in an aggregate or desegregate level. The existing literature that studies energy efficiency in developing countries is quite limited and suggests a great heterogeneity across the research countries.

A key aim of this study is to estimate the 'true' energy efficiency in a panel of developing countries over the period 1989-2008. To that end, SFA analysis will be used and after controlling for a series of important socio-economic factors, this study provides measurements of the 'true' energy efficiency levels for each country in the panel. As illustrated by Filippini and Hunt (2011, 2012) and Filippini et al. (2014), SFA is considered to provide more appropriate measures of energy efficiency than energy intensity. Hence, this study contributes to available literature as this is, as far as is know, the first attempt to apply benchmarking parametric stochastic frontier technique to econometrically estimate the energy efficiency of developing counties. This study also contributes to the literature from an econometric point of view as applies a novel approach introduced by Filippini and Greene (2016) and allows for a separating of the level of energy efficiency into a transient and a persistent part. Necessary information for governments to design an effective energy policies. In the aftermath of Paris agreement in December 2015, where almost all developed and developing countries armed their emissions reduction up to 2020, this study could offer an ample scope and indispensable guide for policy makers around the world operating as a useful tool in designing and implementing national energy strategies and assist to avoid potentially misleading policy decisions.

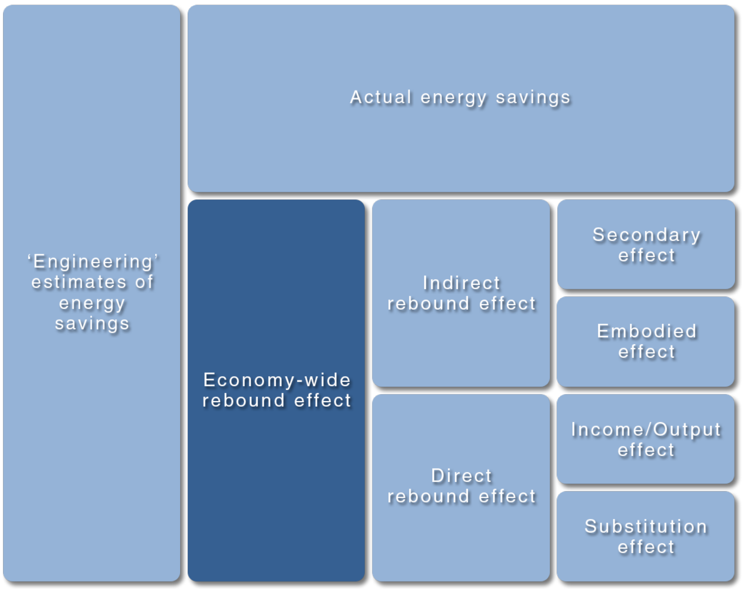
2.3 Theoretical framework on the rebound effect

Nations around the world are seeking ways to reduce their CO_2 emissions as a collective attempt to tackle climate change (UNFCCC, 2012). According to IEA (2016c) energy efficiency is considered to be the most prominent, cost-effective policy that could also be employed forthwith to abate the calamitous environmental effects of the climate change. However, the effectiveness of energy efficiency policies may be imperilled if policy makers do not pay attention in a range of mechanisms known as the 'rebound effects' that may reduce the size of potential energy savings achieved, due to energy efficiency improvements. This is because benefit from the technologies evoke behavioural responses by economic agents (households and firms) that can cause that the full profit of energy savings cannot be cashed.

Jevons (1865) was the first economist who touches upon the idea of the rebound effect with his highly cited work, known as 'Jevons Paradox'. However, the idea of the RE remained on a hiatus until Brookes (1979) and Khazzoom (1980) shed light on the paradoxical relation between increased energy efficiency and increased demand for energy services, when the debate re-emerged and rebound effect (RE) gained prominence in the energy economic literature. Saunders (1992) christens this relation as the 'Khazzoom-Brookes Postulate' and associates RE analysis within neoclassical theory.He suggests that energy efficiency improvements could magnify rather than diminish energy demand highlighting two main paths, (i) by making energy effectively cheaper and (ii) by boosting economic growth. In the first case economic agents will adopt to price changes and they will adjust their energy needs given the new relative prices while in the second case economic growth will inevitably induce higher demand for energy.

Even though there is no clear-cut definition of the rebound in the literature, it is broadly accepted that several mechanisms may reduce potential energy savings from improvements in energy efficiency. Greening et al. (2000) and Sorrell and Dimitropoulos (2007) distinguish those mechanisms into direct, indirect and economy-wide effects. Figure 2.9 illustrates these classifications of the rebound effect. Actual energy savings arising from improvements in energy efficiency in an economy would be less than the expected energy savings (engineering predicted) due to the presence of the economy-wide rebound effect which can be broadly decomposed into the direct and indirect effects. Each of these mechanisms are presented in greater detail below.

Figure 2.9: Clarifications of rebound effect



Source: Own elaboration, based on Sorrell and Dimitropoulos (2007)

2.3.1 Direct rebound

Direct rebound effects refer to specific energy services, such as heating, cooling, lighting and motion. Improved energy efficiency will drop the marginal cost of supplying and consequently, the implicit price of that service will be reduced, thus increasing demand of the specific service.[18] Direct rebound effect can be decompose the into substitution

[18]In general microeconomic theory suggests that a change in the price of a commodity affect the demand of the same commodity as well as other commodities through two channels. As a commodity becomes relatively cheaper for instance, consumers will substitute the other commodities with cheaper one to keep their utility constant (substitution effect). Additionally, as the real disposable income increases consumers are able to consume more from everything and enjoy higher utility (income effect). The total price effect is the sum of individual effects, usually referred as Slutsky decomposition. However, the relative size and the sign of each component may vary widely given specific market and/or product characteristics. For instance, if a commodity considered to be an 'inferior good', the income effect for consumers may reduce

and income/output effect that are equally applied to both consumers and producers.

(a) **Substitution effect**

Both households and firms will adopt to price changes following improvements in energy efficiency.

(i) **Substitution effect for consumers**

Figure 2.10 depicts the decomposition of the rebound effect from a consumers perspective. Initial equilibrium for individual A is at point A where the budget constraint, the slope of which is given by the ratio of the prices of (specific) energy service and other goods, tangent the indifference curve. An improvement in energy efficiency of a specific energy service will reduce the effective price of that service. Thus the slope of the budget constraint changes and the budget line becomes flatter. As the effective price of energy decreases, consumers will move along their initial indifference curves (U_0), substituting other commodities with the relatively cheaper energy service to keep utility constant. This case is called substitution effect and illustrated in figure 2.10 by the movement from A to C.

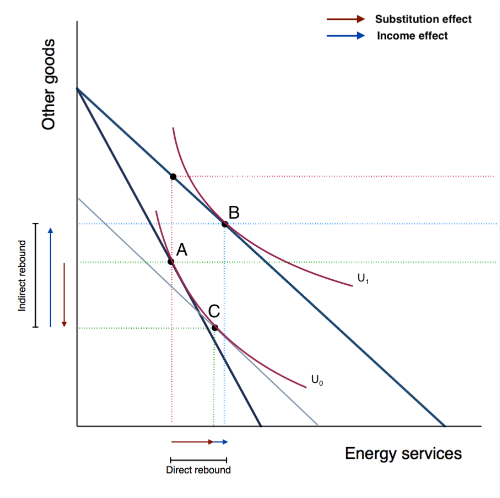
(ii) **Substitution effect for producers**

Reflects the case when the relatively cheaper energy service substitutes for the use of other inputs, such as capital, labour and materials, in the production of a given level of output. Figure 2.11 illustrates the decomposition of the rebound effect from a producer perspective. Similarly with consumers, given the price of energy and non-energy inputs, initial equilibrium for firm which produces a given level of output is at point D where the Isocost line tangent isoquant (Y_0). Following energy efficiency improvement the effective price of energy decreases and therefore the isocost line will pivot outward. [19] As the effective

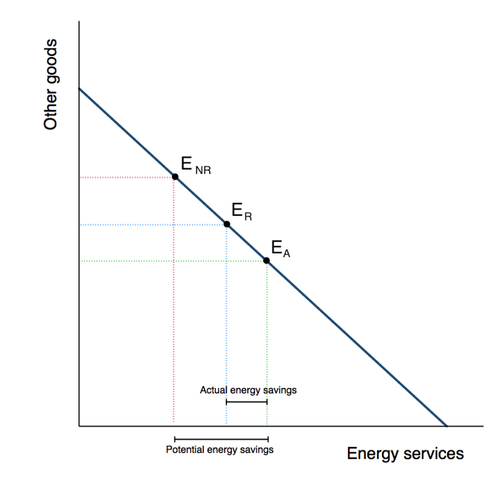
demand of that service, rather than increase.

[19] Substitution is represented in Figure 2.11 with a movement along an isoquant in response to a decrease effective price of energy. This case requires investment in technologies that already exist and thus firms can produce the same level of output by altering their input combination. However, according to Sorrell et al. (2007), it is possible that efficiency improvements refers to the development of new technologies that shift the isoquant to the downward, allowing the same level of output to be produced from a lower level of inputs.

Figure 2.10: Rebound effect: Slutsky decomposition



(a)

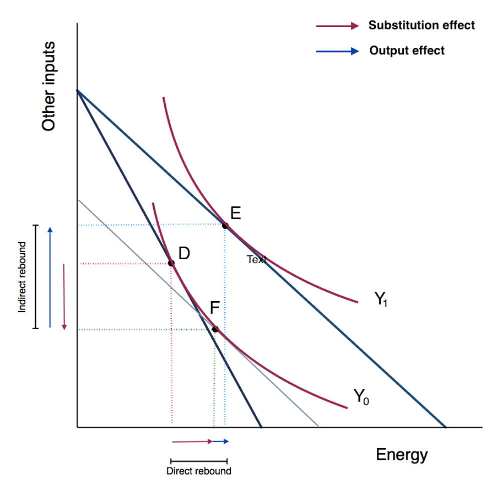


(b)

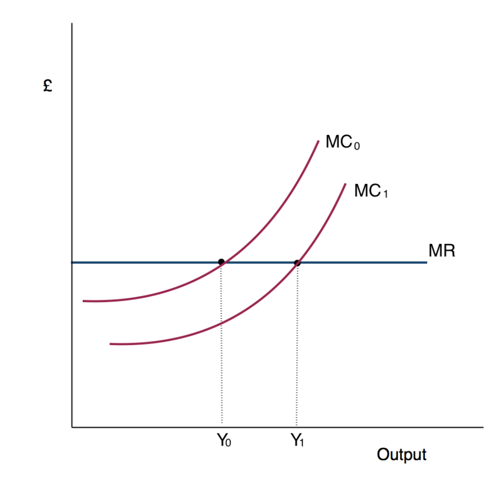
source: Own elaboration based on Thomas and Azevedo (2013).

price of energy decreases, firms will are able to produce the initial amount of output by substituting other inputs with the relatively cheaper energy (movement along the initial isoquant, Y_0). This case is called substitution effect and illustrated in figure 2.11 by the movement from D to F.

Figure 2.11: Substitution and Income effect from producers perspective



(a)



(b)

source: Own elaboration

(b) **Income/Output effect**

(i) **Income effect for consumers**

Lower effective price for energy means higher disposable income for the consumers. Graphically higher income will parallel shift the budget line upward and consumers will reach new equilibrium, away from point A, at point B where they consume more energy as well as other goods and enjoy higher level of utility ($U_1 > U_0$). This case is called income effect and illustrated in figure 2.10 by the movement from C to B.

(ii) **Output effect for producers**

Cost savings due to energy efficiency improvement allow a higher level of output to be produced. Firms no longer produce output Y_0. Given the lower price for input energy, firms maximise profits by producing Y_1, where firms' new marginal cost ($MC_1 < MC_0$) curve with intersects marginal revenue (MR) curve.[20] New equilibrium will be at point E where firm employ more from energy and non-energy inputs and produces more output (Y_1).

2.3.2 Indirect rebound

Improvements in energy efficiency not only directly affect energy consumption, but it is also possible that have impact through indirect channels. Indirect rebound effects can take a number of forms and affect energy demand in different time. According to Sorrell and Dimitropoulos (2007), indirect rebound can be decomposed secondary effects and embodied effects.

(i) **Secondary effects**

Secondary effects are also apparent to both to consumers and producers.[21] As consumers' disposable income increase, equilibrium moves at point B (in figure

[20] MR is fixed and equal to output price for perfectly competitive firms

[21] Greening et al. (2000) suggest that these secondary effects from improvements in energy efficiency are relatively small as energy makes up a small share of total consumer expenditure. However this is not always the case when developing counties involved. Urbanisation usually involves high energy expenditure rates

2.10) where higher level of utility can be achieved (U_1) by increasing demand for both energy and other goods and services. Increasing demand for all goods and services (including energy) in turn create requisiteness for a higher level of output, such that more factor inputs, including energy are required. Hence equilibrium moves from point D at point E where firms produce more output ($Y_1 > Y_2$) using more from both energy and non-energy inputs.

(ii) **Embodied effects**

To achieve energy efficiency, usually some actions (such as installing more efficient appliances) are required. These appliances and/or actions themselves require energy in their production, thus embodied energy effects refer to the energy consumption required to achieve energy efficiency improvement.

2.3.3 Economy-wide rebound

Economy-wide rebound effect refers to the sum of the direct and indirect rebound effects. As an improvement in energy efficiency simultaneously increases consumers' real disposable income and expands production possibilities of firms, economy-wide rebound effect describes eventually a net effect of numerous adjustments that are mutually interdependent and individually characterised by great complexity. Those adjustments, from households and firms, could be highly significant, when aggregated at an economy level (Greening et al., 2000).

Estimating economy-wide rebound effect in a panel of developing counties is one of the objectives of this study. Therefore, having already discussed the clarification of the rebound effects, the literature review hereafter focuses on the concept of the economy-wide or macroeconomic rebound effect.

2.4 Empirical evidence on economy-wide rebound effect

Sorrell and Dimitropoulos (2007) suggest that empirical evidence on the RE is ambiguous and inconclusive highlighting that quite many different definitions of the RE have been used in the literature by different authors. This lack of consistency in definition of the rebound effect, its sources and the relationship between them, as well as lack of a common approach to measure it make the estimation of the economy-wide rebound effect a challenging issue the existing empirical literature both confusing and contradictory. In the rest of the chapter literature related to the economy-wide rebound effect is presented. As the focus if the analysis in this study is the energy efficiency and the rebound effect in developing countries, studies presented hereafter are separated into these two groups for convenience and comparison reasons.

2.4.1 Developed countries

Haas and Biermayr (2000) evaluate the magnitude of the rebound effect for residential space heating in Austria using time-series and cross-section analysis covering the period 1970-1995. Results of this study suggest rebound effect between 20 and 30% which concludes that energy efficiency improvements leads to energy saving and consequently to a reduction in the level of CO_2 emissions. However, actual saving are less than the engineering calculated savings due to the presence of the rebound effect.

Bentzen (2004) estimates the rebound effects for the US manufacturing sector by applying the dynamic OLS method (DOLS) in the context of a translog cost function framework, using time series data over the period 1949-1999. His results indicate a rebound effect for the US manufacturing industry of 24%.

The Computable General Equilibrium (CGE) model is applied by Grepperud and Rasmussen (2004) in the context of macro-economic analysis of rebound effects at industry level. The main focus of this study lies on the effects of energy efficiency improvements in electricity and oil consumption across different sectors of Norwegian economy namely manufacture of pulp and paper, manufacture of metals, chemical and mineral product, finance and insurance, fisheries and road transport while the production technology is represented by nested CES production functions. Results suggest that rebound effects vary across the sectors of the economy. Significant rebound effect appears in manufacturing sectors, but weak or insignificant in the other sectors. For instance, energy efficiency savings in metals manufacturing industry leads to 17.8% increase in electricity consumption and 87.5% increase in oil while the finance and insurance sector witnessed a 36.1% reduction in electricity demand and 1% fall in oil consumption as energy costs constitute a small share of total costs in the sector. Findings of this study are in contrast with those of Saunders (1992), where the demand for energy was found to increase in response to energy efficiency improvements. These differences may attributed to the different aggregation level across these two studies. It is also worth mentioning that even though Saunders (1992) discusses the rebound effects within the framework of the macro-economics neoclassical growth theory, the absence of prices suggests that the economy-wide interrelations are not captured.

Washida (2004) also applies a CGE model to estimate the rebound effects from energy efficiency improvements using data for Japan. Japanese economy is disaggregated into 33 industrial sectors, including *inter alia* energy sectors such as oil products, coal products, electricity and gas supply and the impact of energy efficiency improvements on total CO_2 emissions is simulated for the appraisal of environmental policies designed. Results indicate significant sizes of the rebound effects that vary from 35% to 70% dominated by the elasticity of substitution in industrial technology and consumers' utility functions. Finally, authors argue that failure to take into consideration the rebound effect, environmental policies can be misrepresented. Given the large magnitude of the estimated rebound effects, Washida (2004) suggest that future research should pay attention on the effectiveness of policies such as energy environmental taxes and behavioural changes.

Allan et al. (2007) apply an economy-energy-environment CGE model for all production sectors of the UK economy for the year 2000 to measure the impact of a 5% energy efficiency improvements across all the production sectors. For the calculation of the rebound effects the change in production in energy sectors is compared against the initial intermediate domestic demand for that energy type. This difference is allotted into changes in intermediate demand and in final demand for electricity and non-electricity energy production. In particular, Allan et al. (2007) found that for the total energy demand, rebound is equal to 61.6% and 54.6% in the electricity and other energy accordingly in the short run, while the corresponding long-run total rebound for electricity and other energy production are found to be 27% and 30.8%. In any case there is no evidence for backfire.

Barker et al. (2007) examines the macroeconomic rebound effect for the UK economy arises from improvements in energy efficiency due to implication of energy policies and programmes, using an energy-environment-economy (E3) model. Results suggest that macroeconomic rebound effect emanating from UK energy efficiency policies for the period 2000-2010 is found to reach 11% by 2010, averaged across sectors, while adding the direct rebound effect of 15%, the magnitude of the total rebound effect arising from form the implication of energy efficiency policies is calculated to be 26%.

Brännlund et al. (2007) calculate rebound effects in greenhouse emissions, namely carbon dioxide (CO_2), sulphur dioxide (SO_2) and nitrogen oxide (NO_x). They explore three different scenarios to evaluate the impact of exogenous technological progress, in terms of an increase in energy efficiency, on the consumption choices by Swedish households and thereby emissions of CO_2 , SO_2 and NO_x. They adopt an Almost Ideal Demand (AID) model using Swedish quarterly data for the period 1980:Q_1-1997:Q_4. First scenario assumes 20% increase in energy efficiency in transport sector that lead to rebound effect of the order of 7.5%, 4.1% and 7.9% in CO_2 , SO_2 and NO_x respectively. The second scenario that assumes a 20% increase in energy efficiency for heating resulted in a 7.4%, 11.6% and 4.7% rebound effect in CO_2, SO_2 and NO_x accordingly. Finally, in the last scenario scenario, assuming a 20% increase in energy efficiency for both transportation and heating, the estimated rebound effects for CO_2 is 15.3% while the corresponding levels for SO_2 and NO_x are 16.1% and 12.9% respectively.

Furthermore, the main focus of Vikström (2008) is to present a framework were the rebound effect can be used as part of the explanation of Environmental Kuznets Curve dynamics. He adopts a multisectoral CGE model for a small open economy and assumes efficiency improvement of the order of 15% for all sectors but the energy producing sectors while for the latter an efficiency improvement of 12% is assumed.Vikström (2008) guesstimates a rebound effect of approximately 60%.

Barker et al. (2009) estimate global macroeconomic rebound effect using the a non-equilibrium model E3MG which is sectoral dynamic model of the global economy that is desegregated into 41 production sectors and covers 20 world regions, 12 energy carriers, 19 energy users, 28 energy technologies, 14 atmospheric emissions. Barker et al. (2009) based upon previous work of Barker et al. (2006) who first introduce this novel long-term economic modelling approach in the treatment of technological change. They based on cross- section and time-series data analysis for the period 1973-2002 using formal econometric techniques. Then scenarios are developed to allow the simulation of macroeconomic rebound effects. Results from the study suggest that total global rebound effect, averaged across the sectors of the economy, will reach 31.5% by 2020 while is expected to increase to 51.3% by 2030. Results are in line with theoretical work of Barker et al. (2006).

Hanley et al. (2009) investigate the impact of energy efficiency improvements in Scotland using the CGE framework. They suggest that energy use initially decreases but ultimately increases in a response to efficiency improvements, resulting also in a decline ratio of GDP to CO_2 emissions . Specifically, their results indicate a large short-term rebound effect of 63.2% and 54.4% for electricity and non-electricity energy use accordingly. Additionally, the increase in the magnitude of the rebound effect grew into the 'backfire' phenomenon, reaching 131.6% and 134.1% for electricity and non-electricity energy use respectively. According to Hanley et al. (2009), energy efficiency and the concomitant competitiveness of the most energy intensive sectors of Scottish economy as well as a stimulus to export electricity demand when the cost per unit produced decreases, account for the positive output effect.

Turner (2009) applies CGE framework as well to explore the effects of increased energy efficiency on rebound effects for the UK economy for the year 2000. Unlike Hanley et al. (2009), this study suggests that rebound effects are bigger in the short run than in the long run. In particular, simulations indicate that a 5% exogenous increase in energy efficiency induce a rebound of 59.6% 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. This was driven by the presence of disinvestment effect and seems to be in contrast with the predictions of theoretical work by Wei (2007) and Saunders (2008) but meets theoretical background discussed by the most recent work of Wei (2010). An essential difference between the short and long-run steams from the fact that some production factors, such as capital, are assumed to be fixed in the short term. Therefore it is unattainable for businesses to fully adjust to energy efficiency improvements. Energy efficiency improvements will rise the returns from investments in energy-intensive sectors relative to investments in other sectors. Hence, in the long term, resources will -be reallocated in favour of energy-intensive sectors. Thus, it is rational that the rebound effect is expected to be higher in the long term (Wei, 2007; Saunders, 2008).

Guerra and Sancho (2010) use a combination of input-output analysis and CGE to evaluate economy-wide rebound effects for Spain using 2004 data. It is found that a 5% exogenous increase in energy efficiency will likely result in positive economy-wide rebound effect close to backfire. Specifically, they also found that even in the case of having elasticity of substitution close to zero, the size of the economy-wide rebound effect remains positive and close to 40%. Finally, results of this study reinforce the conclusions of Turner (2009).

In a more recent application of CGE model Broberg et al. (2015) following the analysis of Allan et al. (2007) and Hanley et al. (2009) evaluate the magnitude of the overall economy-wide rebound effect in Sweden using industrial data for 2012. Making use of three different scenarios, they found that economy-wide rebound effect amount to 73, 69 and 78% respectively. Additionally, in sector-specific analysis they porpose results indicate the existence of backfire only in the pulp and paper sector.

Orea et al. (2015) based on the stochastic frontier approach, as proposed by Filippini and Hunt (2011), to estimate the rebound effect associated to energy efficiency improvements. They use an aggregate residential EDF (as described in section 2.2.3) and panel data for 48 US 'states' for period from 1995 to 2011. Finally, Llorca and Jamasb (2017) use data on freight transport sector of 15 European countries over the period 1992 to 2012 and also apply SFA approach to estimate the energy efficiency and the rebound effect as well evaluate the influence of important features of rebound effect in this sector. Results vary from almost zero rebound in Spain to considerable 67% in Denmark.

2.4.2 Developing countries

Sorrell and Dimitropoulos (2007) suggest that empirical evidence from developing world is still very insubstantial, albeit of crucial importance, as energy efficiency is a significant tool to achieve the twofold goal of their national energy strategies of support the increasing energy need so that to continue their economic development and curtail their GHG emissions.

An early example examining the rebound effect concept in a developing country is Dufournaud et al. (1994). They employ an Applied General Equilibrium (AGE) model to simulate the policy of introducing more efficient wood stoves into Sudanese households using data for the period 1982-84. They estimate economy-wide rebound effects in wood consumption in response of using more efficiency stoves amount to 54-59% and authors suggest that energy efficiency policies in the future should be designed in the light of a significant rebound. Similarly, Semboja (1994) employed a static CGE model to assess the impact of energy management policies on Kenya's economy. He suggests that 1% improvement productivity of energy production leads to significant 'back-fire' rebound effects of 170-350% for a and energy and oil end-use respectively. However, Adetutu et al. (2016) suggest, interpretation of these two studies should be quite cautious, due to the high level of energy poverty across many African countries and the sensitivity of CGE analysis to parameter choices.

Li and Yonglei (2012) investigate the energy rebound effect in China due to energy efficiency improvements for three Chinese industries estimating a Cobb-Douglas function in the context of the Solow growth model, using aggregate data for the period 1978-2007. Worth noting that Li and Yonglei (2012) use energy intensity as a proxy of energy efficiency, a drawback that is highlighted in chapter 2 of this study. They argue that China, in recent years, appears a relative large magnitude of the rebound effect that should not be ignored by policy makers. In particular, results indicate an increasing trend of the rebound effect, reaching a peak around 2005, and after that gradually declines till the end of the estimation period. For the period 2000-2005, rebound was estimated 24.83% on average but for the period 2005-2009 increased significantly averaging 133.33% , which Li and Yonglei (2012) attributed to the Chinese government's increased investments in industrial sectors and the relaxed energy policy followed in the wake of the global financial crisis.

Finally, Adetutu et al. (2016) propose a two stage approach approach for the estimation of the macroeconomic RE. In the first stage they use a SEDF to gather estimates of the technical efficiency for a group of 55 countries over the period 1980-2010 while in the second stage they use this estimates as independent variable in a dynamic panel data framework to estimate the magnitude of the short and long run, economy-wide rebound effect. Their results vary from 36-90% in the short and long-run respectively while estimates are slightly larger for developing countries in the panel. They also suggest that failing to account for RE, potential energy efficiency savings may be underestimated by policy makers.

Table 2.2: Summary of studies on economy-wide rebound Effect

Author(s)	Country	Data type	Period	Methodology	Rebound
Panel A: Developed counties					
Haas and Biermayr (2000)	Austria	residential	1970-1995	time-series, cross section	20-30%
Bentzen (2004)	US	manufacturing	1949-1999	DOLS	24%X
Grepperud and Rasmussen (2004)	Norway	multisectoral	1992	CGE	-36.1-87.5%
Washida (2004)	Japan	1995	sectoral	CGE	35-70%
Allan et al. (2007)	UK	aggregate	2000	CGE	27-61.6%
Barker et al. (2007)	UK	aggregate	2000-2010	MDME3	26%X
Brännlund et al. (2007)	Sweden	aggregate	1980-1997	AID	4.1-16.1%
Vikström (2008)	Sweden	1957-1962	sectoral	CGE	60%
Barker et al. (2009)	global	disaggreagate	1973-2002	E3MG	31-52%
Hanley et al. (2009)	Scotland	aggregate	1999	CGE	54.4-134.1%
Turner (2009)	UK	sectoral	2005	CGE	23.1-59.6%
Guerra and Sancho (2010)	Spain	aggregate	2004	CGE, I-O	40-100%
Broberg et al. (2015)	Sweden	sectoral	2012	CGE	-52-109%
Orea et al. (2015)	US	residential	1995-2011	EDF	46-96%
Llorca and Jamasb (2017)	EU-15	trasport	1992-2012	EDF	0-67%
Panel B: Developing counties					
Dufournaud et al. (1994)	Sudan	sectoral	1984-1984	AGE	54-59%
Semboja (1994)	Kenya	aggregate	1976	CGE	170-350%
Li and Yonglei (2012)	China	sectoral	1997-2009	Solow growth model	25-133%
Adetutu et al. (2016)	OECD/non-OECD	aggregate	1980-2010	SEDF/GMM	36-90%

2.4.3 Summary and contributions

International collaboration is required to mitigate the climate impacts from anthropogenic GHG emissions (UN, 2017). Following the Paris agreement, most governments around the world design energy policies, targeting to reduce the level of CO_2 emissions. According to IEA (2015), energy efficiency improvements appear to be the cornerstone of these policies as they suggest that it is the most cost-effective and immediately available means to achieve this goal. However, policies aim at ameliorating disquieting climate effects by improving energy efficiency, in order to curb energy consumption and thus eliminating CO_2 emissions, may proved to be misguided if rebound effects are not considered.

As discussed in Section 2.4, there is a considerable body in economic literature on the notions of the rebound effects and several techniques have been applied to quantify those phenomena. Although the theoretical framework and the existence of the RE is widely accepted, the magnitude varies considerably depending on data and method employed in the studies. Empirical evidence is greater, in terms of quality and quantity of studies, for direct effects than for indirect effects but there is a relative dearth regarding the macroeconomic rebound effects. Besides, Dimitropoulos (2007) suggests that the wide range of methodological and theoretical approaches used in the estimation of the macroeconomic RE as well as the different time frame that the existing empirical studies use, make these studies incomparable and the empirical evidence quite insufficient. Hence, the available pool of empirical evidence on the economy-wide rebound effect is inadequate to generate meaningful insights.

Computable General Equilibrium techniques are the most widely used framework for the analysis of macroeconomic RE. Even though CGE approaches appear many attractive features, challenges are aplenty as well[22] and arise questions as for the realism and the policy relevance of those techniques (Barker, 2004). In particular, CGE models are information intensive such that simulations from these models are based on initial assumptions made about behavioural and market characteristics, the functional form of the production process, the time, sector and region of investigation etc. Different

[22]Sorrell et al. (2007) provide more details about the limitations of CGE models.

assumptions could lead to completely different simulations. This diversity, combined with the limited number of studies available makes it difficult to draw general conclusions.

Besides, Brookes (2000) argues that it is quite impossible to capture a host of individual microeconomic changes due to the price effect (direct, indirect rebound effects) in order to quantify, with sufficient accuracy, the macroeconomic RE. He also highlights the lack of reliable indicator of measurement energy efficiency and progress have been made over time. In this context, the main objective of this study is to provide estimates for economy-wide RE for panel of developing countries between 1989 and 2008 using a two-stage procedure. First, energy efficiency is estimated using Stochastic Frontier Analysis (SFA) and then a dynamic panel framework is used to estimate the short and long-run RE. Additionally, potential saving in CO_2 emissions are estimated considering the magnitude of the rebound effect.

This is a significant contribution in the literature given that adjustments, from households and firms, could be highly significant, when aggregated at an economy level (Greening et al., 2000). Additionally, Herring and Roy (2007), Sorrell and Dimitropoulos (2007) and Chakravarty et al. (2013) argues that macroeconomic RE are likely to be remarkably higher in developing countries because their fast economic growth and development while the demand for energy services is far from saturated.

Chapter 3

Energy demand and energy efficiency in developing countries: A Stochastic Energy Demand Function approach

3.1 Introduction

Amid growing concerns over volatility in energy prices and the global attention towards limiting CO_2 emissions, the need for action by both developed and developing counties to address energy security, climate change and economic stability is under the spotlight as never before. Paris agreement, the first ever universal legally binding climate deal, was the fruit of more than two decades of tortuous international negotiations on combating climate change. However, despite the concerted efforts, global energy-related CO_2 emissions have risen by more than 50% since 1992, driven mainly by economic growth and increasing fossil-energy use in emerging economies (IEA, 2016a).

As described in Chapter 1, shares of developing countries' emissions surpassed those of industrialised countries in 2005, and have kept rising very rapidly as a result of increasing energy use. In particular, energy demand in developing countries has risen more than threefold over the past three decades and according to IEA (2014) is expected to continue increasing rapidly in the future. Many developing countries transitioned from agricultural to the more energy intensive phase of industrial development with concomitant growth in demand for 'modern' energy intensive goods and services. Furthermore, according to IEA (2014) increasing energy demand, particularly in developing counties, has been further augmented by demographic pressure and the increased urbanisation rate while the UNIDO (2010) highlights that access to clean, reliable and affordable energy services is indispensable for prosperity of a country and in case of failure to harness the increasing demand, sustained development may be put in jeopardy.

The IEA (2016d) argues that improved energy efficiency is a critical response to the pressing climate change, economic development and energy security challenges facing the world today. Therefore, improvements in energy efficiency have become a key policy and an important pillar of national energy strategies for many countries around the world. To this end, it is crucial to develop and maintain well-founded indicators and measurements to better inform policymaking and assist decisions makers to formulate policies that are best suited to national objectives. This is of vital importance especially when developing countries are concerned, where more than 1.5 billion people have no access to electricity. Hence, it is momentous for developing countries to meet their growing appetite for energy needs in order to maintain robust socio-economic development and increase living standards.

Given the problems discussed in Chapter 1 regarding the definition and the measurement of energy efficiency as well as problems arise from the use of energy intensity as proxy of energy efficiency, one of the main objectives of this study is, following the approach proposed by Filippini and Hunt (2011), to estimate an aggregate energy economy demand function in a panel of developing countries using Stochastic Frontier Analysis and after controlling for a series of important economic and non-economic factors, to get a 'true' measurement of energy efficiency, consistent with economic theory of production.[1] Thus generating a more reliable energy efficiency indicator and providing valuable information to policy makers to address national and international energy, economic and environmental issues.

The remainder of the chapter is organised as follows: Section, 3.2 elaborates on the methodological framework applied in this study while data used in the analysis and different econometric specifications are introduced in Section 3.3. Econometric results and economic interpretation, as well as the estimated energy efficiency scores and potential CO_2 reductions are presented in Section 3.4 which is followed by Section 3.5 that concludes the chapter.

3.2 Methodology

As explained in previously, the main objective of this chapter is to estimate an aggregate frontier energy demand function synthesising the approaches of energy demand modelling and frontier analysis based on microeconomic production theory, as proposed by Filippini and Hunt (2011, 2012). After controlling for economic and other factors that can vary between countries and affect energy demand, such as income, energy price, climate effects, the size and the structure of economy as well as exogenous technical progress and other exogenous factors, this analysis produces measurements of 'true' energy efficiency. Furthermore, the use of the recently developed econometric technique proposed by Filippini and Greene (2016) allows for the estimation of the persistent and the transient energy efficiency simultaneously. The distinction between the transient and persistent component of energy efficiency is crucial from a policy perspective as refers to different sources of inefficiency and thus completely different strategies and instrument bouquets should be applied by policy makers to deal with.

Energy demand is not a demand per se but it is a derived demand. In particular, an aggregate energy demand it stems from the demand of an economy for energy services such as heating, cooling, lighting, motion etc. In that context, energy along

[1] Filippini and Hunt (2011) as an attempt to distinguish the estimated efficiency scores that gathered from the estimation of a stochastic frontier energy demand function, from the energy intensity uses the term 'underlying energy efficiency'.

with labour and capital can be considered as inputs for the production of a desired level of energy services. From a theoretical point of view, the estimation of such a production function within the stochastic frontier framework provides information about the level of technical efficiency while the estimation of a cost frontier function allows for estimation of the overall productive efficiency. Besides, Kumbhakar and Lovell (2000) illustrate that utilising Shephard lemma it is also possible to estimate a system consisting of the cost frontier function and the associated cost-minimising input demand functions. Then, the input demand function gives the minimum level of input used in order to produce any given level of output and the actual input demand function differs from the stochastic input demand due to the presence of both technical and allocative inefficiency. Furthermore, Evans et al. (2013) and Filippini et al. (2014) suggest that due to data limitations on some inputs or input prices it is possible to estimate only one input demand function,[2] in particular the energy demand function. In that case, the frontier gives the minimum level of energy that can be exploited by an economy in order to produce the desired level of energy services and the difference between the actual energy demand and the estimated frontier represents the inefficiency in the use of energy.

Hence, following Filippini and Hunt (2011, 2012) the following aggregate energy demand function is specified:

$$E_{it} = E(P_{it},\ Y_{it},\ POP_{it},\ A_i,\ HDD_{it},\ CDD_{,it}\ ISH_{it},\ ASH_{it},\ UEDT_t,\ EF_{it}) \tag{3.1}$$

where E_{it} represents the final aggregate energy consumption for country i in year t, P_{it} the real energy price,[3] Y_{it} is the GDP, POP_{it} is the population, A_i is the area size of each country and is constant over time, HDD_{it} and CDD_{it} denote the heating and cooling degree days respectively while ISH_{it} and ASH_{it} the shares of value added of the

[2]Schmidt and Lovell (1979) propose the estimation of a system that consists of a cost frontier function together with all conditional input demand frontier functions. This approach satisfies the theoretical restriction imposed by production theory and simultaneously takes into account the fact that the input allocative efficiency can be different in each input demand frontier function. However, Evans et al. (2013) argues that even though this approach does not completely consider the theoretical restrictions imposed by the production theory, it allows for measurement, in an approximate way, of the energy efficiency that seems to be more precise than energy intensity.

[3]Deflated by the level of the general consumer price index and based on the year 2000.

industrial and agricultural sector accordingly. Additionally, $UEDT_t$ is the Underlying Energy Demand Trend[4] that captures the common impact of technical progress and other unobserved exogenous factors that influence all countries simultaneously. Finally, EF_{it} is the unobserved level of the 'true' energy efficiency of each country in the panel.

Nevertheless, since EF_{it} is not observed directly, it has to be estimated. Therefore, the stochastic frontier approach introduced by Aigner et al. (1977) is used where the level of energy inefficiency of each country is estimated as a regression residual and can be approximated by one-sided, non-negative term following the half normal distribution. Then a panel log-log function of equation 3.1 above can be specified in the following way:

$$\begin{aligned} e_{it} = \alpha + \alpha^p p_{it} + \alpha^y y_{it} + \alpha^{pop} pop_{it} + \alpha^a a_i + \alpha^{hdd} hdd_{it} + \alpha^{cdd} cdd_{it} \\ + \alpha^{ish} ish_{it} + \alpha^{ash} ash_{it} + \alpha^t t + \alpha^{t^2} t^2 + u_{it} + vit \end{aligned} \tag{3.2}$$

where e_{it} is the natural logarithm of the final aggregate energy consumption, p_{it} the natural logarithm of the real energy price, y_{it} is is the natural logarithm of the GDP, pop_{it} represents the natural logarithm of the population, a_i the natural logarithm of the area size, hdd_{it} and cdd_{it} denote the natural logarithms of the heating and cooling degree days respectively while ish_{it} and ash_{it} are the shares of value added of the industrial and agricultural sector accordingly as described above. Furthermore, $t + t^2$ is a time trend that proxies the $UEDT_t$.[5] Finally, the error term in equation 3.2 is comprised of two independent constituents. In particular, v_{it} is a symmetric disturbance that capture the effect of noise and is assumed to be normally distributed and u_{it} that represents the 'waste' energy and assumed to be one-sided, non-negative disturbance that follows the half-normal distribution.

[4]For further discussion on UEDT, see Hunt et al. (2003).

[5]As stated in Filippini and Hunt (2012) an alternative way to capture the effect of a homogenous *UEDT* is to use time dummies. However, this study does not follow this approach since preliminary analysis showed insignificant, as a group, time dummy coefficients. Quadratic time trend was preferred instead in order to capture at least partially the non-linear nature of the *UEDT* as discussed in Hunt et al. (2003) and allow for periods when *UEDT* can be upward sloping and/or periods where UEDT can be downward sloping. Moreover, estimation results with time dummy and time trend were relatively similar.

3.3 Data and econometric specification

The study employs an unbalanced panel data set of 39 developing countries[6] ($i = 1, \dots, 39$) over the period 1989 to 2008 ($t = 1989, \dots, 2008$). Table 3.1 presents the descriptive statistics of the variables used in the analysis.

Table 3.1: Descriptive statistics

Variable	Label	Mean	Std. Dev.
Total final energy consumption (*ktoe*)	E	69,195	177,186.600
GDP (billion 2005 *USD* using *PPPs*)	Y	426.396	974.972
Real consumer price index, energy	P	102.999	44.846
Population (millions)	POP	98.743	272.196
Agriculture, value added (% of *GDP*)	ASH	15.056	10.285
Industry value added (% of *GDP*)	ISH	34.612	10.348
Land area (*sq. km*)	A	1,500,114.500	3,135,588.600
Heating degree days (base 70°*F*)	HDD	18,667.670	15,288.390
Cooling degree days (base 70°*F*)	CDD	5,797.945	4,603.592
CO_2 sectoral approach (*Kt* of CO_2)	CO_2	24,048.100	723,361.500

The data set is based on information gathered from various sources. In particular, E is the aggregate total final energy consumption in thousand tonnes oil equivalent (*ktoe*). The set of control variables includes among others Y which is the GDP in billion 2005 US dollars in Purchasing Power Parity (PPP) and POP which is each country's population in millions. All these variables gathered from the IEA database 'World Energy Balances: World Indicators, 1960-2015' (IEA, 2017*b*). Additionally, data for ASH and

[6] Countries are selected based on International Monetary fund (2015) classification for developed and developing counties and represented in Figure B.1 in appendix B. Then, the selection of the countries in the panel among the pool of developing countries based initially on the availability of the data. 39 selected counties are shown in Table B.1 in appendix B. Nonetheless, countries included in the panel should also meet few criteria imposed as a preliminary evidence of the existence of inefficiency use of energy. Indicators such as electricity access and energy use per capita were essential since counties with low access to electricity and low energy use per capita is more likely to underuse rather than overuse energy. Finally, skewness of the OLS residuals from the regression suggest the existence of inefficiency use of energy in the panel of the selected countries (Figure B.2 in appendix B).

ISH which denote the agricultural value added and industry value added respectively and *A* which is the land area in square kilometres (*sq*. *km*) collected from the World Bank database 'World Development Indicators' (World Bank, 2017). Furthermore, *P* is the real energy price index and data collected from International Labour Organisation Statistics, 'ILOSTAT-ILO database of labour statistics' (International Labour Organisation, 2017). In order to control for the influences of the different climate conditions, heating degree days (*HDD*) and cooling degree days (*CDD*) are used.[7] Data for *HDD* and *CDD* obtained from the King Abdullah Petroleum Studies and Research Centre dataset 'A global degree days database for energy-related applications' (King Abdullah Petroleum Studies and Research Centre, 2015). Finally, in order to examine the effect of potential energy efficiency improvements towards eliminating CO_2, data for CO_2 sectoral approach in thousand tonnes is used, gathered from the IEA database 'CO_2 Emissions From Fuel Combustion' (IEA, 2017*a*).

Following the study of Aigner et al. (1977), stochastic frontier analysis have been subject of a great body of literature resulting in a large number of proposed econometric models to estimate cost and production functions as described in chapter 2. Among others, Pitt and Lee (1981) adapt the original pooled model proposed for panel data and they propose the Random Effect Model (REM) that interprets any unobserved, individual specific, time invariant heterogeneity as inefficiency. REM estimates efficiency scores that are constant over time and hence, intuitively, REM tends to provide information about the persistent efficiency. However, a crucial advantage that panel data models can offer, namely the control of unobserved heterogeneity is overlooked in REM. Contrariwise, Greene (2005) extend the panel data version of the original model proposed by Aigner et al. (1977) by adding individual specific time-invariant effects and thus separating the unobserved time-invariant heterogeneity from time-varying efficiency. In these model, called True Random Effect Model (TREM)[8], any time invariant inefficiency is completely absorbed by the individual specific term and therefore estimated efficiencies tend to provide information about the transient component of

[7] $70°F$ have been chosen as a base temperature for the HDD and the CDD in order to have non zero information for some equatorial developing counties.

[8] Greene (2005) also suggests True Fixed Effect model.

efficiency. Additionally, just recently, Filippini and Greene (2016) proposed a model called Generalised True Random Effect Model (GTREM) that uses a maximum simulated likelihood approach for the estimation of equation (3.2) and provides segregated estimations for the persistent and the transient component of efficiency from the same model, hereafter TGTREM and PGTREM respectively.[9]

The level of energy efficiency can be estimated using the conditional mean of the efficiency term, $E[u_{it}|u_{it}+v_{it}]$, as proposed by Jondrow et al. (1982). Then, the level of energy efficiency can be expressed as follows:

$$EF_{it} = \frac{E^F_{it}}{E_{it}} = \exp\{-\hat{u}_{it}\}$$

where E^F_{it} is the frontier energy demand and E_{it} is the observed energy demand of each country in year t. Efficiency scores closer to unity indicate that countries utilise energy in a rational and efficient way while moving away from unity to zero countries waste energy.

Furthermore, Farsi et al. (2005) argue that RE estimators can be affected by heterogeneity bias as it is possible that the unobserved country specific characteristics may not be distributed independently of the explanatory variables and they propose the use of Mundlak adjustment (Mundlak, 1978) where the correlation of individual effects with explanatory variables is considered in an auxiliary regression given by:

$$\alpha_i = \gamma\bar{X}_{it} + \delta_i \quad \bar{X}_{it} = \frac{1}{T}\sum_{t=1}^{T} X_{it}, \quad \delta_i \sim N(0, \sigma^2_\delta)$$

where $\bar{X}_{it}$ is a vector of the averages of all explanatory variables and γ is the respective vector of coefficients. Hence, the individual-specific stochastic term is divided into two parts: the first component can be explained by a set of exogenous variables, while the remaining component δ_i is orthogonal to explanatory variables. Then, this latter part can be interpreted as inefficiency which can be estimated by comparing each individual to the individual with the minimum δ_i, that is $\hat{\delta}_i - min(\hat{\delta}_i)$. Then GLS

[9]TGTREM stands for the estimated Transient efficiency component from the Generalised True Random Effect Model and PGTREM stands for the estimated Persistent efficiency component from the Generalised True Random Effect Model.

estimators are identical to the FE estimators of the original equation (within estimators) and thus unbiased. Hence, the REM and TREM confine bias in inefficiency estimates by separating inefficiency from the unobserved heterogeneity and thus improving efficiency estimates. This view echoed by Filippini and Hunt (2011, 2012, 2016), Filippini et al. (2014) and Filippini and Zhang (2016).

Given the discussion above, this study employs three alternative models for the estimation of equation 3.2 as an attempt not only to estimate the level of 'true' energy efficiency in developing countries but evaluate the persistent and the transient counterparts of inefficiencies as well.[10] As explained previously, REM with Mundlak adjustment (MREM) provide estimations of energy efficiency that remain constant over time. For that reason, literature suggest that this model tend to give information about the persistent energy efficiency of a country (Filippini and Hunt, 2016). The second model used in this study is the TREM that gives information about the transient efficiency while finally the GTREM is used to estimate both components (persistent and transient) of inefficiency. Table 3.2 provides detailed econometric specifications of these models.

3.4 Empirical Results

The estimation results of the aggregate energy demand frontier models, detailed in previous sections, are provided in Table 3.3. The majority of the estimated coefficients as well as λ[11] appear to have the expected sign and almost all are statistically significant

[10] Three basic models, namely the REM, TREM and the GTREM, along with their Mundlak variations (i.e. MREM, MTREM, MGTREM) had been tested in this study. However, only the results of three preferred models presented here. Full details about the model specifications and estimated results, including all models that used are presented in Tables B.2 and B.3 in the appendix B. Mundlak adjustment seems to control, at least partially the heterogeneity in REM and thus MREM was preferred over the REM. However, concerning the TREM and the GTREM, estimated parameter coefficients as well as efficiency scores were highly correlated with those produced by the respective Mundlak variations but it seems that the introduction of a Mundlak modification in these models renders some of the variables statistically insignificant. For that reason, TREM and GTREM were preferred over the MTREM and the MGTREM.

[11] $\lambda = \sigma_u/\sigma_v$ provides information regarding the relative contribution of the two components of the error term. λ closer to zero indicates that the disturbance noise is the dominant component while nearly infinite λ indicates that the compound error term is dominated by the one-sided error component. Estimated λ shows that the one-sided error component is relatively large in all models and thus indicating that there is considerable inefficiency in the models.

Table 3.2: Econometric specification of stochastic energy demand frontier: country specific effects, error term and inefficiency

	Model I **MREM**	*Model II* **TREM**	*Model III* **GTREM**
Country's effects α_i	$\alpha_i = \gamma \bar{X}_{it} + \delta_i$	$N(\alpha, \sigma_w^2)$	$N(\alpha, \sigma_w^2)$
	$\bar{X}_{it} = \frac{1}{T}\sum_{t=1}^{T} X_{it}$		
Full random error ε_{it}	$\varepsilon_{it} = \delta_i + v_{it}$	$\varepsilon_{it} = w_i + u_{it} + v_{it}$	$\varepsilon_{it} = w_i + h_{it} + u_{it} + v_{it}$
	$\delta_i \sim N^+(0, \sigma_\delta^2)$	$u_{it} \sim N^+(0, \sigma_u^2)$	$u_{it} \sim N^+(0, \sigma_u^2)$
	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$
		$w_i \sim N(0, \sigma_w^2)$	$w_i \sim N(0, \sigma_w^2)$
			$h_i \sim N(0, \sigma_h^2)$
Persistent inefficiency estimator	$E(\delta_i \mid \delta_i + v_{it})$	$\emptyset$	$E(h_i \mid \varepsilon_{it})$
Transient inefficiency estimator	$\emptyset$	$E(u_{it} \mid \varepsilon_{it})$	$E(u_{it} \mid \varepsilon_{it})$

in the TREM and GTREM. Furthermore, variables in logarithmic form can be directly interpreted as elasticities of demand.

Results suggest that energy demand in developing countries is income and price inelastic. In particular, the estimated income elasticity of demand varies from 0.52 in the TREM to 0.59 in the REM while the estimated income elasticity in the GTREM lies between at 0.58. The estimated own price elasticity of demand varies from -0.17 in the MREM to approximately -0.22 in both TREM and GTREM. Additionally, population appears to have positive influence on the energy demand. Namely, the estimated population elasticity is 0.92 but insignificant in the MREM while in the TREM and GTREM population elasticity is notably lower at 0.50 and 0.33 respectively and both are statistically significant. The area coefficient is not significant in the MREM but suggests a positive and significant impact on the energy demand in both TREM and GTREM with the respective elasticities being at 0.03 and 0.11. Furthermore, two climate variables are not significant in the MREM while the influence of the heating degree days and cooling degree days on the energy demand appear to be significant and positive in the TREM and the GTREM. A possible explanation for these results is that heating and/or cooling systems have yet to be widely used in developing counties.

As expected, the estimated coefficients of the shares of the industrial and the agricultural sector are positive, noting that the reference sector is the less energy intensive services sector. Finally, the *UEDT* is captured by the coefficients of the t and t^2 combined. The coefficient of the quadratic component although is statistically significant, is very small relative to linear component. Hence, the persistence of a linear trend is assumed to be captured by the linear trend component and the respective coefficient suggest a positive impact on the energy demand in the TREM and the GTREM and negative impact in the MTREM.[12] The positive sign of the time trend coefficient, is possible to reflect the fact that the increase appetite for energy services in developing countries overcomes any potential benefits from the use of new technologies. It is also likely that the rate of adoption of technologies available in developing countries is quite slow, something that is mirroring in the relatively small estimated efficiency scores compering with results for developed countries in Filippini and Hunt (2011) and Filippini et al. (2014).

3.4.1 Energy efficiency

However, the main focus of Stochastic Frontier Analysis is not the estimation of the goal function (i.e. energy demand function) but the estimation of efficiency scores. Descriptive statistics of the estimated energy efficiency scores are reported in Table 3.4. Results suggest that the estimated average values of the persistent efficiency vary from 70.5% in the MREM to 81.2% in the persistent part of the GTREM (PGTREM) while the transient efficiency is around 89%. In particular, it is 88.1% in the TREM and 89.6% in the transient part of the GTREM (TGREM). These results are in line with Adetutu et al.

[12]This study also tries to estimate the energy demand frontier with the use of time dummies. However the estimated coefficients of the time dummies as a group were statistically insignificant. Graphically representation of time dummies and time trend appear in Figures B.3 and B.4, in appendix B. Surprising enough, time trend from the models appear different patterns over time. However, despite these different patterns between REM and the other two models there is a clear positive effect over time. Finally, time dummies suggest that the effect of the exogenous technological progress is non-linear in nature supporting the $t + t^2$ approximation of UEDT.

Table 3.3: Estimation result

	MREM		TREM	GTREM
	Main equation	Mundlak		
Constant	9.754***		6.074***	4.158***
	(3.692)		(0.094)	(0.119)
α^y	0.586***	0.383*	0.515***	0.578***
	(0.034)	(0.215)	(0.011)	(0.013)
α^p	−0.172***	0.104	−0.213***	−0.221***
	(0.017)	(0.525)	(0.008)	(0.010)
α^{pop}	0.920	−0.652**	0.495***	0.333***
	(0.060)	(0.286)	(0.010)	(0.011)
α^a	−0.108		0.030***	0.115***
	(0.136)		(0.005)	(0.005)
α^{hdd}	0.027	−0.078	0.017***	0.050***
	(0.047)	(0.103)	(0.003)	(0.003)
α^{cdd}	−0.029	−0.409**	−0.046***	0.004
	(0.075)	(0.171)	(.007)	(0.008)
α^{ish}	0.000	−0.003	0.002***	0.004***
	(0.001)	(0.009)	(0.000)	(0.000)
α^{ash}	0.005***	−0.011	0.004***	0.008***
	(0.002)	(0.020)	(0.001)	(0.001)
α^t	−0.012***		0.011***	0.010***
	(0.004)		(0.002)	(0.002)
α^{t^2}	0.001**		−0.001**	−0.001
	(0.000)		(0.000)	(0.000)
λ	4.381*		2.901***	1.550***
	(2.531)		(0.248)	(0.171)
σ	0.529***		0.183***	0.169***
			(0.003)	(0.005)
Log Likelihood	374.361		366.791	346.230

*Note: *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. Standard errors are in parentheses. The sample includes 640 observations. NLOGIT5 econometric software is used for the estimations.*

(2016) estimations about energy efficiency.[13] On average the estimated transient energy efficiency is higher than the persistent energy efficiency, possibly reflecting the lack of necessary energy efficiency regulations in developing countries, structural problems in the production of energy services and any other permanent in character behavioural and managerial failures. These results are in line with existing literature that highlights the low contribution of structural effect in energy intensity.

Table 3.4: Energy efficiency scores

Variable	Mean	Std. Dev.	Min	Max
MREM	0.705	0.203	0.335	0.969
TREM	0.881	0.077	0.391	0.986
PGTREM	0.812	0.004	0.795	0.823
TGTREM	0.896	0.049	0.560	0.974

Besides, the correlation coefficient between the estimated values of the transient efficiency scores obtained with the TREM and the TGTREM, as illustrated in table 3.5, is remarkably high at 0.97, highlighting that both models provide sufficient information regarding the transient energy efficiency. On the contrary, the value of the correlation coefficient between the estimated values of the persistent efficiency scores obtained from the MREM and the PGTREM is very low at 0.07 suggesting that REM may not be a satisfying indicator of the persistent efficiency.[14] A possible explanation for this, is that REM considers any unobserved time-invariant country specific heterogeneity as inefficiency and thus produces lower efficiency scores. Overall, the preferred model is the GTREM which can provide estimates for both the persistent and the transient energy efficiency. Hence, the analysis hereafter is based on the estimations of this model.

[13] Adetutu et al. (2016) estimates of energy efficiency are on average between 81 and 91%. However, it should be noted that using Input Distance Function approach they estimate the level of technical efficiency in the use of energy while in this study the use of energy demand function provides estimations of the overall energy efficiency (both technical and allocative). Therefore, comparisons between these two studies should consider this important difference. Additionally, SFA provides relative efficiency scores given the data set used. Adetutu et al. (2016) use a panel data consists of 55 OECD and non-OECD countries while this study apply a data set for 39 solely developing counties. Again, comparisons of relative efficiency scores and ranking should consider this aspect.

[14] This is further highlighted by the shape of kernel density funtions in figures B.5 and B.6 as well as the scatter diagrams in figures B.7 and B.8, presented in the appendix B.

Figure 3.1 presents the average transient and persistent energy efficiency by country while Figure 3.2 illustrates the map of the countries in the panel given the estimated average value of their transient energy efficiency.

Table 3.5: Correlation coefficients

	MREM	TREM	PGTREM	TGTREM	EI
MREM	1				
TREM	0.045	1			
PGTREM	0.075	-0.009	1		
TGTREM	0.048	0.971	-0.054	1	
EI	-0.460	-0.357	-0.006	-0.354	1

Furthermore, as expected, estimated values of 'true' energy efficiency scores are negatively correlated with energy intensity (EI) and correlation coefficients varies from -0.01 to -0.46. Filippini and Hunt (2011, 2012) argue that the technique used in this study tends to provide useful information and can be an important tool for policy makers as long as the estimated efficiencies are not perfect or near perfect correlated with energy intensity since then, all the necessary information would be gathered from the energy intensity. Nevertheless, this is not the case in this study. This result suggests that energy intensity is a poor proxy of energy efficiency for the developing countries and unless this kind of analysis, as proposed by this study, is undertaken it is possible that policy makers have a misleading picture of the true energy efficiency potentials. This result is also in line with Filippini and Hunt (2011, 2012).

Figure 3.1: Estimated persistent and transient Efficiency in developing countries

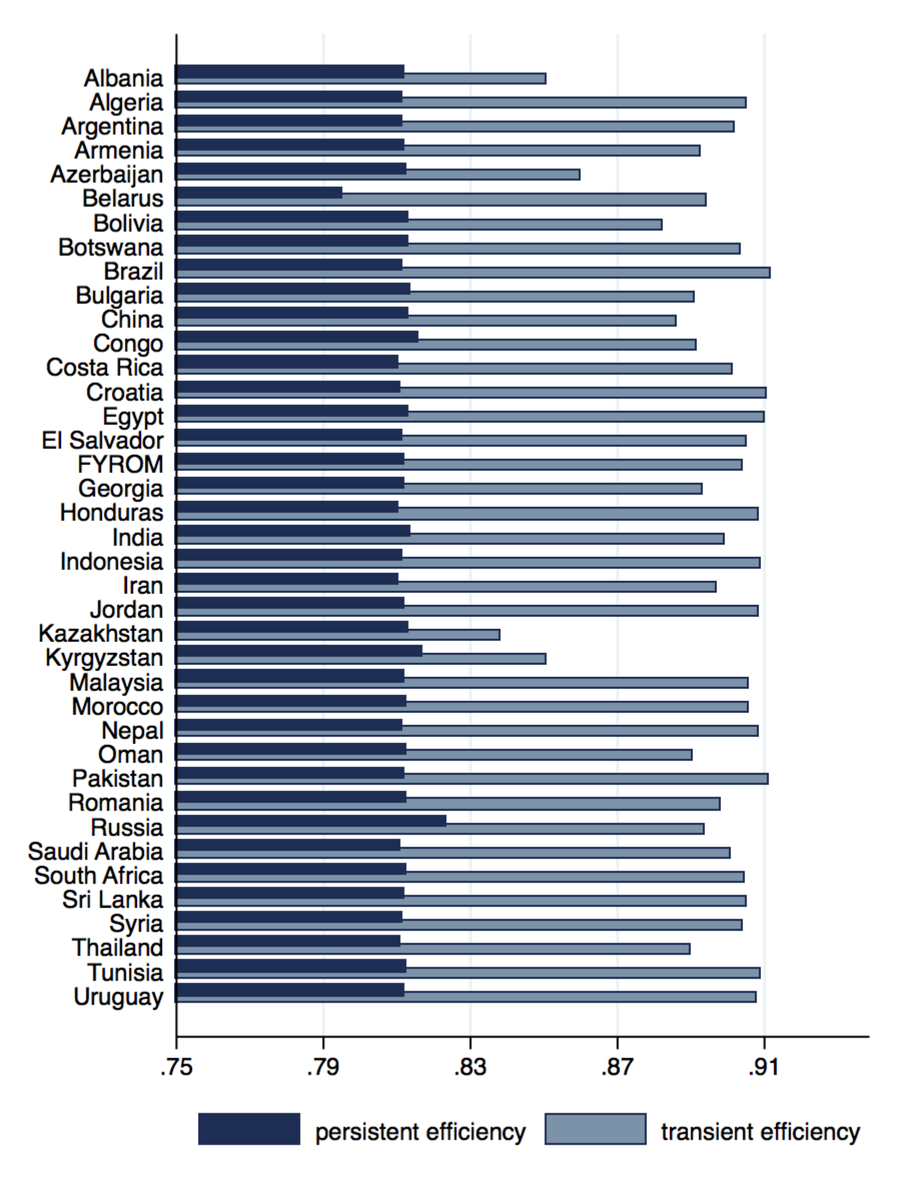


Figure 3.2: Energy efficiency in developing countries

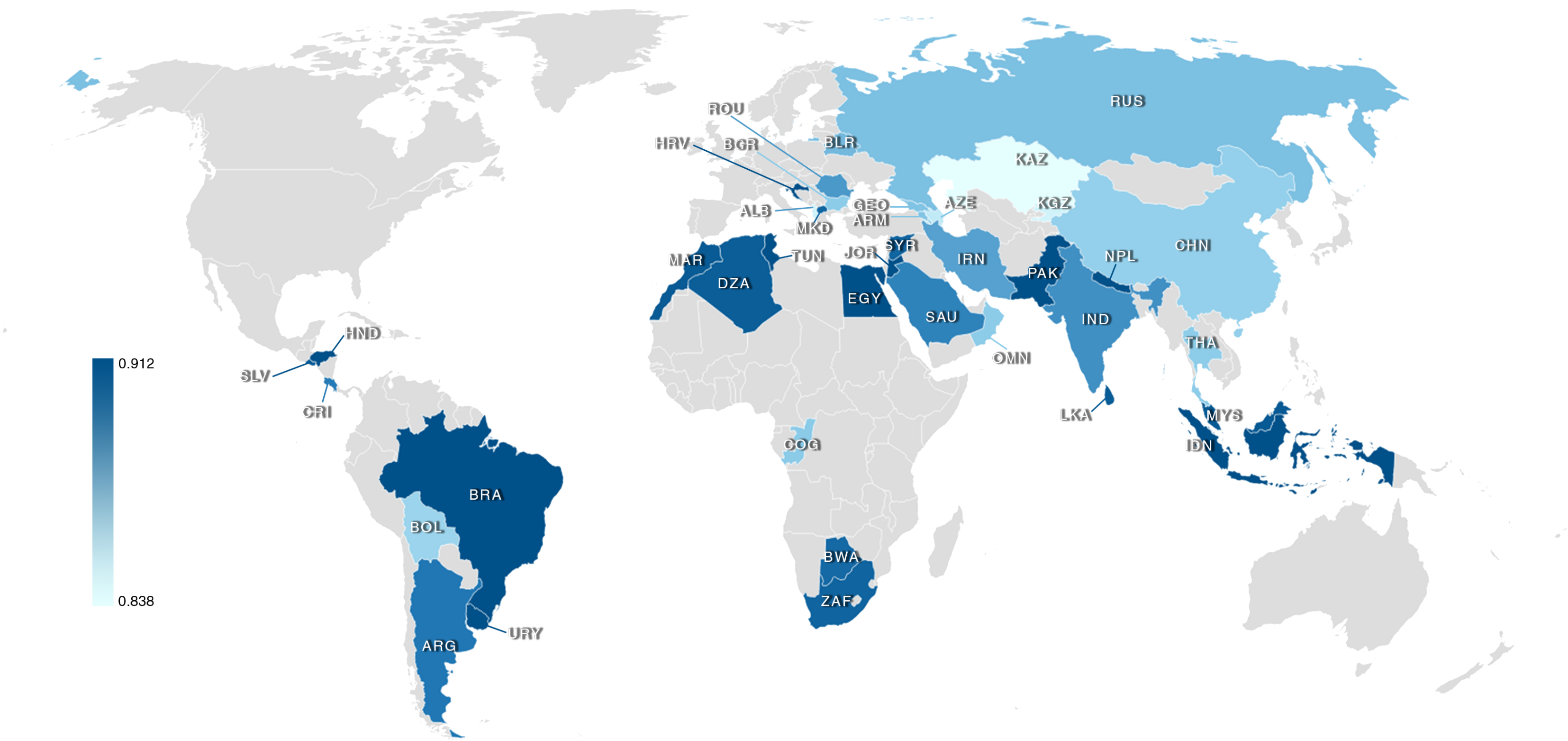


Table 3.6 provides the estimated average 'true' energy efficiency scores obtained from the TGTREM for each country and compares these values with the average energy intensity. Table 3.6 also provides the relative ranking of the countries in the panel with both measurements. Brazil, Pakistan, Croatia, Egypt and Indonesia are the most efficient countries using the TGTREM while Bolivia, Azerbaijan, Kyrgyzstan, Albania and Kazakhstan the least efficient. On the other hand, energy intensity index suggests that Oman, Congo, Algeria, Uruguay and Morocco are the most efficient counties and China, Nepal, Kazakhstan, Belarus and Russia the least efficient ones. Table 3.6 also illustrates that the estimated energy efficiency is negatively correlated with energy intensity, as expected, since when a level of energy efficiency is supposed to increase, energy intensity should decrease. However, this is not always the case. Some countries (i.e. Brazil, Croatia, Egypt, Nepal and Tunisia) appear to have a positive relationship between the estimated energy efficiency and energy intensity. Besides, among the panel there are countries that appear a strong negative correlation (> 90%) between the estimated energy efficiency and energy intensity (i.e. Bolivia, Botswana, Congo, India, Kyrgyzstan, Malaysia, Oman, Saudi Arabia, and Thailand) while for some other countries (i.e. Armenia, Azerbaijan, Belarus, Croatia, Egypt, El Salvador, Indonesia and Jordan) this correlation is significantly lower.

Additionally, for the period 1989-2008 according to the estimated TGTREM, Pakistan, Nepal, Costa Rica , Congo and Oman are ranked 2^{nd}, 8^{th} , 21^{st}, 30^{nth} and 32^{nd} respectively whereas they are ranked 23^{rd}, 36^{th} , 6^{th}, 2^{nd} and 1^{st} accordingly with the energy intensity measurement. Although there is a general negative relationship between estimated energy efficiency and energy intensity this is not one by one regarding the relative rankings. Besides, the Spearman rank correlation coefficient is equal $\rho(37) = .35$ with $p - value = 0.03$ This relationship between two measurements is further illustrated in Figure 3.3.

Table 3.6: Average energy efficiency and energy intensity for the period 1989-2008, ranking and correlation

Country	Average 'true' energy efficiency (TGTREM)		Average energy intensity (toe per thousand 2005*USD PPP*)		Correlation
	Value	Rank	Value	Rank	
Albania	0.850	38	0.095	15	-0.424
Algeria	0.905	15	0.055	3	-0.639
Argentina	0.902	20	0.120	22	-0.421
Armenia	0.893	29	0.130	24	-0.010
Azerbaijan	0.860	36	0.223	33	-0.336
Belarus	0.894	26	0.288	38	-0.391
Bolivia	0.882	35	0.105	18	-0.985
Botswana	0.904	19	0.086	9	-0.913
Brazil	0.912	1	0.088	10	0.555
Bulgaria	0.891	31	0.178	31	-0.879
China	0.886	34	0.245	35	-0.862
Congo	0.892	30	0.050	2	-0.907
Costa Rica	0.901	21	0.071	6	-0.809
Croatia	0.911	3	0.106	19	0.302
Egypt	0.910	4	0.073	7	0.090
El Salvador	0.905	13	0.089	13	-0.244
F.Y.R.O.M	0.904	18	0.110	21	-0.846
Georgia	0.893	28	0.184	32	-0.484
Honduras	0.908	9	0.145	27	-0.462
India	0.899	23	0.140	25	-0.917
Indonesia	0.909	5	0.108	20	-0.399
Iran	0.897	25	0.145	26	-0.640
Jordan	0.908	7	0.102	17	-0.383
Kazakhstan	0.838	39	0.250	37	-.0698
Kyrgyzstan	0.851	37	0.241	34	-0.936
Malaysia	0.906	11	0.088	11	-0.942
Morocco	0.906	12	0.071	5	-0.656
Nepal	0.908	8	0.250	36	0.444
Oman	0.890	32	0.043	1	-0.987
Pakistan	0.911	2	0.122	23	-0.808
Romania	0.898	24	0.160	29	-0.613
Russia	0.894	27	0.317	39	-0.855
Saudi Arabia	0.901	22	0.089	12	-0.961
South Africa	0.904	16	0.153	28	-0.875
Sri Lanka	0.905	14	0.089	14	-0.481
Syria	0.904	17	0.178	15	-0.858
Thailand	0.890	33	0.099	16	-0.967
Tunisia	0.909	6	0.084	8	0.498
Uruguay	0.908	10	0.068	4	-0.687

Figure 3.3: Average energy efficiency Vs. average energy intensity 1989-2008

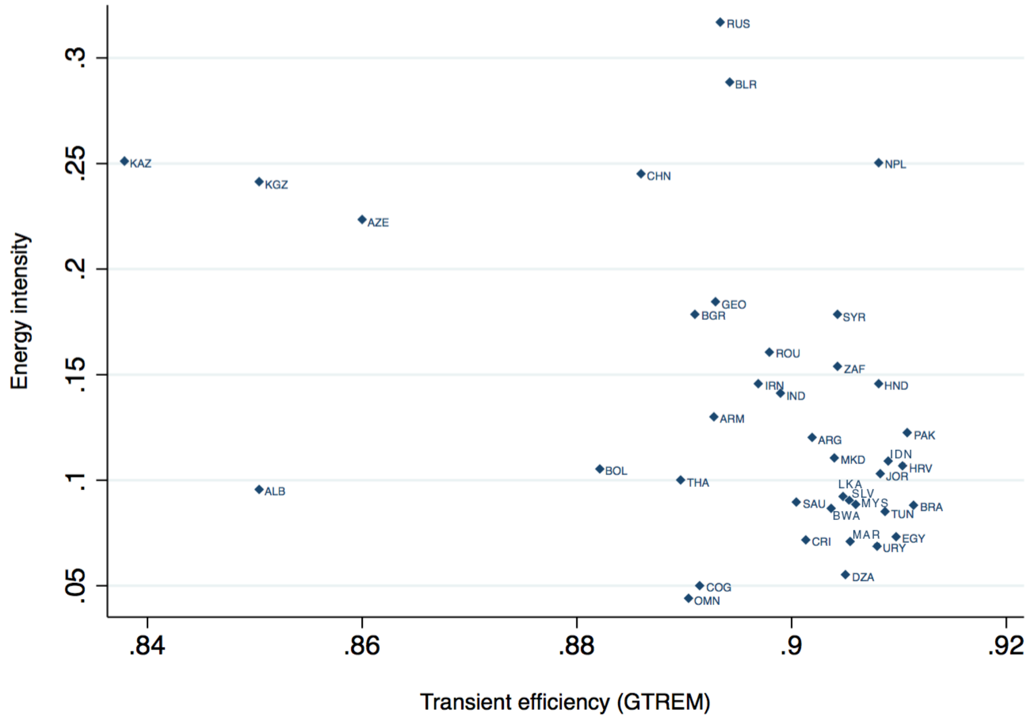


Figure 3.4 shows the comparison between the estimated transient energy efficiency and energy intensity of each country over the period 1989-2008.[15] Figure 3.4 also indicates that there is no clear, common trend regarding energy efficiency improvements. In, particular some countries (i.e. Azerbaijan, Botswana, China, India, Kazakhstan, Kyrgyzstan and Russia) clearly have improved their energy efficiency over the estimated period while some other countries (i.e. Albania, Algeria, Bolivia, Iran, Malaysia, Morocco, Saudi Arabia, Thailand and Tunisia) display a downward sloping trend in energy efficiency. Finally, there is a group of countries where 'true' energy energy efficiency shows some level of fluctuation or is quite steady over the estimated period.

Given the discussion above, estimated energy efficiency tend to give more accurate

[15]It should be noted that this study is based on an unbalance panel data set for the estimation of efficiency scores and for that reason some counties in Figure 3.4 such as Brazil and Honduras are over a shorter period. Additionally, only the estimated transient energy efficiency is used for comparison with energy intensity since the correlation between these two measurements is $-.35$ while the correlation between the persistent energy efficiency and the energy intensity is only $-.01$. Another reason is that the estimated transient energy efficiency appears notable variation among the countries and over the estimated period while persistent efficiency is constant and there are no significant differences among the countries.

information regarding energy efficiency of a country than energy intensity does and hence this study uses the term 'true' energy efficiency to describe the estimated energy efficiency scores and distinguish them from the energy intensity. Worth noting that SFA is a benchmarking technique and hence each county's estimated energy efficiency might not illustrate the precise country's position. However, estimated energy efficiency measurements provide useful information regarding each country's change in energy efficiency over the estimated period and allows for comparisons among the countries in the panel. Additionally, the estimated levels of energy efficiency, is an indication of potential energy savings as well as potential CO_2 emissions reductions if countries were efficient. This is further discussed in the section to follow.

Figure 3.4: Comparison of estimated 'true' energy efficiency with energy intensity by country

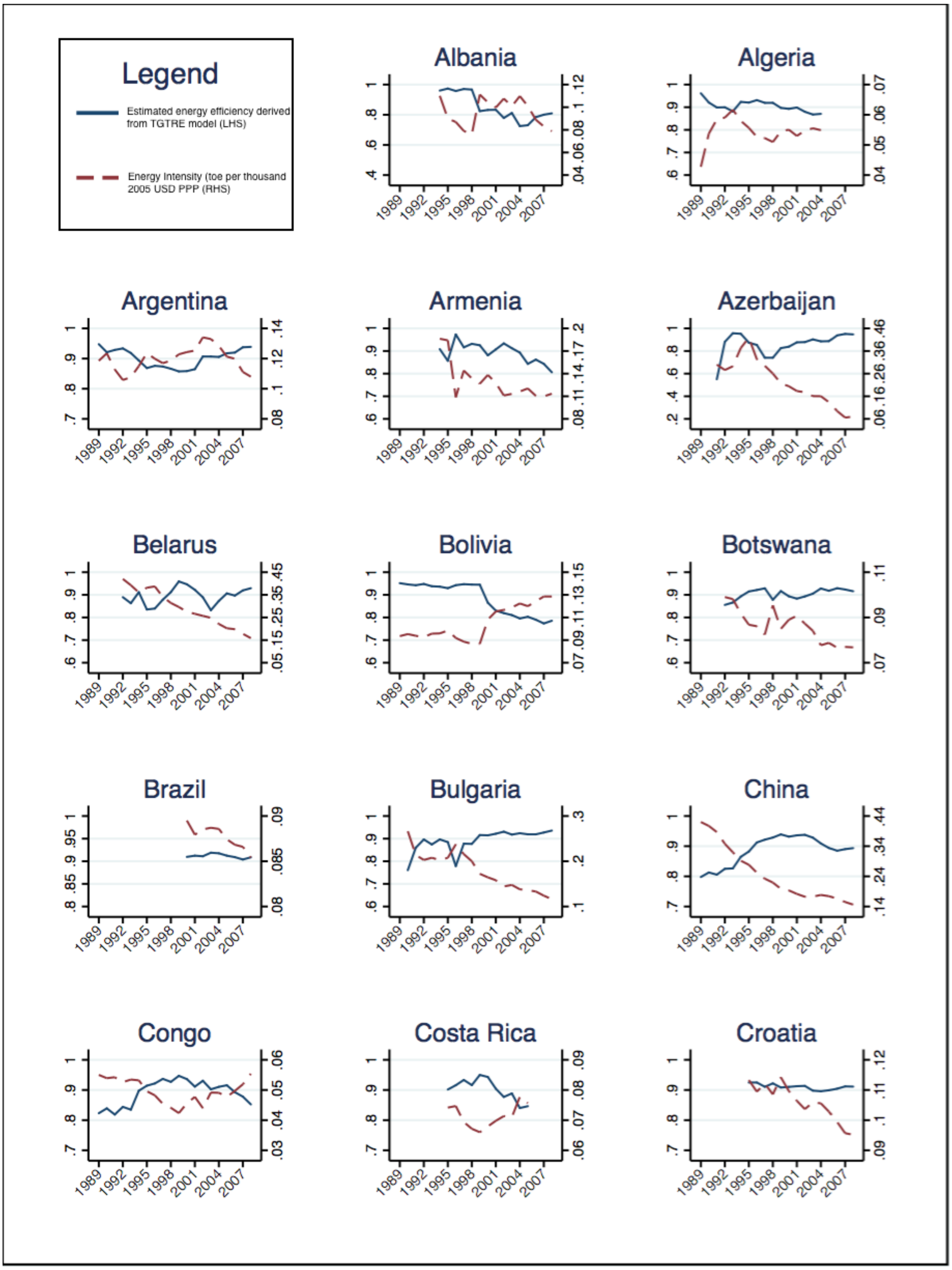


Figure 3.4 Continued

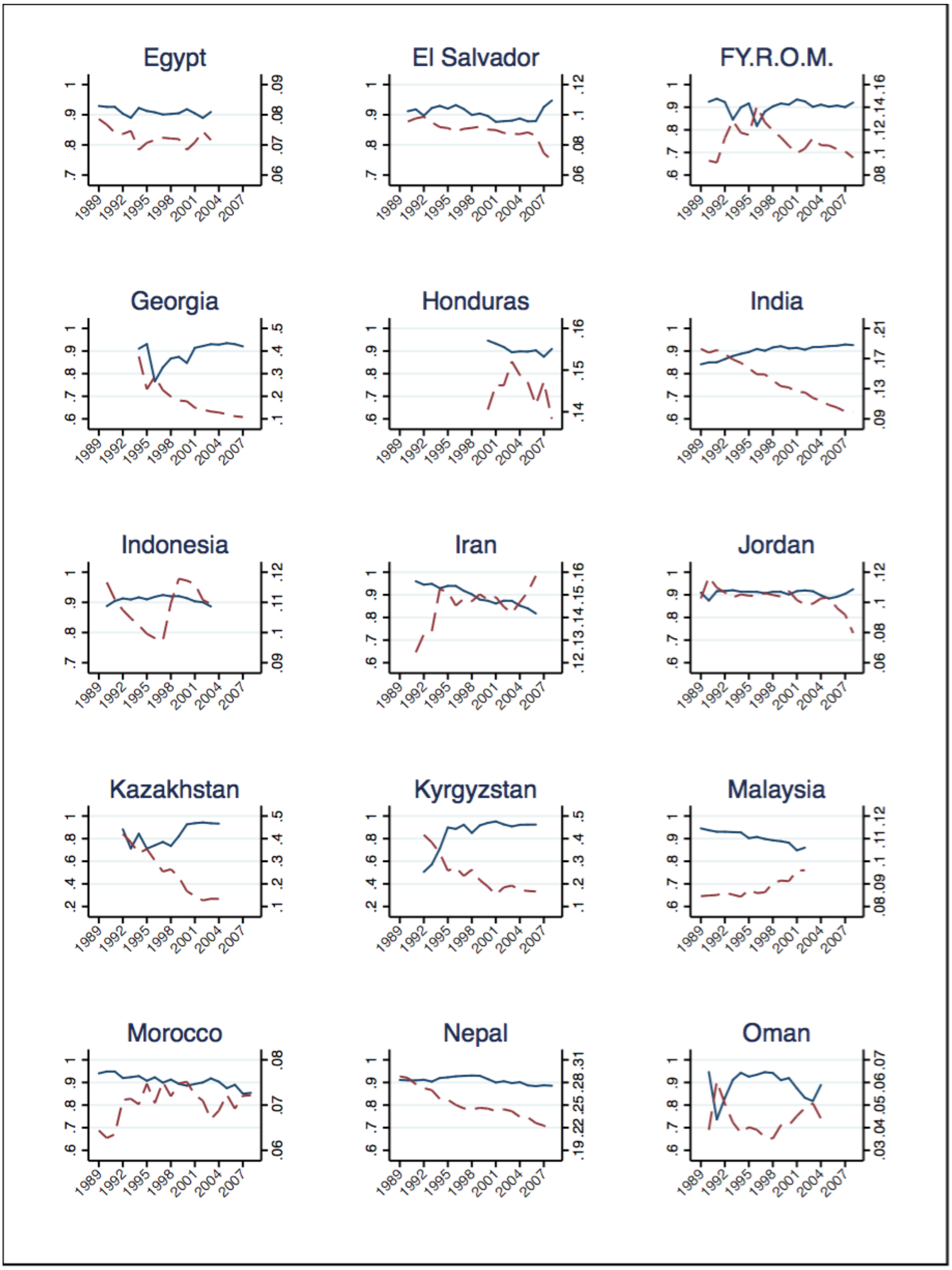
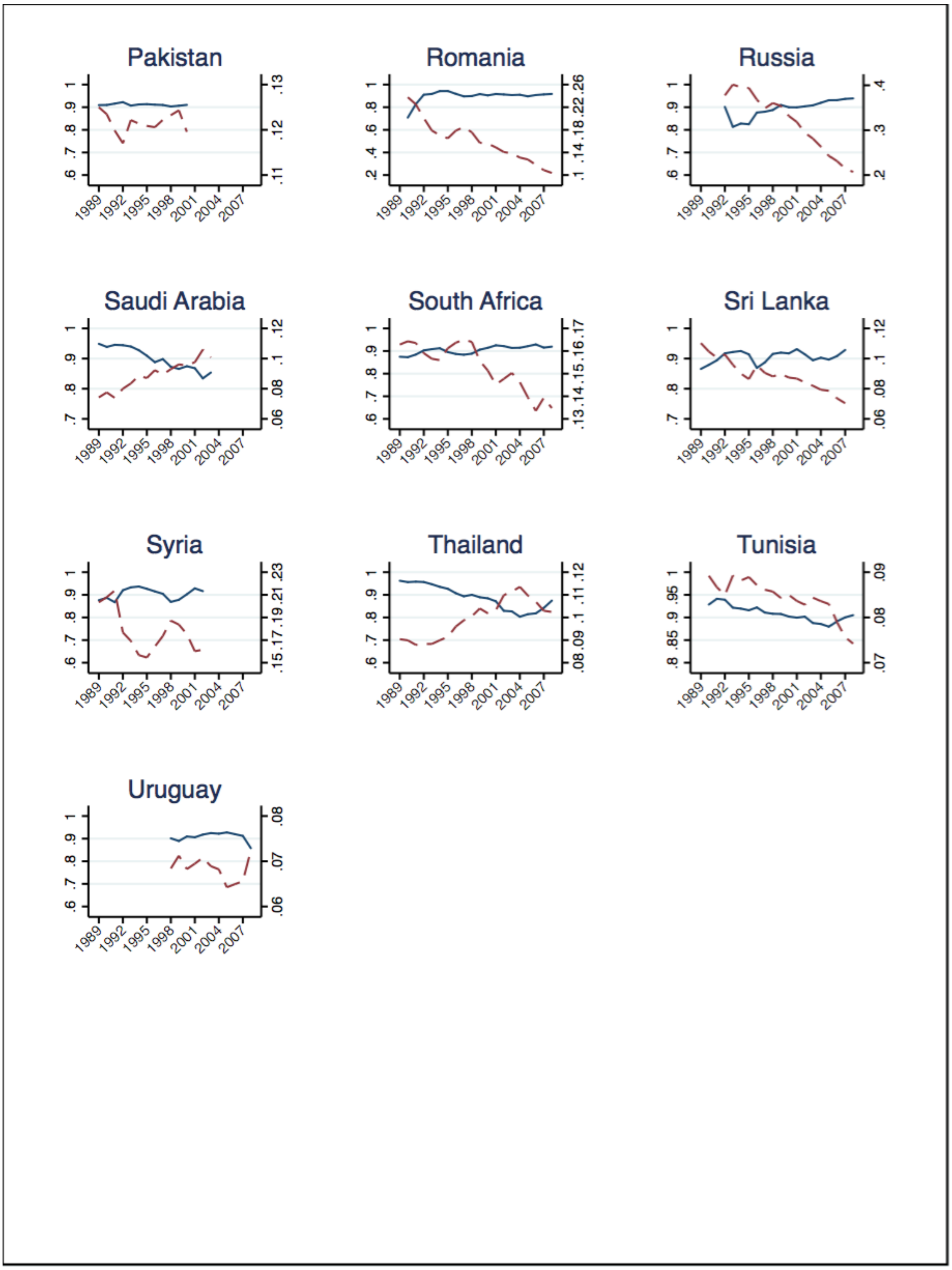


Figure 3.4 Continued



3.4.2 The contribution of energy efficiency towards eliminating CO_2 emissions

The results presented in section 3.4.1 indicate that countries such as China, India and Russia which are among the world's top 5 CO_2 emitters (IEA, 2016a), appear to be in the bottom half of the estimated transient energy efficiency ranking over the period 1989-2008, namely these countries have been ranked 34^{th}, 23^{th}, 27^{th} accordingly. Although Figure 3.4 illustrates that these countries have increased their respective levels of energy efficiency during the estimated period, there are great potentials for further improvements that could offer an ample scope for CO_2 savings. This section evaluates the contribution of energy efficiency improvements towards eliminating CO_2 emissions in the short and the long run by utilising the estimations gathered in previous section.

3.4.2.1 Calculation of CO_2 savings

Following Evans et al. (2013) this study tries to evaluate the impact of energy efficiency improvements on CO_2 emissions. For that reason initially, a CO_2 coefficient ξ_i, is constructed for each country over the period 1989-2008 such that:

$$\xi_i = \frac{\overline{CO2_i}}{\overline{E}_i} \tag{3.3}$$

where $\overline{CO2_i}$ denotes the average CO_2 emission for country i over the estimated period and $\overline{E}_i$ is the average energy consumption for country i over the same period. Additionally, the optimum level of average energy consumption, $\overline{E}_i^*$, if countries operate on their frontier (i.e. fully efficient) will be given by:

$$\overline{E}_i^* = \overline{E}_i \cdot \overline{EF_i} \tag{3.4}$$

where $\overline{EF_i}$ is the average energy efficiency of country i for the period 1989-2008, as estimated in previous section. Therefore, potential energy savings can simply calculated by:

$$E_{savi} = \overline{E}_i - \overline{E}_i^* \tag{3.5}$$

Then, combining equation 3.4 and 3.3, the optimum level of average CO_2 emission, $\overline{CO2}_i^*$ for each country over the estimated period can be calculate by:

$$\overline{CO2}_i^* = \lambda_i \cdot \overline{E}_i^* \tag{3.6}$$

and potential CO_2 savings can be derived by:

$$CO2_{\,savi} = \overline{CO2}_i - \overline{CO2}_i^* \tag{3.7}$$

Using the results from previous section we can compute the short-run and the long-run energy and CO_2 savings for each country in the panel. The preferred model is the GTREM that provides both the transient and the persistent energy efficiency. For the calculation of the short-run savings, the estimated average transient energy efficiency is used by splitting the whole period in two sub-periods, namely 1989-1998 and 1999-2008[16], while the estimated persistent energy efficiency is used for the long-run potential savings. Table 3.7 and 3.8 present the potential short and long-run energy and CO_2 savings respectively, both in actual level and percentages. Results suggest that on average there is some scope for energy and emission savings. In particular, if countries operate on the frontier, average short-run savings varies from 8.85% to 16.21% while in the long-run range from 17.65% to 20.50%. Worth noting, that in the absence of rebound effects[17] any improvement in energy efficiency yields proportionate reductions in the level of energy consumption and consequently in CO_2 emissions. Thus, savings percentages would be exactly the same in terms of energy and CO_2. Unsurprisingly, countries with the lowest estimated energy efficiency scores appear the greatest potentials for savings.

[16]Note that the the study is based on an unbalanced panel data set . For that reason India and Honduras appear no data for the first sub-period in the table 3.7.

[17]Rebound effects are behavioural responses that tend to offset the gains of efficiency improvements (at least partially) and should be considered by policy makers. This thesis also tries to estimates the magnitude of the rebound effect. For further discussion see chapter 4.

Table 3.7: Average energy savings (*Ktoe*) in the short and long term if countries were fully efficient

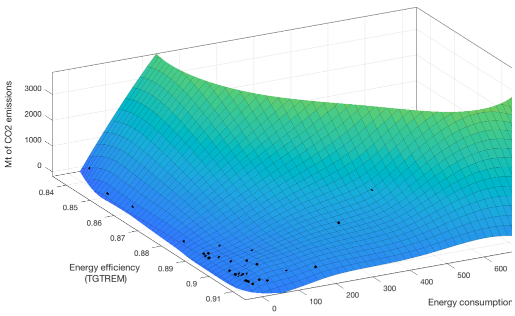
Country	Short-run						Long-run	
	1989-1998		1999-2008		1989-2008		1989-2008	
	actual	%	actual	%	actual	%	actual	%
Albania	34.26	3.42	360.85	20.72	223.55	14.95	280.71	18.78
Algeria	1,082.75	8.24	1,928.08	11.55	1,372.21	9.48	2.727.67	18.85
Argentina	3,629.20	9.73	4,896.44	9.87	4,258.64	9.80	8,182.49	18.83
Armenia	81.29	8.28	176.01	11.93	140.43.	10.71	246.72	18.82
Azerbaijan	1,746.15	18.12	759.03	10.69	1,157.40	14.00	1,550.36	18.75
Belarus	2,583.24	12.44	1,752.69	9.26	2,080.50	10.57	4,035.40	20.50
Bolivia	140.13	5.73	774.25	17.83	399.79	11.78	634.13	18.69
Botswana	121.24	10.60	136.16	8.94	131.54	9.63	255.71	18.71
Brazil	-	-	14,983.32	8.85	14,983.32	8.85	31,914.53	18.85
Bulgaria	1,766.12	14.38	772.72	7.74	1,205.24	10.88	2,063.39	18.63
China	105,563.96	14.23	89,604.06	8.56	101,908.04	11.39	166,940.41	18.66
Congo	73.11	12.43	66.09	9.24	70.61	10.84	120.03	18.42
Costa Rica	164.41	8.33	275.07	10.73	231.56	9.86	445.15	18.95
Croatia	442.39	7.94	620.63	9.35	566.64	8.95	1,195.95	18.89
Egypt	2,200.22	8.79	3,202.56	9.47	2,521.13	9.02	5,228.12	18.70
El Salvador	205.99	8.35	322.93	10.47	264.27	9.46	526.31	18.85
F.Y.R.O.M	168.48	10.59	142.41	8.69	154.99	9.59	303.65	18.78
Georgia	393.47	13.97	195.13	8.88	258.74	10.70	454.57	18.79
Honduras	-	-	312.08	9.18	312.08	9.18	645.19	18.98
India	32,892.96	12.07	28,569.27	8.12	31,517.48	10.09	58,210.94	18.64
Indonesia	8,401.46	8.85	11,683.30	9.51	9,531.39	9.08	19,760.46	18.83
Iran	4,875.58	6.48	15,275.40	14.11	9,445.566	10.29	17,392.77	18.95
Jordan	241.76	9.01	377.73	9.31	308.71	9.16	633.90	18.82
Kazakhstan	9,709.65	22.90	1,954.18	8.41	5,440.20	16.21	6,276.67	18.70
Kyrgyzstan	618.24	23.62	132.15	7.37	325.66	14.95	398.31	18.28
Malaysia	1,571.15	7.99	3,981.97	13.03	2,147.86	9.43	4,285.24	18.82
Morocco	509.15	7.51	1,120.48	11.38	758.14	9.44	1,560.10	18.76
Nepal	527.27	8.26	873.96	10.09	690.19	9.18	1,415.85	18.83
Oman	244.17	9.84	451.12	12.63	319.65	10.95	547.66	18.76
Pakistan	3,707.03	8.86	4,717.11	9.15	3,871.38	8.91	8,161.54	18.78
Romania	3,499.66	11.54	2,238.36	8.98	2,801.35	10.19	5,157.52	18.77
Russia	65,917.23	14.13	34,405.17	8.21	46,696.60	10.65	77,404.75	17.65
Saudi Arabia	3,811.57	7.87	9,401.18	14.08	5,421.63	9.94	10,313.59	18.91
South Africa	5,658.95	10.90	5,049.32	8.21	5,419.18	9.56	10,641.91	18.76
Sri Lanka	590.72	10.12	665.87	8.75	632.38	9.47	1,254.22	18.78
Syria	824.91	9.65	987.59	9.37	872.53	9.57	1,720.01	18.86
Thailand	2,525.55	6.57	9,769.40	15.47	5,597.62	11.02	9,601.03	18.90
Tunisia	328.88	7.70	645.34	10.39	482.43	9.12	992.92	18.77
Uruguay	257.83	9.86	231.36	9.13	233.72	9.20	477.38	18.78

Table 3.8: Average CO_2 savings (*kt*) in the short and long term if countries were fully efficient

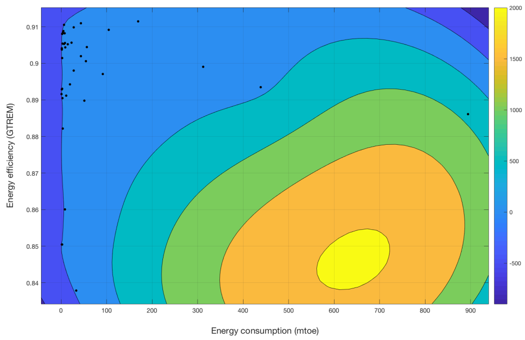
Country	Short-run						Long-run	
	1989-1998		**1999-2008**		**1989-2008**		**1989-2008**	
	actual	%	actual	%	actual	%	actual	%
Albania	62.25	3.42	755.10	20.72	454.02	14.95	570.11	18.78
Algeria	4,604.82	8.24	7,905.92	11.55	5,745.42	9.48	11,420.66	18.85
Argentina	11,320.83	9.73	14,457.48	9.87	12,878.93	9.80	24,745.37	18.83
Armenia	249.91	8.28	449.96	11.93	377.17	10.71	662.62	18.82
Azerbaijan	6,668.00	18.12	3,015.71	10.69	4,481.40	14.00	6,002.89	18.75
Belarus	8,836.39	12.44	5,684.16	9.26	6,907.77	10.57	13,398.51	20.50
Bolivia	342.45	5.73	1,564.86	17.83	868.88	11.78	1.378.19	18.69
Botswana	355.82	10.60	373.80	8.94	369.72	9.63	718.72	18.71
Brazil	-	-	28,508.08	8.85	28,508.08	8.85	60,722.33	18.85
Bulgaria	7,992.07	14.38	3,537.65	7.74	5,484.27	10.88	9,389.17	18.63
China	384,167.81	14.23	397,832.79	8.56	418,619.33	11.39	685,760.25	18.66
Congo	64.65	12.43	71.27	9.24	69.96	10.84	118.92	18.42
Costa Rica	356.03	8.33	539.18	10.73	468.40	9.86	900.46	18.95
Croatia	1,331.11	7.94	1,869.30	9.35	1,706.24	8.95	3,601.21	18.89
Egypt	7,379.74	8.79	10,497.97	9.47	8,378.73	9.02	17,375.11	18.70
El Salvador	325.32	8.35	620.89	10.47	470.12	9.46	936.28	18.85
F.Y.R.O.M	915.47	10.59	752.88	8.69	829.99	9.59	1,626.11	18.78
Georgia	981.23	13.97	359.35	8.88	546.64	10.70	960.39	18.79
Honduras	-	-	583.46	9.18	583.46	9.18	1,206.24	18.98
India	86,151.30	12.07	91,702.55	8.12	93,042.62	10.09	171,844.27	18.64
Indonesia	17,659.68	8.85	27,742.65	9.51	21,121.63	9.08	43,789.30	18.83
Iran	15,659.47	6.48	51,505.80	14.11	31,229.05	10.29	57,504.24	18.95
Jordan	1,006.55	9.01	1,520.83	9.31	1,259.81	9.16	2,586.86	18.82
Kazakhstan	40,073.94	22.90	10,330.12	8.41	24,468.26	16.21	28,230.45	18.70
Kyrgyzstan	1,687.47	23.62	343.22	7.37	869.96	14.95	1,064.04	18.28
Malaysia	5,788.24	7.99	14,942.77	13.03	7,969.34	9.43	15,899.80	18.82
Morocco	1,767.12	7.51	4,057.27	11.38	2,794.91	9.44	5,553.54	18.76
Nepal	118.73	8.26	286.81	10.09	196.35	9.18	402.79	18.83
Oman	1,339.65	9.84	2,867.58	12.63	1,889.95	10.95	3,238.08	18.76
Pakistan	6,458.16	8.86	9,103.39	9.15	6,888.09	8.91	14,521.27	18.78
Romania	14,267.55	11.54	8,310.99	8.98	10,934.14	10.19	20,130.69	18.77
Russia	229,220.39	14.13	124,823.46	8.21	166,335.06	10.65	275,718.64	17.65
Saudi Arabia	15,123.93	7.87	36,985.79	14.08	21,437.86	9.94	40,781.33	18.91
South Africa	29,123.30	10.90	26,382.02	8.21	28,119.98	9.56	55,220.55	18.76
Sri Lanka	572.70	10.12	1,008.82	8.75	799.35	9.47	1,585.37	18.78
Syria	3,075.28	9.65	3,777.68	9.37	3,280.83	9.57	6,467.42	18.86
Thailand	7,744.97	6.57	29,241.93	15.47	16,992.34	11.02	29,145.21	18.90
Tunisia	1,086.50	7.70	2,019.72	10.39	1,541.94	9.12	3,173.58	18.77
Uruguay	554.33	9.86	506.90	9.13	511.17	9.20	1,044.08	18.78

Combining results from section 3.4 and the above calculations some very interesting conclusions can be reached. In particular, most efficient countries tend to consume less energy and consequently emit less CO_2 emissions on average . Figure 3.5 illustrates this conclusion.[18] There is a great concentration of countries (black points) at the corner of the axis with low energy consumption and high energy efficiency level. Also, the colour of the graph and in the 3D plot the high of the graph, represent the level of CO_2 emissions. However, previous conclusion this is not always the case. For instance there are some low efficient countries with low energy consumption (i.e. Albania, Azerbaijan, Kazakhstan and Kyrgyzstan). On the other hand, it is quite alarming that some countries such as China, Russia and India that consume large amount of energy appear to be relatively inefficient.[19]

Figure 3.5: Average CO_2 Vs. average energy consumption and average energy efficiency



(a) 3D plot



(b) contour plot

[18]Matlab software is used to produce figure 3.5. Part (a) of the figure is a 3D representation where the Y axis is the average measure of transient energy efficiency as estimated in section 3.4.1, X axis gives the average level of energy consumption while Z axis (height) represents the average level of CO_2 emissions of each country over the investigated period. Part (b) of the figure is the contour plot of the same graph where the X axis presents the average level of energy consumption of each country , Y axis gives the average level of the estimated transient energy efficiency while the colour of the plot denotes the average level of the CO_2 emissions for each of the country in the panel over the investigated period. The scale legend at the right of the plot provides further information regarding the level of CO_2 emissions and the colours correspondences.

[19]According to IEA (2016a), these three countries are among the world's top-5 energy consumers and carbon emitters.further analysis regarding these three countries and their respective energy policy follow in chapter 5 of this study.

3.5 Conclusions

This chapter uses energy demand frontier model, originally proposed by Filippini and Hunt (2011, 2012) to estimate the level of 'true' energy efficiency for a sample of 39 developing countries over the period 1989-2008. The aggregate energy demand specification controls for income, price, population, area size, the share of the agricultural and the services sector in country's GDP, heating degree days, cooling degree days and a UEDT, expressed by a quadratic time trend, and it is estimated using three alternative econometric techniques, namely the MREM, the TREM and the GTREM. These alternative models represent different sources of information regarding the energy efficiency of a country and thus there is no absolute preferred model among them but a combination of these three could lead to useful conclusions. Overall, REM tend to estimate the level of persistent energy efficiency while the TREM estimates provide information regarding the transient energy efficiency. GTREM proposed by Filippini and Greene (2016) and allows for estimation of both persistent and transient energy efficiency simultaneously.

Estimated results indicate, as expected, that transient and persistent counterparts are quite different in values and not highly correlated. This is because the sources of inefficiency are quite different. Therefore, policy makers should be informed for the level of both transient and persistent energy efficiency in order to be able to design effective energy policies. TGTREM estimates are very highly correlated with estimates produced by the TREM and thus both models could explain trends in transient energy efficiency. On the contrary, correlation between PGTREM estimates and MREM is relatively lower. This is in line with Filippini and Greene (2016) who argue that in REM all the time invariant variables are captured by the individual effects and hence REM produces higher level of inefficiencies. Mundlak adjustment seems to control part of this time invariant heterogeneity.[20] The estimated results also suggest that there is a significant potential for energy saving in developing countries. In particular,

[20]The correlation between REM and the PGTREM is significantly lower that this between MREM and the PGTREM suggesting that Mundlak modification controls, at least partially, the unobserved time invariant heterogeneity. For detailed descriptive statistics of estimated efficiencies and correlation coefficient between all the models, see table B.4 and table B.5 in appendix B.

persistent efficiency, on average, is higher than the transient reflecting the potential lack of structural reforms of economies and the implementation of the necessary regulatory framework that would attract investments on the energy efficiency.

Additionally, results suggest that there are great potentials for energy and CO_2 emission savings if countries operate efficient. generally, most efficient countries tent to use less energy but this is not always the case. Three countries, namely China, India and Russia, which are among the world's top-5 emitters appear to be quite inefficient in the use of energy. Although these countries have increased their respective level of energy efficiency during the estimated period, there is still ample scope for improvements in energy efficiency. In the light of the the Paris agreement, that consider both developed and developing countries equally responsible to design and implement national energy strategies in the direction of reducing their energy consumption and the associated CO2 emissions by 2020, this result is particularly important from a policy making perspective.

In the country level, estimated results are in line with previous studies suggesting great heterogeneity across countries' efficiency scores. The majority of the countries have improved their energy efficiency over the estimated period. However, a group of countries especially and especially Latin America countries present a downward sloping in their energy efficiency scores or appear great volatility and there is no dominant trend. This reflects the fact that developing countries have never been bound to implement environmentally sensitive energy strategies, until recently. Finally, estimated energy efficiency is negative correlated with energy intensity for most of the countries, as expected, but this negative correlation appears great heterogeneity across countries varying from -.01 to -.99. Besides, for some countries results indicate a positive relationship between the estimated 'true' energy efficiency and energy intensity, unveiling the weakness of using energy intensity or the energy consumption to GDP ratio as a proxy of energy efficiency. This result is in line with Filippini and Hunt (2011, 2012) and Filippini et al. (2014). This study is based on the economic theory of production and after controlling for a range of economic and other factors, provides effective energy efficiency measurements that could offer an ancillary instrument to policy makers in order to avoid any potential misguided conclusions.

Chapter 4

Energy efficiency and rebound effect in developing countries

4.1 Introduction

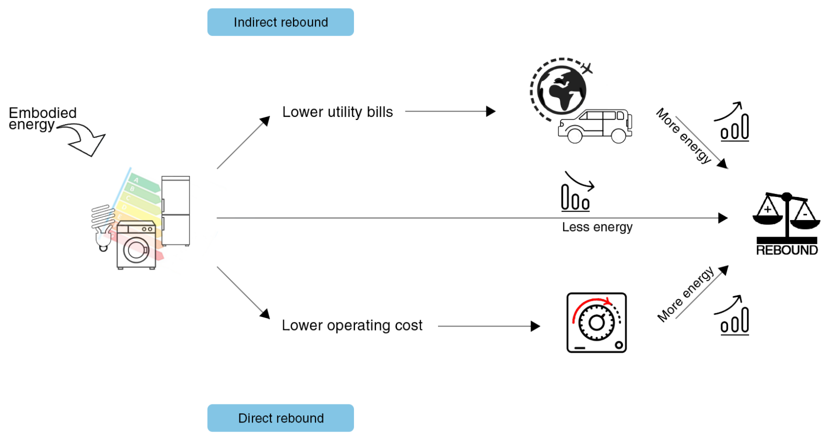
Reducing energy consumption and resultant negative externalities such as GHG emissions is a principal objective for most governments and policy makers across the globe (IEA, 2016c). Energy efficiency not only offers a significant potential for mitigating carbon emissions, but it is also recognised by IEA (2016c) as one of the lowest-cost and immediately available means to address global warming. Therefore, energy efficiency policies are pursued as a way to provide affordable and sustainable energy services. Energy efficiency improvements typically reduce energy demand. Hence, policies to promote such improvements are a key part of national and international energy strategies (UNFCCC, 2017). However, according to IEA (2015), one of the most persistent challenge in designing energy efficiency policy is accounting for the phenomenon called 'rebound effect'. Due to the RE, energy and the associated GHG savings from improvements in efficiency may be less than simple engineering estimates suggest since benefits from improved technologies evoke behavioural responses by economic agents that can cause that the full profit of energy conservation can not be realised.

Jevons (1865) was the first economist who touches upon the idea of the rebound effect but his 'paradox' remained on a hiatus until Brookes (1979) and Khazzoom (1980) shed light on the paradoxical relation between increase energy efficiency and increased demand for energy services. Saunders (1992) associates RE analysis with neoclassical theory and suggests that energy efficiency improvements could magnify rather than diminish energy demand highlighting two main paths for that to be happened. First by making energy relatively cheaper and by boosting economic growth. In the first case households and firms will adopt to price changes and they will adjust their energy needs given the new relative prices while in the second case economic growth will inevitably induce higher demand for energy.

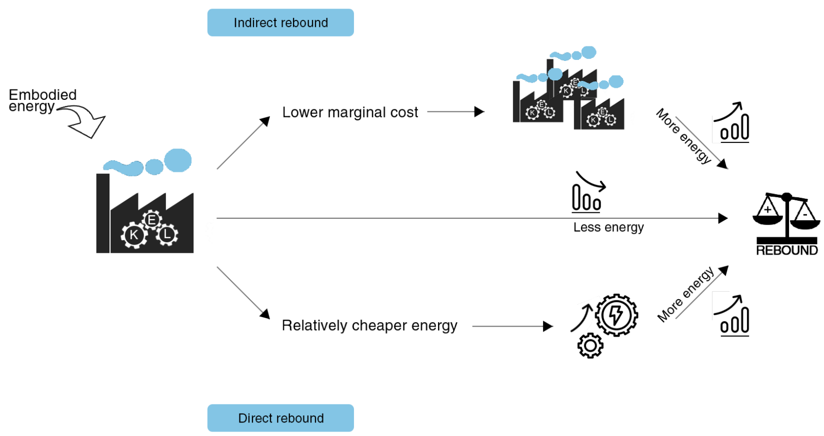
Even though there is no clear-cut definition of the rebound in the literature, it is broadly accepted that several mechanisms may reduce potential energy savings from improvements in energy efficiency. Those mechanisms can be broadly classified into direct, indirect and economy-wide effects.(Greening et al., 2000; Sorrell et al., 2007). Figure 4.1 roughly illustrates those mechanisms where energy efficiency improvements do not reduce energy consumption by the amount suggested by simple engineering models. Technological improvements make energy services relatively cheaper, so consumption of those services tend to increase. For example, the use of more efficient household appliances decreases its operating cost, hence consumers may choose to increase the use of those services (i.e. by increasing the thermostat by few degrees °C or by keeping lights on during the night or by not switching off appliances when leave for holidays) and thereby offsetting some of the energy savings achieved. Similarly, improvements in energy efficiency in production process may lead to increase energy use by substituting other inputs with the relatively cheaper energy. These mechanisms are known as 'direct rebound effect'. Even in the case where economic agents do not change their behaviour, energy savings across the economy may be less than simple engineering calculations. For instance, as the real income of household increases they may spend money saved from lower utility bills on other energy-intensive goods and services. (i.e buying a car, or traveling overseas for holidays). Similarly, firms may decrease their operating cost, encouraging further investment and greater levels of output which actually requires more energy to produce. This is termed the 'indirect rebound effects'. Then economy-wide rebound effect is the sum of direct and indirect rebound effects.

Worth noting that for the production of new energy efficient household appliances or machines in the production line amount of energy is required as well. 'This is termed embodied effects'.

Figure 4.1: Mechanisms of rebound effects



(a) For consumers



(b) for producers

Own elaboration

The magnitude of any RE is of great importance to assessing the effectiveness of energy policies and failure to account the RE may impinge on the implementation of national energy strategies. However, even though there is no dispute in the literature about the existence of the RE the magnitude and even the definition of RE have been the subject of heated debate. Sorrell and Dimitropoulos (2007) suggest that empirical evidence on the RE is ambiguous and inconclusive highlighting that quite many different definitions of the RE have been used by different authors. The debate becomes even more intense regarding economy-wide or macroeconomic RE since the latest describes a net effect of numerous adjustments that are mutually interdependent and individually characterised by great complexity. Those adjustments, from households and firms, could be highly significant, when aggregated at an economy level (Greening et al., 2000). This lack of consistency in definition of the RE, its sources and the relationship between them, as well as lack of a common approach to measure it make the estimation of the economy-wide rebound effect a challenging issue and the scintilla of existing empirical evidence both confusing and contradictory. Therefore, analysts and policymakers tend to ignore those so-called rebound effects, despite the fact that a growing body of academic research suggests that they could be significant.

This study therefore attempts to address the issue relating with the magnitude of the RE and the appropriate modelling approach, by estimating an economy-wide RE for a panel of developing countries using as in chapter 3 data for the period 1989-2008 and a two-stage econometric procedure. Accurate measurements of macroeconomic RE is crucial for several reasons. Both developed and developing countries should collaborate to mitigate and adapt to climate impacts resulting from anthropogenic GHG emissions. Therefore climate change policies, in their nature, require international cooperation among countries, thus creating an imperative for a comparative and consistent measurement of RE. Top-down macroeconomic analyses of several countries over long time horizon is more appropriate given the global nature of climate change. However, empirical evidence from existing literature is far from comprehensive and is dominated by studies on direct RE. Additionally, drawing general inferences and conclusions from segmented studies for specific sectors of an economy and/or specific energy services may be inadequate in the context of global climate change (Allan et al., 2007). Finally, the contribution of this study is important since Herring and Roy (2007), Sorrell and Dimitropoulos (2007) and Chakravarty et al. (2013) argue that macroeconomic RE are likely to be remarkably higher in developing countries because their economic growth and demand for energy services is far from saturated and as far as is known, there is no such a study, of macroeconomic RE across a panel of solely developing countries. This is a significant gap in literature considering that RE arising from aggregate RE from both households and firms are likely to be of great significance (Kydes, 1999). Thus failure to take into consideration the rebound effect, environmental policies can be misrepresented.

The remainder of the chapter is organised as follows: Section, 4.2 discusses the two stages methodological framework applied in this study. In particular, the first stage (Section 4.4.1) describes the modelling approach for the estimation of energy efficiency while the second stage (Section 4.2.2) presents the modelling approach for the estimations of the macroeconomic rebound effect. Data used in the analysis and different econometric specifications are introduced in Section 4.3. The econometric results, the estimated level of energy efficiency and the estimated rebound effects are presented in Section 4.4 which is followed by Section 4.5 that concludes the chapter.

4.2 Methodology

Previous section describes the RE and highlights the reasons that a consistent measurement of macroeconomic RE is crucial from a policy perspective. Therefore, this study estimates an economy-wide RE based on the well established neoclassical growth theory. Saunders (2000) provides the theoretical framework and a clear definition of macroeconomic rebound effect. According to Saunders (2000), energy conservations from improvements in energy efficiency can be defined as the elasticity of energy use with respect to changes in energy efficiency.

$$\eta^E = \frac{\partial E}{\partial EF} \tag{4.1}$$

Where E is the level of energy consumption and EF denotes the energy efficiency. Then the Rebound can be defined as follows:

$$R = 1 + \eta^E \tag{4.2}$$

Given data availability and the scope of the analysis, Sorrell and Dimitropoulos (2007) provide some alternative definitions[1], equivalent to the elasticity of energy use with respect to changes in energy efficiency. Also, the magnitude of R will be determined by the way that an economy performs (Saunders, 2000) and table 4.1 presents the variety of possible rebound effects that can be derived.

Table 4.1: Ranges of rebound effect

Rebound effect	Elasticity	Type	Implication
$R > 1$ or $R > 100\%$	$\eta^E > 0$	Backfire	Potential energy efficiency improvements increase the demand for energy services as relative price of energy falls
$R = 1$ or $R = 100\%$	$\eta^E = 0$	Full rebound	Energy saving through potential energy efficiency improvements exactly offset by increased demand as relative price of energy falls
$0 < R < 1$ or $0\% < R < 100\%$	$-1 < \eta^E < 0$	Partial rebound	Energy saving through potential energy efficiency improvements partially offset by increased demand, as relative price of energy falls
$R = 0$ or $R = 0\%$	$\eta^E = -1$	No/zero rebound	Potential energy improvements are decrease energy demand proportionally
$RE =< 0$ or $R < 0\%$	$\eta^E < -1$	Super-conservation rebound	Potential energy improvements are decrease energy demand more than proportionally

Notes: Own elaboration based on Saunders (2000).

The aim of this study is to estimates the energy efficiency elasticity η^E using two-stages econometric approach based on neoclassical growth theory. In the first step Stochastic Frontier Analysis is used to estimate the level of energy efficiency in a panel of developing countries while in the second step those efficiency scores are used as explanatory variables in a dynamic panel data framework to estimate the short and the long-run economy-wide RE.

[1]Table C.1 in appendix C provides some of those definitions. For further analysis and limitations in the use of each one see Sorrell and Dimitropoulos (2007).

4.2.1 Energy efficiency estimation

The first stage of this analysis employs SFA initially proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) to estimate relative energy efficiency scores for each country in the panel. Production technology can be represented by the input requirement set $L(y) = \{x \mid x \text{ can produce y}\}$ and assuming that $L(y)$ satisfies the regularity conditions, namely closedness, convexity and monotonicity, the definition of the Input Distance Function is given by:

$$D^I(y, x) = \max\{\lambda : x/\lambda \in L(y)\},\ \lambda \geqslant 1 \tag{4.3}$$

The IDF gives the maximum proportional reduction in inpus x keeping the output y unchanged. It can be show that the IDF satisfies the following properties:

(i) is non-decreasing in inputs x: $\dfrac{\partial D^I(y,x)}{\partial x_k} = e^{x_t} \geq 0$ for $k = 1, ..., K$

(ii) is non-increasing in outputs y: $\dfrac{\partial D^I(y,x)}{\partial y_s} = e^{y_s} \leq 0$ for $r = 1, ..., S$

(iii) is homogeneous of degree one in inputs x: $D^I(x/x_k, y) = \dfrac{D^I(y,x)}{x_k}$

(iv) is concave in inputs and quasi-concave in outputs

(v) is equal to unity if x belongs to the frontier of the input set (on the isoquant)

(vi) and the scale elasticity of the technology at time is given by:

$$e^t = -\left(\sum_{s=1}^{S} \frac{\partial D^I(x,y)}{\partial y_s}\right)^{-1} \tag{4.4}$$

In this study, production technology combines inputs capital (K), labour (L) and energy (E) to produce a given level of output (Y) such that the input requirement set can be described by $L(Y) = \{K, L, E \mid (K,\ L,\ E) \text{ can produce Y}\}$ and the input distance function in time t can be re-written as $D^I(y, x, t) = D^I(Y, K, L, E, t)$ which is equal to unity if a country is efficient (i.e. on the frontier) but is greater to one when a country is energy inefficient so that:

$$D^I(Y, K, L, E, t) - u_{it} = 0 \tag{4.5}$$

where u_{it} in a non-negative term that refers to inefficiency. Applying property (iii) by normalising all inputs by the input energy E and making assumptions for the functional form of the distance function we can estimate the level of technical efficiency in the use of energy. For instance, assuming a translog functional form in a panel data context and applying homogeneity condition, equation 4.5 can be rewritten as:

$$-\ln E \approx TL(Y,\ K/E,\ L/E,\ t) + v_{it} - u_{it} \tag{4.6}$$

where $TL(Y,\ K/E,\ L/E,\ t)$ represents the technology as a translog approximation of the distance function. The error term , as in previous chapter consists of two components, the traditional symmetric disturbance v_{it} and the u_{it} which is the non-negative inefficiency component such that $\varepsilon_{it} = v_{it} - u_{it}$. The conditional expectation of the inefficiency error term can be used for the estimation of energy efficiency of each country in each period as follows:

$$TE_{it} = E\left[\exp\{-u_{it}\}\,|\varepsilon_{it}\right] \tag{4.7}$$

Hence, the estimated efficiency evaluates the degree to which, countries could decrease their level of energy use relative to the frontier, holding output constant.

4.2.1.1 Modelling observed heterogeneity

In the development of frontier models different assumptions have been used regarding the inefficiency component allowing for the estimation of time invariant or time varying efficiencies[2], as detailed in Chapter 2. However, an important question about how to introduce observed heterogeneity into the specification of the model aroused a debate and literature has proposed quite many ways to deal with this issue. For instance a vector of extra exogenous variables z_i other than inputs, outputs and costs that can either

[2]Previous chapter discusses the differences between time-varying and time invariant energy efficiency scores and how different models can give information about the transient and persistent inefficiencies

be time-invariant or time varying and characterise the environment that production process takes place, could potentially affect producers performance. In the model proposed in chapter 3, a vector of individual specific environmental variables z_i such as the size of each country, the population, the structure of the economy and climatic conditions, introduced in the goal function, namely the energy demand function. This is a common way to introduce the observed heterogeneity in the model specification. However, it is possible to incorporate this observed heterogeneity in the inefficiency component as well. In this section three additional methods of introducing observed heterogeneity in frontier models are presented.

A vector of observable, country specific, exogenous factors that reflect the operating environment, could potentially affect the level of technical efficiency in each country (Kumbhakar and Lovell, 2000). Hence, observed heterogeneity could be incorporating in frontier models and there are mainly two ways to achieve this, either in the mean of the underlying inefficiency or in the variance of the inefficiency term. Moreover, according to Kumbhakar and Lovell (2000), by evaluating the impact of such exogenous factors in the inefficiency, it is possible to address the problem of conditional heteroscedasticity in the energy inefficiency term, since ignoring heteroscedasticity could lead to inconsistent parameter estimates.

In that context, it is possible to relax the implicit restrictions imposed in previous chapter, that the inefficiency term follows a half normal distribution with zero mean and constant variable. On the contrary, the one-sided error component u_{it}, is assumed to follow the truncated normal distribution with constant variance but now, the mean of the pre-truncation inefficiency depends on z_{it}. Kumbhakar et al. (1991); Huang and Liu (1994) and Battese and Coelli (1995), initially employ this approach where:

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_{it}^{2}) \tag{4.8}$$

and

$$\mu = \phi' z_{it} \tag{4.9}$$

By its definition, since the degree of truncation varies with μ_{it}, the shape of the distribution of the inefficiency term changes as the vector of exogenous variables z_{it} changes.

Nonetheless, there is no specific reason to assume that heterogeneity would be limited to the mean of the underlying inefficiency. Therefore, exogenous variables can be introduced in the variance of the inefficiency term. Reifschneider and Stevenson (1991) was the first to propose such a model[3] while Caudill and Ford (1993); Caudill et al. (1995) and Hadri (1999) follow, assuming the following multiplicative heteroscedasticity of the inefficiency component:

$$u_{it} \sim N^{+}(0, \sigma_{u_{it}}^{2}) \tag{4.10}$$

$$\sigma_{u_{it}}^{2} = \sigma_{u}^{2} \cdot \exp(\gamma' z_{it}) \tag{4.11}$$

while if the vector of environmental variables z_{it} contains an intercept, equation 4.11 can be written as:

$$\sigma_{u_{it}}^{2} = \exp(\gamma' z_{it}) \tag{4.12}$$

The above model satisfies the scaling property, which says that $u(z, \gamma)$ can be rewritten as a scaling function:

$$u(z, \gamma) = h(z, \gamma') \cdot u^{*} \tag{4.13}$$

so that u^{*} does not depend on z. According to Alvarez et al. (2006), the scaling property of the above model adds some desirable dimensions to the stochastic frontier approach. First, scaling property implies that changes in the vector of exogenous variables z affect the scale but not the shape of the distribution of the one-sided error term. Furthermore, Wang and Schmidt (2002) note that the economic interpretation of γ's does not depend on the distribution of inefficiency component. Hence, if the exponential scaling function is used, equation 4.13 can be written as:

[3] The best term to describe such models is heteroscedastic. In the representation of the results, the term 'heteroscedastic model' is used broadly to describe the models that introduce observed heterogeneity in the inefficiency component.

$$u(z_{it}, \gamma) = \exp(z_{it}, \gamma') \cdot u_{it}^{*} \tag{4.14}$$

and then coefficients γ are the derivatives of log inefficiency with respect to the z_{it} $\delta = \partial \ln(u_{it})/\partial z_{it}$.

Additionally, the two-sided disturbance term v_{it} is likely to be affected by heteroscedasticity. Thus, Hadri (1999) extend model described in equations 4.10 and 4.11 proposing a doubly heteroscedastic stochastic frontier model by making the following additinal assumptions:

$$v_{it} \sim N^{+}(0, \sigma_{v_{it}}^{2}) \tag{4.15}$$

$$\sigma_{v_{it}}^{2} = \sigma_{v}^{2} \exp(\gamma' z_{it}) \tag{4.16}$$

Given the discussions above and the advantages of a scaling property in some of the models described, this study incorporates different exogenous, environmental variables into the underlying inefficiency term to capture the impact of demographics, the structure of economy and climate conditions on energy inefficiency. It is worth noting that allowing inefficiency be affected by country specific characteristics enables policy makers to examine the determinants of inefficiency and thus suggesting policy interventions to improve energy efficiency.

4.2.2 Macroeconomic rebound effect estimation

In the second step the main objective is to estimate the magnitude of the economy-wide rebound effect. To achieve this, first a dynamic panel energy demand model is estimated by applying Generalised Methods of Moments (GMM) techniques, following Arellano and Bond (1991). The log-log specification of the dynamic model is specified as:

$$\ln E_{it} = \beta_0 + \psi \ln E_{it-1} + \beta_p \ln P_{it} + \beta_y \ln Y_{it} + \beta_{eff} EF_{it} + \beta_t t \\ + \beta_{peff} P_{it} EF_{it} + \beta_{yeff} Y_{it} EF_{it} + \beta_{py} P_{it} Y_{it} + (\alpha_i + v_{it}) \tag{4.17}$$

where E_{it} is the level of total energy consumption for country i at time t and E_{it-1} is the lagged term of the E that introduced in the model as explanatory variable. Additionally, the set of explanatory variables includes P_{it} that denotes the corresponding energy prices, Y_{it} which is the GDP of each country at time t and EF_{it} is the energy efficiency as estimated from stage one of this study, using SFA. The error term consists of unobserved, time-invariant, country specific characteristics α_i and the traditional disturbance error that captures the effect of noise and assumed to be independently and identically distributed as $v_{id} \sim N(0, \sigma^2)$. Finally, β's are the parameters to be estimated by the model and values of β's will be used for the computation of the elasticity of energy demand with respect to changes in energy efficiency.[4]

As explained above, following Saunders (2000), the RE can be derived by:

$$R = 1 + \eta^E \tag{4.18}$$

where η^E is the elasticity of energy use with respect to changes in energy efficiency.

From the estimation of equation 4.17 short-run and long run elasticities can be computed as:

$$\eta^E_{SR} = \frac{\partial \ln E}{\partial EF} = \beta_{eff} + \beta_{pef} P_{it} + \beta_{yeff} Y_{it} \tag{4.19}$$

$$\eta^E_{LR} = \frac{\beta_{eff} + \beta_{peff} P_{it} + \beta_{yeff} Y_{it}}{1 - \psi} \tag{4.20}$$

And substituting equations 4.19 and 4.20 into 4.18, the short-run and long-run economy-

[4]Following Adetutu et al. (2016) variables have been mean-adjusted, such that the estimated parameters express elasticities at respective sample means. This is a convenient property of translog specification. In particular, translog form provides a second-order approximation of the true function at a given point so that variables can be expressed as deviations from this point (i.e. the mean). Additionally, efficiency scores are not in logarithmic forms, however, as Adetutu et al. (2016) states, can be explained as a measure of elasticity, so that $\eta_E = \dfrac{\partial E}{\partial EF}$.

wide RE can is given by $R_{SR} = 1 + \eta^E_{SR}$ and $R_{LR} = 1 + \eta^E_{LR}$ respectively.

4.3 Data and econometric specification

As in previous chapter, this study employs an unbalanced panel data set of 39 developing countries ($i = 1, \ldots, 39$), over the period 1989 to 2008 ($t = 1989, \ldots, 2008$).[5] Table 4.2 presents the descriptive statistics of the variables used in the analysis. Variables employed in the first stage of this study include the inputs energy (E), capital (K) and labour (L), the output (Y) and the exogenous environmental variables POP, A, ASH, ISH, $TEMP$,$EIMP$ and $CO2$ that denote the population, area, share of agricultural sector, share of industry sector, CO_2 emissions and net energy imports of each country respectively. Additionally, variables for the second step of the analysis include the real energy price index P and the efficiency scores estimated from the first stage EFF. Data set is based on information gathered from several sources.

In particular, E which is the aggregate total final energy consumption in thousand of tonnes equivalent (*ktoe*), Y which is the GDP in billion 2005 US dollars in Purchasing Power Parity (PPP) and POP which is each country's population in millions gathered from the IEA database 'World Energy Balances: World Indicators, 1960-2015' (IEA, 2017*b*). Additionally, K denotes the capital stock in billion 2005 US dollars in PPP and L the labour input in million of persons engaged and data for both variables collected from the Penn World Table, version 8.0. (Feenstra et al., 2015). Furthermore, data for ASH and ISH which present the agricultural value added and industry value added respectively, A which is the land area in square kilometres ($sq.\ km$) as well as $EIMP$ which is the net energy imports of each country as share of total energy use, collected from the World Bank database 'World Development Indicators' (World Bank, 2017) while P is the real energy price index and data collected from International Labour Organisation Statistics, 'ILOSTAT-ILO database of labour statistics' (International Labour Organisation, 2017).

In order to control for the influences of the different climate conditions, heating

[5]As stated in the previous chapter, the number of countries and the time horizon are determined by the availability of data.

Table 4.2: Descriptive statistics

Variable	Label	Mean	Std. Dev.
First stage variables			
Inputs			
Total final energy consumption (*ktoe*)	*E*	69,195	177,186.600
Labour (million people)	L	45.110	137.206
Capital (billion 2005 *USD* using *PPPs*)	K	1,105.267	3,005.872
Outputs			
GDP (billion 2005 *USD* using *PPPs*)	*Y*	426.396	974.972
Environmental Variables			
Population (millions)	*POP*	98.743	272.196
Land area (*sq. km*)	*A*	1,500,114.500	3,135,588.600
Agriculture, value added (% of *GDP*)	*ASH*	15.056	10.285
Industry value added (% of *GDP*)	*ISH*	34.612	10.348
Temperature=HDD+CDD(base 70°*F*)	*TEMP*	24,265.620	12,243.460
Energy imports net (% of energy use)	*EIMP*	-67.584	265.911
CO_2 sectoral approach (*Kt* of CO_2)	*CO2*	248,048.100	723,361.500
Second stage variables			
Real consumer price index, energy	*P*	102.999	44.846
Estimated technical efficiency	*EFF*	0.854	0.148

degree days (*HDD*) and cooling degree days (*CDD*) are used.[6] Data for *HDD* and *CDD* obtained from the King Abdullah Petroleum Studies and Research Centre dataset 'A global degree days database for energy-related applications' (King Abdullah Petroleum Studies and Research Centre, 2015). Finally, in order to examine the effect of CO_2, data for CO_2 sectoral approach in thousand tonnes is used, gathered from the IEA database

[6] 70°*F* have been chosen as a base temperature for the HDD and the CDD in order to be in line with the previous chapter.

'CO_2 Emissions From Fuel Combustion: CO_2 Emissions from Fuel Combustion' (IEA, 2017*a*).

4.3.1 Stage one: Energy efficiency econometric specification

The main objective of the first stage of the analysis is to estimate the energy oriented technical efficiency. Therefore, the IDF that gives the maximum amount by which the input vector can be radially contracted such that the output vector remains feasible, is used.[7] Then, the estimated efficiency evaluates the degree to which, countries could decrease their level of energy use relative to the frontier, holding output constant. Assuming that capital K, labour L and energy E are the inputs for the production of output Y [8] and applying a translog approximation for the IDF, equation 4.6 can be written as:

$$
\begin{aligned}
-\ln E = {} & \beta_0 + \beta_y \ln Y + \beta_k \ln K^* + \beta_l \ln L^* + \frac{1}{2}\beta_{yy}(\ln Y)^2 + \frac{1}{2}\beta_{kk}(\ln K^*)^2 + \frac{1}{2}\beta_{ll}(\ln L^*)^2 + \\
& + \beta_{yk}(\ln Y)(\ln K^*) + \beta_{yl}(\ln Y)(\ln L^*) + \beta_{kl}(\ln K^*)(\ln L^*) + \\
& + \beta_t t + \beta_{tt} t^2 + \beta_{yt}(\ln Y)t + \beta_{kt}(\ln K^*)t + \beta_{lt}(\ln L^*)t + v_{it} - u_{it}
\end{aligned}
\tag{4.21}
$$

where $K^* = K/E$ and $L^* = L/E$ are the normalised inputs. Additionally, symmetry restrictions have been imposed on the parameters of the inputs interaction terms so that $\beta_{kl} = \beta_{lk}$ in order to ensure continuity of the IDF. Finally, given certain assumptions

[7] As the one-sided error term in equation 3.2 measures the level of true energy efficiency, the elasticity of energy demand with respect to changes in energy efficiency will be given by $\eta^E = \dfrac{\partial e_{it}}{\partial u_{it}}$. Given the definition of the rebound effect rebound effect as provided in equation 4.18, it is clear that stochastic energy demand frontier model that includes an inefficiency term as an explanatory variable implicitly provides a direct measure of the rebound effect. However, η^E in equation 3.2 is by definition equal to -1. That is the Stochastic Frontier Energy Demand Model, as described in chapter 3, imposes a zero rebound effect and therefore an alternative two stages technique that allows both the the estimation of energy oriented technical efficiency in the first step and the estimation of the macroeconomic rebound effect in the second step is followed in this chapter. It is worth noting that both techniques, in particular, the estimation of a stochastic energy demand function as well as the estimation of an input demand function, provide measurements of energy efficiency from an economics perspective and therefore an economic based energy efficiency indicator more accurate than the simple energy intensity ratio.

[8] The inputs and the output variables as well as the exogenous environmental variables are in mean-corrected logarithms such that estimated first order coefficients can be interpreted as elasticities at the sample mean.

for the mean and the distribution of v_{it} and u_{it}, as described below and using ML estimation, is possible to get the radial energy-oriented estimation of technical efficiency as $TE_{it} = \exp\{-u_{it}\}$.

4.3.2 Energy efficiency analysis

As explained in previous section, this study incorporates different exogenous, environmental variables (POP, A, ISH, ASH, $TEMP$, $CO2$ and $EIMP$) into the underlying inefficiency term to capture the impact of demographics, the structure of economy, climate conditions and other country specific characteristics on energy inefficiency. Besides, Kumbhakar and Lovell (2000) argues that such environmental variables may play an important role in shaping the operating environment across the different countries. For instance, extreme climatic conditions (i.e. equitorial or sub-Saharan countries with hot temperature) would possibly lead to completely different practices regarding the energy use and in turns this may affect efficiency levels. Additionally, population and area size may affect the level of energy use, required to deliver given levels of output. Furthermore, the structure of economy may characterise the nature of the production technology in terms of energy required to produce a given level of output while finally, a net energy importer country or a big emitter country may have strong motivation to adopt more efficient technologies in the use of energy. Thus, this study explores different models to incorporate the effect of such exogenous factors on the inefficiency. Table 4.3 describes the econometric specification of the models used in the analysis. In particular, five models used in the analysis to follow, namely the pooled model (PM), time-decay (Battese-Coelli) model (BCM), the pooled conditional mean model that introduces heterogeneity in the mean of the underlying inefficiency (HM), the single conditional heteroscedastic model (SH) that incorporates exogenous variables in the variance of the one-sided error term and finally the double conditional heteroscedastic model (DH) that allows exogenous factors affect the variance of the two-sided disturbance term as well.

Table 4.3: Econometric specification of the error term

	Model I	*Model II*	*Model III*	*Model IV*	*Model V*
	PM	**BCM**	**HM**	**SH**	**DH**
Full random error	$\varepsilon_{it} = u_{it} + v_{it}$	$\varepsilon_{it} = u_{it} + v_{it}$	$\varepsilon_{it} = u_{it} + v_{it}$	$\varepsilon_{it} = u_{it} + v_{it}$	$\varepsilon_{it} = u_{it} + v_{it}$
Inefficiency component	$u_{it} \sim N^{+}(0, \sigma_u^2)$	$u_{it} = \exp\{-\eta(t-T)\} u_i$	$u_{it} \sim N^{+}(\mu_{it}, \sigma_{it}^2)$	$u_{it} \sim N^{+}(0, \sigma_{u_{it}}^2)$	$u_{it} \sim N^{+}(0, \sigma_{u_{it}}^2)$
			$\mu = \phi' z_{it}$		
Disturbance component	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_{v_{it}}^2)$
				$\sigma_{u_{it}}^2 = \sigma_v^2 \exp(\gamma' z_{it})$	$\sigma_{u_{it}}^2 = \sigma_v^2 \exp(\gamma' z_{it})$
					$\sigma_{v_{it}}^2 = \sigma_v^2 \exp(\gamma' z_{it})$

Note: PM=Pooled model, BCM= Battese-Coelli 92, time-decay model, HM=Conditional mean, SH=Single conditional heteroscedasticity, DH=Double conditional heteroscedastic.

4.3.3 Stage two: Rebound effect econometric specification

In the second stage of the analysis this study provides estimates of the economy-wide rebound effect as described in in section 4.2.2. In order to allow for a distinction between short-run and long-run adjustments autoregressive models are widely used in the literature. Due to mainly psychological and technological reasons, economic agents may not be able to adjust their energy consumption habits immediately, following any changes in prices and/or income. The process of change may involve some immediate disutility. Additionally, when capital or income changes, then, initially the capital or appliance stock is fixed, thus short-run adjustments are limited. Therefore, partial adjustment approach in energy demand modelling is required. However, serious econometric problems may arise from the estimation of the dynamic panel equation 4.17. First, E_{it} is a function of time-invariant country specific heterogeneity α_i. Hence the E_{it-1} which is one of the explanatory variables is correlated with the error term. Furthermore, the presence of E_{it-1} as independent variable in the model gives rise to autocorrelation. Additionally, according to Asafu-Adjaye (2000), Paul and Bhattacharya (2004) and Hossein et al. (2012), some of the explanatory variables may not be strictly exogenous[9], since causality may run in both directions and thus being correlated with

[9]The hypothesis of not strictly exogenous explanatory variables was tested by using the Wu-Hausman test statistic for endogeneity, following Adetutu et al. (2016). First, explanatory variables regressed on instruments and other exogenous variables and in a second stage the residuals from the first regression are used as additional regressor in the original equation $E = g(P, Y, EFF)$. Statistic suggests that all three variables could be potential endogenous rejecting the null hypothesis of no endogeneity. This was quite important results and it was considered in the selection of the instrumental variables for the GMM estimation. Two-step system GMM estimation allows for treating variables of the model either as strictly exogenous, endogenous or predetermined Roodman (2006). Results of the two stages test are presented

past or current realisations of the error term, causing endogeneity problems. For instance causality may run from energy consumption to GDP and vice versa. Therefore Ordinary Least Square (OLS) estimator is biased and inconsistent (Roodman, 2006).

Since traditional procedures for estimating a Dynamic Panel Data model, such as fixed and random effect or pooling OLS considered unsuitable, an alternative approach suggested by Anderson and Hsiao (1982). They propose the transformation of equation 4.17 by first differencing. As a result, the unobserved time-invariant country specific effect is eliminated. However, ΔE_t will be then correlated with Δv_{it}. According to Anderson and Hsiao (1982), $\Delta E_{i,t-2}$ or simply $E_{i,t-2}$ can be used as instrument to estimate the model leading to 'difference' or 'level' estimators.[10] Although those estimator they are consistent are not necessarily efficient. Thus, Arellano and Bond (1991) propose the GMM procedure where first difference in the regression equation are taken to eliminate the country specific effect and then particular moment conditions for the lagged dependent variable are exploited to create a set of instruments that increases efficiency and construct the one-step and two-step GMM estimators. They also suggest a variant of those estimators which is robust to heteroscedasticity such that the robust two-step estimator is asymptotically efficient over the one-step estimator. However, it produces downward biases standard errors unless the sample is very large. Windmeijer (2005) proposes a small sample correction for the two step estimator that eliminates the problem of downward bias in the standard errors, so the two-step estimator with this correction seems superior to one-step.

Given the discussion above, this study applies a two-step system GMM, as proposed by Arellano and Bond (1991) and developed by Arellano and Bover (1995) and Blundell and Bond (1998), to estimate equation 4.17. Then estimated parameters are used to compute the sort-run and the long-run efficiency elasticities of energy demand and the respective rebound effects, as described in previous section.

at Tables C.3; C.4 and C.5 in appendix C.

[10] More information regarding the GMM estimation procedure for Dynamic Panel Data model can be found in C.

4.4 Empirical Results

4.4.1 Stage one: Energy efficiency estimation

As discussed previously, five models are examined in this study, two homoscedastic and three heteroscedastic[11], namely the pooled model (PM), the time-decay Battese-Coelli model (BCM), the pooled conditional mean model that introduces heterogeneity in the mean of the underlying inefficiency (MH), the single conditional heteroscedastic model (SH) that incorporate exogenous variables in the variance of the inefficiency component and the double conditional heteroscedastic model (DH) that additionally assumes that the variance of the disturbance term is affected by the set of exogenous variables. In order to conclude to the preferred one, model performance is checked both econometrically and theoretically. First, robustness is examined using the likelihood ratio (LR), which approximately follows a chi-square distribution and the Wald test. Table 4.4 presents the relative statistics and the conclusions for each of the robustness test. In addition, the theoretical appropriateness of the preferred model is assessed by examine in what degree satisfies regularity conditions.

Table 4.5 presents the results of estimated first-order coefficients[12] and the effects of exogenous variables on the inefficiency. All the estimated first-order coefficients on inputs and outputs appear the appropriate signs and they are all statistically significant. Additionally, The BCM model indicates that technical efficiency is time varying and specifically, increasing over time. This is supported by the statistically significant η of 0.022. Furthermore, the estimated statistically significant λ of 24.32 highlights the presence of inefficiency in the model. This is further supported by the LR score of 1,852.39 that exceeds the Kodde-Palm critical value of 5.41 at 1% significance level, and hence the null hypothesis that $\sigma_u = 0$ is is clearly rejected. A drawback of BCM is that permits efficiency scores to monotonically increase (or decrease) by parameterising inefficiency as a function of time, as described in table 4.3. Similarly, allowing for exogenous inefficiency effects, in the HM model, the expectation of u_{it} is monotonic in

[11]The most appropriate term for the conditional mean model could be 'heterogeneity' and not 'heteroscedasticity'. However, for simplicity reasons the term 'heteroscedastic' is used to refer to the models that allow exogenous variables affect either the mean or the variance of the inefficiency.

[12]Full results of the preferred model are presented in table C.2 in the appendix C.

Table 4.4: Preferred model robustness tests

	LR	Critical value (1%)	Wald	p-value	Decision
Presence of inefficiencies (BCM Vs LSM)					
H_0 $\sigma_u = 0$	1,852.387	5.412			Reject H_0
Presence of single heteroscedasticity (SHM Vs PM)					
H_0 $\sigma_u = constant$	434.403	16.812	37.380	0.000	Reject H_0
Presence of double heteroscedasticity (DHM Vs SHM)					
H_0 $\sigma_v = constant$	298.844	16.812	53.610	0.000	Reject H_0
Specification of the preferred model (Translog Vs Cobb-Douglas)					
H_0 Cobb-Douglas fits better	126.784	23.209	110.970	0.000	Reject H_0

Note: LSM=Least Square Model

environmental variables z_{it} as the specification of μ_{it} is monotonic in z_{it} (Alvarez et al., 2006).

However, in reality, inefficiency is more likely to vary in a non-monotonic way. Therefore, the SH model is estimated and tested against the PM with no exogenous effects using both the LR and Wald tests under the null hypothesis of homoscedasticity in the variance of the one-sided inefficiency component. The null is rejected at 1% significance level, given that the LR statistic of 434.40 exceeds the chi-square distribution, with 9 degrees of freedom (d.f.) critical value of 21.67. This is also supported by the Wald statistic of 37.38 with a p-value of 0.00. Additionally, assuming that exogenous variables affect both error components, the DH model is tested, as an unrestricted variation of SH model, under the null hypothesis that the parameters in the variance of the two-sided disturbance term is constant. LR statistic of 298.84 exceeds the critical value of 21.67 at 1% significance level, rejecting the null. Finally, in order to check the appropriateness of the selected functional specification of the model the Translog specification is tested, as an unrestricted variant of the Cobb-Douglas specification, under the null hypothesis that the Cobb-Douglas functional form fits better the dataset. LR statistic of 126.78 exceeds the chi-square distribution with 10 d.f. critical value of

110.97, rejecting the null. Therefore, based on these diagnostics, the DH model where the exogenous environmental variables affect both the inefficiency component and the two-sided error term with a Translog approximation of the IDF is the preferred model and thus all the subsequent analysis is based on that model.

The regularity conditions are also examined to determine at what degree the preferred model, following the robustness test, satisfies the appropriate economic properties, namely monotonicity and concavity while the scale elasticity of the production technology is evaluated as well. Relative results of the regularity conditions are presented in Table 4.6. Estimated first order coefficients of inputs and outputs describe the respective elasticities at sample means. As expected, the model appears positive elasticities for inputs and negative for output and all are statistically significance at 1% significance level, suggesting that the underlying production technology is monotonic at the sample mean, meaning that is non-decreasing in inputs and non-increasing in output.

Additionally, this study examines whether the model satisfies monotonicity condition at each data point of the sample. In particular, monotonicity is confirmed at 100% for the output, 76% for input capital and 98% for the input labour. Furthermore, scale elasticity is estimated at 1.015 and is significant at 5 and 10% significance level, suggesting increasing returns to scale (IRS) at the sample mean while 81% of data points appear also IRS. Finally, concavity in inputs requires the Hessian matrix of the second order derivatives of the IDF with respect to the inputs, to be negative semidefinite. The necessary and sufficient condition for negative semidefinite Hessian matrix is that all the odd-numbered principal minors of the Hessian to be non-positive and all the even-numbered principal minors of the Hessian to be non-negative. This can be confirmed by examining the sign patterns of the principal minors of the Hessian which with mean corrected data can be written as:

$$H(\tilde{x}) = \begin{bmatrix} h_{kk} & h_{kl} \\ h_{kl} & h_{ll} \end{bmatrix} = \begin{bmatrix} \beta_{kk} + e_k^2 - e_k & \beta_{kl} + e_k e_l \\ \beta_{kl} + e_k e_l & \beta_{kk} + e_l^2 - e_l \end{bmatrix} \tag{4.22}$$

Table 4.5: First stage SFA results Translog specification

	Homoscedastic models		**Heteroscedastic models**		
	PM	BCM	HM	SH	DH
Constant	0.399***	1.818***	0.389***	0.309***	0.440***
	(0.037)	(0.085)	(0.092)	(0.056)	(0.014)
$\ln(gdp)$	−0.994***	−0.304***	−0.986***	−1.028***	−0.985***
	(0.012)	(0.014)	(0.042)	(0.017)	(0.007)
$\ln(capital/energy)$	0.337***	0.100***	0.427***	0.273***	0.470***
	(0.028)	(0.017)	(0.047)	(0.027)	(0.019)
$\ln(labour/energy)$	0.274***	.776***	0.380***	0.257***	0.280***
	(0.028)	(0.021)	(0.078)	(0.042)	(0.028)
t	0.001	−0.049***	−0.025***	−0.010***	−0.001
	(0.003)	(0.003)	(0.007)	(0.003)	(0.002)
Parameters in μ and σ_u					
ζ^{pop}			0.024	0.391	0.145
			(0.112)	(0.407)	(0.257)
ζ^{a}			0.059	0.015	−0.479*
			(0.075)	(0.265)	(0.146)
ζ^{ash}			0.064**	0.048**	0.113***
			(0.013)	(0.028)	(0.020)
ζ^{ish}			0.007	−0.022**	0.014
			(0.007)	(0.027)	(0.019)
ζ^{temp}			0.048	2.757***	0.544**
			(0.176)	(0.877)	(0.232)
ζ^{imp}			0.003**	0.007***	0.009***
			(0.001)	(0.003)	(0.002)
ζ^{co2}			0.071	−0.056***	−0.139
			(0.073)	(0.301)	(0.203)
ζ^{t}			−0.014	−0.080*	0.045**
			(0.016)	(0.043)	(0.021)
ζ^{t^2}			−0.014	−0.010	−0.013**
			(0.016)	(0.011)	(0.007)
λ	1.576***	24.322***			
	(0.139)	(0.007)			
η		0.022***			
		(0.001)			

**** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. Standard Errors are in parentheses. PM=Pooled model, BCM=Battese-Coelli 92, time-decay, model, HM=Conditional mean, SH=Single conditional heteroscedasticity, DH=Double conditional heteroscedastic. Maximum-likelihood estimations of the models were obtained using NLOGIT5 econometric software.*

Table 4.6: Regularity tests

Monotonicity				
	Elasticity	Parameter	standard errors	Outside sample mean
y at sample mean	e_y	-0.985	0.007	100%
k at sample mean	e_k	0.470	0.019	76%
l at sample mean	e_l	0.280	0.028	98%
Scale elasticity				
	Parameter	standard errors	Wald test	IRS over sample
e^t at sample mean	1.015	0.007	5.370	81%
			$H_0 : e^t = 1$	
			reject at 5 and 10%	
Concavity				
	Function	Principal minors	Values test	Outside sample mean
H at sample mean	**H(h)**	First order	-0.083	162 points
			-0.321	25%
		Second order	-0.071	

Although the majority of the first order minors appear the appropriate negative sign (56%), overall 25% of sample points satisfy the necessary alternating pattern in the sign of the principal minors. The satisfaction of monotonicity and concavity[13] (at least partially) properties indicates that the specification of the IDF, satisfactory approximates the true production function and efficiency estimates from this model can be considered reliable.

[13]According to Coelli et al. (2005), many studies using IDF in the literature fail to satisfy the concavity condition. Hence alternative estimation techniques, such as Bayesian framework, have been proposed by O'Donnell and Coelli (2005). However given the robustness of the preferred model and the strong satisfaction of the monotonicity property and partially satisfaction of the concavity property it is assumed that the specification of the IDF approximated the true production function quite satisfactory for the scope of the analysis. Different specifications also tested. Following Adetutu et al. (2016), a KLEM type production function also examined and the number of points in the sample that satisfy concavity slightly increased. However, including the input 'materials' in the model, the skewness of the OLS residuals gets the opposite sign suggesting lack of inefficiencies.

4.4.1.1 Estimated Efficiency scores

Descriptive statistics of estimated energy oriented technical efficiency, derived from the models used in the analysis, are presented in Table 4.7. The estimated average technical efficiency of the preferred model is about 85% with a degree of variation around it, as shown by the standard deviation of 0.15. Also, Table 4.8 gives the correlation between the estimated technical efficiencies from the different models. The estimated energy oriented efficiency of each country gives a relative measure of efficiency among the countries in the panel and over the period investigated.

Table 4.7: Descriptive statistics of estimated efficiency scores

Variable	Mean	Std. Dev.	Min	Max
PM	0.705	0.124	0.286	0.924
BCM	0.282	0.260	0.002	0.982
HM	0.691	0.207	0.279	0.967
SH	0.764	0.205	0.280	0.999
DH	0.853	0.148	0.292	0.999

Table 4.8: Correlation coefficients

	PM	BCM	HM	SH	DH
PM	1				
BCM	0.385	1			
HM	0.708	0.466	1		
SH	0.899	0.318	0.858	1	
DH	0.602	0.193	0.494	0.670	1

Average energy oriented technical efficiency scores and the relative ranking of the countries is presented in Table 4.9. Results suggest that Congo, Oman, Brazil, Honduras and Nepal are on average, among the most efficient countries in the panel while on the contrary, Romania, Armenia, Belarus Russia and Kyrgyzstan the least efficient ones. Additionally, most of the countries in the panel increase the level of their technical efficiency over the estimated period, especially after 1995, as illustrated in Figure 4.2.

Table 4.9: Average estimated technical energy efficiency and relative ranking

Country	Efficiency score	Ranking
Albania	0.892	21
Algeria	0.946	13
Argentina	0.849	27
Armenia	0.594	36
Azerbaijan	0.692	34
Belarus	0.575	37
Bolivia	0.910	19
Botswana	0.892	22
Brazil	0.991	3
Bulgaria	0.694	32
China	0.715	31
Congo	0.999	1
Costa Rica	0.972	8
Croatia	0.829	28
Egypt	0.962	10
El Salvador	0.979	6
F.Y.R.O.M	0.903	20
Georgia	0.739	30
Honduras	0.991	4
India	0.953	12
Indonesia	0.935	14
Iran	0.874	25
Jordan	0.922	17
Kazakhstan	0.693	33
Kyrgyzstan	0.566	39
Malaysia	0.880	24
Morocco	0.932	15
Nepal	0.986	5
Oman	0.992	2
Pakistan	0.919	18
Romania	0.635	35
Russia	0.573	38
Saudi Arabia	0.965	9
South Africa	0.883	23
Sri Lanka	0.972	7
Syria	0.819	29
Thailand	0.925	16
Tunisia	0.873	26
Uruguay	0.956	11

Figure 4.2: Estimated energy oriented technical efficiency by country

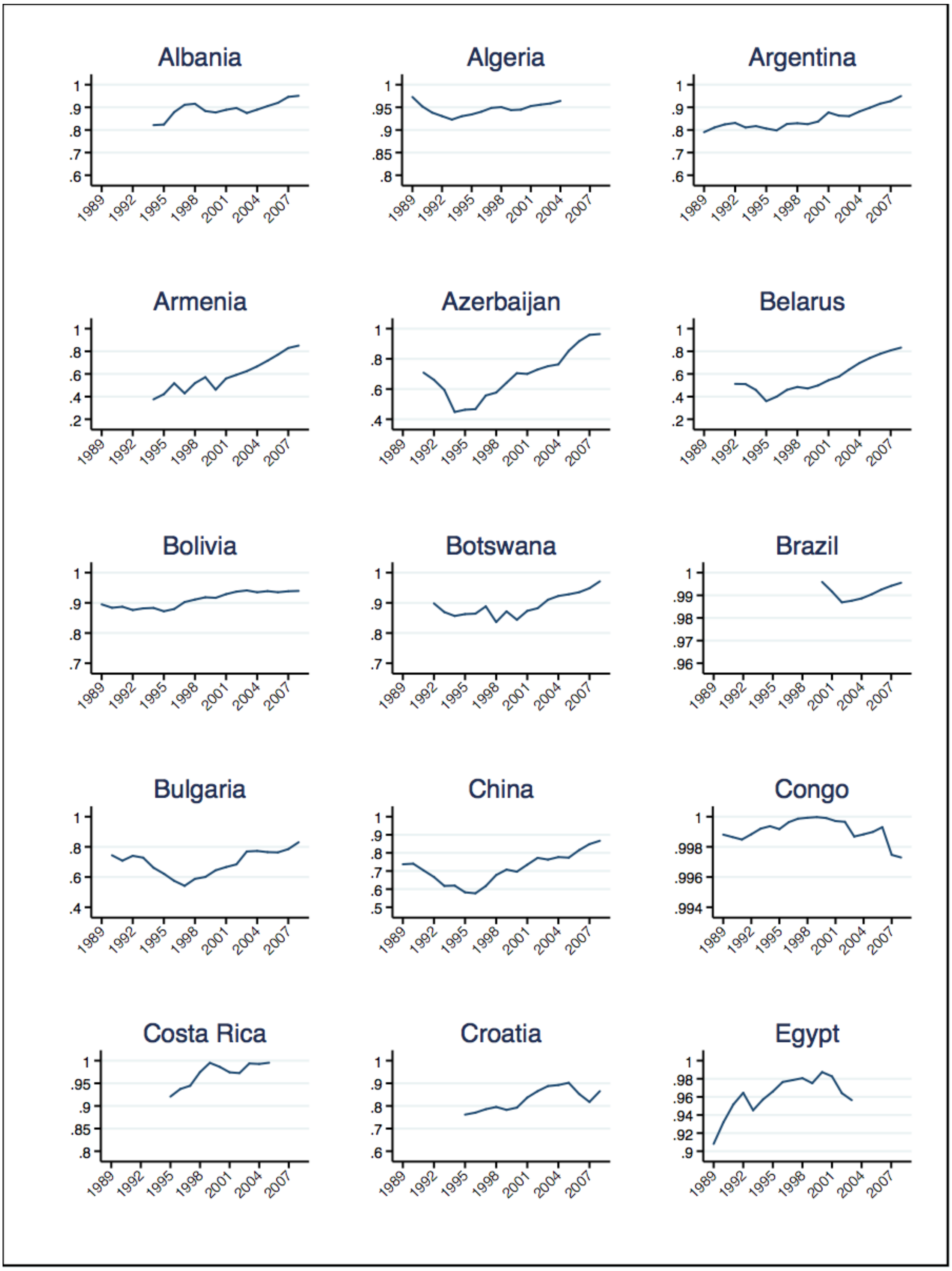


Figure 4.2 Continued

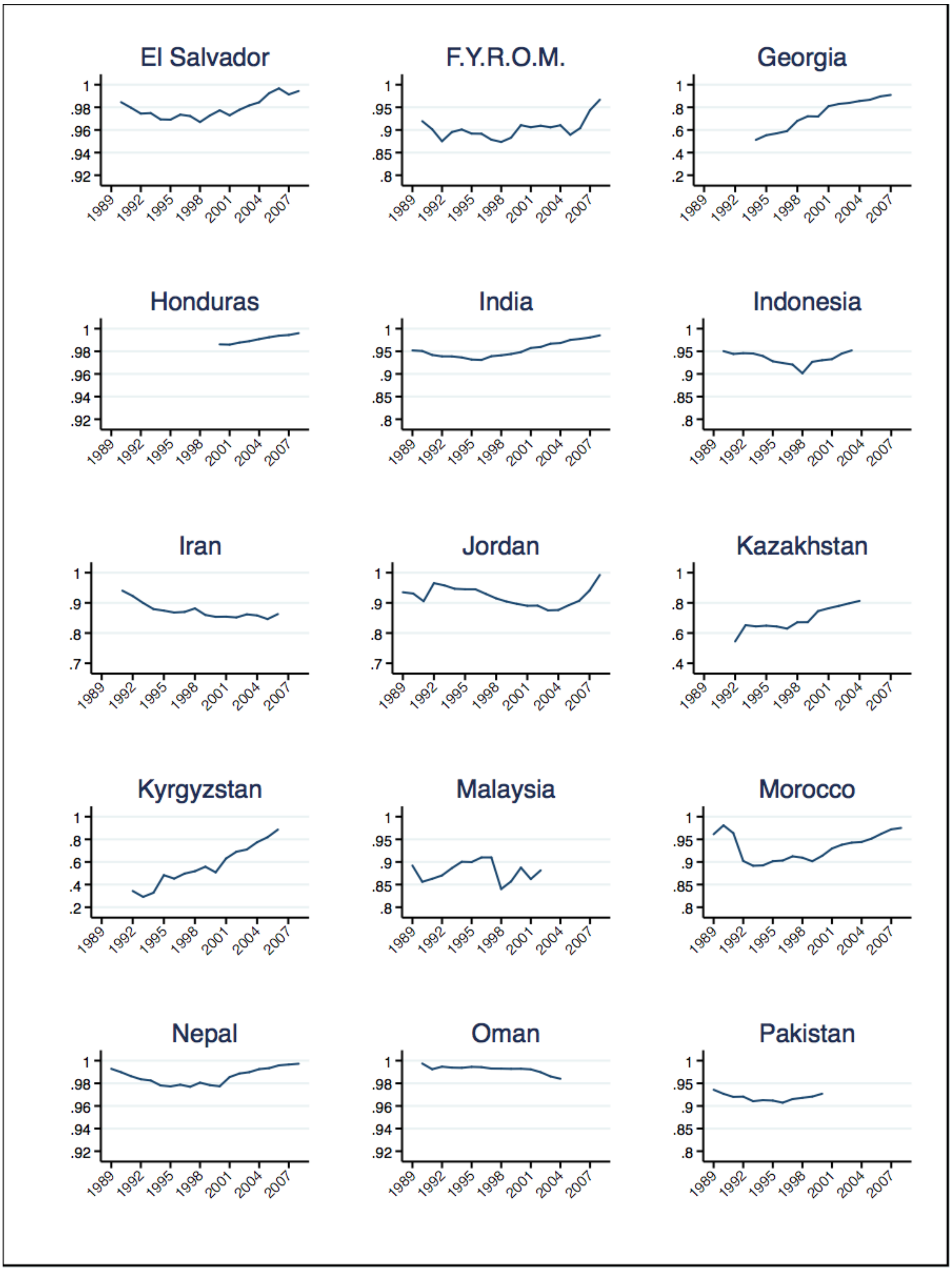
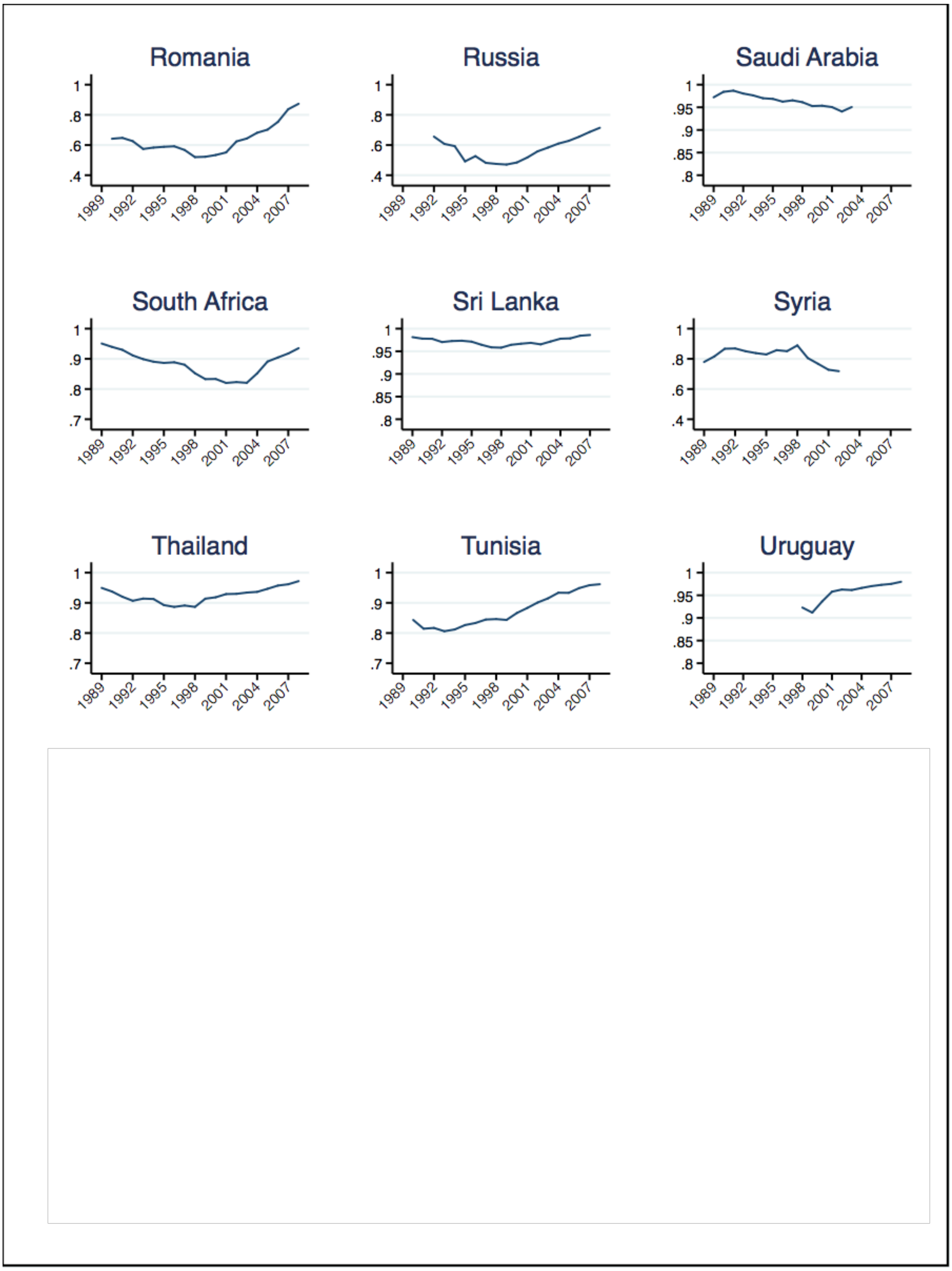


Figure 4.2 Continued



4.4.2 Stage two: Rebound effect estimation results

The results of the estimated two-step system GMM are presented in Table 4.10. Most of the estimated coefficients appear to have the expected sign and are statistically significant at least at 10% significance level with the exception of the price[14] and the time trend coefficients. Roodman (2006) argues that a credible estimate for ψ should be less than the unity since values above 1.00 imply an unstable dynamic, with accelerating divergence away from equilibrium. Also, Roodman (2006) suggest that the lag dependant coefficient should lie within the upward biased OLS estimation limit and the downward biased fixed effect estimation limit, or close to the aforementioned limits. In the case of this study the OLS coefficient of the lag dependant variable estimated at 0.75 while the fixed effect estimated coefficient is 0.95. Hence the two-step system GMM estimated value of 0.77 lies between the credible range and is clearly less than 1.00. Additionally, the null hypothesis of no autocorrelation is applied to the differenced residuals. The test for AR(1) process in first differences usually rejects the null (this is also the case with this study) but this is expected since $\Delta v_{it} = v_{it} - v_{i,t-1}$ and $\Delta v_{i,t-1} = v_{i,t-1} - v_{i,t-2}$ both contains $v_{i,t-1}$. However, the test for AR(2) is more important, detecting autocorrelation in levels and for the system-GMM to be reliable, it is required to fail to reject the null. Given the p-value of 0.53, the null hypothesis of second order serial correlation can not be rejected. Additionally the null hypothesis of the the Hansen test of over identified restrictions can not be rejected, based on the chi square probability of 0.50, implying that the instruments are valid. Both specification tests imply that the moment conditions underlying the two-step system GMM model are strongly supported.

Sorrell et al. (2007) and Gillingham et al. (2016) suggest that energy efficiency improvements can be either exogenous or endogenous (i.e. price or policy induced). Therefore, following Adetutu et al. (2016), a model with interaction terms between energy efficiency, energy price and income is explored. Statistically significant coefficients, at 10% significance level, suggest that this assumptions is supported by the data set. This, also allow researchers and policy makers to assess the effects of energy efficiency

[14]This is not surprising given that empirical evidence supports such results for developing countries (Kebede et al., 2010).

Table 4.10: GMM Estimation result

Dependant variable E	Estimated coefficients
e_{t-1}	0.7705***
	(0.0510)
y	0.2583***
	(0.0503)
p	-0.0404*
	(0.0245)
eff	-0.4534***
	(0.1553)
$y * eff$	-0.0001*
	(0.0000)
$p * eff$	0.0005*
	(0.0002)
$p * y$	2.99e-07*
	(0.0000)
t	1.5071
	(0.4181)
Number of instruments	39
AR(1)	0.004
AR(2)	0.573
Hansen test	0.502

**** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. Windmeijer standard errors are in parentheses. STATA13 econometric software is used for the estimations*

on energy demand arising from a unit change either in energy price or income.

It is generally assumed that higher energy prices (or level of income) stimulate technological progress, such that a higher energy prices results in energy efficiency improvements and thus decreasing energy consumption. However, the positive sign of the estimated coefficient of the interaction term between energy prices and efficiency suggest that this is not the case in developing countries, probably due to unmet demand for energy. Furthermore, the interaction terms between price, income and efficiency, allow for separation of price or income induced effects from other exogenous efficiency effects thus eliminating the issue of overestimated efficiency elasticity. The later can possibly explain the statistically insignificant coefficient of the time trend since it is possible that some of the exogenous effects have been captured from the interaction terms.

Following the analysis, estimated coefficient from the GMM dynamic panel data energy model, can be used for the calculation of the the sort run and the long run energy efficiency elasticities as described in previous section. Then, on average, the estimated efficiency elasticities are equal to -42.5 and -185.6% in the short run and the long run accordingly, yielding respective rebound effects of 57.4% and -85% , at the sample mean. these results are in line with Adetutu et al. (2016) who suggest that RE magnitudes for non-OECD countries are on average 56%. Furthermore, results are in line with Roy (2000) who suggests that the RE for case of India is around 50%. The estimated long run rebound suggests that energy efficiency gain is likely to stimulate a more than proportionate decrease in energy consumption in the LR. This result actually highlights the remarkable potential for energy efficiency to reduce energy demand in developing countries and is consistent with the idea that in the long run, previous experience and knowledge is expected to enhance energy efficiency savings.

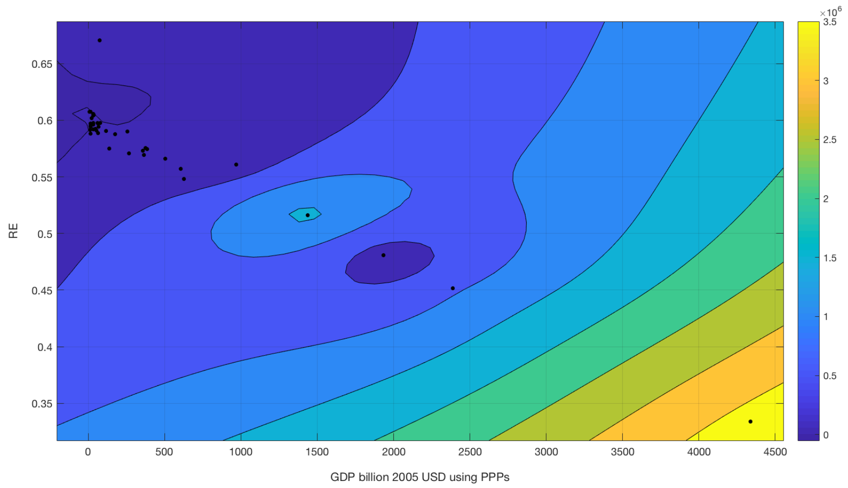
Additionally, in order to compute REs for each country in the panel over the estimated time period, point efficiency elasticities are calculated.[15] In particular, the estimates reveal significant variation in the magnitude of the short run RE from 5% in China in 2008 to 83% in Belarus the same year. Table 4.11 gives the average short and long run estimated RE for each country. Results also suggest that there is no evidence of 'backfire' which contradicts Adetutu et al. (2016) who argues in favour of 'backfire' in few developing countries, namely India, Indonesia, Iran, Philippines, Russia, South Africa, Tanzania and Venezuela.

A very encouraging conclusion of the analysis is the declining trend in the RE of the bigger emitter countries i.e. China, India and Russia. However, countries appear a great range in trends regarding the RE over time. In particular RE in some countries decreases over the estimated period such as Brazil, China, India and Malaysia while

[15]Full results are presented in Tables C.6 and C.7 in Appendix C.

for some other countries the opposite is the case, like Albania, Algeria, Bulgaria, Congo and Romania. Overall, it seams that more developed countries appear lower RE. This negative relationship between RE and economic development is also highlighted by the Figure 4.3[16], where counties (black points in the graph) with higher RE appear on the left top corner of the graph while wealthier counties significant lower RE. However, economic development trigger inevitable with higher demand for energy and consequently higher GHG emissions.

Figure 4.3: Rebound effect Vs. GDP level and CO_2 emissions



Regarding the long run RE estimates, the estimated partial adjustment mechanism of the model depicts the desired (or potential targeted level) of RE for each country in the panel. The country-specific long run estimates as illustrated in Table 4.11 reflect widespread super-conservation RE for all the countries in the sample reflecting tremendous potential for energy efficiency improvements to reduce energy demand level.

Finally, as discussed in Chapter 1, the ultimate objective of any energy policy is the elimination of the anthropogenic GHG emissions. Taking into account the level

[16]This figure is a contour plot where the X axis presents the average level of GDP of each country , Y axis gives the average level of the estimated short-run rebound effects while the colour of the plot denotes the average level of the CO_2 emissions for each of the country in the panel over the investigated period. The scale legend at the right of the plot provides further information regarding the level of CO_2 emissions and the colours correspondences.

Table 4.11: Estimated average SR and LR rebound effect (%)

Country	SR Rebound effect	LR Rebound effect
Albania	60.77	-70.93
Algeria	57.08	-87.01
Argentina	56.92	-87.71
Armenia	59.13	-78.08
Azerbaijan	59.26	-77.52
Belarus	67.05	-43.58
Bolivia	59.20	-77.76
Botswana	59.72	-75.50
Brazil	48.09	-126.18
Bulgaria	58.85	-79.32
China	33.40	-190.20
Congo	59.41	-76.87
Costa Rica	60.54	-71.92
Croatia	59.78	-75.25
Egypt	57.44	-85.43
El Salvador	59.64	-76.87
F.Y.R.O.M	59.52	-76.39
Georgia	58.81	-79.48
Honduras	60.17	-73.56
India	45.15	-139.00
Indonesia	56.08	-91.35
Iran	54.84	-96.79
Jordan	60.43	-72.41
Kazakhstan	57.50	-85.17
Kyrgyzstan	60.73	-71.11
Malaysia	59.01	-78.61
Morocco	59.08	-78.32
Nepal	59.77	75.31
Oman	59.43	-76.79
Pakistan	57.33	-85.94
Romania	58.79	-79.58
Russia	51.61	-110.83
Saudi Arabia	55.72	-92.95
South Africa	57.54	-85.01
Sri Lanka	59.75	-75.38
Syria	59.08	78.29
Thailand	56.60	-89.10
Tunisia	59.69	-75.63
Uruguay	60.47	-72.24

Table 4.12: Potential CO_2 savings when countries an at the frontier with and without rebound effect (%)

Country	CO_2 savings without rebound	CO_2 savings with rebound
Albania	10.77	4.23
Algeria	5.37	2.31
Argentina	15.09	6.50
Armenia	40.64	16.61
Azerbaijan	30.79	12.54
Belarus	42.52	14.01
Bolivia	8.99	3.67
Botswana	10.81	4.35
Brazil	0.85	0.44
Bulgaria	30.58	12.59
China	28.54	19.01
Congo	0.09	0.04
Costa Rica	2.85	1.12
Croatia	17.09	6.87
Egypt	3.83	1.63
El Salvador	2.07	0.84
F.Y.R.O.M	9.70	3.93
Georgia	26.06	10.73
Honduras	0.93	0.37
India	4.68	2.57
Indonesia	6.53	2.87
Iran	12.60	5.69
Jordan	7.80	3.09
Kazakhstan	30.75	13.07
Kyrgyzstan	43.40	17.04
Malaysia	12.03	4.93
Morocco	6.76	2.77
Nepal	1.39	0.56
Oman	0.77	0.31
Pakistan	8.12	3.46
Romania	36.52	15.05
Russia	42 .72	20.67
Saudi Arabia	3.50	1.55
South Africa	11.70	4.97
Sri Lanka	2.79	1.12
Syria	18.10	7.41
Thailand	7.52	3.26
Tunisia	12.70	5.12
Uruguay	4.38	1.73

of energy efficiency, policy makers could have a clear picture about the potentials of energy savings and in turns CO_2 savings. Furthermore, as IEA (2015) argues, policy makers should consider the magnitude of the RE when design the appropriate effective strategies. In this context, potential CO_2 savings can be calculated assuming that countries are technical efficient and following the methodology as described in chapter 3. However, due to the presence of RE those potentials are partially offset. Table 4.12 presents average CO_2 savings with and without considering the RE. It is clearly, that the magnitude of the potential RE is of vital importance to assessing the effectiveness of national and international energy policies. Hence, policy makers need to fully assess and account for any potential REs when planning energy efficiency strategies to ensure that they pose pragmatic targets.

4.5 Conclusions

The REs operate through a variety of different mechanisms and according to Dimitropoulos (2007) the lack of clarity about the definition and its sources has led to persistent confusion. Thus, RE is very difficult to quantify and has become one of the most debated concepts in the energy economics literature. These challenges are even more clear for macroeconomic RE, which is arguably the most relevant to the global climate change, given that international cooperation is required to eliminate the global in nature environmental problems. Thus the limited number of empirical evidence to date provides an insufficient basis to draw general conclusions. Therefore, this study uses two stages econometric approach to estimate the economy-wide RE for 39 developing countries over the period 1989-2008, and as far as is known, it is the first attempt to examine RE across a panel of developing countries, using an econometric techniques and a consistent dataset.

At the first stage of the analysis, energy-oriented technical efficiency is estimated using SFA framework. Then, the estimated efficiency scores are used as regressor in a dynamic panel data energy demand model to compute the short run and long run efficiency elasticity of energy demand using a two-step system GMM approach. Following

Saunders (2000), the short and the long run RE from these efficiency elasticities can be computed. Results suggest that REs across the sampled countries and the estimated period are at 57.4% and -85.6% in the short and the long run respectively, indicating tremendous potential for energy savings through energy efficiency improvements in the future.

Additionally, given the evidence presented above, it can be argued that any energy forecast derived from expected improvements in energy efficiency may have been underestimated by failing to account for the macroeconomic RE. And this issue is of vital importance in the context of developing countries where the energy needs is still far from saturations and these countries are in economic growth trajectory with a growing appetite for energy. However, rebound effects have been neglected when assessing the potential impact of energy efficiency policies. An main conclusion of this study is that REs are of sufficient significance and failure to be considered could contribute to shortfalls in the effectiveness of energy and climate policy target. Thus, unless this study is undertaken, it might be impossible to precisely evaluate the potential benefits of energy efficiency improvements.

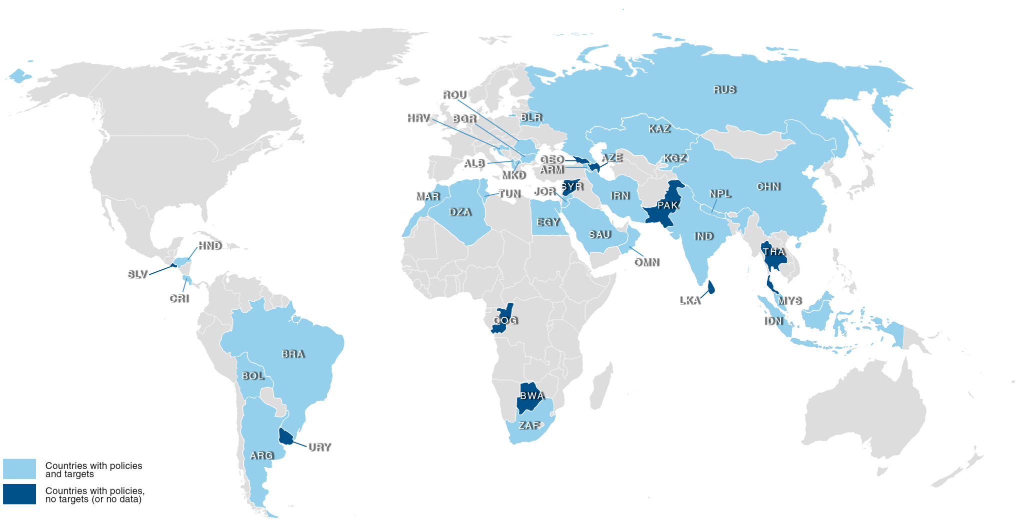
Chapter 5

Conclusions, policy implementation and future work

5.1 Introduction

In December 2015, the plenary halls at 'Le Bourget' erupted in standing ovations, marking the adoption of the Paris Agreement and thus ensuring the global cooperation and commitment to tackling climate change. Following the agreement, more than 190 governments from all over the world submitted their Nationally Determined Contributions (NDCs), setting appropriate policies and targets to reduce emissions in ways that best align with their respective socio-economic characteristics and aspirations for the future requirements in order to remain in a sustainable growth trajectory. That is of crucial importance for the case of developing countries where demand for energy services is far from saturated and almost two billion people lack access to electricity (IEA, 2016d). Achieving the emission reduction targets of the NDCs is a momentous challenge for every country and the universe and harnessing energy demand is a vital tool to mitigate anthropogenic GHG emissions (IEA, 2016a). According to IEA (2016d), improvements in energy efficiency considered as the most cost-effective and immediately available means to achieve those goals, since energy efficiency improvements reduce the amount of energy needed to support sustainable economic growth. Therefore most of the governments are seeking ways to improve their energy efficiency and espouse the benefits that it offers in pursuit of their national policy goals, especially in emerging economies. This is further highlighted in Figure 5.1. All the countries investigated in this thesis have designed energy efficiency policies, while the vast majority of them have set clear targets.

Figure 5.1: Developing countries with energy efficiency policies and targets



Data source: United Nations Environmental Programme (2016)

5.2 Energy efficiency

Effective energy policies require among others accurate measurements and evaluation of energy efficiency across countries and over time. However, despite the fact that energy efficiency is in trite use, it is arguably difficult to define or even conceptualise. Furthermore, Filippini and Hunt (2011, 2012), in line with IEA (2009), argue that energy intensity, which is the most often energy efficiency indicator used in macroeconomics analysis, is not an accurate indicator of energy efficiency. Therefore, a key objective of this thesis is to estimate the level of the energy efficiency using data for a panel of 39 developing countries for the period from 1989 to 2008. This thesis examines two different methodologies to estimate energy efficiency. In particular, in Chapter 3 the estimation of a stochastic energy demand function allows for measurements of the transient end persistent 'true' energy efficiency. The stochastic energy demand function gives the minimum level of input energy used in order to produce any given level of output and the actual energy demand function differs from the stochastic due to the presence of both technical and allocative inefficiency. Results are in line with Filippini and Hunt (2011) suggesting that energy intensity should not be considered as a de facto standard indicator of energy efficiency. While, by controlling for a range of socio-economic factors, the measurements of 'true' energy efficiency obtained by this analysis are deemed more appropriate and hence it is argued that this analysis should be undertaken to avoid potentially misleading advice to policy makers.

Additionally, in Chapter 4 the energy oriented technical efficiency is estimated using an input distance function approach. However, estimated inefficiency in the latter case represents only the technically inefficiency. Therefore these two measurements do not express exactly the same concept. However, since both estimates derived from econometric procedures based on economic theory of production and consider country specific socio-economic characteristics are more reliable measurements of energy efficiency than the simple energy intensity ratio. Table 5.1 presents the relative ranking of the countries in the investigated panel using these three measurements (i.e. 'true' energy efficiency derived from the GTREM, energy oriented technical efficiency derived from the DH model and the energy intensity) and the correlation between them.

Besides, efficiency measurements from the estimation of Stochastic Energy Demand function in chapter 3 as well as from the estimation of the Input Energy demand function in chapter 4 would appear to be negatively correlated with energy intensity for most countries (i.e. the level of energy intensity decreases with an increase of the level of energy efficiency), but with some exceptions. This is to be expected from energy economics theory since energy intensity is the inverse ratio of the economic-thermodynamic indicator of energy efficiency proposed by Patterson (1996). It is worth noting, that if these techniques were to be a useful tool for teasing out true energy efficiency, then a perfect, or even near perfect, negative correlation would not be expected since all the useful information would be contained in energy intensity indicator. However, this is definitely not the case, as for some countries energy intensity is a reasonable

Table 5.1: Comparison between average 'true' energy efficiency (TGTREM), energy oriented technical efficiency (DH) and energy intensity for the period 1989-2008, ranking and correlations

Country	Ranking			Correlation		
	TGTREM	EI	DH	TGTREM-EI	TGTREM-DH	EI-DH
Albania	38	15	21	-.42	-.43	-.53
Algeria	15	3	13	-.64	.08	-.78
Argentina	20	22	27	-.42	.32	-.03
Armenia	29	24	36	-.01	-.60	-.74
Azerbaijan	36	33	34	-.34	.24	-.94
Belarus	26	38	37	-.39	.25	-.89
Bolivia	35	18	19	-.99	-.88	.81
Botswana	19	9	22	-.91	.47	-.74
Brazil	1	10	3	.56	-.71	-.44
Bulgaria	31	31	32	-.88	.32	-.54
China	34	35	31	-.86	.10	-.45
Congo	30	2	1	-.91	.64	-.73
Costa Rica	21	6	8	-.81	-.26	-.17
Croatia	3	19	38	.30	-.79	-.61
Egypt	4	7	10	.09	-.46	-.78
El Salvador	13	13	6	-.24	-.11	-.61
F.Y.R.O.M	18	21	20	-.85	.22	-.58
Georgia	28	32	30	-.48	.56	-.93
Honduras	9	27	4	-.46	-.70	-.28
India	23	25	12	-.92	.50	-.80
Indonesia	5	20	14	-.40	-.73	.21
Iran	25	26	25	-.64	.76	-.81
Jordan	7	17	17	-.38	.31	-.27
Kazakhstan	39	37	33	-.70	.64	-.92
Kyrgyzstan	37	34	39	-.94	.70	-.86
Malaysia	11	11	24	-.94	.13	-.34
Morocco	12	5	15	-.66	-.18	-.58
Nepal	8	36	5	.44	-.88	-.32
Oman	32	1	2	-.99	.38	-.33
Pakistan	2	23	18	-.81	-.02	.30
Romania	24	29	35	-.61	-.04	-.55
Russia	27	39	38	-.86	.40	-.61
Saudi Arabia	22	12	9	-.96	.95	-.95
South Africa	16	28	23	-.88	-.45	.11
Sri Lanka	14	14	7	-.48	-.08	-.16
Syria	17	15	29	-.86	-.18	.22
Thailand	33	16	16	-.97	-.42	.37
Tunisia	6	8	26	.50	-.79	-.86
Uruguay	10	4	11	-.69	.15	-.31
Spearman correlation				.35	.44	.67

Note: GTREM=Transient Generalised True Random effect Model, EI=Energy Intensity, DH=Double Heteroscedastic Model.

Figure 5.2: Comparison of estimated energy efficiency derived from TGTRE model with energy oriented technical efficiency derived from estimation of DH model by country

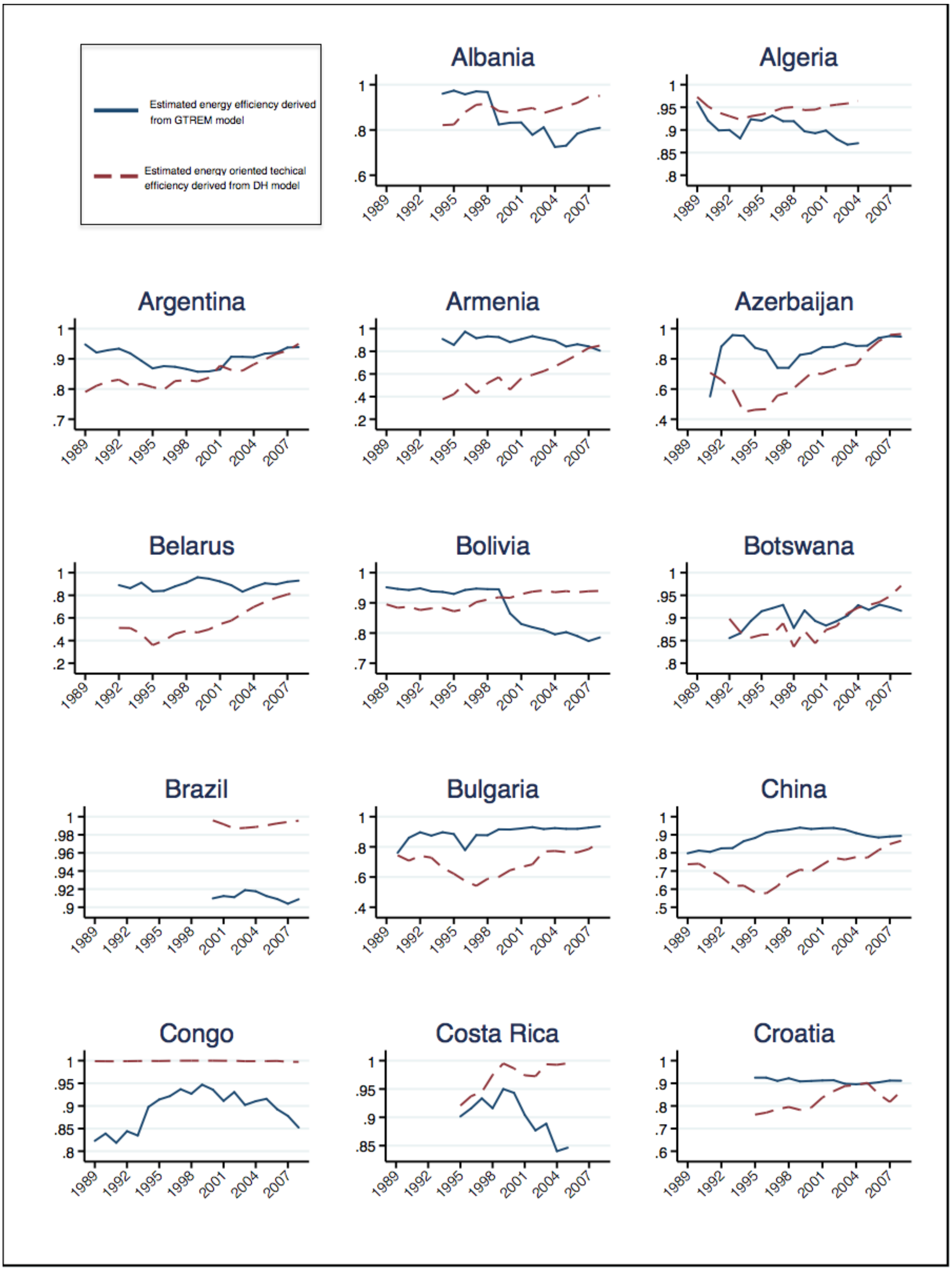


Figure 5.2 Continued

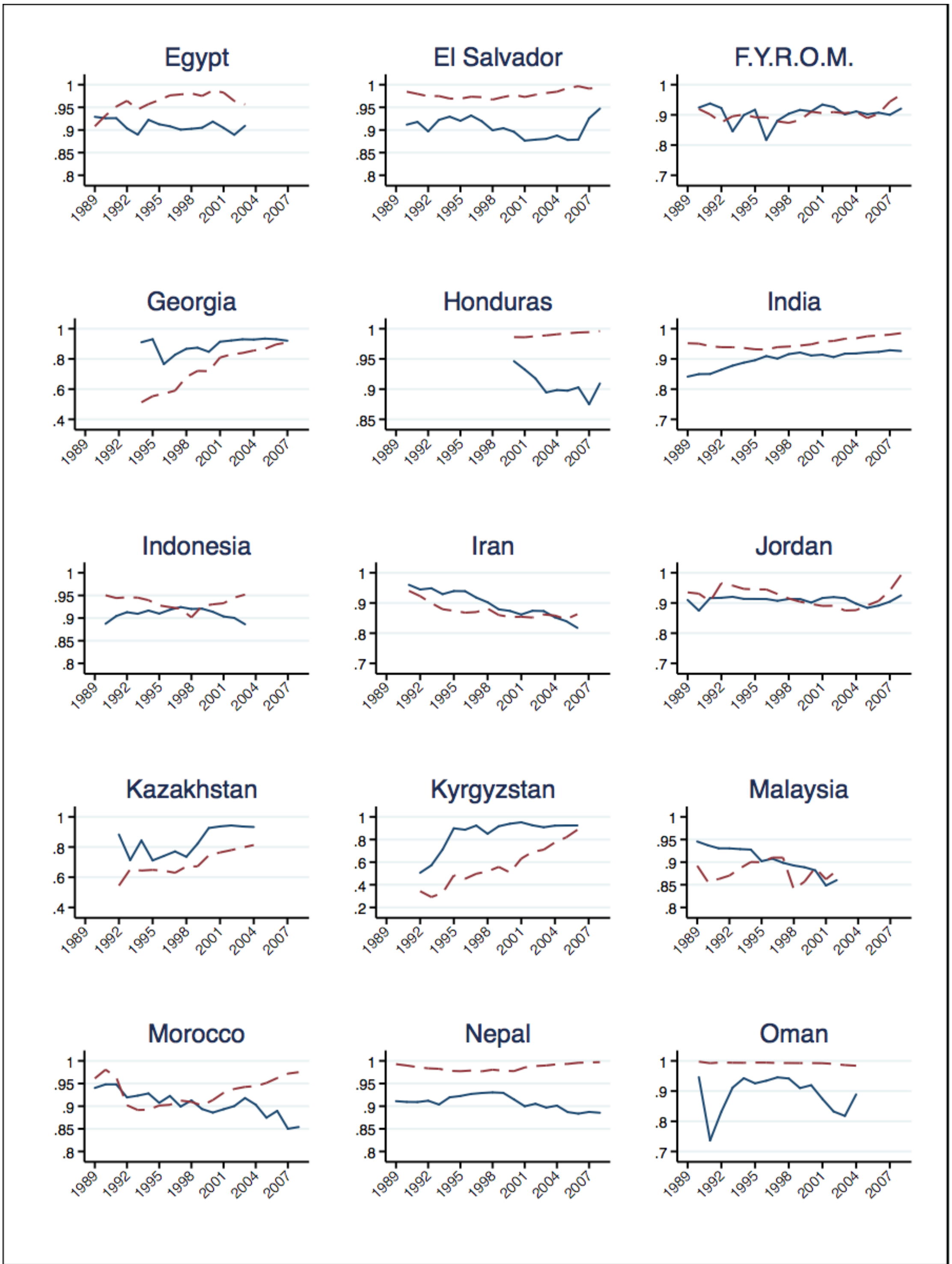
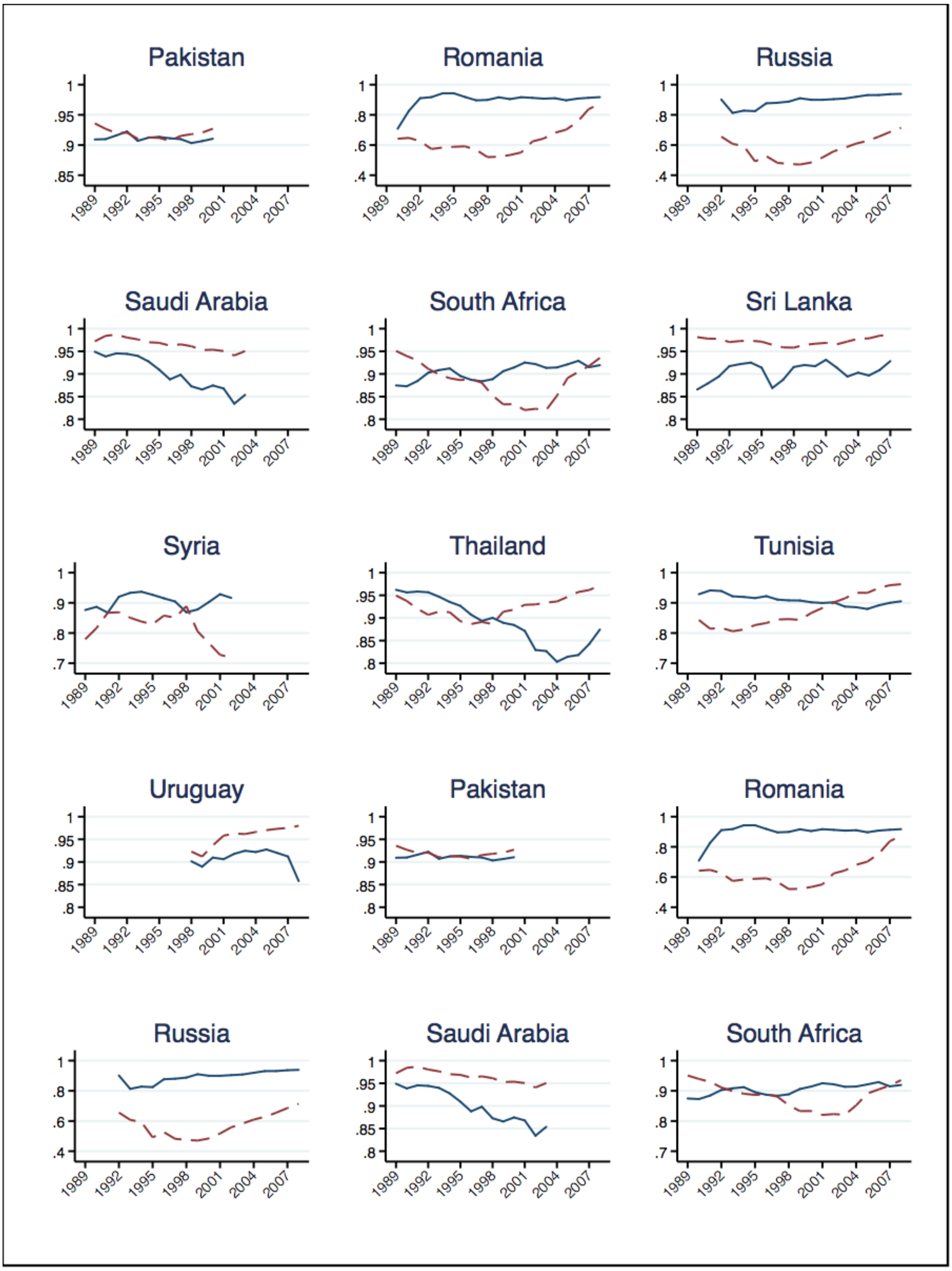


Figure 5.2 Continued



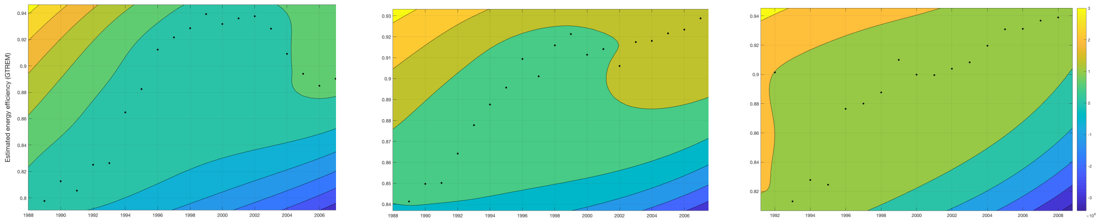
proxy (i.e. appears near perfect, negative correlation) for energy efficiency, whereas for others it is a very poor proxy (low negative or even positive). Hence, unless the analysis undertaken here is conducted it is arguably not possible to identify for which countries energy intensity is a good proxy and for which it is a poor proxy.

Results also suggest that energy intensity ratio is a relatively better approximation of technical efficiency as there is a relative consensus in terms of relative ranking. In particular it is found that the same set of countries appear to be most or least efficient among the panel of the countries. This is also supported by the Spearman correlation value between the ranking produced by the energy intensity and the energy oriented technical efficiency which is 0.67, much higher than the respective Spearman correlation value of 0.35 between the 'true' energy efficiency derived from the GTREM and the energy intensity. Additionally, the relationship over time between the energy oriented technical efficiency and the 'true' energy efficiency is presented in Figure 5.2. For some countries, values from these two measurements change over time in a very similar way such as Nepal, Russia and Saudi Arabia while for some other counties the opposite is the case such as Albania, Armenia and Romania. Thus highlighting that those two measurements represent different concept of efficiency, namely the (energy oriented) technical efficiency and the overall energy efficiency (both technical and allocative). This is as far as is know the first attempt to model energy efficiency using a panel data set of solely developing counties and compering both approaches.

In terms of results, a very encouraging conclusion from both studies is that largest emitter countries such as China, India and Russia increase their level of energy efficiency over time. Figure 5.3 presents the relationship between the 'true' energy efficiency and CO_2 emissions of China, India and Russia over time. The level of energy efficiency over time is illustrated as black points on the plot, for every year in the investigated period. Furthermore the colour of the plots denotes the level of the CO_2 emissions for each year. The scale legend at the right of the plot provides further information regarding the level of CO_2 emissions and the colours correspondences. Energy efficiency appears an increasing trend in all three countries. However, fast economic development of those countries requires increasing demand for energy. As a consequence, the level of

CO_2 emissions has been increased as well over the estimated period.

Figure 5.3: CO_2 Vs. energy efficiency over time



(a) China (b) India (c) Russia

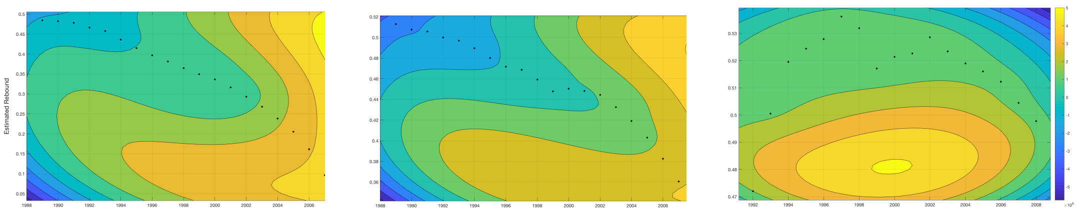
5.3 Rebound effect

Furthermore, according to IEA (2015), one of the most persistent challenge in designing and implementing energy efficiency policy is accounting for the phenomenon called 'rebound effect'. Benefits from the technologies evoke behavioural responses by economic agents that can cause that the full profit of energy conservation can not be cashed. As policies to stimulate energy efficiency improvements are an important part of national and international policies to tackle climate change, the magnitude of the potential rebound effect is of vital importance to assessing the effectiveness of such policies. Therefore, policy makers need to fully assess and account for any potential rebound effects when planning energy efficiency strategies to ensure that they pose pragmatic targets.

However, despite the remarkable growth of the RE in economic literature, analysts and policymakers tend to ignore those rebound effects possibly due to the lack of consensus regarding their magnitude, and even their definition. Dimitropoulos (2007) notes that several studies in the literature offer key insights into the impact of RE on micro-scale behavioural responses to efficiency improvements providing reliable estimates of direct rebound effects in specific end-use energy services. However, evidence of the scale of economy-wide RE, which is the most relevant to climate change, is not conclusive, due to the complex interaction of multifold economic actors and mechanisms of RE (Dimitropoulos, 2007). Therefore, as far as is know there is no study in economic literature of economy-wide RE that covers solely developing countries. Hence, this thesis attempts to address the issue relating with the magnitude of the RE and the appropriate modelling approach, by estimating economy-wide RE for a panel of 39 developing countries using data for the period 1989-2008 and a two-stage econometric procedure. In the first stage a SFA is employed to estimate the energy oriented technical efficiency, as described in Chapter 4 and in the second stage, short run and long run efficiency elasticities of energy demand are estimated using a dynamic panel model approach. Then, economy-wide RE computed following Saunders (2000).

In terms of results, this thesis suggests that rebound effect on average could erode more than 50% of energy savings from energy efficiency improvements. The relatively stable estimates over the investigated period could possible illustrate the absence of any policy targeting to mitigate the magnitude of the RE in developing countries. Hence, any variation on the level of the RE over years is rather symptomatic result of the different dynamics of economies.

Figure 5.4: CO_2 Vs. rebound effect over time



(a) China (b) India (c) Russia

However, encouraging result is that the largest emitter countries such as China, India and Russia, present a decreasing trend in their respective RE. In particular Figure 5.4 illustrates the relationship between the the RE and CO_2 emissions over time for these countries. The level of the estimated rebound effect over time is illustrated as black points on the plot, for every year in the investigated period. Furthermore, the colour of the plots denotes the level of the CO2 emissions for each year. The scale legend at the right of the plot provides further information regarding the level of CO2 emissions and the colours correspondences. It is clear that as economies develop over time the magnitude of the RE declines. However, increasing needs in energy to support economic development leads to higher levels of of CO_2 emissions. Furthermore, results suggest that efficacious energy policy should consider the magnitude of the RE.

5.4 Policy implementation

In terms of policy perspective this thesis concludes to the following points:

First, the slightly higher average rebound effect estimates for the more developed countries in the panel is consistent with the reasoning that emerging economies are on a growth trajectory that demand greater energy consumption, to the extent that energy savings are easily 're-spent' to fuel further growth. According to Wolfram et al. (2012), households that come out of poverty and join the middle class, which is the case for more developing countries, they tend to boost their welfare by purchasing goods and services that require energy to be produced and or used. They also argue that energy demand forecasts for developing countries may be understated by their failure to capture this effect, a part of which may be embodied in RE. This is an alarming result for policy makers that designing and implementing effective energy efficiency policies that account for the level of rebound effect in developing countries might represent one of the most challenging energy and climate policy issues in the future.

In this context, given that energy efficiency gains could be exogenous or endogenous due to effects of energy prices, regulations, national or international policies, lifestyle etc. on energy efficiency, this thesis explores a model with interaction between energy efficiency and the other regressors (energy price and GDP). Results show that these assumptions are accepted by the data since both coefficients are statistically significant at least at 10% significance level. The interaction terms indicate that, ceteris paribus, higher economic growth stimulated energy augmenting technological progress so that higher economic standards result in a greater energy-reducing efficiency effect. However, opposite seems to be the case with energy prices.

Besides, it is important to mention that achievements of reductions in energy demand and associated CO_2 emissions through price induced efficiency improvements, may require rising energy prices over time such that increase in energy prices keep pace with the improvements in energy efficiency. Thus, carbon pricing policies such as carbon taxes could potentially offer tools to eliminate part or all of the energy demand rebound resulting from improvements in energy efficiency. However, it should be noted, that applying economy-wide pricing mechanisms, will be a blunt tool to counteract the impact of efficiency improvements which may vary quite significantly from sector to sector. Furthermore implementation of such policies face practical challenges, especially in the developing world and will invariably encounter political and moral obstacles since increasing energy price may result in loss of economic welfare. Therefore, a deeper understanding of the main drivers of the RE is required, in sectorial level, to further assist policy makers. Further research could focus on decomposing the economy wide RE in the sectors of each economy. However, detailed data set is required and in the case of developing countries this may be a significant challenge.

Additionally, estimation results suggest that wealthier countries tend to use energy more efficiently. Rising energy efficiency has arguably been a critical driver of both long-term economic growth and decarbonisation of energy supply mix. Higher rates of economic growth typically lead to higher rates of energy efficiency, as growth drives a more rapid increase in energy demand and accelerates the turnover of existing capital stock, both of which typically accelerate the adoption of innovation and the use of new technology that is more efficient and less carbon intensive.

The process of transition from an economy fuelled mostly by solid biomass to more modern and specialised fuels such as natural gas as well as electricity production that stems from renewables sources is expected to continue for much of the coming century in emerging economies. This 'modernisation' of developing world drives both a diversification of energy supplies mix and a proliferation of the ways in which energy is used. Both processes result in increase in energy efficiency and a decline in economy-wide RE, as relatively more expensive, lower carbon fuels and processes find specified uses for which they are economically optimised. This point, is a strong argument for accelerating efficiency gains even in the presence of RE. Therefore, this thesis does not attempt to downplay the role of energy efficiency improvements, but rather argues that designing and implementing efficacious energy policy should consider country specific characteristics and needs as well as potential energy efficiency improvements and the magnitude of the rebound effects. Otherwise, the result could be climate mitigation efforts that routinely fall short of emissions reduction objectives.

Bibliography

Adetutu, M., Glass, A. and Weyman-Jones, T. (2016), 'Economy-wide estimates of rebound effects: Evidence from panel data', *The Energy Journal* **37**(3), 251–269.

Afriat, S. N. (1972), 'Efficiency estimation of production functions', *International Economic Review* pp. 568–598.

Aigner, D. J. and Chu, S.-F. (1968), 'On estimating the industry production function', *The American Economic Review* pp. 826–839.

Aigner, D., Lovell, C. A. K. and Schmidt, P. (1977), 'Formulation and estimation of stochastic frontier production function models', *Journal of Econometrics* **6**(1), 21–37.

Alberini, A. and Filippini, M. (2015), 'Transient and persistent energy efficiency in the us residential sector: Evidence from household-level data'.

Allan, G., Hanley, N., McGregor, P., Swales, K. and Turner, K. (2007), 'The impact of increased efficiency in the industrial use of energy: a computable general equilibrium analysis for the united kingdom', *Energy Economics* **29**(4), 779–798.

Alvarez, A., Amsler, C., Orea, L. and Schmidt, P. (2006), 'Interpreting and testing the scaling property in models where inefficiency depends on firm characteristics', *Journal of Productivity Analysis* **25**(3), 201–212.

Anderson, T. W. and Hsiao, C. (1982), 'Formulation and estimation of dynamic models using panel data', *Journal of econometrics* **18**(1), 47–82.

Ang, B. W. (2006), 'Monitoring changes in economy-wide energy efficiency: From energy-gdp ratio to composite efficiency index', *Energy Policy* **34**(5), 574–582.

Arellano, M. and Bond, S. (1991), 'Some tests of specification for panel data: Monte carlo evidence and an application to employment equations', *The review of economic studies* **58**(2), 277–297.

Arellano, M. and Bover, O. (1995), 'Another look at the instrumental variable estimation of error-components models', *Journal of econometrics* **68**(1), 29–51.

Asafu-Adjaye, J. (2000), 'The relationship between energy consumption, energy prices and economic growth: time series evidence from asian developing countries', *Energy economics* **22**(6), 615–625.

Barker, T. (2004), 'The transition to sustainability: a comparison of general–equilibrium and space–time–economics approaches', *Tyndall Centre for Climate Change Research, Norwich Google Scholar* .

Barker, T., Dagoumas, A. and Rubin, J. (2009), 'The macroeconomic rebound effect and the world economy', *Energy efficiency* **2**(4), 411–427.

Barker, T., Ekins, P. and Foxon, T. (2007), 'The macro-economic rebound effect and the uk economy', *Energy Policy* **35**(10), 4935–4946.

Barker, T., Pan, H., Köhler, J., Warren, R. and Winne, S. (2006), 'Decarbonizing the global economy with induced technological change: scenarios to 2100 using e3mg', *The Energy Journal* pp. 241–258.

Battese, G. E. and Coelli, T. J. (1988), 'Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data', *Journal of econometrics* **38**(3), 387–399.

Battese, G. E. and Coelli, T. J. (1992), Frontier production functions, technical efficiency and panel data: with application to paddy farmers in india, *in* 'International applications of productivity and efficiency analysis', pp. 149–165.

Battese, G. E. and Coelli, T. J. (1995), 'A model for technical inefficiency effects in a stochastic frontier production function for panel data', *Empirical economics* **20**(2), 325–332.

Bentzen, J. (2004), 'Estimating the rebound effect in us manufacturing energy consumption', *Energy economics* **26**(1), 123–134.

Bhattacharyya, S. C. (2011), *Energy Economics: Concepts, Issues, Markets and Governance*, Springer London, London.

Blundell, R. and Bond, S. (1998), 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of econometrics* **87**(1), 115–143.

Boyd, G. A. (2008), 'Estimating plant level energy efficiency with a stochastic frontier', *The Energy Journal* **29**(2), 23–43.

Brännlund, R., Ghalwash, T. and Nordström, J. (2007), 'Increased energy efficiency and the rebound effect: effects on consumption and emissions', *Energy economics* **29**(1), 1–17.

Broadstock, D. C., Li, J. and Zhang, D. (2016), 'Efficiency snakes and energy ladders: A (meta-) frontier demand analysis of electricity consumption efficiency in chinese households', *Energy Policy* **91**, 383–396.

Broberg, T., Berg, C. and Samakovlis, E. (2015), 'The economy-wide rebound effect from improved energy efficiency in swedish industries–a general equilibrium analysis', *Energy Policy* **83**, 26–37.

Brookes, L. (1979), 'A low energy strategy for the uk by g leach et al: a review and reply', *Atom* **269**, 3–8.

Brookes, L. (2000), 'Energy efficiency fallacies revisited', *Energy Policy* **28**(6), 355–366.

Caudill, S. B. and Ford, J. M. (1993), 'Biases in frontier estimation due to heteroscedasticity', *Economics Letters* **41**(1), 17–20.

Caudill, S. B., Ford, J. M. and Gropper, D. M. (1995), 'Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity', *Journal of Business & Economic Statistics* **13**(1), 105–111.

Chakravarty, D., Dasgupta, S. and Roy, J. (2013), 'Rebound effect: How much to worry?', *Current opinion in environmental sustainability* **5**(2), 216–228.

Chambers, R. G. (1988), *Applied production analysis: a dual approach*, Cambridge University Press.

Charnes, A., Cooper, W. W. and Rhodes, E. (1978), 'Measuring the efficiency of decision making units', *European Journal of Operational Research* **2**(6), 429–444.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J. and Battese, G. E. (2005), *An introduction to efficiency and productivity analysis*, Springer Science & Business Media.

Coelli, T. and Perelman, S. (1996), Efficiency measurement, multiple-output technologies and distance functions: With application to european railways, Technical report, CREPP.

Colombi, R., Kumbhakar, S. C., Martini, G. and Vittadini, G. (2014), 'Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency', *Journal of Productivity Analysis* **42**(2), 123–136.

Cornwell, C., Schmidt, P. and Sickles, R. C. (1990), 'Production frontiers with cross-sectional and time-series variation in efficiency levels', *Journal of econometrics* **46**(1-2), 185–200.

Debreu, G. (1951), 'The coefficient of resource utilization', *Econometrica* **19**(3), 273–292.

Dimitropoulos, J. (2007), 'Energy productivity improvements and the rebound effect: An overview of the state of knowledge', *Energy Policy* **35**(12), 6354–6363.

Dong, Y., Firth, M., Hou, W. and Yang, W. (2016), 'Evaluating the performance of chinese commercial banks: A comparative analysis of different types of banks', *European Journal of Operational Research* **252**(1), 280–295.

Dufournaud, C. M., Quinn, J. T. and Harrington, J. J. (1994), 'An applied general equilibrium (age) analysis of a policy designed to reduce the household consumption of wood in the sudan', *Resource and Energy Economics* **16**(1), 67–90.

Evans, J., Filippini, M. and Hunt, L. C. (2013), The contribution of energy efficiency towards meeting co2 targets, *in* R. Fouquet, ed., 'Handbook on Energy and Climate Change', Edward Elgar Publishing, Oxford, chapter 8, pp. 175–223.

Farrell, M. J. (1957), 'The measurement of productive efficiency', *Journal of the Royal Statistical Society.Series A (General)* **120**(3), 253–290.

Farsi, M., Filippini, M. and Kuenzle, M. (2005), 'Unobserved heterogeneity in stochastic cost frontier models: an application to swiss nursing homes', *Applied Economics* **37**(18), 2127–2141.

Feenstra, R. C., Inklaar, R. and Timmer, M. P. (2015), 'The next generation of the penn world table', *The American Economic Review* **105**(10), 3150–3182.
URL: *www.ggdc.net/pwt*

Filippini, M. (2012), *Elements of the Swiss market for electricity*, Springer Science & Business Media.

Filippini, M. and Greene, W. (2016), 'Persistent and transient productive inefficiency: a maximum simulated likelihood approach', *Journal of Productivity Analysis* **45**(2), 187–196.

Filippini, M. and Hunt, L. C. (2011), 'Energy demand and energy efficiency in the oecd countries: A stochastic demand frontier approach', *Energy Journal* **32**(2), 59–80.

Filippini, M. and Hunt, L. C. (2012), 'Us residential energy demand and energy efficiency: a stochastic demand frontier approach', *Energy Economics* **34**(5), 1484–1491.

Filippini, M. and Hunt, L. C. (2015b), 'Measurement of energy efficiency based on economic foundations', *Energy Economics* **52, Supplement 1**, S5–S16.

Filippini, M. and Hunt, L. C. (2016), 'Measuring persistent and transient energy efficiency in the us', *Energy Efficiency* **9**(3), 663–675.

Filippini, M., Hunt, L. and Zoric, J. (2014), 'Impact of energy policy instruments on the estimated level of underlying energy efficiency in the eu residential sector', *Energy Policy* **69**, 73–81.

Filippini, M. and Zhang, L. (2016), 'Estimation of the energy efficiency in chinese provinces', *Energy Efficiency* pp. 1–14.

Fouquet, R. (2008), *Heat, power and light: revolutions in energy services*, Edward Elgar Publishing, Cheltenham, UK and Northampton, MA, USA.

Gillingham, K., Rapson, D. and Wagner, G. (2016), 'The rebound effect and energy efficiency policy', *Review of Environmental Economics and Policy* **10**(1), 68–88.

Greene, W. (2005), 'Fixed and random effects in stochastic frontier models', *Journal of Productivity Analysis* **23**(1), 7–32.

Greene, W. H. (1980), 'Maximum likelihood estimation of econometric frontier functions', *Journal of econometrics* **13**(1), 27–56.

Greene, W. H. (2008), 'The econometric approach to efficiency analysis', *The measurement of productive efficiency and productivity growth* **1**, 92–250.

Greening, L. A., Greene, D. L. and Difiglio, C. (2000), 'Energy efficiency and consumption-the rebound effect-a survey', *Energy policy* **28**(6), 389–401.

Grepperud, S. and Rasmussen, I. (2004), 'A general equilibrium assessment of rebound effects', *Energy economics* **26**(2), 261–282.

Guan, Z., Kumbhakar, S. C., Myers, R. J. and Lansink, A. O. (2009), 'Measuring excess capital capacity in agricultural production', *American Journal of Agricultural Economics* **91**(3), 765–776.

Guerra, A.-I. and Sancho, F. (2010), 'Rethinking economy-wide rebound measures: an unbiased proposal', *Energy Policy* **38**(11), 6684–6694.

Haas, R. and Biermayr, P. (2000), 'The rebound effect for space heating empirical evidence from austria', *Energy policy* **28**(6), 403–410.

Hadri, K. (1999), 'Estimation of a doubly heteroscedastic stochastic frontier cost function', *Journal of Business & Economic Statistics* **17**(3), 359–363.

Hamidi, S. and Akinci, F. (2016), 'Measuring efficiency of health systems of the middle east and north africa (mena) region using stochastic frontier analysis', *Applied health economics and health policy* **14**(3), 337–347.

Hanley, N., McGregor, P. G., Swales, J. K. and Turner, K. (2009), 'Do increases in energy efficiency improve environmental quality and sustainability?', *Ecological Economics* **68**(3), 692–709.

Hastings, J. S. and Shapiro, J. M. (2013), 'Fungibility and consumer choice: Evidence from commodity price shocks', *The quarterly journal of economics* **128**(4), 1449–1498.

Herring, H. and Roy, R. (2007), 'Technological innovation, energy efficient design and the rebound effect', *Technovation* **27**(4), 194–203.

Hicks, J. R. (1935), 'Annual survey of economic theory: The theory of monopoly', *Econometrica* **3**(1), 1–20.

Hossein, A., Yazdan, G. F. and Ehsan, A. G. (2012), 'The relationship between energy consumption, energy prices and economic growth: case study (opec countries)', *OPEC Energy Review* **36**(3), 272–286.

Huang, C. J. and Liu, J.-T. (1994), 'Estimation of a non-neutral stochastic frontier production function', *Journal of productivity analysis* **5**(2), 171–180.

Hunt, L. C., Judge, G. and Ninomiya, Y. (2003), 'Modelling underlying energy demand trends', *Chapter* **9**, 140–174.

Huntington, H. G. (1994), 'Been top down so long it looks like bottom up to me', *Energy Policy* **22**(10), 833–839.

IEA (2009), Progress with implementing energy efficiency policies in the g8, Technical report, OECD/IEA, Paris.
URL: *https://www.iea.org/publications/freepublications/publication/G8Energyefficiencyprogressreport.pdf*

IEA (2014), World energy outlook 2014, Technical report, OECD/IEA, Paris.
URL: *http://www.iea.org/publications/freepublications/publication/world-energy-outlook-2014.html*

IEA (2015), Capturing the multiple benefits of energy efficiency, Technical report, OECD/IEA, Paris.
URL: *http://www.iea.org/publications/freepublications/publication/capturing-the-multiple-benefits-of-energy-efficiency.html*

IEA (2016a), CO_2 emissions from fuel combustion highlights, Technical report, OECD/IEA, Paris.
URL: *http://www.iea.org/publications/freepublications/publication/co2-emissions-from-fuel-combustion—2016-edition—excerpt—key-trends.html*

IEA (2016c), Energy efficiency market report 2016, Technical report, OECD/IEA, Paris.
URL: *http://www.iea.org/publications/freepublications/publication/energy-efficiency-market-report-2016.html*

IEA (2016d), Energy efficiency indicators highlights 2016, Technical report, OECD/IEA, Paris.
URL: *http://www.iea.org/publications/freepublications/publication/energy-efficiency-indicators-highlights-2016.html*

IEA (2017*a*), 'Co_2 emissions from fuel combustion: Co_2 emissions from fuel combustion'.
URL: *http://www.iea.org*

IEA (2017*b*), 'World energy balances: World indicators, 1960-2015'.
URL: *http://www.iea.org*

International Labour Organisation (2017), 'Ilostat-ilo database of labour statistics'.
URL: *http://www.ilo.org/global/statistics-and-databases/lang–en/index.htm*

International Monetary fund (2015), 'Country composition of weo groups'.

Jevons, W. S. (1865), *The Coal Question: An Inquiry Concerning the Progress of the Nation, and the Probable Exhaustion of Our Coal-Mines*, Macmillan and Co., London.

Jimenez, R. and Mercado, J. (2014), 'Energy intensity: A decomposition and counterfactual exercise for latin american countries', *Energy Economics* **42**, 161–171.

Jondrow, J., Lovell, C. K., Materov, I. S. and Schmidt, P. (1982), 'On the estimation of technical inefficiency in the stochastic frontier production function model', *Journal of econometrics* **19**(2-3), 233–238.

Kebede, E., Kagochi, J. and Jolly, C. M. (2010), 'Energy consumption and economic development in sub-sahara africa', *Energy economics* **32**(3), 532–537.

Khazzoom, J. D. (1980), 'Economic implications of mandated efficiency in standards for household appliances'.

King Abdullah Petroleum Studies and Research Centre (2015), 'A global degree days database for energy-related applications'.
URL: *https://datasource.kapsarc.org/explore/dataset/a-global-degree-days-database-for-energy-related-applications/*

Kopp, R. J. (1981), 'The measurement of productive efficiency: A reconsideration', *The Quarterly Journal of Economics* **96**(3), 477–503.

Kumbhakar, S. C. (1990), 'Production frontiers, panel data, and time-varying technical inefficiency', *Journal of econometrics* **46**(1-2), 201–211.

Kumbhakar, S. C., Ghosh, S. and McGuckin, J. T. (1991), 'A generalized production frontier approach for estimating determinants of inefficiency in us dairy farms', *Journal of Business & Economic Statistics* **9**(3), 279–286.

Kumbhakar, S. C. and Hjalmarsson, L. (1995), 'Labour-use efficiency in swedish social insurance offices', *Journal of Applied Econometrics* **10**(1), 33–47.

Kumbhakar, S. C. and Lovell, C. K. (2000), *Stochastic frontier analysis: an econometric approach*, Cambridge: Cambridge University Press, Cambridge.

Kydes, A. S. (1999), 'Energy intensity and carbon emission responses to technological change: The u.s. outlook', *The Energy Journal* **20**(3), 93–121.

Lee, Y. H. and Schmidt, P. (1993), 'A production frontier model with flexible temporal variation in technical efficiency', *The measurement of productive efficiency: Techniques and applications* pp. 237–255.

Li, L. and Yonglei, H. (2012), 'The energy efficiency rebound effect in china from three industries perspective', *Energy Procedia* **14**, 1105–1110.

Lin, B. and Du, K. (2013), 'Technology gap and china's regional energy efficiency: A parametric metafrontier approach', *Energy Economics* **40**, 529–536.

Lin, B. and Long, H. (2015), 'A stochastic frontier analysis of energy efficiency of china's chemical industry', *Journal of Cleaner Production* **87**, 235–244.

Lin, B. and Wang, X. (2014), 'Exploring energy efficiency in china's iron and steel industry: A stochastic frontier approach', *Energy Policy* **72**, 87–96.

Llorca, M. and Jamasb, T. (2017), 'Energy efficiency and rebound effect in european road freight transport', *Transportation Research Part A: Policy and Practice* **101**, 98–110.

Lundgren, T., Marklund, P.-O. and Zhang, S. (2016), 'Industrial energy demand and energy efficiency-evidence from sweeden', *Resource and Energy Economics* **43**, 130–152.

Mardani, A., Zavadskas, E. K., Streimikiene, D., Jusoh, A. and Khoshnoudi, M. (2017), 'A comprehensive review of data envelopment analysis (dea) approach in energy efficiency', *Renewable and Sustainable Energy Reviews* **70**, 1298–1322.

Marin, G. and Palma, A. (2017), 'Technology invention and adoption in residential energy consumption: A stochastic frontier approach', *Energy Economics* **66**, 85–98.

Meeusen, W. and van den Broeck (1977), 'Efficiency estimation from cobb-douglas production functions with composed error', *International Economic Review* **18**(2), 435–444.

Mundlak, Y. (1978), 'On the pooling of time series and cross section data', *Econometrica* **46**(1), 69–85.

Murillo-Zamorano, L. R. (2004), 'Economic efficiency and frontier techniques', *Journal of Economic surveys* **18**(1), 33–77.

Myers, J. G. and Nakamura, L. (1978), *Saving energy in manufacturing*, Ballinger, Cambridge.

O'Donnell, C. J. and Coelli, T. J. (2005), 'A bayesian approach to imposing curvature on distance functions', *Journal of Econometrics* **126**(2), 493–523.

Orea, L., Llorca, M. and Filippini, M. (2015), 'A new approach to measuring the rebound effect associated to energy efficiency improvements: An application to the us residential energy demand', *Energy economics* **49**, 599–609.

Otsuka, A. and Goto, M. (2015), 'Estimation and determinants of energy efficiency in japanese regional economies', *Regional Science Policy & Practice* **7**(2), 89–101.

Patterson, M. G. (1996), 'What is energy efficiency?', *Energy Policy* **24**(5), 377–390.

Paul, S. and Bhattacharya, R. N. (2004), 'Causality between energy consumption and economic growth in india: a note on conflicting results', *Energy economics* **26**(6), 977–983.

Peters, A., Sonnberger, M., Dütschke, E. and Deuschle, J. (2012), Theoretical perspective on rebound effects from a social science point of view: Working paper to prepare empirical psychological and sociological studies in the rebound project, Technical report, Working paper sustainability and innovation.

Pitt, M. M. and Lee, L.-F. (1981), 'The measurement and sources of technical inefficiency in the indonesian weaving industry', *Journal of Development Economics* **9**(1), 43–64.

Population Reference Bureau (2017), 'Human population: Population growth', Population Reference Bureau, [online].
URL: *http://www.prb.org/Publications/Lesson-Plans/HumanPopulation/PopulationGrowth.aspx*

Reifschneider, D. and Stevenson, R. (1991), 'Systematic departures from the frontier: A framework for the analysis of firm inefficiency', *International Economic Review* **32**(3), 715–723.

Richmond, J. (1974), 'Estimating the efficiency of production', *International economic review* pp. 515–521.

Roodman, D. (2006), 'How to do xtabond2: An introduction to difference and system gmm in stata'.

Roy, J. (2000), 'The rebound effect: some empirical evidence from india', *Energy Policy* **28**(6-7), 433–438.

Saunders, H. D. (1992), 'The khazzoom-brookes postulate and neoclassical growth', *The Energy Journal* pp. 131–148.

Saunders, H. D. (2000), 'A view from the macro side: rebound, backfire, and khazzoom-brookes', *Energy policy* **28**(6), 439–449.

Saunders, H. D. (2008), 'Fuel conserving (and using) production functions', *Energy Economics* **30**(5), 2184–2235.

Schmidt, P. and Lovell, C. A. K. (1979), 'Estimating technical and allocative inefficiency relative to stochastic production and cost frontiers', *Journal of Econometrics* **9**(3), 343–366.

Schmidt, P. and Sickles, R. C. (1984), 'Production frontiers and panel data', *Journal of Business & Economic Statistics* **2**(4), 367–374.

Semboja, H. H. H. (1994), 'The effects of an increase in energy efficiency on the kenya economy', *Energy Policy* **22**(3), 217–225.

Shen, X. and Lin, B. (2017), 'Total factor energy efficiency of china's industrial sector: A stochastic frontier analysis', *Sustainability* **9**(4), 646.

Simar, L. and Wilson, P. W. (2000), 'A general methodology for bootstrapping in non-parametric frontier models', *Journal of applied statistics* **27**(6), 779–802.

Sorrell, S. and Dimitropoulos, J. (2007), Ukerc review of evidence for the rebound effect: Technical report 2: Econometric studies, Technical report, UKERC, London.

Sorrell, S. et al. (2007), 'The rebound effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency'.

Stevenson, R. E. (1980), 'Likelihood functions for generalised stochastic frontier estimation', *Journal of econometrics* **13**(1), 57–66.

Thomas, B. A. and Azevedo, I. L. (2013), 'Estimating direct and indirect rebound effects for us households with input–output analysis part 1: Theoretical framework', *Ecological Economics* **86**, 199–210.

Toma, P., Miglietta, P. P., Zurlini, G., Valente, D. and Petrosillo, I. (2017), 'A non-parametric bootstrap-data envelopment analysis approach for environmental policy planning and management of agricultural efficiency in eu countries', *Ecological Indicators* **83**, 132–143.

Turner, K. (2009), 'Negative rebound and disinvestment effects in response to an improvement in energy efficiency in the uk economy', *Energy Economics* **31**(5), 648–666.

UN (2017), 'Towards a climate agreement', United Nations, [online].
URL: *http://www.un.org/climatechange/towards-a-climate-agreement/*

UNFCCC (2012), Decisions adopted by the conference of the parties, Technical report, United Nations Framework Convention on Climate Change.

UNFCCC (2017), 'Climate get the big picture', United Nations Framework Convention on Climate Change, [online].
URL: *http://bigpicture.unfccc.int/*

UNIDO (2010), Energy for a sustainable future, Technical report, United Nations for Industrial Development Organisation.
URL: *http://www.un.org/millenniumgoals/pdf/AGECCsummaryreport[1].pdf*

United Nations Environmental Programme (2016), Renewable energy and energy efficiency in developing countries: contributions to reducing global emissions, Technical report, United Nations.

Vikström, P. (2008), 'Energy efficiency and energy demand: a historical cge investigation on the rebound effect in the swedish economy 1957'.

Voigt, S., Cian, E. D., Schymura, M. and Verdolini, E. (2014), 'Energy intensity developments in 40 major economies: structural change or technology improvement?', *Energy Economics* **41**, 47–62.

Wang, H.-J. and Schmidt, P. (2002), 'One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels', *journal of Productivity Analysis* **18**(2), 129–144.

Washida, T. (2004), 'Economy-wide model of rebound effect for environmental efficiency', *Topic 1-Opening Session* p. 292.

Wei, T. (2007), 'Impact of energy efficiency gains on output and energy use with cobb–douglas production function', *Energy Policy* **35**(4), 2023–2030.

Wei, T. (2010), 'A general equilibrium view of global rebound effects', *Energy Economics* **32**(3), 661–672.

Windmeijer, F. (2005), 'A finite sample correction for the variance of linear efficient two-step gmm estimators', *Journal of econometrics* **126**(1), 25–51.

Winsten, C. (1957), 'Discussion on mr. farrell's paper', *Journal of the Royal Statistical Society* **120**, 282–284.

Wolfram, C., Shelef, O. and Gertler, P. J. (2012), How will energy demand develop in the developing world?, Working Paper 17747, National Bureau of Economic Research.
URL: *http://www.nber.org/papers/w17747*

World Bank (2017), 'World development indicators'.
URL: *http://www.wb.org*

Zhang, X.-P., Cheng, X.-M., Yuan, J.-H. and Gao, X.-J. (2011), 'Total-factor energy efficiency in developing countries', *Energy Policy* **39**(2), 644–650.

Zhou, P. and Ang, B. W. (2008), 'Linear programming models for measuring economy-wide energy efficiency performance', *Energy Policy* **36**(8), 2911–2916.

Zhou, P., Ang, B. and Zhou, D. (2012), 'Measuring economy-wide energy efficiency performance: a parametric frontier approach', *Applied Energy* **90**(1), 196–200.

Appendix A

Theoretical framework and Literature Review

Table A.1: Functional forms

Name	General equation
Linear	$y = \alpha + \sum_{i=1}^{N} \beta_i x_i$
Log-Log	$\ln(y) = \alpha \sum_{i=1}^{N} \beta_i ln(x_i)$
Quadratic	$y = \alpha + \sum_{i=1}^{N} \beta_i x_i + \sum_{i=1}^{N} \sum_{j=1}^{N} \gamma_{ij} x_i x_j$
Translog	$ln(y) = \alpha + \sum_{i=1}^{N} \beta_i ln(x_i) \sum_{i=1}^{N} \sum_{j=1}^{N} \gamma_{ij} ln(x_i) ln(x_j)$

Duality and Cost Functions

Let $C(E, x_i, w_i, p_E, y) = \min\left\{\sum_{i=1}^{h} w_i x_i + p_E E : y = f(x_i, E)\right\}$ is a cost function where x_i denotes all the inputs, but energy, E is the input energy, w_i is the input price for input i=1,...,h, p_E is the price for input energy and y is the output. Furthermore, the cost function has the following properties:

i. is non decreasing in input prices.

ii. is homogeneous of degree 1 in input prices.

iii. is concave in input prices.

iv. is continuous in input prices (for non-negative input prices).

Then, minimising the cost function, we get:

$$\min C(E, x_i, w_i, p_E) = \sum_{i=1}^{h} w_i x_i + p_E E$$

subject to

$$y = f(x_i, E)$$

and the Lagrangian will be given by:

$$\mathcal{L} = \sum_{i=1}^{h} w_i x_i + p_E E + \lambda\Big(y - f(x_i, E)\Big)$$

First order conditions imply:

$$\frac{\partial \mathcal{L}}{\partial x_i} = w_i - \lambda f_{x_i} = 0$$

$$\frac{\partial \mathcal{L}}{\partial E} = p_E - \lambda f_E = 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = y - f(x_i, E) = 0$$

Eliminating λs, by dividing the first two equations:

$$\frac{w_i}{p_E} = \frac{f_{x_i}}{f_E}$$

solution to this system of equations for $i = 1, ..., h$ will be given by:

$$x_i^* = x(w_i, p_E, y)$$

$$E^* = E(w_i, p_E, y)$$

where x_i^* is the cost minimising input demand for input factor i given input prices w_i and output level y while E^* is the cost minimising input demand for input energy given the price for energy p_E and output y.

Such that:

$$\min C^* = \sum_{i=1}^{h} w_i x_i^* + p_E E^* = C(w_i, x_i, p_E, E, y)$$

and using Shephard's lemma we get:

$$\frac{\partial C^*}{\partial w_i} = x_i^*$$

$$\frac{\partial C^*}{\partial p_E} = E^*$$

Along with additional time-varying or invariant covariates that affect energy demand and can capture individual specific observed heterogeneity E^* is the conditional input energy demand function as described in equation 2.53.

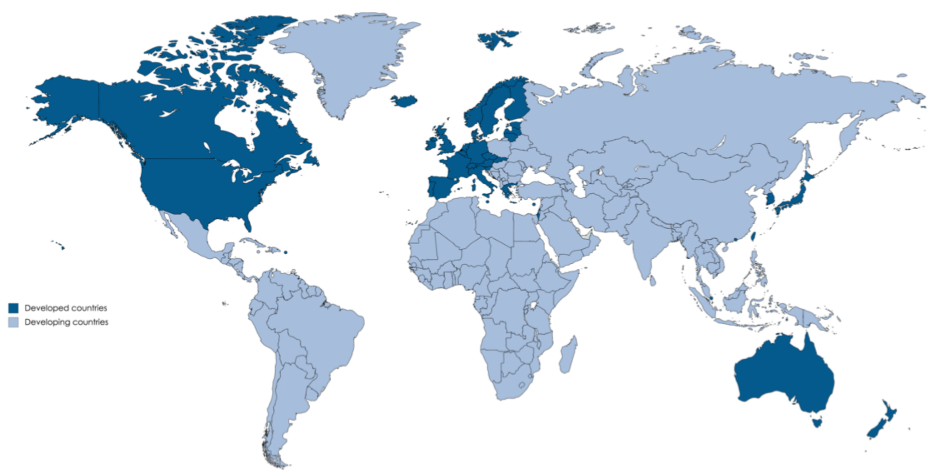
Table A.2: Distributional assumptions of the components of the combined error term

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

Appendix B

Energy demand and energy efficiency in developing countries: A Stochastic Energy Demand Function approach

Figure B.1: Map of developed and developing countries



data source: IMF

Table B.1: Panel of 39 developing countries

Country name	ISO-code	Geographic specification
Albania	ALB	Europe
Algeria	DZA	Africa
Argentina	ARG	Latin America
Armenia	ARM	Commonwealth of Independent States
Azerbaijan	AZE	Commonwealth of Independent States
Belarus	BLR	Commonwealth of Independent States
Bolivia	BOL	Latin America
Botswana	BWA	Africa
Brazil	BRA	Latin America
Bulgaria	BGR	Europe
China	CHN	Asia
Congo	COG	Africa
Costa Rica	CRI	Latin America
Croatia	HRV	Europe
Egypt	EGY	Africa
El Salvador	SLV	Latin America
F.Y.R.O.M	MKD	Europe
Georgia	GEO	Commonwealth of Independent States
Honduras	HND	Latin America
India	IND	Asia
Indonesia	IDN	Asia
Iran	IRN	Middle East
Jordan	JOR	Middle East
Kazakhstan	KAZ	Commonwealth of Independent States
Kyrgyzstan	KGZ	Commonwealth of Independent States
Malaysia	MYS	Asia
Morocco	MAR	Africa
Nepal	NPL	Asia
Oman	OMN	Middle East
Pakistan	PAK	Middle East
Romania	ROU	Europe
Russia	RUS	Commonwealth of Independent States
Saudi Arabia	SAU	Middle East
South Africa	ZAF	Africa
Sri Lanka	LKA	Asia
Syria	SYR	Middle East
Thailand	THA	Asia
Tunisia	TUN	Africa
Uruguay	URY	Latin America

Note: Georgia is not a member of the Commonwealth of Independent States, but is included in this group for reasons of geography and similarity in economic structure

Figure B.2: Kernel density of the OLS residuals and skewness

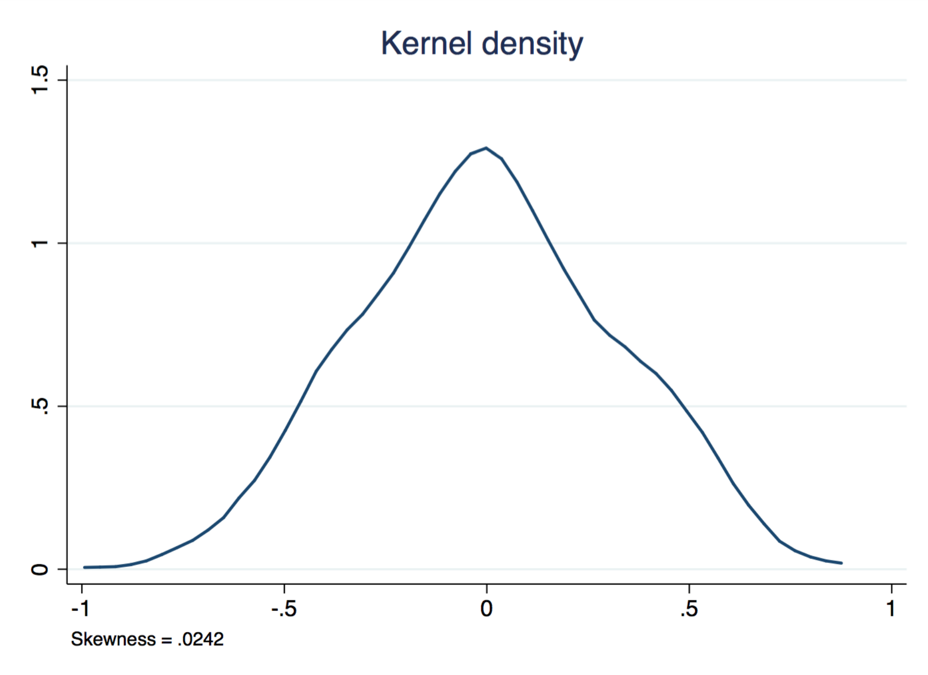


Table B.2: Econometric specification of SEDF: effects, error term and inefficiency

	REM	MREM	TREM	MTREM	GTREM	MGTREM
Country's effects α_i	α	$\alpha_i = \gamma\bar{X}_{it} + \delta_i$	$N(\alpha, \sigma_w^2)$	$\alpha_i = \gamma\bar{X}_{it} + w_i$	$N(\alpha, \sigma_w^2)$	$\alpha_i = \gamma\bar{X}_{it} + w_i$
		$\bar{X}_{it} = \frac{1}{T}\sum_{t=1}^{T} X_{it}$		$\bar{X}_{it} = \frac{1}{T}\sum_{t=1}^{T} X_{it}$		$\bar{X}_{it} = \frac{1}{T}\sum_{t=1}^{T} X_{it}$
Full random error ε_{it}	$\varepsilon = u_i + v_{it}$	$\varepsilon_{it} = \delta_i + v_{it}$	$\varepsilon_{it} = w_i + u_{it} + v_{it}$	$\varepsilon_{it} = w_i + u_{it} + v_{it}$	$\varepsilon_{it} = w_i + h_i + u_{it} + v_{it}$	$\varepsilon_{it} = w_i + h_i + u_{it} + v_{it}$
	$u_i \sim N^+(0, \sigma_u^2)$	$\delta_i \sim N^+(0, \sigma_\delta^2)$	$u_{it} \sim N^+(0, \sigma_u^2)$	$u_{it} \sim N^+(0, \sigma_u^2)$	$u_{it} \sim N^+(0, \sigma_u^2)$	$u_{it} \sim N^+(0, \sigma_u^2)$
	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$
			$w_i \sim N(0, \sigma_w^2)$	$w_i \sim N(0, \sigma_w^2)$	$w_i \sim N(0, \sigma_w^2)$	$w_i \sim N(0, \sigma_w^2)$
					$h_i \sim N(0, \sigma_h^2)$	$h_i \sim N(0, \sigma_h^2)$
Persistent inefficiency estimator	$E(u_i \vert \varepsilon_{it})$	$E(\delta_i \vert \delta_i + v_{it})$	$\emptyset$		$E(h_i \vert \varepsilon_{it})$	$E(h_i \vert \varepsilon_{it})$
Transient inefficiency estimator		$\emptyset$	$E(u_{it} \vert \varepsilon_{it})$	$E(u_{it} \vert \varepsilon_{it})$	$E(u_{it} \vert \varepsilon_{it})$	$E(h_i \vert \varepsilon_{it})$

- ***REM*** *proposed by Pitt and Lee (1981) considers the individual random effects as inefficiency rather than unobserved heterogeneity as in the traditional random effects model. Hence, estimation results of the REM provide information on the persistent part of the inefficiency in the use of energy. One drawback of this model is that any time-invariant individual-specific unobserved heterogeneity is considered inefficiency. Therefore, this REM tends to overestimate the level of 'persistent' inefficiency in the use of energy.*
- *In* ***MREM****, as proposed by Farsi et al. (2005), the unobserved heterogeneity bias problem is solved (at least partially) since the time-invariant unobserved heterogeneity is captured by the coefficients of the group mean of the time-varying explanatory variables of the Mundlak adjustment and not by the inefficiency component. Therefore, it is expected that the level of estimated energy efficiency obtained with MREM to be higher than the one obtained with REM. Estimation results confirm this point, as illustrated in Table B.4.*
- *In* ***TREM****, the constant term, α in equation 3.2, is substituted with a series of individual-specific random effects that take into account all unobserved socioeconomic and environmental characteristics that are time-invariant. Thus, TREM distinguishes the time-invariant unobserved heterogeneity w_i from the time varying level of efficiency component u_{it}. However, any time-invariant or persistent component of inefficiency is completely absorbed in the individual-specific constant terms. Therefore, generally TREM provide information only for the transient energy efficiency. Finally, for the REM and TREM, energy efficiency is estimated as shown inJondrow et al. (1982)*
- *The* ***GTREM*** *gives the possibility to estimate simultaneously the persistent and transient part of inefficiency and is obtained by adding to the TREM a time persistent inefficiency component h_i. Therefore, this model considers a four-part disturbance with two-time varying components and two time-invariant components. Additionally, h_i, captures the persistent inefficiency in the use of energy while u_{it} captures the transient inefficiency. Finally, Colombi et al. (2014) provide a theoretical construct of the model while Filippini and Greene (2016) develop a straightforward empirical estimation method which is followed in this thesis. The model is essentially a TREM consists of two part disturbance, one time varying ($v_{it} + u_{it}$) and one time invariant ($w_i + h_i$), in which each of the two parts has its own skew normal distribution rather than normal distribution. The computation of energy efficiency requires a one time, post estimation application of GHK simulation and NLOGIT5 econometric software is used for the estimations of all models.*

Table B.3: Summary of SFA studies on energy efficiency

	REM	MREM		TREM	MTREM		GTREM
		Main equation	Mundlak		Main equation	Mundlak	
Constant	6.804***	9.754***		6.074***	6.985***		4.158***
	(1.605)	(3.692)		(.094)	(.159)		(.119)
α^{y}	.585***	.586***	.383*	.515***	.502***	.453***	.578***
	(.021)	(.034)	(.215)	(.011)	(.023)	(.027)	(.013)
α^{p}	−.187***	−.172***	.104	−.213***	−.197***	−.155***	−.221***
	(.014)	(.017)	(.525)	(.008)	(.010)	(.051)	(.010)
α^{pop}	.581***	.920	−.652**	.495***	.808***	1.610***	.333***
	(.059)	(.060)	(.286)	(.010)	(.050)	(.0051)	(.011)
α^{a}	.111	−.108		.030***	. − 025***		.115***
	(.109)	(.136)		(.005)	(.005)		(.005)
α^{hdd}	6.804	.027	−.078	.017***	.020	−.007	.050***
	(.039)	(.047)	(.103)	(.003)	(.039)	(.039)	(.003)
α^{cdd}	.062	−.029	−.409**	−.046***	−.032	−.251***	.004
	(.047)	(.075)	(.171)	(.007)	(.035)	(.036)	(.008)
α^{ish}	.002***	.000	−.003	.002***	.001	−.002**	.004***
	(.001)	(.001)	(.009)	(.000)	(.001)	(.001)	(.000)
α^{ash}	.006***	.005***	−.011	.004***	.004***	.001	.008***
	(.001)	(.002)	(.020)	(.001)	(.001)	(.001)	(.001)
α^{t}	−.002	−.012***		.011***	.002		.010***
	(.003)	(.004		(.002)	(.002)	(.075)	(.002)
α^{t^2}	.000	.001**		−.001**	.000		−.001
	(.000)	(.000)		(.000)	(.000)	(.075)	(.000)
λ	7.071*	4.381*		2.901***	2.061***		−.001
	(4.191)	(2.531)		(.248)	(.243)	(.075)	(.000)

*Note: *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. Standard errors are in parentheses. The sample includes 640 observations. NLOGIT5 econometric software is used for the estimations. GTREM with Mundlak modification does not converge.*

Figure B.3: Estimated time dummy coefficients (relative to 1989)

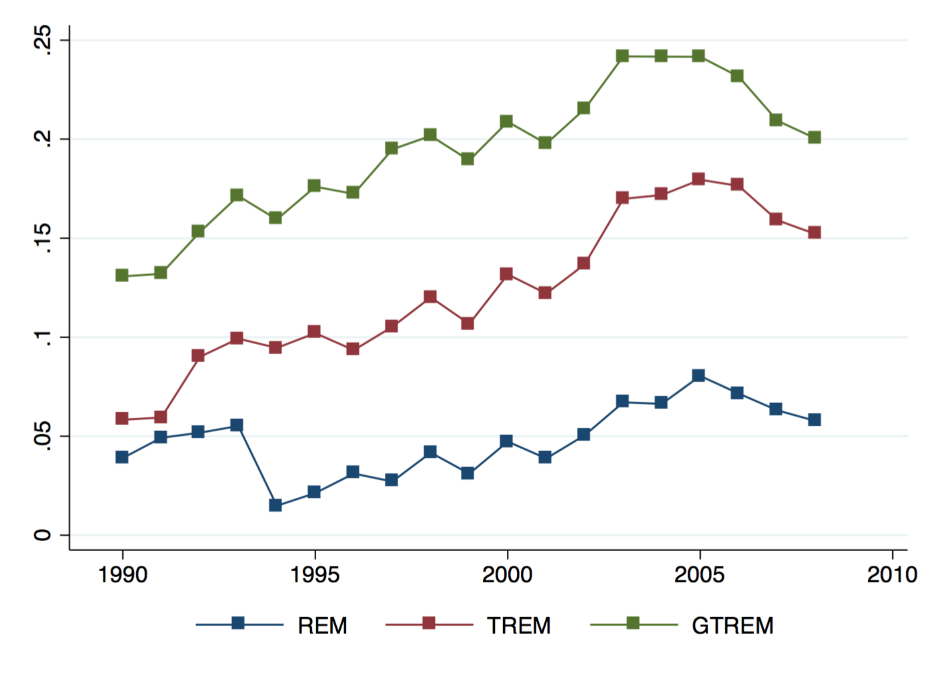


Figure B.4: Estimated time trend coefficients

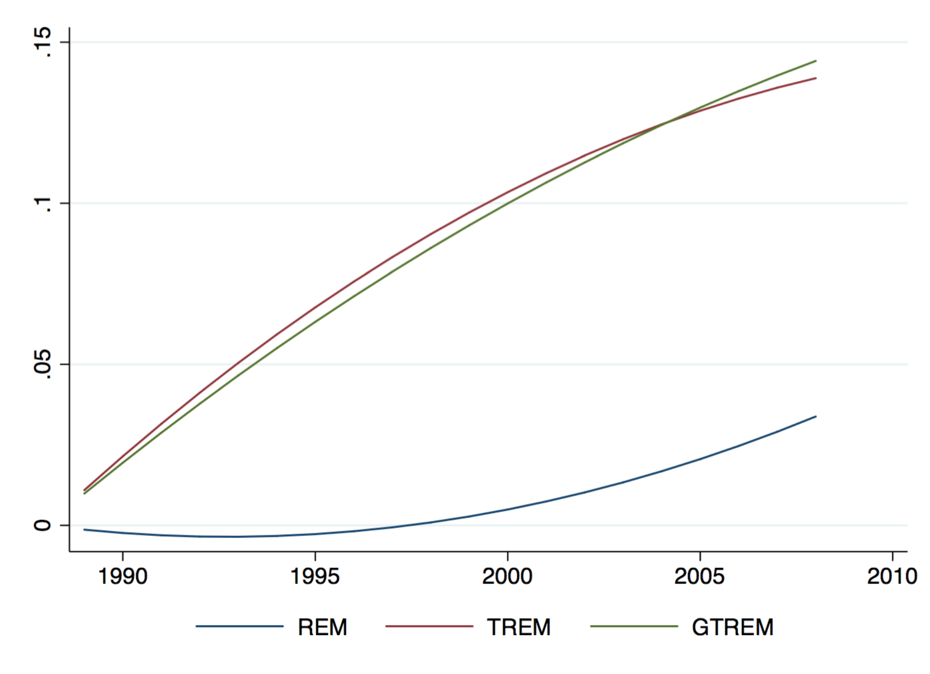


Figure B.5: Kernel densities of the estimated persistent energy efficiency from PGMREM and MREM

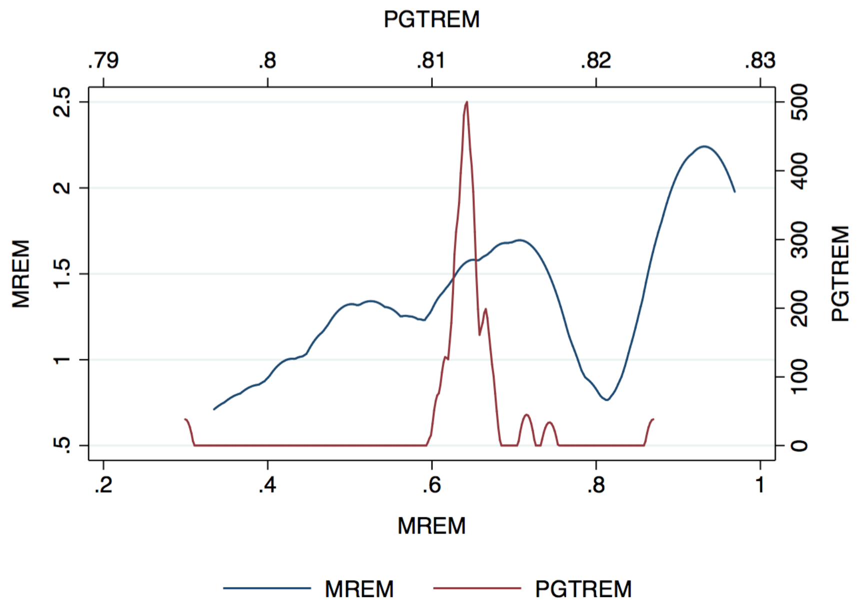


Figure B.6: Kernel densities of the estimated persistent energy efficiency from TGMREM and TREM

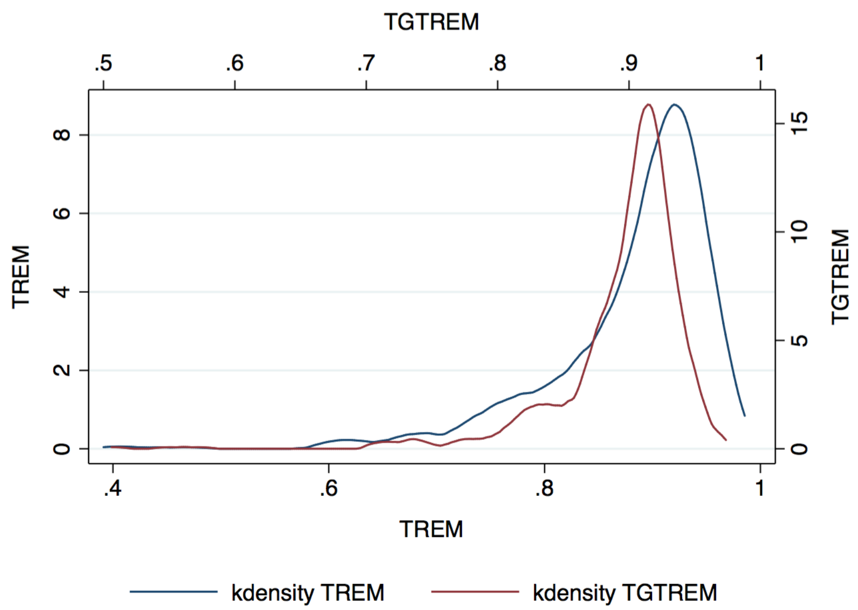


Figure B.7: Scatter diagram of estimated average persistent energy efficiency from PGMREM and MREM

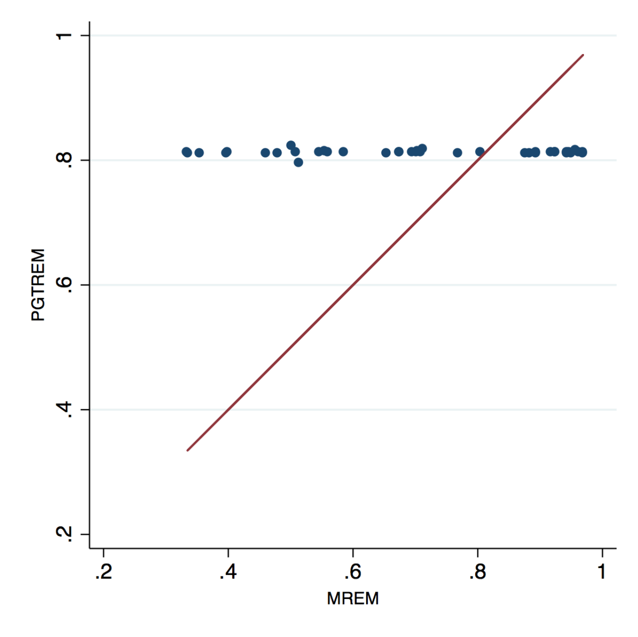


Figure B.8: Scatter diagram of estimated average transient energy efficiency from TGM-REM and TREM

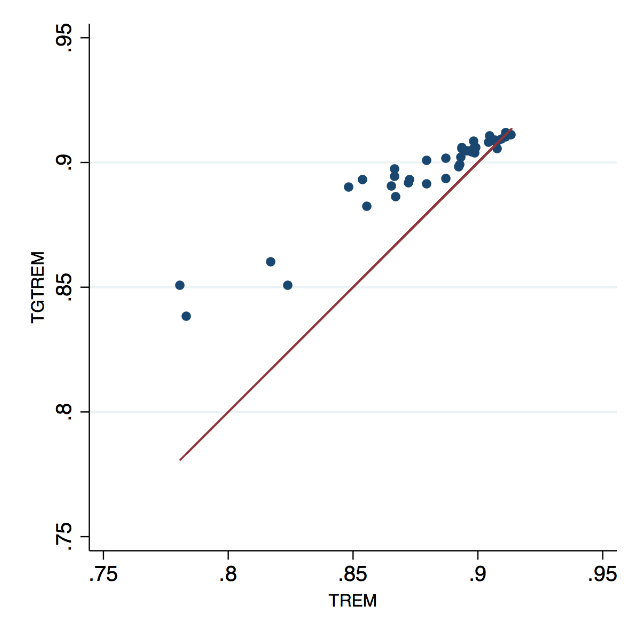


Table B.4: Energy efficiency scores

Variable	Mean	Std. Dev.	Min	Max
REM	.539	.219	153	.981
MREM	.705	.203	.335	.969
TREM	.881	.077	.391	.986
MTREM	.884	.072	.403	.986
PGTREM	.812	.004	.795	.823
TGTREM	.896	.049	.560	.974

Note: GTREM with Mundlak modification does not converge.

Table B.5: Correlation Coefficients

	REM	MREM	TREM	MTREM	PGTREM	TGTREM	EI
REM	1						
MREM	.618	1					
TREM	.064	.046	1				
MTREM	.046	.040	.992	1			
PGTREM	.129	.075	.-009	-.015	1		
TGTREM	.057	.048	.971	.962	-.054	1	
EI	-.455	-.460	-.357	-.329	-.006	-.354	1

Note: GTREM with Mundlak modification does not converge.

Appendix C

Energy efficiency and rebound effect in developing countries

Table C.1: Alternative definitions of energy conservation from improvement in energy efficiency

Definition 1	$\eta_\varepsilon(E) = \eta_\varepsilon(S) - 1$
Definition 2	$\eta_\varepsilon(E) = -\eta_{P_S}(S) - 1$
Definition 3	$\eta_\varepsilon(E) = -\eta_{P_E}(S) - 1$
Definition 4	$\eta_\varepsilon(E) = -\eta_{P_E}(E) - 1$

Note: $\eta_\epsilon(E)$ is the energy efficiency elasticity of the demand for energy, $\eta_\epsilon(S)$ expresses the energy efficiency elasticity of the demand for useful work, $\eta_{P_S}(S)$ is the cost elasticity of demand for useful work, $\eta_{P_E}(S)$ denotes the elasticity of demand for useful work with respect to changes in energy prices alone and $\eta_{P_E}(E)$ is the own price elasticity of energy demand

GMM estimation procedure for the Dynamic Panel Data model

Consider an AR(1) model with unobserved individual-specific effects as follows:

$$y_{it} = \theta y_{it-1} + \alpha_i - u_{it} \tag{C.1}$$

One main problem with Dynamic Panel Data analysis is that any time-invariant country characteristics (fixed effects) may be correlated with the explanatory variables. The fixed effects are contained in the error term ε_{it} in equation C.1, which consists of the unobserved country-specific effects α_i, and the observation-specific errors u_{it}:

$$\varepsilon_{it} = \alpha_i + u_{it} \tag{C.2}$$

To cope with this problem the difference GMM uses first-differences to transform equation C.1. Then, by transforming the regressors by first differencing the fixed country-specific effect is removed, because it does not vary with time. From equation C.2 we get:

$$\begin{aligned} \Delta\varepsilon_{it} =& \Delta\alpha_i + \Delta u_{it} \\ \varepsilon_{it} - \varepsilon_{it-1} =& (\alpha_i - \alpha_i) + (u_{it} - u_{it-1}) \end{aligned}$$

Since the focus is on the role of initial conditions it is assumed that α_i and u_{it} are independently distributed across i and have the familiar error components structure in which:

$$E(\alpha_i) = 0, \quad E(u_{it}) = 0, \quad E(\alpha_i u_{it}) = 0 \qquad \text{for } i = 1, ..., N \text{ and } t = 2, ..., T \tag{C.3}$$

and

$$E(u_{it}u_{is}) = 0 \qquad \text{for } i = 1, ..., N \text{ and } \forall t \neq s. \tag{C.4}$$

In addition, there is the standard assumption that initial conditions y_{i1} are predetermined

$$E(y_{i1}u_{it}) = 0 \qquad \text{for } i = 1, ..., N \text{ and } t = 2, ..., T \tag{C.5}$$

Conditions C.3-C.5 imply moment restrictions that are sufficient to estimate θ parameter in equation C.1. for $T \geq 3$

Additionally, in the absence of any further restrictions on the process generating the initial conditions, the autoregressive error components model implies the following $m = \frac{1}{2}(T-1)(T-2)$ orthogonality conditions which are linear in the θ parameter in equation 4.17.

$$E(y_i^{t-2}\Delta u_{it}) = 0 \qquad \text{for } t = 3, ..., T \tag{C.6}$$

where $y_i^{t-2} = (y_{i1}, y_{i2}, ...y_{iT-2})'$ and $\Delta u_{it} = u_{it} - u_{it-1} = \Delta y_{it} - \theta\Delta y_{it-1}$. These depend only on the assumed absence of serial correlation in the time-varying disturbances u_{it}, together with the restriction in equation C.5. The moment restrictions in equation C.6 can be expressed more compactly as:

$$E(Z'^{i}\bar{u}_i) = 0 \tag{C.7}$$

where Z_i is the $(T-2) \times m$ matrix given by:

$$Z_i = \begin{bmatrix} y_{i1} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & y_{i1} & y_{i2} & \dots & 0 & \dots & 0 \\ 0 & \vdots & \dots & \dots & \dots & \dots & 0 \\ 0 & 0 & 0 & \dots & y_{i1} & \dots & y_{iT-2} \end{bmatrix}$$

and $\bar{u}_i$ is the $(T-2)$ vector $(\Delta u_{i3}, \Delta u_{i4}, ..., \Delta u_{iT})'$. These are the moment restrictions exploited by the standard linear first-differenced GMM estimator, implying the use of lagged levels dated $t-2$ and earlier as instruments for the equations in first-differences. According to Arellano and Bond (1991), this yields a consistent estimator of θ. The GMM estimator based on these moment conditions minimises the quadratic distance

$(\bar{u}'ZA_NZ'\bar{u})$ for some metric A_N, where Z' is the $m \times N(T-2)$ matrix $(Z_1', Z_2', ..., Z_N')$ and $\bar{u}'$ is the $N(T-2)$ vector $(\bar{u}_1', \bar{u}_2', ..., \bar{u}_N')$. Then the first difference GMM estimator for θ is given as

$$\hat{\theta}_{\text{dif}} = (\bar{y}_{-1}'ZA_NZ'\bar{y}_{-1})^{-1}\bar{y}_{-1}'ZA_NZ'\bar{y} \tag{C.8}$$

where $\bar{y}_i'$ is the $(T-2)$ vector $(\Delta y_{i3}, \Delta y_{i4}, ..., \Delta y_{iT})$, $\bar{y}_{-1}'$ is the $(T-2)$ vector $(\Delta y_{i2}, \Delta y_{i3}, ..., \Delta y_{iT-1})$ and $\bar{y}$ and $\bar{y}_{-1}$ are stacked across individuals in the same way as u.

Alternative choices for the weights A_N give rise to a set of GMM estimators based on the moments conditions all of which are consistent for large N and finite T, but which differ in their asymptotic efficiency. In general, the optimal weights are given by:

$$A_N = \left(\frac{1}{N}\sum_{i=1}^{N} Z_i'\hat{\bar{u}}_i\hat{\bar{u}}_i'Z_i\right)^{-1} \tag{C.9}$$

However, according to Blundell and Bond (1998), this first-difference GMM estimator has been found to have poor finite sample properties, in terms of bias and imprecision when the lagged levels of the series are only weakly correlated with subsequent first-differences, so that the instruments available for the first-differenced equations are weak. In these case, it may be appropriate to consider alternative estimators that are likely to have better finite sample properties in the context of persistent series such as the system GMM. For a detailed discussion on GMM estimators see Roodman (2006).

Table C.2: Double heteroscedastic model full results

Dependent variable	Estimated coefficients
Parameters in goal function	
Constant	0.440***
	(0.014)
$ln(Y)$	-0.984***
	(0.007)
$ln(K^{/}E)$	0.239***
	(0.013)
$ln(L/E)$	0.470***
	(0.019)
$ln(Y)^2$	-0.054***
	(0.010)
$ln(K/E)^2$	0.099***
	(0.031)
$ln(L/E)^2$	-0.072
	(0.053)
$ln(Y) * ln(K/E)$	-0.108***
	(0.015)
$ln(Y) * ln(L/E)$	-0.021
	(0.017)
$ln(K/E) * ln(L/E)$	-0.425 ***
	(0.038)
t	-0.001
	(0.002)
t^2	-0.001**
	(0.000)
$t * ln(Y)$	0.010 ***

	(0.002)
$t * ln(K/E)$	-0.005**
	(0.002)
$t * ln(L/E)$	0.017***
	(0.003)
Parameters in σ_v	
Constant	-6.071***
	(0.623)
ζ^{pop}	-1.530 ***
	(0.532)
ζ^{a}	-0.549
	(0.409)
ζ^{ash}	0.015
	(0.063)
ζ^{ish}	0.081**
	(0.041)
ζ^{temp}	3.294***
	(1.069)
ζ^{CO2}	1.687***
	(0.473)
ζ^{eimp}	-0.005***
	(0.002)
ζ^{t}	-0.184**
	(0.083)
ζ^{t^2}	-0.037*
	(0.021)

Parameters in σ_u	
Constant	-2.435 ***
	(0.231)
ζ^{pop}	0.140
	(0.257)
ζ^{a}	0.480***
	(0.146)
ζ^{ash}	0.113***
	(0.020)
ζ^{ish}	0.014
	(0.019)
ζ^{temp}	0.544 **
	(0.232)
ζ^{CO2}	-0.139
	(0.203)
ζ^{eimp}	0.009***
	(0.002)
ζ^{t}	0.045**
	(0.021)
ζ^{t^2}	-0.0133**
	(0.007)

**** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.*

Standard Errors are in parentheses.

Table C.3: Original estimation, energy demand model

Dependant variable $\ln E$	Estimated coefficients
constant	6.962***
	(0.161)
$\ln y$	1.051***
	(0.008)
$\ln p$	-0.079**
	(0.034)
eff	-2.415***
	(0.962)

Table C.4: First stage: Regression of explanatory variables on instruments and exogenous variables

	Model I	*Model II*	*Model III*
Dependant variables:	$\ln y$	$\ln p$	eff
constant	3.698***	3.938***	0.916***
	(0.696)	(0.079)	(0.723)
$\ln y$		0.012	-0.008*
		(0.010)	
$\ln p$	0.193	-0.053***	
	(0.161)		(0.018)
eff	-0.602*	-.246***	
	(0.348)	(0.085)	(0.348)
$y * eff$	0.004***	-0.001*	
	(0.000)	(0.000)	(0.000)
$p * eff$	0.4003	0.008***	0.002***
	(0.002)	(0.000)	(0.000)
$y * p$	-0.001***	7.71e-07**	-1.42e-06**
	(0.000)	(0.000)	(0.000)
t	-0.28***	0.008***	-0.-001***
	(0.009)	(0.002)	(0.001)

Table C.5: Second stage: Original estimation with residuals from the first stage, energy demand model

Dependant variable $\ln E$	Estimated residuals from:		
	Model I	*Model II*	*Model III*
constant	6.904***	6.632***	6.708***
	(0.162)	(0.046)	(0.177)
$\ln y$	1.069***	1.049***	1.049***
	(0.011)	(0.008)	(0.008)
$\ln p$	-0.083**	0.004	-0.123***
	(0.033)	(0.008)	(0.036)
eff	-2.422***	-2.468***	-1.872***
	(0.097)	(0.097)	(0.191)
res_y	-0.04***		
	(0.017)		
res_p		-0.187**	
		(0.681)	
res_{eff}			-0.720***
			(0.220)

Table C.6: Rebound effect by country, 1989-1998

Country	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
Albania						58.4	59.0	58.9	58.7	58.9
Algeria	56.5	56.0	56.1	56.1	56.4	55.8	56.5	56.9	57.6	58.0
Argentina	57.0	57.9	57.8	57.6	57.9	57.3	57.6	57.6	57.5	57.3
Armenia						57.9	58.8	58.5	58.9	59.0
Azerbaijan			58.6	54.9	54.6	54.6	54.8	55.7	58.1	59.1
Belarus				56.8	58.1	58.3	63.0	62.2	62.3	60.9
Bolivia	58.4	58.4	58.8	58.6	58.8	58.8	58.7	58.8	58.9	59.0
Botswana				61.1	60.7	60.5	60.0	59.6	59.6	59.3
Brazil										
Bulgaria		56.9	57.8	57.6	57.6	57.3	57.1	58.2	58.3	58.5
China	48.4	48.2	47.8	46.6	45.7	43.6	41.5	39.7	38.1	36.5
Congo	58.5	58.4	58.6	58.7	58.9	58.1	58.1	58.8	58.9	59.6
Costa Rica							61.0	60.8	60.3	59.6
Croatia							59.6	59.6	59.6	59.4
Egypt	56.1	56.3	57.1	58.6	58.9	58.8	58.4	58.0	57.9	57.6
El Salvador		59.9	59.1	59.2	58.6	58.6	58.7	58.7	58.5	59.0
F.Y.R.O.M		60.2	60.6	58.6	59.2	58.8	58.5	58.8	58.8	58.8
Georgia						55.2	57.3	56.9	57.5	58.0
Honduras										
India	51.3	50.8	50.6	50.0	49.7	49.0	48.0	47.2	46.9	45.9
Indonesia		59.1	58.4	58.1	58.3	57.6	56.8	56.0	55.3	54.3
Iran			54.6	54.9	54.9	54.4	54.0	54.0	54.3	54.9
Jordan	60.8	60.1	60.2	60.1	60.2	60.2	60.0	59.9	59.9	59.8
Kazakhstan				53.9	55.0	54.8	55.9	56.9	58.7	59.5
Kyrgyzstan				63.5	62.9	60.0	58.8	58.6	58.6	59.0
Malaysia	60.8	60.7	60.4	60.0	59.6	59.2	59.0	58.4	58.3	58.3
Morocco	59.3	59.2	59.0	58.9	59.0	58.9	59.0	59.2	59.2	59.1
Nepal	58.9	59.2	59.0	59.1	59.4	59.3	59.0	59.0	59.1	58.8
Oman		59.5	59.5	59.4	59.3	59.4	59.4	59.4	59.4	59.4
Pakistan	57.6	57.6	57.7	57.4	57.4	57.2	57.1	57.0	57.	57.5
Romania		58.5	56.3	56.1	57.7	56.8	56.7	56.6	57.2	57.4
Russia				47.2	50.1	52.0	52.4	52.8	53.6	53.2
Saudi Arabia	56.8	56.5	56.0	54.9	54.5	54.5	56.1	56.0	55.9	55.8
South Africa	57.7	57.7	57.6	57.6	57.8	57.8	57.7	57.6	57.5	57.6
Sri Lanka	60.3	59.8	60.0	59.6	59.8	60.1	60.0	59.6	59.3	59.0
Syria	58.3	58.0	58.2	58.7	58.3	58.9	60.0	59.6	59.3	59.3
Thailand	58.0	57.6	57.3	57.1	56.8	56.5	56.2	55.8	56.1	56.8
Tunisia		59.7	59.6	59.7	59.7	59.8	59.7	59.6	59.6	59.6
Uruguay										59.6

Table C.7: Rebound effect by country, 1999-2008

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Albania	59.1	59.8	60.0	60.3	60.4	61.8	63.4	63.7	64.1	64.9
Algeria	57.8	58.2	58.1	57.9	57.8	57.7				
Argentina	57.5	57.5	57.6	57.0	56.7	56.3	55.9	55.2	54.7	54.3
Armenia	59.7	59.8	59.7	59.6	59.5	59.2	59.3	59.2	58.9	58.9
Azerbaijan	59.6	59.7	59.6	59.4	59.3	59.4	62.3	62.6	68.4	65.9
Belarus	57.0	59.5	63.0	68.4	78.5	78.5	76.4	77.0	77.4	82.7
Bolivia	59.3	59.7	59.8	60.0	60.1	60.1	59.9	59.8	59.4	58.9
Botswana	59.2	59.8	59.9	59.8	59.5	59.4	59.8	59.2	58.9	59.0
Brazil		49.3	49.4	49.0	48.9	48.1	47.9	47.6	46.7	45.9
Bulgaria	59.2	59.5	59.4	59.7	60.1	60.3	60.4	60.2	60.0	60.0
China	34.9	33.7	31.7	29.3	26.8	23.8	20.5	16.2	9.6	5.4
Congo	59.7	59.8	60.7	60.3	59.9	60.0	59.9	60.3	60.6	60.4
Costa Rica	59.5	59.7	60.6	60.7	60.7	61.3	61.8			
Croatia	59.3	59.5	59.9	59.9	60.0	60.0	60.1	60.1	59.9	59.9
Egypt	57.0	57.0	56.9	56.7	56.4					
El Salvador	59.0	59.7	61.0	60.6	60.7	60.3	60.3	60.6	60.6	60.1
F.Y.R.O.M	58.9	59.8	59.7	59.7	59.8	60.0	60.0	60.1	60.2	60.2
Georgia	59.0	59.8	59.8	60.0	59.7	59.8	59.5	60.3	60.5	
Honduras		59.8	59.7	60.1	60.3	60.4	60.3	60.4	60.3	60.2
India	44.8	45.0	44.8	44.4	43.2	41.9	40.3	38.2	36.1	35.0
Indonesia	53.6	53.5	53.8	54.8	55.6					
Iran	55.6	56.0	55.9	55.7	55.3	54.9	54.4	53.6		
Jordan	59.7	59.7	59.8	60.1	60.2	60.3	60.6	61.7	61.5	63.9
Kazakhstan	59.4	59.1	58.8	58.7	58.5	58.3				
Kyrgyzstan	59.3	59.8	60.7	61.8	61.7	61.7	62.2	62.2		
Malaysia	58.0	57.9	57.9	57.7						
Morocco	59.2	59.2	59.2	59.1	59.1	59.1	59.1	59.0	59.0	58.8
Nepal	58.7	59.7	59.7	59.7	60.2	60.3	61.1	61.7	61.5	61.8
Oman	59.4	59.4	59.4	59.5	59.5	59.5				
Pakistan	56.9	57.2								
Romania	58.4	58.9	59.1	60.0	60.3	60.8	61.3	61.5	61.6	61.7
Russia	51.7	52.1	52.3	52.9	52.2	51.9	51.6	51.2	50.4	49.8
Saudi Arabia	55.9	55.8	55.8	55.8	55.6					
South Africa	57.6	57.6	57.6	57.4	57.3	57.5	57.4	57.3	57.2	57.4
Sri Lanka	58.8	59.4	59.4	59.3	59.7	59.8	59.9	60.5	60.9	
Syria	59.5	59.5	60.0							
Thailand	56.7	56.8	57.1	57.0	56.7	56.6	56.3	56.2	55.8	54.6
Tunisia	59.6	59.5	59.5	59.5	59.5	59.6	59.9	60.0	60.1	60.0
Uruguay	59.5	59.7	59.7	60.0	60.9	61.2	61.2	61.2	61.1	61.1