

Essays on Deregulation in the Electricity Generation Sector

By

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Dedication

To

Tomilola and Olusegun, for your unending love and support

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Abstract

Over that past three decades, power sector reform has been a key pillar of policy agendas in more than half of the countries across the world. This thesis specifically concerns the empirical investigation of the economic performance of the international electricity generation industry. Drawing on the stochastic frontier analysis techniques, the thesis considers the influence of reform as exogenous factors in shifting frontier technology as well as shaping inefficiency function directly -determinants and heteroscedasticity variables. The first essay uses an extensive panel dataset of 91 countries over the period 1980 to 2010 to measure the impact of deregulation on efficiency and total productivity growth using stochastic input distance frontier (SIDF). Three specific issues are addressed in the first essay: (1) the relationship between deregulation and technical efficiency, (2) the extent of the rank correlation of the country intercepts with deregulation via their position on the frontier, (3) the trend of total factor productivity and its components. We establish a positive impact of deregulation on efficiency and some compelling evidence suggesting that the country intercepts equally account for the influence of deregulation aside efficiency.

In particular, the technical efficiency index from the first paper reveals that most OECD European countries are consistently efficient. Building on this finding, the second essay investigates the performance in term of cost efficiency for electricity generation in OECD power sector while accounting for the impact of electricity market product regulatory indicators. Empirical models are developed for the cost function as a translog form and analysed using panel data of 25 countries during the period 1980 to 2009. We show that it is necessary to model latent country-specific heterogeneity in addition to time-varying inefficiency. The estimated economies of scale are adjusted to take account of the importance of the quasi-fixed capital input in determining cost behaviour, and adjusted economies of

scale are verified for the OECD generation sector. The findings suggest there is a significant impact of electricity market regulatory indicators on cost. Cost complementarity between generation and emissions found to be significant, indicating the possibility of reducing emissions without necessarily reducing electricity generation.

Finally, the third essay examines the performance of electric power industry's using consistent state-level electricity generation dataset for the US contiguous states from 1998-2014. We estimate stochastic production frontier for five competing models in order to identify the determinants of technical inefficiency and marginal effects. We find evidence of positive impacts of deregulation on technical efficiency across the models estimated. Our preferred model shows that deregulated states are more efficient in electricity generation than non-deregulated states. The result of the marginal effects shows that deregulation has a positive and monotonic effect on the technical efficiency.

Key words: Cost efficiency, Deregulation, Electricity generation, Heterogeneity, Input distance function, Panel data, Power reform, Market structure, Marginal effect, Stochastic frontier analysis, Total factor productivity.

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Chapter 1: Introduction

1.1 Background

Beginning from the early 1980s, significant structural change has taken place in the electricity industry the world over. The power sector market reform was driven by plethora of reasons. Notable among them are political factors, financial crises (pressure on public budget), rapid technological advancement and the globalisation of the world economy. More importantly, the institutional arrangements have become unpopular and property rights need reallocation (Toba, 2007). Historically, the industry characteristic meant that it was more efficient to operate in the form of natural monopoly. In other words, a large electricity utility was considered to achieve economies of scale and operate more efficiently if it can generate, transmit and distribute electric power.

The unbundling of the vertically integrated power sector into different constituent components represents the flagship of the many dimensions of electricity market reform. The attendant organisation structure allows for the continual regulation of the monopoly transmission and distribution networks while the potentially competitive generation and retail segments are subject to deregulation. Of particular interest is the claim that competition drives efficiency gains, which can be substantial considering the fact that generation accounts for an unusually large share of value added in the sector, as much as 65%. (see Sioshansi, 2011). This has informed the bedrock of the empirically analysis of thesis on generation segment of the electricity industry. Indeed, two apparent reasons can be adduced to the attention given to this strategic segment.

First, the issue of supply security and the reliability of the electricity system. This is a fundamental issue that relates to the ability of the system to withstand contingencies, such as changes in generator availability and having a sufficient supply of generation capacity readily accessible to maintain system security under all but the most extreme circumstances. In addition, the possibility of equipment failure and primary input price fluctuations makes the supply of electricity uncertain, while continuous acquisitions of more installed capacity to guarantee security of supply and reliability of electricity system could be counterproductive to efficiency (See Morey, 2001, Delma and Tokat, 2005). Thus, reliability of electric power supply is one of the main motivating factors for technical innovation and change in market organization. Moreover, electricity demand worldwide is projected to balloon by over 50 per cent which could be matched appreciably by increasing energy supply in the next 20 years, especially cleanly-generated electricity (See EIA, 2016 IEA, 2013). What is more, global electricity demand is increasing twice as fast as overall energy use and represents the fastest growing form of end-use energy consumption. Therefore, expanding world electricity demand growth while at the same time ensuring secured and reliable electricity generation for sustainable economic growth, allied with greater efficiency of electricity generation, poses problems for governments and regulators.

Second, concerns about climate change and the decarbonisation of electricity policy objectives to increase renewable and combined heat and power (CHP) energy contribution to the energy supply. The electric power industry is one of the biggest contributors to the global emission of CO₂ due to the use of fuels like coal for power generation. The need for electricity generation to be clean and safe has never been more obvious, nor have those attributes ever been as popularly supported. Environmental consequences of electricity generation are important issues, as production of electricity from any form of primary energy

has some environmental effect, and some risk. Arguably, the variation in the costs of internalisation of the external costs of CO₂ emissions and choice of technological investment for cleaner generation is central to cost complementarities in the process of joint production of electricity output and undesirable products.

1.2 Overview and contributions of this research

This thesis contributes essentially to the literature on power sector market reform as well as efficiency and productivity literature. Recently, debates on the restructuring-efficiency nexus has been a fertile area for research following the structural changes to the competitive and regulatory environments of the electricity industry. Notwithstanding the growing popularity of the studies on electricity market reform, there is seemingly contention about its benefits, as global findings on the success of electricity reform are surprisingly mixed. One would have expected to find convincing evidence of ex-post efficiency gains from deregulation success showing up from the different econometric studies carried out by many scholars. However, demonstrating this has been laced with difficulty as pointed out by Jamasb et al. (2004). This thesis revisits the on-going debate over the impact of deregulation, primarily from the standpoint of cross-country and US state level analysis. This study therefore is significant in many respects.

First, this thesis provides a novel approach by measuring the impact of reform using a country intercept. This represents a clear departure from the traditional efficiency measurement of deregulation benefits. Greene (2005a, b) posits that if latent heterogeneity exists across countries and not adequately accounted for, all time-invariant heterogeneities will be pushed into the intercept term and, finally, into the inefficiency term. This potentially causes inefficiency to pick up latent cross-country variation that is not in any way related to

inefficiency, thereby resulting in underestimation of the overall efficiency level. Therefore, this thesis intends to contribute to the literature by demonstrating further empirical evidence on deregulation using ‘true’ panel data stochastic frontier models which control for time-invariant heterogeneities. More importantly, accounting for deregulation in this model reveals the extent of the rank correlation of the country intercepts with deregulation via their position on the frontier. This also provides an additional framework for benchmarking countries in order to identify the best-practice vis-a-vis policy reform as a complement to efficiency benchmark.

Second, reshaping market structure by unbundling the dominant vertically integrated firm is expected to lower the cost of production. While this argument is usually based on the long run cost function assumption, it is possible that there is short run non-optimality in the utilisation of the stock of capital. This situation could be warranted due to the absence of static equilibrium optimality in relation to cost associated with adjustments, external factor and time in generation. Given the foregoing, treating capital as a quasi-fixed input in the model provides an interesting motivation for the thesis to reveal an intriguing development with regards to cost structure and economies of scale in the face of market product regulatory indicators.

Third, the behaviour of competing power generators in relation to environmental and social welfare aspects arising from power market reform is sometimes neglected in the analysis of cost structure. More often than not, the possibility of reducing carbon emission without a corresponding reduction in generation output is constrained. This thesis extends the output to include this undesirable carbon emission output, such that cost characteristics of generation i.e. cost complementarity and non-jointness of electricity output and carbon emission can be

evaluated. This thesis also contributes to the literature by providing estimation tests and procedure for the theoretical underpinnings complementarity and non-jointness of desirable and undesirable products.

Again, the conventional efficiency and productivity analysis usually comes at the cost of ignoring long-term (persistent) inefficiency when measuring reform impact, even when firm heterogeneity is accounted for. Efficiency arising from electricity reform in this analysis therefore may be misleading as a firm may eliminate part of its inefficiency by removing some of the short-run rigidities, while other sources of inefficiency might stay with the firm over time (see Kumbhakar et al., 2014). Decomposing this inefficiency into persistent and residual differs from standard stochastic frontier models, and this constitutes a new idea in the literature, hence another motivation for this thesis.

Lastly, the modelling impact of deregulation has been considered to be monotonic in nature in the efficiency literature. It suffices to say that the existing modelling approach has since been taken for granted in most efficiency studies. This monotonic impact might not necessarily apply in all cases as exogenous factors can positively (negatively) affect the mean and variance efficiency when their values are within a certain range, and then the impacts turn negative (positive) for values outside the range (See Wang 2002, 2003). This thesis analyses the classical and newly developed panel data stochastic frontier models from the simplest situation to the more complicated situations with applicable restrictions on different alternative models. This offers ex-post information on the dynamic nature of the marginal effect which gives the actual magnitude of the impact of deregulation.

1.3 Research questions

This thesis consists of three independent but related essays which quantitatively examine the impact of power sector market reform on efficiency using country and state level data. In order to achieve the objectives of this study, the research is centred on the following questions in a bid to offer some plausible answers.

Q1: Do countries with significant reform progress attain higher efficiency in electricity generation compared to their counterparts with little or no reform?

Q1.1: Do unobserved heterogeneities measure the influence of deregulation?

Q1.2: What is the key driver of total productivity growth?

Q2: What are the impacts of the electricity regulatory reform indicators on cost efficiency?

Q2.1: Does cost complementarity exist between generation and carbon emission?

Q2.2: Is there any difference between scale economies in the long run and the short run?

Q3: Does restructuring shape the mean and variance of electricity generation inefficiency?

Q3.1: What is the dynamics of the marginal effects of electricity restructuring on efficiency?

1.4 Structure of the Thesis

Chapter 2 of the thesis provides a general literature review of the theoretical and empirical evidence of reform and performance in the electricity supply industry. The literature review surveys the efficiency studies in the existing literature on electricity sector reforms. The

chapter also incorporates original and recent developments in theoretical methodologies to measure efficiency with a central emphasis on the parametric stochastic frontier approach.

Chapter 3 of the thesis quantitatively examines the efficiency of cross-country electricity generation using an input distance function approach by incorporating country specific factors to influence the production frontier. This chapter considers national electricity generation data of 91 countries which makes the study inclusive and reliable. Several frontier models, including the true fixed effect and true random effect model were estimated to investigate technical efficiency of electricity generation. The chapter also examines the total factor productivity change and its decomposition to unravel the potential driving forces behind productivity progress. Two fundamental, yet unresolved, research questions are addressed in this chapter. First, whether countries with a high level of political freedom¹, an indication of a condition precedent to adoption and implementation of electricity market reform, achieve a significant level of technical efficiency than other countries which are autocratic. Second, whether deregulation is being measured by unobserved heterogeneity rather than efficiency components.

Chapter 4 assesses cost efficiency and market structure of twenty-five OECD countries while relaxing the long run assumption of cost function in order to accommodate inter-temporal sub-optimal quasi-fixed capital input. Specifically, the chapter evaluates the impact of market product regulatory indicators such as the degree of vertical integration, entry barriers, public ownership and overall market reform on the cost of production. Besides electricity generation output, carbon emission is also considered as an undesirable output and are both modelled as the dependent variables. This chapter also extends the frontier models to include

¹ Political freedom is measured by political rights index, on integers ranging from 1 (most freedom) to 7 (least freedom).

the four-way error components model that specifies two stochastic inefficiency terms (residual and persistent inefficiencies) and other two components; the time invariant heterogeneity and idiosyncratic error term. The underlying issues of exhaustion of economies of scale in the generation segment are reconsidered through the estimation of both the long run and short run economies of scale. The chapter also addresses the research question whether cost complementarity exists between electricity output generation and carbon emission.

Chapter 5 empirically examines the performance of electric power industry's using state-level electricity generation dataset for the forty-eight US contiguous states. Adopting a general-to-specific estimation approach, five alternative models were estimated and compared stochastically in order to identify the determinants of technical inefficiency and marginal effects. Given the differences in the interstate electricity reform milestone in the United State, the competing models contain some variables that account for heterogeneity and heteroscedasticity in the models. Exogenous variables such as reform variables, political index and some socioeconomic variables are modelled to affect the mean of the inefficiency, variance of the inefficiency or both. Further evidence of the potential efficiency gain accruable from reform to the deregulated state was confirmed in this chapter. The chapter ends with a discussion on the last research question which is centred on the recent the debate relating to monotonic and non-monotonic magnitude of deregulation on inefficiency.

Chapter 6 concludes the thesis by summarising the findings from the three empirical chapters, and revisits the research question. This chapter also highlights the contributions of the research and offers suggestions for future work.

Chapter 2: Literature Review

2.1 Introduction

This chapter contains a review of the literature and theoretical framework for the three essays in this thesis. The chapter starts with a discussion on the general overview of power sector reform and the electricity market deregulation structure. It then proceeds to discuss organisation and competition of the electricity supply industry. Issues of market power, privatisation and regulation of the industry are discussed thereafter. A brief explanation of the theory of liberalisation is also provided. Afterwards, the discussion focuses on empirical studies regarding the impact of reform, while the last sub-sections provide an extensive review on the methodological theoretical framework.

2.2 Overview

Network utilities such as electricity, gas, telecommunications and water are public utilities which require a fixed network to deliver their services. The economic significance of these network industries is widely recognised in modern society and their contribution to the socioeconomic life of nations has become indispensable. They make up a large fraction of an economy's productive capital. For instance, Forman-Peck and Millward (1994, p.3) posit that between 1850 and 1960 network utilities accounted for between 18 and 30 percent of the total net fixed assets in the United Kingdom, always larger than the share of manufacturing industry.

Traditionally, the Electricity Supply Industry (ESI), like other network industries, was dominated by state-owned, vertically integrated power companies. The functional segments of the utilities were typically bundled under the same management and government control. The argument espousing this arrangement suggests that power companies are better organised as a vertically integrated firm, whereby the firm that generates electricity also transmits it over high tension transmission voltage lines, distributes it over low tension distribution voltage lines, and retail it by billing the end users. The ownership by one sole firm (government) helped to ensure the necessary coordination among the different segments (generation, transmission and distribution). The economic arguments for large vertically integrated electricity companies which were significant in size also rested on a claim that vertical economies were significant (Pollitt, 2007). In some parts of the world, these utilities were regulated private companies, while in others they were public companies or government agencies.

For many years, this earlier structure of the electric utility industry was centred on the economic theory that an integrated system of electricity supplied by efficient, low cost utility generation, transmission, and distribution was a classic natural monopoly. Regardless of ownership and the level of vertical integration, geographical monopolies were the norm (Kirshen and Strbac, 2004, p. 1). This idea of natural monopoly is based on the existence of economies of scale throughout the relevant range of production on the market. This means one firm was thought to produce goods less expensively than if there were any other combination of firms in the market, as average costs declined as output increased (Joskow and Schmalensee, 1983, pp. 29–20; Newbery, 2001a, pp. 1–2). The implication of the economies of scale was that it might result in inefficient and unstable prices as they create rents that will be fought over and tends to persist due to the durable, long lived and

immovable nature of the network. The capital outlay of the network of electric utility is large and sunk, shifting the balance of bargaining advantage shifts from consumer to investor. Given that these utilities are directly linked to the consumer; they offer their owner potentially large exploitative power. Thus, in order to address the challenge facing investors and consumers, while at the same time balance the interests and powers, the utilities were either state owned or operate under regulations set by government institutions (Newbery, 1997). Government ownership of the monopoly (or public regulation) was often justified on the grounds that the state was the custodian of the public interest and therefore would be the least likely to act in an opportunistic manner, as monopolists were prone to do (Gratwick and Eberhard, 2008).

2.2.1 The root of electricity deregulation

The past three decades have witnessed efforts throughout the world towards restructuring electricity industry. This has been carried out in many countries across the world within the framework of liberalisation, restructuring, competition, regulatory reform, and privatisation (Jamash & Pollitt, 2008). The performance of the electricity sector varied widely across countries. In many developing countries, the sector was characterized by low labour productivity, poor service quality, high system losses, inadequate investment in power supply facilities, unavailability of service to large portions of the population, and prices that were too low to cover costs and support new investment (World Bank 1994, Bacon and Besant-Jones 2001, Besant-Jones 1993). In developed countries, sector performance was considerably better, but high operating costs, construction cost overruns on new facilities, costly programs driven by political pressures, and high retail prices required to cover these costs stimulated pressures for changes that were expected to reduce costs and retail prices (Joskow 1998a, 2000).

The motivation for electricity sector reform has been slightly different in different countries, despite the common objective to improve the performance of the industry. In the developed countries, the main objective has been to improve the performance of a relatively efficient system. On the other hand, the burden of price subsidies, low quality of service, low collection rates, high network losses, poor service coverage and frequent power outage have meant that many governments in developing countries are no longer willing, or able, to support the existing systems (Newbery, 2004; Joskow, 1998). However, the overarching motive of liberalisation has been to create a new institutional arrangement for the electricity sector that ensures society benefits through prices that reflect the efficient economic cost of supplying electricity and a service quality that reflects consumer valuation (Nagayama, 2007; Joskow, 2008). The electricity reforms have been implemented in each country based on its economic, political and historical circumstances.

In the United Kingdom, for example, privatisation of a state-owned enterprises reinforced the market orientation of the Thatcher government and its interest in reducing the costs of domestic coal subsidies. Similar ideological and political explanations can be found from Norway to New Zealand. Budgetary shortfalls, foreign debt, the preferences of donor agencies such as the World Bank and the perceived poor performance of state-owned firms, facilitated electricity reform in developing countries (Spiller & Martorell, 1996; World Bank, 1995; World Energy Council, 1998). The financial development institutions made new power sector loans contingent on government commitments to introduce reform. However, there has been a common theme of growing disaffection with the electricity market model of the past and a belief that the success found in "deregulation" of other industries, such as airlines or telephones, could be repeated in the case of electricity production and delivery (Hogan, 2002).

Three important trends that have contributed to the significant changes in global electricity industry are economic, market logics and technological changes. First, electricity sector reform dates back to the oil price shock in the 1970s which resulted in higher fuel prices, with its attendant impact on the oil importing countries' socioeconomic status. For instance, Britain growth's rate was 7.0% between 1947 and 1974, but fell to 1.4% from then till 1990, while US growth fell from 7.3% to 2.6% between the same period (Newbery, 1997). This shock systematically changed the conditions for power sector investments. The cost of power generation increased due to a hike in oil prices and this was passed to the customer directly. The increased public awareness in the 1980s of the excessive cost and poor quality service associated with state ownership without the forces of competition necessitated a demand for a competitive market to reduce the cost of electricity production while ensuring improved quality and security of electricity supply. Similarly, there was a huge financial burden on the state due to the demand for additional generating capacity, as well as the need to upgrade existing distribution and transmission networks. The inability of the state sector to finance needed expenditure and new investment and maintenance especially in the rapidly industrialised emerging economies, has been a driving force for the restructuring of electricity industry.

Second, the "idea" of markets took hold from the early 1980s. This new neo-classical economic theory insisted that free and competitive markets were more efficient than government agencies at delivering basic services, and that divestiture of state-owned assets would have flow-on social benefits in terms of improved resource allocation, innovation, and ultimately, greater employment opportunities. In part, the focus on markets for power reflected a new thinking about ways to organize the power sector so that it did not fully have the attributes of a natural monopoly (e.g, Joskow and Schmalensee, 1983).

Third, rapid improvement in technology in generation and digitalisation of meter and dispatched power serve as a key force for electricity reform (APEREC, 2000; Bacon and Besant-Jones, 2001). The significant concepts of economies of scale, where a central source of power supplied by a single firm seemed diminished in the 1980s as a result of technological innovation. Due to the existence of economies of scale and scope, efficiency gains, cannot be achieved through competition because parallel networks have hardly been profitable and network operations usually demand a high degree of coordination. However, technological changes have weakened the industry's natural monopoly features and thereby change the cost and access structure in a more liberalization-friendly direction (Askim and Claes, 2011). For example, the development of natural gas combine cycle turbine (CCGT) with high thermal efficiency, rapid installation time and low emission levels results in relatively low-cost electricity generation. This development of information and communication technologies enabled the electricity system to be organized and controlled without vertical integration, as exemplified in the wholesale power pool² and on constantly changing market prices for electricity, thereby reducing transactions cost.

2.2.1.1 Electricity Market Deregulation Structure

The electricity sector's reform began in Chile (1982), England & Wales (1989), Norway (1991) and the trend spread to Latin American countries and the rest of the world subsequent to the 1990s. Although deregulation of electric power sector in the USA, Australia, countries in Europe, and some selected countries in Latin America are already advanced, countries in Africa and the Middle East have been late in implementing reforms and reforms have only been gradually taking effect in Eastern Europe and Asia (Nagayama, 2007). Electricity

² ICT has created a platform in the wholesale power pool such that there is access to real time information on all aspects of their operation

reforms are primarily designed to introduce competition in the upstream production and downstream supply functions of the industry structure, and to use economic regulation of the wholesale and retail electricity markets to promote competition and protect consumer's interest (Bacon and Besant-Jones, 2001). Although there are variations in the reform structures, depending on countries, the choice of deregulation model, timing and sequencing of the deregulation became crucial economic issues. The UK deregulation model has been in the vanguard for many reform programmes implemented by other countries and have closely agreed common elements which are as follows;

1. Restructuring the industry in order to enable the introduction of competition. This means breaking up or vertically unbundling the incumbent monopoly utilities, possibly into separate generation, transmission, distribution and retail suppliers of electricity. It also involves horizontal splitting of generation and supply.
2. Development of a competitive market by allowing wholesale and retail competition, and new entry into generation and supply.
3. Privatisation, where feasible, of the unbundled generators, transmitters, distributors or suppliers, and allowing new private sector actors.
4. Development of a new regulatory framework. Instead of direct regulation by a government department, the establishment of 'independent' or quasi-independent regulatory bodies, in the forms of offices and commissions, has been favoured, drawing particularly on the regulatory models of the USA and UK.

The key elements of restructuring, privatisation and development of regulatory reform for the electricity reform process generally involve some series of generic sequences for full liberalization of power markets. These reform steps had been formulated rather roughly as follows: corporatization, commercialisation; primary enabling legislation; establishment of an

independent regulator; creation of independent power producers (IPPs); restructuring, privatisation and competition (Williams and Ghanadan, 2006). The preliminary steps: corporatization, commercialization, passage of energy legislation and the establishment of an independent regulator are required to transform the electricity industry from a government agency or department into a commercial enterprise. Although there are some noticeable similarities as well as differences across the countries with respect to the above models and do not necessarily represent the reform paths of the pioneer countries exactly. For instance, Norway liberalised its electricity market without privatisation, the industry remaining almost literally in public hands. The reforms in most Latin American countries have broadly followed similar paths to the generic sequence model outlined above, with Brazil being an exception as some privatization took place prior to establishment of a regulator (Jamashb, 2006). Until recently, New Zealand attempted an approach without regulation while relying on market competition to provide market discipline to participants. The New Zealand government subsequently imposed price control regulation on the plant suppliers due to the failure of competition to control pricing (Patterson and Cornwall, 2000).

The reform in much of continental EU (with the exception of Spain and the Netherlands), in Japan and in a large portion of the US have been partial liberalisation or simply continuing with a regulated vertically integrated monopoly as against the generic textbook model (Joskow 2006a; Haas, et al., 2006). The England and Wales electricity reform is adjudged the standard for electricity reform (Joskow, 2008). This approach dubbed “standard prescription” (Hunt, 2002, p. 8, 15, 239) or “standard model” (Littlechild, 2006, p. xviii), as it follows the basic architecture of the textbook model and have led to significant improvement in many dimensions (Joskow, 2008), allowing competition in all parts of this sector where it was feasible. Regardless of the variation in reform across countries, the sequencing of reform,

especially at the generation segment, is very important to ensure their long-term sustainability. Bacon and Besant-Jones (2001) argue that the legal and regulatory framework should be set up before sale of assets of the restructured power supplier while major restructuring should precede the creation of privatization to avoid problems with stranded assets. Furthermore, the scope for introducing competition to the wholesale power generation market should be incorporated into the initial structural reforms to the power market.

2.2.1.2 Organisation and Competition

Electricity supply industry restructuring has been driven largely by generation technological changes and this has led major reorganisation in industry. The industry is no longer considered as a vertically integrated natural monopoly activity; rather it is regarded as a set of separate but inter-related activities with distinctive economic characteristics (Jamasp, 2006). This has then shifted electric power electric power generation and retail supply business toward a free, competitive environment, allowing a local monopoly in the power transmission section promoting economic efficiency (Nagayama, 2009).

Liberalisation of the electricity industry has brought the issue of market competitiveness to the front line. The argument for liberalisation is that competition provides stronger and less manipulable incentives to efficiency than regulation. Perfect competition would provide the strongest incentives for efficiency and would transfer all the gains to consumers and thus solve the problem of bargaining over rents. As electricity is extremely costly to store and requires supply and demand balancing, generation must closely match demand on a continuous basis. Delivery of the product consumed must take place through a potentially congested transmission network. The combination of very inelastic short-run demand and supply (at peak times) with the real-time nature of the market (costly nature and grid

reliability requirements) makes the electricity market vulnerable to the exercise of market power (Borenstein and Bushnell, 2000). These attributes must be recognized and incorporated into the successful design of competitive markets and regulatory institutions to avoid performance failures (Joskow, 2003).

Following the liberalization of the electricity market, different types of companies and organizations play a role in the electricity market. Since markets have evolved at different rates and in somewhat different directions in each country or region, not all these entities will be found in each market. In some cases, one company or organization may perform more than one of the functions described below:

Generating companies (gencos) produce and sell electrical energy. They may also sell services such as supervision; voltage control and reserve that the system operator needs to maintain the quality and security of the electricity supply. A generating company can own a single plant or a portfolio of plants of different technologies. Generating companies that coexist with vertically integrated utilities are sometimes called independent power producers (IPP).

Transmission companies (transco) own transmission assets such as lines, cables and transformers. They operate this equipment according to the instructions of the independent system operator. Transmission companies are sometimes subsidiaries of companies that also own generating plants. An independent transmission company (ITC) is a transmission company that does not own generating plants and also acts as an independent system operator. They may also act as the spot and capacity balance market maker.

Distribution companies (discos) own and operate distribution networks. In a traditional environment, they have a monopoly for the sale of electrical energy to all consumers connected to their network. In a fully deregulated environment, the sale of energy to consumers is decoupled from the operation, maintenance and development of the distribution network.

Retailers then compete to perform this energy sale activity. One of these retailers may be a subsidiary of the local distribution company. Retailers buy electrical energy on the wholesale market and resell it to consumers who do not wish, or are not allowed, to participate in this wholesale market. Retailers do not have to own any power generation, transmission or distribution assets. Some retailers are subsidiaries of generation or distribution companies. All the customers of a retailer do not have to be connected to the network of the same distribution company.

A market operator (MO) typically runs a computer system that matches the bids and offers that buyers and sellers of electrical energy have submitted. It also takes care of the settlement of the accepted bids and offers. This means that it forwards payments from buyers to sellers following delivery of the energy.

The independent system operator (ISO) is usually responsible for running the market of last resort, that is, the market in which load and generation are balanced in real time. Markets that close some time ahead of real time are typically run by independent for-profit market operators. The independent system operator (ISO) has the primary responsibility of maintaining the security of the power system. It is called independent because in a

competitive environment, the system must be operated in a manner that does not favour or penalize one market participant over another.

Effective competition in electricity markets is a feature of successful electricity supply industry restructuring. Competition has been described as the backbone of electricity reform which brings efficient performance and lower electricity tariffs. Competition in the electricity industry generally implies competition only in the generation of electricity and in the commercial functions of wholesaling and retailing (Hunt, 2002). These two segments, generation and supply, are the deregulated functions in order to ensure that prices are set in the competitive markets and not by regulators. The degree of competition permitted can vary depending on which restructuring model has been used, for example the single-buyer model, wholesale competition (which can itself take various forms), or retail competition (Lovei, 1996; Hunt and Shuttleworth, 1996). Economists since Adam Smith have argued that competition not only provides incentives for firm to minimise production costs but also restrains prices and ensures that consumers satisfy their wants at least cost. Competition leads to greater allocative efficiency, since prices are related more closely to marginal costs, and provides incentives for management to minimise waste and maximise productive efficiency.

Under monopolistic conditions, in contrast, the cost can be passed onto consumers in the form of higher prices. Therefore, competition in the product market is an important driver of cost reduction and product innovation. However, many reforming countries have experienced difficulties in enforcing competition in electricity markets (Joskow, 2003). According to Sioshansi (2008), the US has experienced slow paced growth in retail competition in recent years while transition to a national competitive electricity market has been stalled. He cited reasons for this, among other things, as mixed results in a number of states that have

introduced retail competition, problems of some wholesale markets and lack of interest by the US Congress to push retail competition at the national level. Germany also provides a good example of how reform without the creation of competitive market can result in performance problems (Brunekreet and Bausknecht, 2006). The German electric power system continues to be dominated by a few large vertically integrated utilities which prevent competition.

2.2.1.3 Market Power

Lack of effective competition has been recognised to result in market power, and therefore poses a major obstacle to competition in the generation sector of the electricity supply industry. Significant wholesale market power problems have been identified empirically in several countries (Wolfram, 1999; Borenstein, Bushnell and Wolak 2000; Joskow and Kahn, 2002; Sweeting, 2007). Electricity possesses practically all of the product features that support producers to display market power. According to Wolak (2004), the technology of electricity production historically favoured large generation facilities to be owned by relatively few numbers of firms, with generation capacity ownership concentrated in small areas these regional wholesale markets. Thus, this makes the wholesale market sustainably less competitive and enhances the ability to exercise market power. In the same vein, Joskow (2003) argues that market power can be attributed to interactions between the attributes of electricity networks, too few competing generating companies, wholesale market design flaws, vertical integration between transmission and generation that creates the incentive and opportunity for exclusionary behaviour, excessive reliance on spot markets rather than forward contracts, and limited diffusion of real time prices and associated communications and control technology that facilitates the participant of demand in wholesale spot markets.

A deregulated market for electricity provides very strong incentives for least-cost production by a profit-maximising generating firm. However, if a firm or set of firms possess market

power, they will alter their production patterns in ways that violate the assumption of market-wide least –cost production. Market power on the part of sellers is the ability to profitably maintain prices above competitive levels by restricting output below competitive levels (Werden, 1996). This has consequences for significant consumer harm as a result of firms simply engaging in unilateral profit-maximising behaviours given the action of their competitors. In the U.K., for example, as posited by Sweeting (2007), generators exercised increasing market power in the wholesale electricity market in the second half of the 1990s which caused prices to stay above marginal costs, a behaviour that was consistent with tacit collusion or with them increasing Pool prices to raise prices in future contracts. Similarly, market power in the California wholesale market was a significant factor during the crisis. There was an exercise of market power by some generators as they withheld supply in a tight situation, resulting in rapid increase in wholesale prices which subsequently caused prices to rise markedly above costs (Borenstein, et. al, 2000; Joskow and Kahn, 2002).

Mitigation strategies against market power have become an important component of the wholesale market deregulation process. Diagnosing market power associated with unregulated supplies of generation services requires significant analytical challenges (Borenstein et. al., 1995; Werden, 1996). The preliminary step involves identification of market power by cost and the availability of transmission capacity (Joskow and Schmalensee, 1983, ch. 12). Having identified significant market power problems in the power market, mitigation can be through subjecting incumbent generators to some type of incentive–based price regulation, mandatory forward contracts, and market design improvements. Market power also can be mitigated by horizontal divestiture of the existing generating facilities as a way of creating additional independent competitive suppliers, to avoid the creation of dominant firms and to ensure a balanced resource mix among the competing firms (Joskow,

1997; Jamasb, 2006). The horizontal restructuring of the generation segment potentially creates an adequate number of competing generators to mitigate against the market power and to ensure that the wholesale markets are reasonably competitive. In the electricity prices case of the U.K., for example, the problem of potential power in the pool was addressed only after a lengthy process of new IPPs entries when the regulator took actions that led to forced divestiture of the two incumbent monopolist generators resulting in a less concentrated generation sector to encourage competition which have indeed led to substantial efficiency gains (Newbery, 1999; Peerbocus, 2007). Therefore, given that the restructuring process is an evolutionary one, regulators and market monitors are expected to actively adapt to changing conditions by improving market structure and design, market monitoring and market power mitigation.

2.2.1.4 Privatisation and Economic Regulation

Since the power sector liberalisation wave, a number of countries have privatised their electricity industry to replicate the British experience. Two central arguments are advocated in favour of privatisation. First, privatisation of the electricity sector in Britain was driven by the belief that private ownership changes the motive of the erstwhile public enterprises so as to increase its productive efficiency. This position is prompted by some schools of thought who argue that government has no business in the running of public utilities such as electricity. In principle, economic theory suggests that privatisation may improve resource allocation (Vickers and Yarrow, 1988). Second, governments find the revenues raised by selling the utilities to be useful for a number of political reasons, although the revenue-raising motive is controversial, and the validity has been dismissed as a rationale for privatisation in the developed countries (Vickers and Yarrow, 1991). Privatisation is sometimes regarded as either a purely ideological phenomenon or as a response to the perceived poor performance of

state-owned industries. (Parker and Saal, 2003 p.42). Privatisation of electric utilities is mainly about ownership rather than control, as utilities can face remarkably similar regulation under public or private ownership.

Privatisation of state-owned utility is often considered as most advanced part of reform. The England and Wales electricity sector, for example, were almost completely unbundled and restructured before privatisation. After privatisation, almost all the distribution network operators (DNOs) became joint investors with independent power producers (IPP) in building gas-fired combined cycle gas turbine (CCGT) generation stations, whose high efficiency, low capital costs, modest economic of scale and use of cheap fuel made them attractive competitors to the predominantly coal-fired generation of National Power and PowerGen (Bergman, et al. 1999, p.91). Privatisation is necessary but not sufficient, and it is often assumed as the end point of liberalisation, although it is a least common step in electricity reforms as it is not necessarily associated with liberalisation process. Norway provides a good example that a state and locally owned electricity sector can be efficient and implement necessary reforms. Competition is difficult to achieve within the public sector, so there is natural complementarity between liberalisation and privatisation (Newbery, 1997). Hence, privatisation remains an option to improve efficiency of network companies by reducing distortions and improving incentives as private firms can be expected to be aggressive in dealing with the regulators (Nepal, Menezes and Jamasb, 2014).

International experiences of privatisation show that the distribution segment is often subject to privatisation, subsequently followed by the generation segment. Privatisation of the transmission network is less common as it is strategic importance for the national economy and viewed as an economically and politically undesirable step. The main arguments for

privatising distribution network are a reduction in technical losses due to new investment and a reduction in commercial losses, especially in the developing countries. In most developing economies, privatization of power has occurred in the form of operating concessions and greenfield investments, as well as state asset sales, as opposed to complete transfer of the entire electricity supply chain to the private sector, as occurred in Britain (Zhang, Parker and Kirkpatrick, 2008).

Privatisation raised new regulatory questions that did not arise when utilities had always been under private ownership, and where regulation had evolved organically (Newbery, 2001, p.5). The relationship between the government, together with regulator and the privatised utility, is one of principal (the regulator) and agent (the utility) as in the standard literature. The principal-agent model in economics has drawn attention to the importance for achieving economic efficiency of principals monitoring and controlling agent behaviour effectively (Vickers and Yarrow, 1988). Principal-agent theory, especially when coupled with the arguments from public choice theory, provides a very powerful theoretical rationale for privatisation to increase efficiency (Parker, 2000). It has been argued that private ownership is better positioned to solving the challenges attributable to principal-agent relationships and the lack of pressure to induce maximising behaviour. Thus, successful privatization of network companies requires incentive-based regulation that allows investment to be adequately rewarded from unsubsidised revenues while maintaining quality, but contains restrictions that permit effective competition for the network services (Newbery (2004). In practice when a public utility is privatised, a regime of regulation and monitoring is typically chosen, and the regulation often takes a simple form such as price cap regulation in the UK or rate of return regulation in the U. S.

Regulation is crucially important in assessing the privatisation of monopolies while the latent competitive elements still need regulatory oversight to ensure that markets are not manipulated nor market power abused. The electricity networks are capital intensive and exhibit natural monopoly characteristics where competition is not feasible or desirable, and make entry to network business potentially restricted. A system for setting price charged by this regulated monopoly is needed to minimise inefficiencies associated with monopoly pricing. An independent regulatory body is usually formed by government to set the regulated price in a way that allowed the regulated firm to recover the efficient cost of providing the service. In the US and Japan, network transmission is governed by cost based regulation where the regulated firm is compelled to charge a price that would ideally prevail in a perfectly competitive market which is equal to the efficient cost of production plus a market-determined rate of return on capital. Thus, the firm can earn revenues equal to their historical costs including a return on investment corresponding to the cost of capital. It also provides firms with an incentive to over/under invest in plant, inflate costs, and cross subsidize. It has been increasingly criticized for its inefficiency. The central problem of rate-of-return regulation is that linking revenues to cost reduces the incentive to cut costs, notably as over-capitalisation of the regulatory asset base otherwise known as Averch-Johnson effect³. Regulators generally try to remedy these perverse incentives through regulatory lag, sliding scales, and efficiency audits/reviews.

However, some countries such as Italy and Norway use price-or revenue cap regulation (Al-Sunaidy and Green, 2006), while the UK uses a combination of regulations called hybrid regulation. The regulators in the UK combine elements of rate of return regulation and price cap regulation to create their form of RPI-X regulation. Price cap regulation sets the

³ The Averch-Johnson effect is the tendency of regulated companies to engage in excessive amounts of capital accumulation in order to expand the denominator in the ratio of profit to capital, i.e. lower the apparent return on capital.

maximum average revenue that a regulated firm is allowed to charge for its outputs for a specific price control period. The regulator sets a cap with an incentive factor X , to induce lower costs which take the form of $RPI-X$ price capping in which the initial price is allowed to escalate at an annual percentage rate equal to $RPI-X$, where RPI is the annual growth rate in the consumer price index and X is productivity growth rate (Weyman-Jones, 2003 p.496). Although service quality and infrastructure development may be hampered in price regulation, it is less vulnerable to "cost-plus" inefficiency, cross-subsidization and over-capitalization, and reduces the effects of cost information asymmetries between firms and regulators. The initial level of X is set by the government at the time of privatization as part of the privatization process, whereas X is reset at periodic reviews every four or five years by the regulator as part of the, continuing regulatory process (Beesley and Littlechild, 1989). Arguably, rate-of-return regulation, which appears to allow utilities to recover their investment costs, is more vulnerable to opportunistic liberalisation than price regulation, which offers no such guarantee, and where investors expect to earn a higher risk premium in compensation.

2.3 The Theory of Liberalisation and Economic Performance

Liberalisation has been a prominent component of policy advice for utility sectors of both developed and developing countries for the last three decades owing to the demonstrative effect of the pioneering reform in the UK, Chile and Norway. Among the benefits claimed to spring from it, economic efficiency (i.e. reduced costs and/or prices) is probably the most important. Along with economic reasons come other political and financial objectives. Other ancillary benefits include reduction of the budget deficit, wider share ownership, increased efficiency of the government, reduced power of the public-sector unions and even personal profit (Pollitt, 1995). Based on efficiency considerations, D'Souza and Megginson (1999)

argued that not only the customers of privatized enterprises enjoy benefits from privatization, but also, as the enterprises become more efficient, the whole economy will benefit. Whether privatization (the often-assumed end point of liberalisation) actually leads to that improvement in efficiency has been the subject of what appears to be a considerable amount of research, both theoretical and empirical. And yet economists continue to argue about, and conduct research on, the connection between the potential gains in efficiency and privatisation.

Many theoretical postulates have been advanced by the privatization advocates to support the reasons why liberalisation might improve economic performance. These theories explain the differences between state-owned and private firms and what these differences imply for firm efficiency (Villalonga, 1999, Arocena and Oliveros, 2012). The argument is based on the belief that firms under private hands perform better than under public ownership. The three well-known theoretical arguments supporting the position on why liberalisation can lead to economics performance are (1) Agency Theory; (2) Property Rights Theory; and (3) Public Choice.

2.3.1 Agency Theory

Agency problems in industrial organisation stems from the principal-agent theory, which presumes publicly owned firms and separation of ownership and control (Jensen and Meckling, 1976). The principal-agency theory (following Vickers and Yarrow, 1988) is a supposition that explains the relationship between principals and agents in business who does not share the same objectives. According to agency theory, control is more difficult when information asymmetry increases between the principal and agents and when successive delegation increases managerial discretion (Fama and Jensen, 1995). The theory is concerned

precisely with this problem of information and incentives, and addresses a central question: what is the optimal incentive scheme for the principal to lay down for the agent? An agent who is supposed to take decisions on behalf of the principal may act otherwise as he has objectives and constraints, which may conflict with that of the principal. The principal wants to induce the agent to act in his (principal's) interest, but he does not have full information about the circumstances and behaviours of the agent, and so has a monitoring problem. This prevents the principal from successfully telling the agent what to do, for he cannot fully observe what is happening. An outcome that diverges from the optimal outcome is possible if there is information asymmetry in favour of the agent. Asymmetric information leads to a moral hazard problem since the agent may use the principal's ignorance as an excuse to supply a sub-optimal level of efforts. Therefore, the agent can be expected to exploit the information advantage that may adversely affect the outcome of the decision taken.

The theory points to the separation of ownership and control as the main source of the relative poorer performance of public firms. The owners of public enterprises are less likely to monitor the behaviour of managers while managers in private companies are more disciplined by a number of external control mechanisms. Thus, most of the state-owned utilities are not being controlled and managed efficiently. Following privatization exercise in UK, Caves (1990), finds evidence on the behaviour of the public enterprises which is consistent with an organizational model of the relevant principal-agent relationships. On the control dimension, empirical result supports the prediction that the privately-controlled firms are more efficient than agent-led firms (Durand and Vargas, 2003). To manage principal-agent relationships, agency theory suggests governments should write complete contracts (e.g., laws and regulations) that adequately protect public interests and prevent privatized firms' opportunistic behaviours. Or at least, the contract should be such that an optimal

outcome is elicited given the possibility that an agent will optimise for himself under whatever contract is specified (Holmstrom, 1979).

Furthermore, addressing the agency problems in strategic economic sectors (financial, utilities, mining, steel, telecommunications, transportation) has led to the reduction of the role played by government as a dominant actor in the economy and to favour the emergence of an active private sector. Private ownership potentially induces corporate governance through better monitoring of managers for improved performance and profits maximization. Agency theories suggest that both private ownership and competition provide strong incentives to improve technical efficiency. Theoretical and empirical considerations suggest that private ownership leads to better outcome in terms of performance. Empirical analyses show that privatization has contributed to the growth of stock market capitalization and trading all over the world (Megginson and Netter, 2001). Meanwhile all relevant laws or regulations that apply to the privatized firms should be specified by every privatization deal, and enforcement of the contracts should be followed (Ramamurti, 2000).

In the context of electricity sector, these theoretical predictions provide good cases in the electric utilities. Although there are difficulties in controlling the behaviour of monopolistic incumbent privately owned electric utilities due to the firm's ability to game the regulators arising from asymmetric information which might prevent the regulator from observing actual efficiencies and cost structures (see Joskow 2003, 2005; Stigler and Friedland, 1962) However, liberalisation of the sector ensures the opening up of the market to new entrants and the demerging of the incumbent into competitive firms. Thus, privatisation in the absence of liberalisation is unlikely to improve efficiency, and may introduce additional market distortions (Domberger and Piggott, 1986). Moreover, the separation of the different constituent segments of the sector introduces competition into the generation chain which

provides managers of privately owned generation firms in competitive markets to face high powered incentives to increase firm productivity. These institutional changes tend to ameliorate the potential principal-agent dilemma created between regulators and managers of privately-owned electric utilities.

2.3.2 Property Rights

A major theme in the literature on the economics of property rights is the argument that public ownership is inherently less efficient than private ownership and a change in allocation of property rights will affect incentive structure, and hence, performance. Property rights are mainly concerned with the relationship between ownership rights, incentives and economic efficiency. Drawing from Alchian (1965), property rights theory involves a clearer assignment of property rights to those with a comparative advantage in the ownership of particular assets. This position is based on the fact that various forms of ownership give rise to different economic incentives and therefore, different economic performances. Property rights theory argues that different institutional settings, such as ownership type, provide decision-makers with different rights to the use of economic resources, thus imposing different constraints upon them. These constraints will affect the costs and rewards of production and might systematically affect the behaviour of consumers and firms. Public ownership is diffused among all members of society, and no member has the right to sell his share therefore performs less than private firms, where rights to profits are clearly defined (Alchian 1965, De Alessi, 1969). There is little economic incentive for any owner to monitor the behaviour of the firm's management, but ownership of private firms is concentrated among fewer individuals, each having the right to sell his shares; and thus the owners have incentives to scrutinize management to ensure efficiency in the production of goods or

services. Managers in public firms do not suffer the economic consequences of their decisions, which limit their incentives to reduce economic waste and maximize profitability. The presence of soft budget constraints prevents public enterprises from bankruptcy, since any possible gap between income and expenditures is balanced by the government. In contrast, the threat of bankruptcy and takeover prevent the managers of private firms seeking only their own advantage. They are residual claimants who benefit directly from efficiency and hence have greater incentives to monitor managers. Moreso, under public ownership, since no one has a clear claim over the residual assets of SOE, there will be no market for corporate control, and hence no threat of takeover to discipline managers who are not maximizing profit (Vickers and yarrow, 1988). The process of deregulation and liberalisation allows contracting out and financing of the utilities activities to be undertaken by more efficient firms, and thus a fully integrated SOE with little contracting out and commercial freedom is unlikely to minimize costs (Pollitt, 1997).

2.3.3 Public Choice

Public Choice theory is based on the central argument that politicians, bureaucrats and government officials are more concerned with the maximization of their own objectives, like votes, power and prestige, than with the pursuit of the general interest and the efficiency of their decisions. The rationale for this approach is that such bodies are themselves agents for, and therefore properly should act in the best interest of, the wider public. If the public official monopolizes service delivery, then the result is over supply and inefficiency (Blaise and Dion, 1992, Jackson, 1982). By contrast, if services are contracted out, then the pressure of a competitive market leads to improved performance. For the public, who are the ultimate owners of the firm, the costs of monitoring this public-sector behaviour (e.g. information gathering, lobbying) are likely to offset the benefits (e.g. less taxes, or more efficient public

spending). This is not the case, however, for interest groups such as trade unions, which makes state-owned enterprises an easy target for rent-seeking activity. Thus, Public choice theorists concentrate on the process which generates demand and on its manipulation by management, in the face of efficiency monitoring difficulties or even disinterest on the part of the members of the polity.

Drawing on the public choice literature, particularly the theory of bureaucracy associated with Niskanen (1968), bureaucrats and politicians who may be responsible for running publicly owned- utilities are not literally interested in the profitability of the enterprise or in minimising its costs. Rather, they may have the objective of maximising the budget of their department as it allows them to maximise departmental discretionary expenditure, which may be the function of the employee of the enterprise. In like manner, bureaucracy may be found within the utility where managers place a premium on their personal interest at the expense of the corporation or society (Pollitt, 1997). As described in Newbery and Green (1996, p. 58), Britain's former generation and transmission monopoly, the CEGB, was inflexible, bureaucratic, secretive and largely out of political control, as such a bureaucracy had a tendency to build expensive nuclear and coal plants in a culture where engineering was the dominant discipline rather than finance. Niskanen (1971, 1975) further argued that public firms will perform less efficiently than their private counterparts. The rationale behind Niskanen's argument is that, in terms of scale efficiency, it can be expected that publicly owned enterprises will not be scale efficient and would be expanded beyond the optimal level.

2.4 Empirical studies on the impact of reform

The central objective of privatisation, restructuring, deregulation, and liberalising access to networks and markets all seek to improve operational and investment efficiency of regulated or state-owned industries (Newbery and Pollitt, 2007). In developed economies, the emphasis is on raising productivity and reducing costs of production and this is reflected in the studies of power sector undertaken in these countries, which focus on performance at the enterprise level. Economic growth, distributional and poverty effects are important components in assessing the welfare impact of electricity reform in lower-income economies, although the relative weight that is given to each of these objectives will vary between countries and over time (Parker and Kirkpatrick, 2005).

The methodologies often used to assess the impact of reform are based on price or cost comparisons in publicly-owned and privately-owned electric utilities which might not be sufficient to gauge a firm or industry's economic performance accurately. It is possible that these financial indicators might be more a reflection of the distortions themselves rather than of the performance of the firm or industry in question. Moreover, in several literatures on the impact of the privatisation, restructuring, deregulation, and liberalising of the electricity industry, there are other approaches to the measurement of the impact of the power reform. The commonly used approaches are the econometric studies and the efficiency and productivity analysis. They all, whether explicitly or implicitly, fully or partially aim to assess the impacts of electricity reform on price, generation investment, the productivity and efficiency of the electricity industry and the wider economy.

2.4.1 Econometric Studies

Several econometric studies have investigated the impact of electricity reforms on price in developing and developed countries using regression analysis. One of the earlier studies is Steiner (2001) who investigates the impact of electricity market reform on final electricity prices using panel data for 19 OECD countries for the period 1986-1996. She tests the assumption that lower industrial electricity prices, lower industrial to residential price ratios and higher capacity utilization rate are expected to stem from liberalization, restructuring, and private ownership. She finds that regulatory reforms, in most cases, cause a decline in the industrial price and an increase in the price gap between industrial customers and residential customers, revealing that industrial customers have the advantages of receiving much lower end-user's energy prices as a result of market reform. On the contrary, the finding shows that unbundling of the vertical chain has no significant impact in lowering electricity prices but induced a lower industrial to residential price ratio and higher capacity utilization rates and lower reserve margins. In similar vein, Hattori and Tsutsui (2004) examine again the impact of the regulatory reforms on price in the electricity supply industry, using panel data for 19 OECD countries for the period 1987–1999 and compares the results with an earlier study by Steiner. Consistent with Steiner (2000), they find that expanded retail access is likely to lower the industrial price and increase the price differential between industrial customers and household customers. They also find that the effect of unbundling on the level of industrial price is statistically insignificant. However, in contrast with Steiner (2000), they find that the introduction of a wholesale spot market did not necessarily lower the price and may possibly have resulted in a higher price.

Nagayama (2007) examines how each policy reform measure influenced electricity prices using panel data for 83 countries during the period from 1985 to 2002. He finds that variables

such as the entry of independent power producers (IPP), unbundling of generation and transmission, establishment of a regulatory agency, and the introduction of a wholesale spot market have had a variety of impacts on electricity prices, some of which were at variance with expectations. The research findings also suggest that neither unbundling nor introduction of a wholesale pool market on their own necessarily reduces the electric power price and has a tendency for the price to raise in every market modelled. This result is also consistent with Nagayama (2009), where findings suggest that the development of liberalization models in the power sector does not necessarily reduce electricity prices using panel data from 78 countries in four regions (developed countries, Asian developing countries, the former Soviet Union and Eastern Europe, and Latin America) for the period from 1985 to 2003.

Zhang, Parker and Kirkpatrick (2008) provide an econometric assessment of the effects of privatization, competition and regulation on the performance of the electricity generation industry using panel data for 36 developing and transitional countries covering the period 1985–2003. They concluded that on their own privatization and regulation (PR) do not lead to obvious gains in economic performance, though there are some positive interaction effects. By contrast, introducing competition does seem to be effective in stimulating performance improvements in terms of greater electricity generation, generating capacity and improved labour productivity. Cubbin and Stern (2006) argue that both regulatory law and higher quality regulatory governance are positively and significantly associated with higher per capita generation capacity while controlling for privatization and competition in 28 developing economies over 1980–2001. Jamasb and Pollitt (2007) demonstrate that the use of performance targets combined with a penalty and reward incentive regulation system has improved the quality of service in the UK distribution utilities. Erdogdu (2011) also examines the impact of electricity industry reforms on residential and industrial electricity price-cost

margins and their effect on cross-subsidy levels between consumer groups using panel data for 63 developed and developing countries covering the period 1982–2009. The study finds there is no uniform pattern for the impact of the reform process as a whole on price- cost margins and cross-subsidy levels as each individual reform step has a different impact on price-cost margins and cross-subsidy levels for each consumer and country group.

2.4.2 Efficiency and productivity studies

Efficiency and productivity studies are appropriate for evaluating how successfully inputs are converted into outputs in relation to best practices; hence the approach is relevant to the research study. In line with widely cited methodology, there are two methods which have almost monopolised the vast literature on efficiency measurement, especially for the electricity supply sector. They are programming (non-parametric) or statistical (parametric) techniques. An increasing number of recent studies on the efficiency of the electricity sector are using frontier methods such as data envelopment analysis (hereafter, DEA) and stochastic frontier analysis (hereafter, SFA). DEA is a non-parametric technique which uses piecewise linear programming to calculate (rather than estimate) the efficient or best-practice frontier of a sample while SFA is a statistical technique which estimates the efficient or best-practice frontier of a sample. These have involved the estimation of both production and cost functions.

Several empirical studies have examined the impact of reform on efficiency among publicly-owned and privately-owned power plants. Kleit and Tecrell (2001) apply Bayesian stochastic frontier analysis (SFA) that imposes concavity and monotonicity restrictions to study the cost efficiency of 78 US power plants operating in 1996. The study finds efficiency gains immediately after the deregulation and restructure of the electricity industry in the US.

Atkinso and Halabi (2005) develop a constrained cost-minimization model for thermal and hydro generation to obtain the shadow price of water and to determine the qualitative effect of these constraints on allocative efficiency. Using panel data from 1986–1997, they assess the economic efficiency of the hydro industry by estimating a stochastic distance frontier and price equations from the dual cost-minimization problem and found dramatic increases in technical change and productivity change, with positive efficiency change for all years after privatisation but the last. They equally observe a dramatic decline in allocative inefficiencies over the sample period and concluded that market reform plays an important role in increasing plant efficiency in Chile.

Furthermore, Estachea and Martin (2005) analyse the impact of alternative regulatory regimes on the labour productivity of electricity distribution firms in Latin America. They find that incentive-based regimes lead to higher labour productivity than rate-of-return regulation, and privatized firms operating under rate of return have, at most, similar labour productivity as public firms. Scully (1998) tests the hypothesis that privatization is efficiency-improving by estimating a translog cost function for all electrical supply firms in New Zealand over the period, and finds that the reforms had substantial cost-reducing effects. Economies of scale were found to exist over the entire size range of the firms. The reforms that were begun in 1988 had substantial cost-reducing effects. The reforms are found to have benefitted customers, with the real price of electricity falling 16.4 per cent over the period 1982–94.

Kumbhakar and Hjalmarsson (1996) analyse productive efficiency in Swedish retail electricity distribution during 1970-1990. They examine whether ownership of the distribution companies has any systematic impact on efficiency, returns to scale and technical

change. The study shows that privately owned companies are relatively more efficient, and evidence of scale economies and technical progress. Weyman-Jones (1991) applies a non-parametric linear programming methodology to measure productive efficiency of the regulated electricity distribution industry in England and Wales. The study finds that only five of the twelve boards are technically efficient, and that there are wide divergences in their performance.

A few studies find that privatisation has no effect on productivity, for instance, See and Coelli (2014) measures the total factor productivity (TFP) growth of Tenaga Nasional Berhad (TNB) from 1975 to 2005 using the Tornqvist index method. The study finds no direct evidence that positive changes in productivity are attributable to industry restructuring and suggest that the partial privatisation of TNB and the introduction of private entry were insufficient to produce improved TFP performance. In the same vein, See and Coelli and See (2013) examine the total factor productivity (TFP) growth of the Malaysian electricity generation industry over the 1998 to 2005 period. The stochastic frontier analysis (SFA) approach is used to measure TFP change and decompose TFP growth into efficiency change and technical progress. They find that it achieved average annual TFP growth of 2.33 percent, with technical change contributing the most to the TFP growth over the eight-year period. They concluded that that there is no clear evidence indicating the role of privatisation in the change in productivity after the restructuring period.

Filippini, Hrovatinic and Zoric (2004) carry out a study focusing on the efficiency and regulation of Slovenian electricity distribution. They estimate a cost frontier function on a sample of Slovenian electricity distribution utilities over the 1991–2000 period. The results show that Slovenian distribution companies are cost inefficient with average cost inefficiency

of distribution utilities in the sample being around 35%. Arocena & Waddams-Price (2002) examine generating efficiency of Spanish public and private electricity generators using data from 1984 – 1997. The research findings challenge some of the conventional wisdom on productive efficiency in the public and private sectors under both cost of service and incentive regulation as publicly owned generators were more efficient under cost of service regulation; private (but not public) firms responded to incentive regulation by increasing efficiency, bringing their productivity to similar levels. Pollitt (1995), using an international sample of electricity generation plants, detects small differences in productivity efficiency in favour of private plants of the order of 2 to 5 per cent, but publicly-owned plants had a higher variance in their efficiencies.

Barros (2008) estimates changes in total productivity on the hydroelectric energy generating plants of the Portugal Electricity Company by means of data envelopment analysis (DEA). He concludes that some plants experienced productivity growth while others experienced a decrease in productivity. Estachea, Tovar and Trujillo (2008) analyses efficiency levels in Africa's electricity firms via a sample of 12 operators providing services in the 12 country members of the Southern Africa Power Pool between 1998 and 2005. Using a data envelopment analysis (DEA) decomposition to identify the sources of the changes in TFP, the results suggest fairly comparable levels of efficiency in the region and performance levels and evolution quite independent of the degree of vertical integration, the presence of a private actor, or the main sources of energy supply. The study concludes that no clear correlation could be associated with the adoption of reforms during the sample period. This is the first documented efficiency study on the electricity sector on Africa.

Meibodi (1998) estimates technical efficiency in electricity generation using Iranian data and data from the World Bank and arrives at a similar conclusion. The study suggests that market reforms, such as privatisation, are not a good choice to resolve industry problems and to reach the production frontier. Bishop and Thomas (1992) uses a weighted index approach to estimate the total factor productivity (TFP) of nine of the largest British enterprises nationalised industries, including the electricity industry from 1970 to 1990. The study did not find evidence of efficiency gains after the privatisation of the electricity industry.

Similarly, Estache and Rossi (2005) shows for electricity distribution that privatized firms operating under rate-of-return regulation have, at most, similar labour efficiency as public firms. The result is controversial as the privatised firms do not show better improvements in labour efficiency than public firms. Hjalmarsson and Veiderpass (1992) also examines productivity growth of electricity distribution in Sweden on multiple output-input frameworks using DEA. The study indicates a higher rate of productivity growth due to economies of density when measured over a period of 17 years. The study shows further that there is no significant difference in productivity growth between types of ownership or economic organisation.

There are also studies on international comparisons of electric utilities efficiency, for instance Hattori, Jamasb and Pollitt (2004) examine the relative performance of electricity distribution systems in the UK and Japan between 1985 and 1998 using cost based benchmarking with data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods. The results suggest that the productivity gain in UK electricity distribution has been larger than in the Japanese sector. The findings further indicate that while both sectors exhibit efficiency improvements, the efficiency gap between the frontier firms and less efficient firms has

widened. Using data envelopment analysis (DEA), Vaninsky (2006) estimates the efficiency of electric power generation in the United States for the period of 1991 through 2004. Operating expenses and energy loss are used as inputs, utilization of net capacity, as an output. The results point to a relative stability in efficiency from 1994 through 2000 at levels of 99–100% with a sharp decline to 94–95% in the years following. The study of Hawdon (1996) for the productive efficiency of the power sector in 82 countries shows that the privatising group of eight countries exhibit significantly higher efficiency than the non-privatising group.

Domah (2002) conducts a comparative technical efficiency analysis of electricity generators in 16 small island economies using panel data, and two methodologies: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The results indicate no apparent differences in the production structure between islands and non-island electric utilities, nor any evidence suggesting that they are less technically efficient. He suggests that benchmarking of small islands, using non-island generating utilities as comparators, is both feasible and desirable given the lack of historical generation data for most small islands. Zhang and Bartels (1998) investigate the efficiency of the electricity distribution industries in Australia, Sweden and New Zealand by employing DEA to examine the effect of sample size on the mean productive efficiency of firms. They find that as sample size increases the estimated mean technical efficiencies decrease generally. The rates of decrease also depend on the sample size. When sample size is small the rate is high and when size is large the rate is low.

Several studies have also attempted to examine the productivity growth impact of privatisation including labour productivity measures. Privatization and the application of

high-powered regulatory mechanisms has led to improvements in labour productivity in electric distribution systems in England and Wales, Argentina, Chile, Brazil, Peru, New Zealand and other countries (Newbery and Pollitt, 1997, Bacon and Beasant-Jones, 2001, Estache and Rodriguez-Pardina, 1998). Bishop and Thomson (1992) investigate labour productivity and total factor productivity of the British electricity supply industry before and after privatization over the period 1970 to 1990. The results are inconclusive as the electricity the industry was only privatized very late in the period studied (1989–90). The results in fact show that total factor productivity growth for the electricity supply industry was greater in the 1970s than it was in the 1980s (2.3 percent on average versus 1.4 percent). Lawrence, Swan, and Zeitsch (1991) find that various state-owned components of the Australian electricity industry substantially improved their levels of productivity after structural reform in the 1990s.

Aghdam (2011) examines whether the Australian electricity industry's efficiency measures truly improved as a result of the reform-driven changes using the Malmquist Total Factor Productivity Index approach. The results reveal that the productivity gains in the industry have been largely driven by technological improvements and, to a lesser extent, by reform-induced comparative efficiency gains. The result further shows that, on average, at national level and for the entire industry, there are efficiency gains that, to large extent, can be attributed to functional unbundling and public corporatisation and, to a lesser extent, to market restructuring and privatisation. The results, however, reveal that the reform-driven changes have made an insignificant contribution to comparative efficiency at the level of thermal generation. See and Coelli (2009) examines TFP growth using Törnqvist index methods, finding that there is no direct evidence of productivity improvements attributable to privatization. They argue that it is not clear whether consumers have benefited from this,

since the Power Purchase Agreements (PPAs) have generally been quite generous to the IPPs in terms of risk sharing and prices paid. Abbott (2006) applies DEA Malmquist approach to estimate total factor productivity of the electricity supply industry over the period 1969 to 1999. The results indicate that there has been a substantial improvement in the performance of the industry since the mid-1980s and productivity performance of the industry did speed up after 1991.

Although conventional wisdom has taken the superiority of private ownership for granted, the intellectual debate over the benefits of private over public ownership of productive resources remains inconclusive as empirical studies of the relative efficiency of public and private firms have often appeared to be inconsistent with the theoretical prediction (Kumhakar and Hjalmarsson, 1998). Thus, there is no consensus on the impact of power sector reform based on the evidence from the country and firm-level studies. However, many empirical studies have given credence and are broadly favourable to power sector reform, suggesting that deregulation; competition and privatisation often lead to improvements in production, productive efficiency, prices and service delivery, while also confirming that each of the policy reform instruments alone may not be sufficient to raise economic performance. It is not surprising that there is growing literature and empirical evidence on the impact of electricity sector reform where different reform activities are transforming the structure and the operating environment of the industry across many countries. A summary of the selected frontier empirical studies is presented in Table 2.1 where it reveals a mixed evidence of the impact of electricity reform on economic performance, an important justification that underpin a further study using latest development in frontier econometrics.

Table 2.1: Selected past studies on efficiency & productivity

Authors	Method(s)^a	Data	Variable used^b	Main findings
Weyman-Jones (1991)	DEA	12 UK electricity boards, 1986/87	O: Domestic sale, commercial sale, industrial sales I: Labour, capital	(i) Only five of the twelve boards are technically efficient, with wide divergences in performance.
Hjalmarsson and Veiderpass (1992)	DEA	289 Swedish retail electricity distributors, 1970-1986	O: Low voltage electricity received by customers, high voltage electricity received by customers, number of low voltage electricity customers, number of high voltage electricity customers I: Low voltage power lines, high voltage power lines, transformer capacity, hours worked	(i) High rate of productivity growth due to economies of density. (ii) No significant differences in productivity growth between different types of ownership or economic organization.
Førsund and Kittelsen (1998)	DEA Malmquist	150 Norwegian electricity distributors, 1983- 1989	O: Distance index, number of customers, electricity delivered I: Capital, labour, energy loss, materials	(i) Positive productivity growth averaging nearly 2% per year, and it is mainly due to frontier technology shift.

Kumbhakar and Hjalmarsson (1998)	DEA	300 Swedish retail electricity distributors, 1970-1990	<p>O: Low voltage electricity received by customers, high voltage electricity received by customers, number of low voltage electricity customers, number of high voltage electricity customers</p> <p>I: Low voltage power lines, high voltage power lines, transformer capacity, Labour</p>	<p>(i) Privately owned companies are relatively more efficient.</p> <p>(ii) The persistent efficiency differences between private and publicly owned firms indicate the impact of yardstick competition.</p>
Kleit and Terrell (2001)	Bayesian SFA	74 US power generation plants, 1996	<p>O: Annual electricity output, peak electricity output, cost</p> <p>I: Wage rate, price of fuel, price of capital</p>	<p>(i) Plants could reduce costs by up to 13% by eliminating production inefficiency.</p> <p>(ii) Most plants operate at increasing returns to scale, suggesting further cost savings could be achieved through increasing output.</p>
Arocena and Waddams-Price (2002)	DEA Malmquist	33 publicly and privately-owned power plants in Spain, 1984-1997	<p>O: Electricity generated, availability, three pollutants (i.e. sulphur dioxide, nitrogen oxide and particulates)</p> <p>I: Nameplate generating capacity, labour, fuel</p>	<p>(i) Publicly owned generators were more efficient under cost of service regulation.</p> <p>(ii) Private firms responded to incentive regulation by increasing efficiency, bringing their productivity to similar levels.</p>

Domah, 2002	SFA and DEA	16 small islands' generators and 121 US investor-owned utilities, 1994-2000.	<p>O: Electricity generated</p> <p>I: Labour, installed capacity, fuel consumption</p> <p>D: Per capital consumption of electricity, number of customer, capacity factor, Island dummy, connection dummy</p>	<p>(i) No apparent differences in the production structure between islands and non-islands electric utilities.</p> <p>(ii) No any evidence suggesting that they are less technically efficient.</p>
Estache et al. (2004)	SFA and DEA	84 electricity distributors from 10 South American countries, 1994 – 2001.	<p>O: Number of customers, electricity sales, service area</p> <p>I: Distribution network length, transformer capacity, labour</p> <p>D: Resident sales share, GDP per capita</p>	(i) The levels of efficiency are not consistent across the different methods of frontier estimation
Hattori et al (2004)	SFA and DEA	21 utilities (12 UK RECs and 9 Japanese electric utilities), 1985-1998.	<p>O: Number of customers, electricity delivered</p> <p>I: Total expenditure, operating expenditure</p> <p>D: Customer density, load factor</p>	<p>(i) Despite both sectors exhibiting efficiency improvements, the efficiency gap between the frontier firms and less efficient firms has widened.</p> <p>(ii) Multiple techniques recommended in comparative analysis and in incentive regulation.</p>

Lam and Shiu (2004)	DEA and Tobit Regression	30 provinces in China, 1995-2000.	O: Electricity generated I: Nameplate generating capacity, labour, fuel D: Fuel efficiency, capacity utilisation, State Power Corporation control dummy	(i) Technological change accounts for almost all the TFP growth. (ii) Municipalities and coastal provinces have higher technical efficiency and TFP growth
Rungsuriyawiboon and Coelli (2004)	SFA cost function, SFA input distance and Törnqvist index numbers	61 electricity generation companies in the United States, 1986-1998.	O: Net steam electric power generation I: Aggregate fuel, aggregate labour and maintenance, capital	(i) The results from the stochastic cost frontier are discarded because they are found to differ from those obtained using the other techniques. (i) The introduction of incentive regulation has not had the desired positive effect upon the economic performance of the firms involved.
Estache and Rossi (2005)	DEA Malmquist	127 electricity distributors from 14 Latin American countries, 1994- 2001.	Ed: Labour Ex: Number of customers, electricity delivered, service area, distribution network length	(i) Incentive-based regimes lead to higher labour productivity than rate-of-return regulation (ii) Privatized firms operating under rate of return have, at most, similar labour productivity as public firm

Atkinson and Halabi (2005)	Stochastic distance frontier	16 Chilean hydroelectric power generation plants, 1986-1997.	O: Price and quantity of electricity outputs I: Price and quantity of labour, capital and water, hydrologic conditions	(i) Increases in technical change and productivity change, with positive efficiency change for all years but the last. (ii) Dramatic decline in allocative inefficiencies over our sample period. The overutilization of labour to capital and water has fallen over time.
Abbott (2006)	DEA Malmquist	6 states in Australia, 1969-1999.	O: Electricity consumed I: Capital, labour, energy used	(i) Substantial improvement in the performance of the industry since the mid-1980s which pre-dates the substantial restructuring of the industry in the early 1990s.
Barros (2008)	DEA Malmquist and censored Tobit regression	25 hydroelectric plants in Portugal, 2001-2004.	O: Electricity generated, capacity utilisation I: Capital, labour, operation costs, investment costs D: Plant location, plant age, variation in rainfall, time trend	(i) Hydroelectric plants exhibit on average improvements in technical efficiency as well as technological change. (ii) The increase in technological change is higher than the increase in technical efficiency
Estache et al. (2008)	DEA Malmquist	12 electricity utilities from 12 Southern African countries, 1998-2005.	O: Electricity generated, number of customers, electricity sales I: Nameplate generating capacity, labour	(i) Fairly comparable levels of efficiency in the region and performance levels. (ii) No clear correlation could be associated with the adoption of reforms during the last decade of the sample period

Chang et al. (2009)	SFA cost function	25 power plants in Taiwan, 1995-2006.	O: Electricity generated I: Fuel price, price of capital investment, wage	(i) The power generation exhibits an increasing return to scale across all the power plants based on the pooled data. (ii) Installed capacity has a positive relationship with cost efficiency while the factor of working years has a negative relationship
Jaraite and Di Maria (2012)	DEA Malmquist	24 European Union countries, 1996-2007.	O: Electricity generated, CO2 and SO2 emissions I: Nameplate generating capacity, labour, fuel	(i) Carbon pricing led to an increase in environmental efficiency and to an outward shift of the technological frontier
See and Coelli (2012)	SFA	14 thermal power plants in Malaysia, 1998-2005.	O: Electricity sent-out I: Undepreciated capital stocks, labour, fuel, other inputs D: Ownership, plant type, plant size, age, fuel type, time trend	(i) Ownership, plant size and fuel type have a significant influence on technical efficiency levels. (ii) Publicly-owned power plants obtain lower average technical efficiencies than privately-owned power plants. (ii) Larger power plants with more capacity and gas-fired power plants tend to be more technically efficient than other power plants.

See and Coelli (2014)	Törnqvist index numbers	14 thermal power plants in Malaysia, 1975-2005.	<p>O: Electricity delivered to residential customers, electricity delivered to household customers</p> <p>I: Undepreciated capital stocks, labour, fuel, other inputs</p> <p>D: IPP participation, change in ownership, plant capacity utilisation, time trend</p>	(i) No direct evidence of productivity improvements attributable to the industry restructuring.
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^a DEA: data envelopment analysis, SFA: stochastic frontier analysis

^bO:Output(s), I:Input(s), Ed: Endogenous, Ex: Exogenous, D: explanatory variables

2.5 Review of Methodological Framework

2.5.1 Background

The concept of technology in general, and production function in particular, is one of the foundations of contemporary microeconomic theory. The neoclassical economics assumption is hinged on the premise that all decision-making units are producing the maximum possible output, minimising cost or maximising profit given the limited input, and that producers are always efficient. However, in real terms, producers are not always fully efficient, and even some proponents of the rational choice theory admit there are cases in the real world where some firms perform better than others. Thus, in reality some firms produce more with less. This difference may be explained both in terms of efficiency, as well as by unforeseen exogenous shocks outside the firm's control.

In welfare economics, the Pareto-Koopmans concept of efficiency (Pareto (1909), Koopmans (1951)) says "A DMU (decision-making unit) is fully efficient if and only if it is not possible to improve any input or output without worsening some other input or output (Cooper et al. (2007))". Koopmans (1951) in his rather technical monograph provided a definition of technical efficiency whereby "A possible point in the commodity space is called efficient whenever an increase in one of its coordinates (the net output of one good) can be achieved only at the cost of a decrease in some other coordinate (the net output of another good)." Thus, a technically inefficient producer could produce the same outputs with less of at least one input, or could use the same inputs to produce more of at least one output.

Debreu (1951) adopted this definition to develop a measure of efficiency, or, quoting his words: "A numerical evaluation of the "dead loss" associated with a non-optimal situation (in the Pareto sense) of an economic system is sought. Use is made of the intrinsic price systems associated with optimal situations of whose existence a noncalculus proof is given. A coefficient of resource utilization yielding measures of the efficiency of the economy is introduced. The treatment is based on vector-set properties in the commodity

space". The overarching idea of this measure is to determine the distance between the produced output and the output that could have been produced given the inputs. Shephard (1953) used the same concept of distance functions, yet he stated it as a problem if a producer uses too many inputs to produce a certain amount of outputs.

This can thus be viewed as a dual orientation of the technical component of economic efficiency, which is output augmenting and input conserving. With an output augmenting orientation their measure is defined as the maximum radial expansion in all outputs that is feasible with a given technology and inputs. With an input conserving orientation their measure is defined as (one minus) the maximum equiproportionate (i.e. radial) reduction in all inputs that is feasible with a given technology and outputs. In both orientation, a value of unity indicates technical efficiency because no radial adjustment is feasible, and a value different from unity indicates the severity of technical inefficiency.

Farrell (1957), drawing from the work of Koopmans (1951) and Debreu (1951), explains how to define efficiency and productivity and how to calculate the benchmark technology and efficiency measures. His work on efficiency measures is based on radial uniform contractions or expansions from inefficient observations (observed) to the frontier (unobserved). The production frontier is specified as the most pessimistic piecewise linear envelopment data (the function being as close as possible to the observations) and the frontier is calculated solving a system of linear equations, obeying the two conditions on the unit isoquant (slope not positive and no observed point lies between it and the origin; input-oriented approach). It introduced a method to decompose the overall efficiency of a production unit into its technical and allocative components.

2.5.2 Efficiency and Productivity

In measuring the economic performance of a producer, it is commonplace to describe them as being more or less "efficient," or more or less "productive." They reflect the overall performance of the production unit. Basically, productivity examines the relationship between input and output in a given production process

(Coelli, Rao et al. 1998). Thus, productivity is expressed in an output versus input formula for measuring production activities. It does not merely define the volume of output, but output obtained in relation to resources employed. This ratio is easy to calculate if the producer uses a single input to produce a single output. In the more likely event that the producer uses several inputs to produce several outputs, the outputs in the numerator must be aggregated in some economically sensible way, as must the inputs in the denominator, so that productivity remains the ratio of two scalars. The concept of productivity is closely related to that of efficiency. While the terms productivity and efficiency are often used interchangeably, efficiency does not have the same precise meaning as productivity.

However, efficiency of a producer means comparison between observed and optimal values of its output and input. This involves comparing observed output to maximum potential output obtainable from the input, or comparing observed input to minimum potential input required to produce the output, or some combination of the two. In these two comparisons the optimum is defined in terms of production possibilities, and efficiency is technical. It is also possible to define the optimum in terms of the behavioural goal of the producer. In this event efficiency is measured by comparing observed and optimum cost, revenue, profit, or whatever goal the producer is assumed to pursue, subject, of course, to any appropriate constraints on quantities and prices. In these comparisons the optimum is expressed in value terms, and efficiency is economic (Fried et al, 2008).

The productivity of a firm can be improved by producing goods and services with fewer inputs or producing more output for the same input. Therefore, increasing productivity implies either more output is produced with the same amount of inputs or that fewer inputs are required to produce the same level of output (Roger, 1998). The highest productivity (efficient point) is achieved when maximum output is obtained for a particular input level. Hence, productivity growth encompasses change in efficiency, and increasing efficiency definitely raises productivity (Roger, 1998).

2.5.3 Type of Efficiency

The literature often distinguishes between the two types of productive efficiency: technical and allocative. The technical component refers to the ability to avoid waste by producing as much output as input usage allows, or the ability to obtain the maximum potential firm performance (output) from a given set of input. In contrast, allocative efficiency reflects the firm's ability to use optimal quantities, given their respective prices and technologies adopted; it mainly depends on the prices related to the factors of production. Allocative and technical efficiency combine to provide an overall economic efficiency measure. When a firm achieves maximum output from a particular input level, with the utilisation of input at least cost, it is considered an overall efficient firm. Generally, the term efficiency refers to technical efficiency which is considered as a basic measurement for determining the level of adoption in innovative technology, and over production efficiency (Lambarra, et al., 2007).

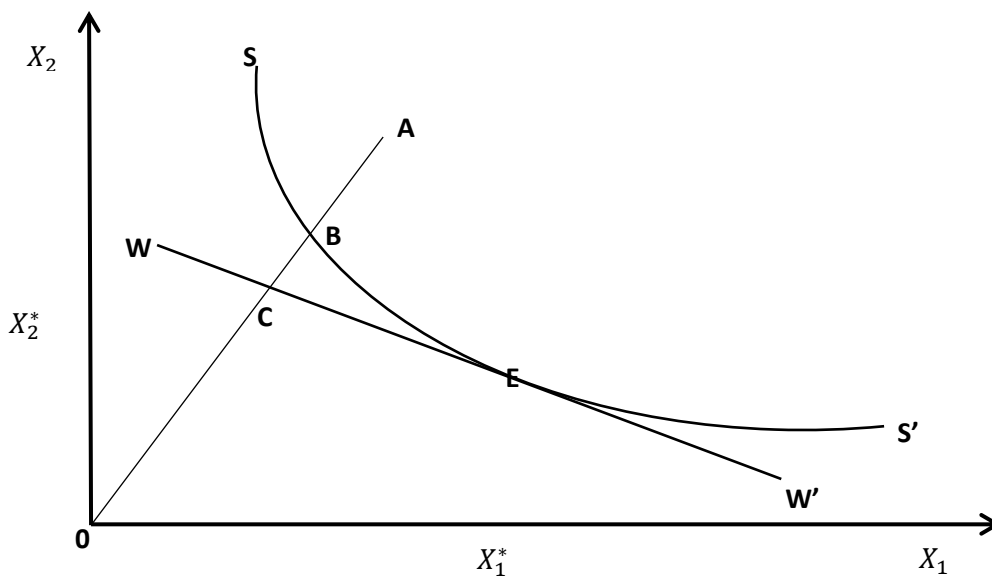
Debreu (1951) and Farrell (1957) introduced a measure of technical efficiency. Their measure is defined as one minus the maximum equiproportionate reduction in all inputs that still allows continued production given outputs. A score of unity indicates technical efficiency because no equiproportionate input reduction is feasible, and a score less than unity indicates technical inefficiency. Following Farrell (1957), measuring technical efficiency can be obtained by using input and output quantity without introducing prices of these inputs and outputs. Technical efficiency can be decomposed into three components: scale efficiency (the potential productivity gain from achieving optimal size of a firm), input congestion (increase in some input and decrease in some) and pure technical efficiency. To decompose technical efficiency into its three components it is required to relax the long run assumptions, allowing for variable returns to scale (increasing or decreasing) and situations of weak disposability where an increase in one input can lead to a decrease in output.

Suppose that a firm produces a single output (Y) by using two inputs (X_1 and X_2) under the assumption of constant returns to scale. In figure 2.1 below, the SS' curve denotes the amount of X_1 and X_2 to produce an

identical amount of Y , which represents the isoquant of fully efficient firms could allow measurement of technical efficiency. Therefore, efficiency is determined by the points B and E located on the SS' curve. All things being equal, every combination along the isoquant (for instance, point B and E) is considered efficient while any point above is considered as technical inefficiency since the producer can contract the use of input without reducing the output level. Isocost line WW' represents the proportion of the input prices. A producer attains minimum cost at point E where line WW' is tangent to the curve SS' . Assuming a producer uses quantities of inputs X_1^* and X_2^* at point A to produce a unit of output is technically inefficient, and the technical inefficiency of the firm could be represented by the distance AB. The technical efficiency (TE) of a producer is most commonly measured by the ratio:

$$TE = OB/OA$$

Figure 2.1: Technical and allocative efficiency



The ratio has a value between zero and one, and thus indicates the degree of technical efficiency of the productive unit. A value of one is an indication of full technical efficiency of the producer. For example, a producer is technically efficient at point B because it is a fully efficient point which is located on the isoquant curve SS' . This implies the producer chooses the right input mix. Given the input price ratio,

represented by the slope of isocost line WW' , the allocative inefficiency can be estimated since by moving from B to E, the same level of output could be produced at a lower cost through adjustment of input use until the ratio of marginal products equal the ratio of input prices. The allocative efficiency of a productive unit operating a point A is measured by the ratio:

$$AE = OC/OB$$

If the producer is economically efficient, i.e. both technically and allocatively efficient, the total economic efficiency is given by the ratio:

$$EE = OC/OA.$$

This ratio is termed Farrell as the overall efficiency of the producer is measured by the product of technical and allocative efficiency. Farrell laid a foundation for the efficient frontier as a benchmark for measuring the relative performance of a productive unit. In Farrell's approach, the measurement of economic efficiency is linked to the use of a frontier production function, in opposition to the notion of average performance underlying most of the econometric literature on the production function up to the time of Farrell's contribution.

2.6 Efficiency Measurement Techniques

A number of analytic techniques have been developed to estimate production frontiers and the associated inefficiency of individual organisations. These techniques can be broadly categorised into two; parametric methods which use econometric techniques to estimate the parameters of a pre-defined functional form, and non-parametric methods which place no conditions on the functional form, but the efficiency level is calculated from the sample observation. The parametric methods include deterministic frontier analysis (DFA) and stochastic frontier analysis (SFA), which are similar to the conventional regression analysis.

2.6.1 Non-Parametric Technique

The non-parametric methods or the mathematical programming technique is mainly data envelopment analysis (DEA) which deals with multiple input and multiple output production technologies. The methodology was introduced by Charnes, Cooper and Rhodes (1978). DEA applies operational programs to construct a piecewise linear production possibility frontier. DEA uses a linear combination of inputs and outputs of best practices producers to come up with an efficient frontier. The producers that lie on the frontier are the efficient ones while those that do not lie on the frontier can be considered as inefficient and individual inefficiency scores will be calculated for each one of them. The main advantage of DEA is that no explicit specification functional form needs to be imposed on the data, and DEA can easily accommodate multiple outputs. Moreover, a DEA model does not require any assumption about the distribution of efficiency scores, as in the case of stochastic frontier analysis. This implies that efficiency estimates may be biased under the production process which is largely involved stochastic elements.

2.6.2 Parametric Technique

Parametric frontier techniques are models in which a parametric functional form for the production frontier function is assumed. There are various methods of estimating the production frontier function, and the choice of method may depend on whether distribution assumptions on the error components are made or not. Parametric frontiers can be broadly classified into two approaches. One approach is not to make specific distribution assumptions on the error components and this approach is labelled as the deterministic frontier analysis. Another is to impose very specific distribution assumptions on the error components, and apply maximum likelihood (ML) methods, and this approach is labelled as the stochastic techniques frontier analysis. Unlike the DEA or other non-parametric models where the efficient frontier is calculated from the data sample, the parametric frontier is econometrically estimated based on the notion that a functional mathematical relationship exists between inputs and output. Parametric frontiers can be broadly classified into deterministic and stochastic techniques.

2.6.2.1 Deterministic Frontier Analysis

In deterministic frontier analysis, variation resulting from noise and inefficiency are lumped together and are attributed to inefficiency. Aigner and Chu (1968) generalise the work of Debreu and Farrell by providing deterministic approach to the measurement of technical efficiency. They suggest linear and quadratic programming as estimation methods that would constrain the ‘residuals’ to be positive. Alternatively, OLS can be used since the slope parameters are estimated consistently. Two econometric methods are introduced in deterministic frontier analysis; corrected ordinary least squares (COLS), by Winsten (1957), and modified ordinary least squares (MOLS) deterministic frontier analysis, by Afriat (1972) and Richmond (1974). Both models estimate parameters by OLS in the first step and adjust the intercept parameter in the second step.

Adopting cross-sectional models and supposing that output is completely determined by the inputs used via a production function that is the same for all producers in an industry, then the production frontier can be written as

$$y_i = f(x_i; \beta) \tag{2.1}$$

Where y_i is the scalar output of producer i , $i = 1, \dots, N$, x_i is a vector of K inputs used by the producer i , $f(x_i; \beta)$ represents the production function (e.g a Cobb-Douglass or transcendental logarithm production function, and β is a vector of technology parameters to be estimated which is equal to all the producers. The β can be estimated by carrying out a regression of y on x_i . This regression is expected to give a good fit since a complete determination is assumed. In this model, all producers produce exactly the output that is predicted by the amount of input and the production function. If efficiency is included in the model, the producers may produce less than the value predicted in Equation (2.1). This can be done through multiplication of the right-hand side of the Equation by a parameter that has a value between zero and one. The production frontier model can be re-written as

$$y_i = f(x_i; \beta).TE_i \tag{2.2}$$

In equation (2.2), the TE_i is the output-oriented technical efficiency of producer i . The production function $f(x_i; \beta)$ is deterministic as no stochastic error component is involved. The slack between an observed level of output and the frontier is attributed solely to inefficiency. If the producer lies on the frontier, the efficiency term is equal to one, and is fully efficient. However, if the efficiency term is less than one, it will provide a shortfall between the observed output and the maximum feasible output, hence the producer is inefficient. Therefore, the output-oriented technical efficiency TE_i can be defined as the ratio of actual output level to maximum level of output feasible under the current technology used.

$$TE_i = \frac{y_i}{f(x_i; \beta)} \quad (2.3)$$

In equation (2.3), the entire shortfall of observed output from maximum feasible output is attributed to technical inefficiency. Moreover, the production function with its parameters is needed in order to estimate the technical efficiency component (TE) and for estimating the parameters of the production function, TE is needed. A deterministic frontier can be estimated by re-writing (2.3) as

$$y_i = f(x_i; \beta) \cdot \exp(-u_i) \quad (2.4)$$

Since $TE_i = \exp(-u_i)$, this can be transformed into logarithms as $\ln TE_i = -u_i$, and subsequently gives $u_i = -\ln TE_i \approx 1 - \ln TE_i$.

By adopting logarithms in both sides, the deterministic production frontier model becomes

$$\ln y_i = \ln f(x_i; \beta) - u_i \quad (2.5)$$

Having parameterised the production technology, both corrected least square (COLS) and modified ordinary least squared (MOLS) can be employed to estimate the parameter vector and to obtain the estimates of u_i .

Then estimates of firm specific technical efficiency can be derived by $TE_i = \exp(-u_i)$

However, a deterministic frontier assumes deviations from the production frontier are under the control of the firm. Attributing all deviations from the production frontier to inefficiency is conceptually unappealing. Statistical noise such as favourable or unfavourable external events (luck, weather, regulatory-competitive environments and other random conditions) would be inappropriately treated as inefficiency, suggesting that deterministic measures of inefficiency are subject to severe distortions. This approach is also criticised in so far as no allowance is made for measurement error and other statistical noise as error arising from specifying an appropriate functional form is also regarded as inefficiency by deterministic techniques.

2.6.2.2 Stochastic Frontier Analysis

Stochastic frontier analysis is an alternative approach that addresses the criticism of the deterministic frontier approach by allowing the specification of both inefficiency and random error. The approach makes an observed firm face the production frontier which is randomly constructed by incorporating random conditions such as luck, sampling and mis-specification errors, which might be outside the firm's control, but which are lumped together and are attributed to inefficiency in the deterministic approach (Førsund and Jansen, 1977; Greene, 2009). SFA has the potential of capturing the effects of random unobserved firm specific factors. Moreover, it also allows hypothesis testing and inferences to be made on the parameters and the inefficiency term of the model⁴. However, SFA requires a number of assumptions, which often make it less-flexible and restrictive. Proponents argue in favour of stochastic frontier models because of the superior conceptual treatment of noise.

Following the seminal paper of Farrell (1957), stochastic frontier analysis has its origins in two papers independently and simultaneously proposed by Aigner, Lovell and Schmidt (1977), and Meeusen and van don Broeck (1977), followed by Battese and Corra (1977). These three original works develop a concept of the composed error: a conventional symmetrically distributed stochastic component that is known as random error term (as it captures all the statistical noise, measurement error and exogenous shocks outside the control of the producers over their production) and a stochastic component with a one-sided distribution

⁴ Although this property is not only peculiar to SFA but also COLS approach.

error term, which represents the inefficiency. Since then, the SFA has been developed by several collaborators and there have been a vast range of applications in the literature⁵: Schmidt and Lovell (1979), Jondrow et al. (1982), Greene (1980), Stevenson (1980), Lee (1983), Koop and Diewert (1982), Pitt and Lee (1981), Schmidt and Sickles (1984), Cornwell, Schmidt and Sickles (1990), Kumbhakar (1990) Battese and Coelli (1992), among other researchers.

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

$$y_i = f(x_i; \beta) \cdot \exp(v_i) \cdot TE_i \quad (2.6)$$

where $[f(x_i; \beta) \cdot \exp(v_i)]$ represents the stochastic production frontier.

Since $TE_i = \exp(-u_i)$, producer's actual output can be written as

$$y_i = f(x_i; \beta) \cdot \exp(v_i - u_i) \quad (2.7)$$

The logarithm transformation of the production technology can be written

$$\ln y_i = \ln f(x_i; \beta) + \varepsilon_i \quad (2.8)$$

$$\varepsilon_i = v_i - u_i \quad (2.9)$$

Where ε_i is a composed error consisting of two components v_i and u_i . v_i represents the two-sided noise component and u_i is the nonnegative technical inefficiency term. The noise component v_i is assumed to be independently, identically distributed and symmetrically distributed independently of u_i . Thus, the error term is not symmetrical, since $u_i \geq 0$. Suppose that v_i and u_i are distributed independently of x_i , estimation of equation (2.8) by Ordinary Least Squares (OLS) gives consistent estimates of the parameters except β_0 , since $E(\varepsilon_i) = -E(u_i) \leq 0$. Producer specific estimates of inefficiency can be achieved by Jondrow, Lovell, Materov and Schmidt (1982) who suggested estimating the expected value of the

⁵ For literature surveys see Greene (1993)

inefficiency component conditional on the measured overall error. This procedure requires distributional assumptions on both error components. If distributional assumptions are made about v_i and u_i , therefore, the technical inefficiency term u_i can be extracted from the estimates of ε_i .

The assumption made about the distribution of the noise term v_i is $v_i \sim iidN(0, \sigma_v^2)$. However, there is no consensus about the assumption for the distribution of the technical inefficiency term u_i . Aigner, Lovell and Schmidt (1977) and Meeusen and van don Broeck (1977) proposed two type of distributions i.e. half-normal and exponential distribution, a later extension generalised these distributions into truncated normal at zero as proposed by Stevenson (1981) and Gamma distribution proposed by Green (1990). In the case of a normally distributed noise term, inefficiency term, and a half-normally distributed inefficiency term, the stochastic production frontier model given in equation (2.8) is assumed to have the following distribution assumption.

- i) $v_i \sim iidN(0, \sigma_v^2)$
- ii) $u_i \sim iidN^+(0, \sigma_u^2)$, i.e., a nonnegative half normal;
- iii) v_i and u_i are distributed independently of each other, and of the regressors.

Following a half normal distribution, the density function of $u \geq 0$ is given by the function

$$f(u) = \frac{2}{\sqrt{2\pi}\sigma_u} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2}\right\} \quad (2.10)$$

The density function of v is

$$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot \exp\left\{-\frac{v^2}{2\sigma_v^2}\right\} \quad (2.11)$$

Building on the independence assumption, the joint densities function of v_i and u_i , is the product of their individual density function and is given as

$$f(u, v) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right\} \quad (2.12)$$

Given that $\varepsilon = v-u$, the joint density function of u and ε is

$$f(u, \varepsilon) = \frac{2}{2\pi\sigma_u\sigma_v} \cdot \exp\left\{-\frac{u^2}{2\sigma_u^2} - \frac{(\varepsilon + u)^2}{2\sigma_v^2}\right\} \quad (2.13)$$

By integrating u out of $f(u, \varepsilon)$, the marginal density function of ε_i is obtained as follows;

$$\begin{aligned} f(\varepsilon) &= \int_0^{\infty} f(u, \varepsilon) du = \frac{2}{\sqrt{2\pi}\sigma} \cdot \left[1 - \Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right] \cdot \exp\left\{-\frac{\varepsilon^2}{2\sigma^2}\right\} \\ &= \frac{2}{\sigma} \cdot \phi\left(\frac{\varepsilon}{\sigma}\right) \cdot \Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right), \end{aligned} \quad (2.14)$$

Where $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $\lambda = \sigma_u/\sigma_v$ and $\Phi[.]$ and $\phi[.]$ are the standard normal cumulative distribution and density functions.

The asymmetry of the distribution of the error term is a central feature of the frontier model. A central parameter in normal -half normal distribution can be represented by the asymmetry parameter:

$$\lambda = \frac{\sigma_u}{\sigma_v} \quad (2.15)$$

The larger λ is, the more marked the asymmetry will be. On the other hand, if λ is equal to zero, then the symmetric error component dominates the one-side error component in the determination of ε_i . Thus, the

composed error term is explained by the random disturbance v_i , which follows a normal distribution. ε_i therefore has a normal distribution. The distribution parameters σ_u , σ_v and λ are estimated along with the technology parameters β by maximum likelihood. To test the hypothesis that $\lambda = 0$, we can compute a Wald statistic or likelihood ratio test both based on the maximum likelihood estimator of λ ⁶. Coelli (1995) tests as equivalent hypothesis $\gamma = 0$ against the alternative $\gamma > 0$, where

$$\gamma = \frac{\sigma_u}{\sigma_u + \sigma_v} \quad (2.16)$$

A value of zero for the parameter γ indicates that the deviations from the frontier are entirely due to noise, while a value of one would indicate that all deviations are due to technical inefficiency.

The technical inefficiency can be obtained after obtaining the estimates of the technology parameters. Estimation of u_i is the central focus of the analysis. With parameter estimates in hand, one can obtain a direct estimate of $\varepsilon_i = v_i - u_i$. An estimate of u_i can be obtained from the conditional distribution of u_i given ε_i as it contains whatever information concerning u_i in ε_i . Jondrow et al. (1982) and Battese and Coelli (1988) proposed two estimators widely used in the literature.

Jondrow, Lovell, Materov and Schmidt (1982) showed that if $u_i \sim N^+(0, \sigma_u^2)$, the conditional distribution of u given ε is

$$f(u | \varepsilon) = \frac{f(u, \varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi\sigma_*^2}} \cdot \exp\left\{-\frac{(u - \mu_*)^2}{2\sigma_*^2}\right\} / \left[1 - \Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right] \quad (2.17)$$

Where $\mu_* = -\varepsilon \sigma_u^2 / \sigma^2$ and $\sigma_*^2 = \sigma_u^2 \sigma_v^2 / \sigma^2$. They posit that since $f(u/\varepsilon)$ is distributed as $N^+(\mu_*, \sigma_*^2)$, the mean of the distribution can serve as a point estimator of u_i . This is given by

⁶ Coelli (1995) shows that the likelihood ratio test is asymptotically distributed as a mixture of Chi squared distributions

$$E(u_i | \varepsilon_i) = \mu_{*i} + \sigma_* \left[\frac{\phi(-\mu_{*i}/\sigma_*)}{1 - \Phi(-\mu_{*i}/\sigma_*)} \right] = \sigma_* \left[\frac{\phi(\varepsilon_i \lambda / \sigma)}{1 - \Phi(\varepsilon_i \lambda / \sigma)} - \left(\frac{\varepsilon_i \lambda}{\sigma} \right) \right] \quad (2.18)$$

Thus, the estimate of u_i can be obtained from

$$TE_i = \exp(-\hat{u}_i) = \exp(-E(u_i | \varepsilon_i)) \quad (2.19)$$

Battese and Coelli (1988) proposed the alternative point estimator for TE_i :

$$TE_i = E(\exp -u_i | \varepsilon_i) = \left[\frac{1 - \Phi(\sigma_* - \mu_*/\sigma_*)}{1 - \Phi(-\mu_*/\sigma_*)} \right] \cdot \exp \left\{ -\mu_* + \frac{1}{2} \sigma_*^2 \right\} \quad (2.20)$$

Note that the estimator is the expected value of the inefficiency term given an observation on the sum of inefficiency and the firm specific heterogeneity. Their estimator is preferred to the JLMS estimator because $1 - E(u_i | \varepsilon_i)$ only includes the first order term in the approximation of the power series $\exp(-u_i | \varepsilon_i)$. Therefore, the B&C estimator can be viewed as the exact expression of the mean of the distribution of technical efficiency, whereas the JLMS estimates are the exact expressions of the central tendencies of a first order approximation to the distribution of technical efficiency⁷.

Regrettably, these estimators suffer a major drawback as they are not consistent estimators of u_i , even though they are unbiased since, regardless of N, the variance of the estimate remains zero. In addition, there are two more drawbacks for cross-sectional stochastic production frontier models. There is a problem of assumption that technical inefficiency is independent of the inputs and the assumptions on the distributional forms of statistical noise and technical inefficiency.

⁷ See Green (1993) for detail

2.6.2.3 Frontier Panel Data Model

The panel data framework allows us to resolve many drawbacks associated with the cross-sectional stochastic frontier models as noted by Schmidt and Sickles (1984). One advantage of using panel data is that it gives an opportunity to examine and model behaviour of technical efficiency over time. The three problems can be corrected by using panel data. In particular, panel data allows relaxation of the assumption of independence and avoidance of distribution assumptions (or testing them when they are imposed). Furthermore, with panel data it is possible to construct estimates of the efficiency levels of each producer that are consistent as the number of observations per producer increases. This means that inefficiency can be estimated more precisely. Repeated observations on a sample of producers in panel data estimation techniques help to correct all these limitations. The general panel data model can be given as:

$$y_{it} = \alpha_i + x_{it}\beta + v_{it} - u_{it} \quad i = 1, \dots, N; t = 1, \dots, T. \quad (2.21)$$

Where y_{it} represents the log output of producer, x_{it} denotes the vector of independent variables (e.g. inputs), $x_{it}\beta$ represents a linear parameter technology, v_{it} represents random noise, u_{it} is the nonnegative technical inefficiency term and α_i represents the individual effect.

In a panel data production frontier model, there is a distinction concerning the time dimension of the inefficiency term. In the first case technical efficiency can vary across producers, but is assumed to be kept constant over time for each producer, whereas in the second case, technical efficiency not only is allowed to vary across producers but also allowed to change over time for each producer.

2.6.2.3.1 Time-Invariant Technical Efficiency

In this section a model with time-invariant inefficiency will be presented.

Equation (2.21) can be rewritten as follows:

$$y_{it} = \alpha + x_{it}\beta + v_{it} - u_i \quad i = 1, \dots, N; t = 1, \dots, T. \quad (2.22)$$

By defining $\alpha_i = \alpha - u_i$ we have the standard panel data model

$$y_{it} = \alpha_i + x_{it}\beta + v_{it} \quad (2.23)$$

It is assumed that the v is $iidN(0, \sigma_v^2)$, and is uncorrelated with the inputs \mathbf{x} . This last assumption is needed for the consistency of the within and generalised estimators of the parameter vector β , which are derived from the OLS estimation of equation (2.23) under a fixed effect model and a random effect model respectively.

2.6.2.3.2 The Fixed-Effects Model

The fixed effects model in the frontier modelling framework is based on Schmidt and Sickles's (1984) treatment of the linear regression model. The model assumes no distributional assumption about the inefficiency u_i and therefore, u_i is allowed to be correlated with the inputs or with the random noise v_{it} . The inefficiency u_i (and therefore the intercept α_i) is treated as fixed, as simple producer specific intercept parameters to be estimated which can be estimated consistently and efficiently by ordinary least squares.

The basic framework is a linear model can be written as equation (2.23),

$$y_{it} = \alpha + X_{it}\beta + v_{it} \quad i = 1, \dots, N; t = 1, \dots, T$$

Where $\alpha_i = \alpha - u_i$ is reinterpreted and treated as the producer specific intercept or inefficiency term. Estimation is accompanied in three equivalent ways: 1) by suppressing the constant term and adding a dummy variable for each of the N producers, or 2) by keeping the constant term and adding $(N-1)$ dummies, or 3) using the within transformation, in which all the data will be expressed in terms of deviation from producer means and the N intercepts are recovered as means of the producer specific residuals. Each variant is referred to as least square with dummy variable (LSDV for short).

By applying ordinary least squares estimation to the model (2.23) combined for all T observations for each producer, the within estimator is derived. It can be shown to be consistent as either N or T goes to infinity.

Once the within estimator is available, an estimate of the intercept terms α_i is possible, by employing normalisation,

$$\hat{\alpha} = \max_i \hat{\alpha}_i \quad (2.24)$$

and then \hat{u}_i can be estimated as

$$\hat{u}_i = \hat{\alpha} - \hat{\alpha}_i, \quad i = 1, 2, \dots, N \quad (2.25)$$

which ensures that $\hat{u}_i \geq 0$. Therefore, the producer-specific but time-invariant technical inefficiencies are then given as:

$$TE_i = \exp(-\hat{u}_i) \quad (2.26)$$

This means that the production frontier is normalised in terms of the best producer in the sample and technical efficiency of other producers is measured relative to the efficient producer. A significant advantage of the fixed effects model lies in the fact that the statistical properties of the estimators obtained do not depend on the assumption of uncorrelatedness of the regressors with the firm effects. A necessary condition for the estimate of the intercept $\hat{\alpha}_i$ to be consistent is that the time period is very large, $T \rightarrow \infty$, whereas to have an accurate normalisation and a consistent separation of intercept α from the one-sided inefficiency terms u_i , a large number of production units $N \rightarrow \infty$ is required. This means that if N is small it is only possible to compare efficiencies across production units, but not to an absolute standard (100%). In contrast to the MLE cross-sectional model, the fixed-effects panel data model provides the consistent estimates of producer specific technical efficiency.

A major problem associated with the within estimation of fixed-effects is that if important time-invariant regressors are included in the frontier model, these will show up as inefficiency in equation (2.22). Thus, the estimated fixed effects (u_i), will capture both variation across producers in time-invariant technical

efficiency and all phenomena that vary across producers but are time invariant for each producer. Unfortunately, this occurs whether or not the other effects are included as regressors in the model. This problem can be solved if one makes assumptions about the uncorrelatedness of effects and regressors and/or about the distribution of the effects, which leads us to the random-effects panel data model.

2.6.2.3.3 The Random -Effects Model

The first developments in the sphere of random effect models were the work of Pitt and Lee (1981). The authors considered a model with distributional assumptions about the error term where $v_{it} \sim iid N(0, \sigma_v^2)$ represents noise, $u_i \sim iid N^+(0, \sigma_u^2)$ represents the distribution of the non-negative component which translates the inefficiency of the model and u_i and v_i are distributed independently of each other, and of the regressors.

As referred in Greene (2003), the random effects model is obtained by assuming that the inefficiency terms u_i are treated as one sided i.i.d. random variables, uncorrelated with the regressors x_{it} and the statistical noise v_{it} for all t. This modification allows one to include some time invariant variables in the model. However, no distributional assumptions for the effects are made., although they are still assumed to be nonnegative. The assumption of the random noise v_{it} is as before. With these modifications of assumptions, the model (2.19) is rewritten in a slightly different way, defining:

$$\begin{aligned}
 \alpha^* &= \alpha - \mu, \text{ where } \mu = E(u_i) \text{ and } u_i^* = u_i - \mu \\
 y_{it} &= [\alpha - E(u_i)] + x_{it}\boldsymbol{\beta} + v_{it} - [u_i - E(u_i)] \\
 &= \alpha^* + x_{it}\boldsymbol{\beta} + v_{it} - u_i^*
 \end{aligned} \tag{2.27}$$

The parameters are estimated by generalised least squares (Greene, 2003). If further distributional assumption on the error components is tenable (e.g. normal and half normal distributional assumption used

in Pitt and Lee, 1981 and normal and truncated normal distributional assumption used in Kumbhakar, 1987 and Battese and Coelli, 1988), the parameters are estimated.

Then random-effects producer specific technical efficiency can be estimated either by using the two-step generalised least square (GLS) method, or by the maximum likelihood estimation (MLE) method if further distributional assumption on the error components is tenable (e.g. normal and half normal distributional assumption used in Pitt and Lee, 1981 and normal and truncated normal distributional assumption used in Kumbhakar, 1987 and Battese and Coelli, 1988). In the case of no distributional assumption made on the error component, GLS is the appropriate method of estimating the producer specific technical efficiency. This method involves, at first stage, OLS estimation to obtain parameters estimates. Schmidt and Sickles (1984) show that when N is small, GLS is useless unless σ_v^2 and σ_u^2 are known a priori. They also illustrate that when both N and T are large, GLS is feasible, but less efficient than the within estimator. Therefore, in the unrealistic case when the covariance matrix of the error $v_{it} - u_i^*$ is known, that is, σ_v^2 and σ_u^2 are known, the GLS estimator for $\hat{\alpha}^*$ and β' is BLUE (best linear unbiased estimator), and consistency is ensured either when $N \rightarrow \infty$ or when $T \rightarrow \infty$. However, in the more realistic case that σ_v^2 and σ_u^2 are not known, it is appropriate to use the feasible generalised least square method (FGLS) to estimate the variance of the compound error $\hat{V}[\varepsilon] = \hat{V}[u_i] + \hat{V}[v_i] = \hat{\sigma}_u^2 + \hat{\sigma}_v^2$. The FGLS estimator is still consistent as $N \rightarrow \infty$, if it is based on the consistent estimates of σ_v^2 and σ_u^2 . Estimates of the producer specific technical efficiency are then obtained by

$$TE_i = \exp\{-\hat{u}_i\} \quad (2.28)$$

with $\hat{u}_i = \max\{\hat{u}_i^*\} - \hat{u}_i^*$ and u_t^* resulting from the average values residuals of FGLS estimation:

$$\hat{u}_i^* = \frac{1}{T} \sum_t (y_{it} - \hat{\alpha}^* - \hat{\beta}x_{it}) \quad (2.29)$$

where $\alpha^* = \alpha - \mu$

In these conditions, the estimate obtained for individual inefficiency translates, just as in the case of the fixed effect model, the distances between the intercept of each productive unit and the greatest intercept

relating to the productive unit considered efficient. The frontier is then moved to the greatest intercept estimated in the sample. The BLUP (best linear unbiased predictor) by Lee and Griffiths (1979) is an alternative estimator of \hat{u}_i^* and is given by:

$$\hat{u}_i^* = - \left[\frac{\hat{\sigma}_u^2}{T\hat{\sigma}_u^2 + \hat{\sigma}_v^2} \right] \cdot \sum_t (y_{it} - \hat{\alpha}^* - \hat{\beta}x_{it}) \quad (2.30)$$

The GLS estimator for both estimates from the above two alternative methods are consistent when simultaneously N and $T \rightarrow \infty$ and the variances of the two components of the error term are known. When these are unknown, it is necessary that $T \rightarrow \infty$ for the variance of u to be estimated consistently and that N or $T \rightarrow \infty$ for the FGLS estimator of the variance.

The advantages offered by the FGLS estimator are that it allows the inclusion of time-invariant variables and gives more efficient estimates than the within estimator of the fixed. Nevertheless, the efficiency advantage depends on the orthogonality of the regressors and the inefficiency term, a condition which is often rejected by the data; in addition, the gain in terms of efficiency vanishes as $T \rightarrow \infty$. For this reason, Schmidt and Sickles (1984) point out that the random effects model is more suitable for short panels in which correlation is empirically rejected. Hausman and Taylor (1981) developed a test, based on Hausman (1978), for the hypothesis that the error terms are uncorrelated with the regressors. If the null hypothesis of non-correlation is accepted, a random-effects model is chosen, otherwise a fixed-effects model is appropriate. The Hausman test is a test of the orthogonality assumption that characterises the random effects estimator, which is defined as the weighted average of the between and the within estimator.

The main advantage in using panel data is that it allows relaxation of the strong assumptions required in the estimation of a cross-section, namely assumptions on the independence of the components of the error term and the regressors, and distributional assumptions on the inefficiency and statistical noise. However, it is still possible to make these assumptions in the panel data context and therefore a maximum likelihood estimator

of the parameters of the model can be obtained. Thus, MLE can be used to estimate the time-invariant producer specific technical efficiency.

2.6.2.3.4 Time-Varying Technical Inefficiency

The earlier models (Pitt and Lee, 1980; Schmidt and Sickles, 1984; Kumbhakar, 1987; among others) treated technical efficiency as time invariant. The fixed effect, random effect and maximum-likelihood models share the assumption of time invariance in the component of technical inefficiency i.e. technical inefficiency is constant over time. This assumption is restrictive, and it seems quite implausible to assume that technical efficiency would remain constant over a prolonged period of time when the environment is competitive. When the panels are short, it may make sense to assume time invariant technical efficiency. However, when there are sufficient data observed on the same productive unit in various period time lengths, it is more appropriate to consider the time effect on this component error while analysing the efficiency of a productive process. In these circumstances, it is improbable that the productive unit continues to present a constant measurement of inefficiency in all the periods of observing their production. Thus, subsequent researchers allowed technical efficiency to vary over time, but they model efficiency as a systematic function of time (Kumbhakar, 1990; Cornell, Schmidt and Sickles, 1990; Battese and Coelli, 1992; Lee and Schmidt, 1993).

Cornwell *et al.* (CSS) (1990) and Kumbhakar (1990) were among the first to propose a stochastic production frontier panel data model with time variation technical efficiency. Suppose the assumption of a time invariant inefficiency term is relaxed, the model to be examined is then given as:

$$y_{it} = \alpha_{it} - \beta x_{it} + v_{it} \quad (2.31)$$

Where $\alpha_{it} = \alpha_t - u_{it}$ and $u_{it} \geq 0$. Given that it is possible to estimate α_{it} , the following estimate of inefficiency term can be obtained:

$$\hat{u}_{it} = \hat{\alpha}_t - \hat{\alpha}_{it} \quad (2.32)$$

where $\hat{\alpha}_t = \max_i (\hat{\alpha}_{it})$.

As in the time-invariant panel data models, the estimation of time-varying panel data models also involves two stages just as in the time-invariant panel data models. In the first stage the objective is to estimate the parameters describing the structure of production technology, while in the second stage producer specific technical efficiency is obtained. The problem with the specification above is that with an $N \times T$ panel, it is impossible to estimate all of the $N \cdot T$ intercepts, the K slopes and σ_v^2 . To avoid this problem, Cornwell, Schmidt and Sickles (1990) replace α_{it} with a flexible parameterized function of time with parameters that vary over time. The quadratic form of this is:

$$\alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2 \quad (2.33)$$

As a result, only $N \cdot 3$ intercepts need to be estimated with this setup. Additionally, the ratio of parameters to be estimated to the number of observations is $\frac{(3N+K+1)}{N} T$.

Analogous to time-invariant panel data model, either fixed-effects or random-effects approach can be used to model the time-varying technical efficiency. If the distributional assumption is tenable, maximum likelihood approach can be pursued as well. The FE model has two methods for obtaining technical efficiency depending on the size of $\frac{N}{T}$. In the first attempt suggested in CSS (1990), If the ratio is relatively large, it provides a path to allow technical efficiency to vary both over producers and over time, then the u_{it} 's are deleted from equation (2.26). The slopes are estimated from the residuals, and the residuals are regressed on a constant, t and t^2 to obtain the estimates of θ_{i1} , θ_{i2} and θ_{i3} . This procedure will produce a value for $\hat{\alpha}_{it}$ being

$$\hat{\alpha}_{it} = \hat{\theta}_{i1} + \hat{\theta}_{i2}t + \hat{\theta}_{i3}t^2 \quad (2.34)$$

In the second procedure, as suggested by Kumbhakar and Lovell (2000), if $\frac{N}{T}$ is relatively small, then the u_{it} 's are included in the model. In this case, the parameters of equation (2.34) are estimated as the

coefficients of dummies interacted with t and t^2 . This will give a similar estimated form of the intercepts.

The estimated intercepts determine \hat{u}_{it} , which is equal to

$$\hat{u}_{it} = \max_i (\hat{\alpha}_{it}) - \hat{\alpha}_{it} \quad (2.35)$$

Finally, technical efficiency be estimated by using the analogous procedure provided for time-invariant fixed-effects model for a specific producer in period t ,

$$TE_i = \exp(-\hat{u}_i) \quad (2.36)$$

Similar to the time-invariant fixed-effects model, the time-varying fixed-effects model cannot handle the potential existence of time-invariant regressors. As a result of this, CSS also produce a time-varying random-effects model to incorporate the time-invariant regressors. The RE model is estimated in almost exactly the same manner as the time invariant case. The GLS estimator is used and consistency hinges on the uncorrelatedness of u , v and the regressors. For a large T , it has the same properties as the time invariant model and is less efficient than the FE method. There are alternative formulations for modelling the time varying u_{it} . Lee and Schmidt (1993) specify u_{it} as

$$u_{it} = \alpha(t)u_i \quad (2.37)$$

where $\alpha(t)$ is a function of a set time dummy variables. Varying technical efficiency can be estimated using both fixed- and random-effects models, in which α_t s are treated as coefficients of the (fixed or random) effects u_i . Once the α_t s and the u_i are estimated,

$$\hat{u}_{it} = \max_i (\hat{\alpha}_t \hat{u}_i) - \hat{\alpha}_t \hat{u}_i \quad (2.38)$$

Thus, $TE_i = \exp(-\hat{u}_i)$ can be obtained from the equation. The specification has the advantage of allowing technical efficiency to vary over time and it is more flexible than the CSS model since it does not

restrict u_{it} to any particular parametric term. The problem with this approach lies in the fact that it is nonlinear and requires a more complicated estimator.

Kumbhakar (1990) specifies a form of $\alpha(t)$ to be

$$\alpha(t) = [1 + \exp(\gamma t + \delta t^2)]^{-1} \quad (2.39)$$

where $0 \leq \alpha(t) \leq 1$

and $\alpha(t)$ can be monotonically increasing or decreasing, concave or convex depending on the signs and magnitudes of the parameters γ and δ . Principally, Kumbhakar's specification only requires two additional parameters to be estimated, γ and δ , compared to $N \cdot 3$ additional parameters in CSS model and T-1 additional parameters in Lee and Schmidt model.

Kumbhakar (1990) and Battese and Coelli (1992) proposed alternative parameterization which specify a form of $\alpha(t)$ to be

$$\alpha(t) = [\exp -\eta(t - T)] \quad (2.40)$$

where $\alpha(t)$ is non-negative and decreasing at an increasing rate if $\eta > 0$, increasing at an increasing rate if $\eta < 0$ and constant if $\eta = 0$. The case in which η is positive is likely to be appropriate when producers improve their level of technical efficiency over time. The exponential specification of the behaviour of the producer effects over time (equation (2.40)) is a rigid parameterization in that technical efficiency must either increase at a decreasing rate ($\eta > 0$), decrease at an increasing rate ($\eta < 0$) or remain constant ($\eta = 0$). In order to allow greater flexibility in the nature of technical efficiency, a two-parameter specification would be required. An alternative two-parameter specification of $\alpha(t)$ proposed by Battese and Coelli (1992) allows the nonmonotonic variation of technical efficiency and is defined as:

$$\alpha(t) = 1 + \eta_1(t - T) + \eta_2(t - T)^2 \quad (2.41)$$

where η_1 and η_2 are unknown parameters. This model permits firm effects to be convex or concave, but the time-invariant model is the special case in which $\eta_1 = \eta_2 = 0$.

2.6.2.3.5 Model That Separate Firm Heterogeneity from Inefficiency

A notable drawback of the above time-invariant and time-varying panel data models is their limitation in the presence of unobserved time-invariant heterogeneities. In the time-varying fixed- and random-effects model, u_{it} is supposed to capture all but only time-invariant and time-varying inefficiency. In the presence of any time-invariant heterogeneity, they will be absorbed into u_{it} . Thus, any time-invariant heterogeneity will be pushed into α_i and ultimately into \hat{u}_i . Like the time-invariant fixed-effects model, the time-varying fixed-effects model cannot include any time-invariant heterogeneity due to the LSDV estimator as well. Therefore, the above panel data models must be modified to address the presence of time-invariant heterogeneities. Greene (2005a, b) explored the issue by reformulating the stochastic frontier specifically with the introduction of the ‘true’ (in his term) fixed-effects and random-effects model for panel data. The proposed models, viz., the ‘true-fixed’ and ‘true random’ effects frontier models separate producer effects (fixed or random) from inefficiency, where inefficiency can either be *iid* or can be a function of exogenous variables⁸.

The ‘true’ fixed-effects following Greene (2005) is written as

$$y_{it} = \alpha_i + \beta x_{it} + v_{it} - u_{it} \quad (2.42)$$

where α_i is the producer specific intercept intended to capture all the time-invariant heterogeneities. This form retains the distributional assumptions of the stochastic frontier model, allows for freely time varying inefficiency, and allows the heterogeneity term to be correlated with the included variables. Regressors, inefficiency term and random error term are mutually uncorrelated. Within groups the least squares estimation of this model still produces consistent estimates of β , but loses the important information in the model about u_{it} . Maximum likelihood estimation is considered for the estimation of the model. Unlike the

⁸ Battese and Coelli (92) or Greene (2005) models have become popular among researchers because they are less restrictive in that they both allow inefficiency to change over time.

usual fixed-effects specification, in which the fixed effects are interpreted as inefficiency, the fixed effects in Greene's model represent the unobserved heterogeneity.

An alternative proposed by Greene (2005) is a 'true' random effects form. It is specified as

$$y_{it} = \alpha + \omega_i + \beta x_{it} + v_{it} - u_{it} \quad (2.43)$$

u_{it} , v_{it} and ω_i are assumed to be uncorrelated with each other. In the "true" random-effects model, ω_i (which is assumed to have an iid normal distribution) is a time-invariant and producer-specific random term variable meant to capture unobserved heterogeneity or producer specific heterogeneity. Time variation in inefficiency is achieved by removing restrictions on u_{it} and allowing it to vary unsystematically through time⁹

The model of Kumbhakar and Hjalmarrsson¹⁰ (1993) is essentially that in equation (2.43). However, their interpretation and estimation method differ substantially. While in Greene's 'true' random-effects model, MLE is used straightforwardly to estimate all the parameters Each of our formulations reinterprets the time invariant term as firm specific heterogeneity, rather than as the inefficiency. If, in fact, the inefficiency for any firm is time invariant, or nearly so, the models will accommodate that without assuming it. Kumbhakar and Hjalmarrsson (1993) use a two-stage estimation strategy in which within group (LSDV) OLS or feasible GLS is used to estimate parameters followed by MLE of v_{it} and u_{it} with distributional assumption provided.

2.6.2.3.6 Model Separate Persistence and Time-Varying Inefficiency

Although some of the models discussed above (Greene (2005) The "true fixed effect" and "true random effect" models) can separate firm-heterogeneity from time-varying inefficiency, these models fail to consider persistent technical inefficiency. Recognizing the extent of persistence inefficiency is essential,

⁹ Detailed steps of MLE estimation are provided in Greene (2005:24-25).

¹⁰ See Kumbhakar and Lovell, 2000 for detail.

particularly in short panels, because it shows the effect of input like management (Mundlak, 1961) as well as other unobserved inputs which vary across firms but not over time. Therefore, provided there is a change that affects the management style of individual firms, such as a change in government policy toward the industry, a change in firm-ownership etc., it is improbable that the persistent inefficiency components will change. By contract, the residual components of inefficiency might change over time without any change in the operation of the firm. Hence, a clear distinction between persistent and residual components of inefficiency is important in efficiency analysis in that a utility generator might eliminate part of its inefficiency by removing some of the short-run rigidities, while some other sources of inefficiency might stay with the firm over time. Unless persistent inefficiency is reduced, utility generators might not be able to survive in the long run, especially if competitors are more efficient.

Kumbhakar, Lien and Hardbaker (2014), (KLH, hereafter) deals with the persistent inefficiency by specifying a four-way error component model. The model separates time-invariant (persistent) inefficiency components from time-invariant heterogeneity. The model is a modified and extended version of a model proposed by Kumbhakar, and Heshmati (1995), in which technical inefficiency is assumed to have a persistent firm-specific (time-invariant) component and a time-varying residual component. The extended model includes separate four components; two which are stochastic inefficiency terms (residual and persistent inefficiencies) and the other two are time invariant heterogeneity and idiosyncratic error terms. The four-way error component model written as follows;

$$y_{it} = \alpha_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \mu_i + v_{it} + \eta_i + u_{it} \quad (2.44)$$

where μ_i , is the inter-firm unobserved heterogeneity, which is a time-invariant random error assumed to be a zero mean, constant variance normally distributed random variable, $\mu_i \sim Nid(0, \sigma_\mu^2)$, v_{it} is the idiosyncratic error, which is a time-varying random error assumed to be a zero mean, constant variance normally distributed random variable, $v_{it} \sim Nid(0, \sigma_v^2)$. η_i is time-invariant inefficiency, which is a time-invariant random error assumed to be a zero mean, constant variance normally or exponentially distributed random

variable truncated below at zero, $\eta_i \sim Nid^+(\mu, \sigma_\eta^2)$ or $f(\eta) = \sigma_\eta \exp(-\sigma_\eta^2 \eta)$. u_{it} time-varying inefficiency, which is a time-varying random error assumed to be a zero mean, constant variance normally or exponentially distributed random variable truncated below at zero, $u_{it} \sim Nid^+(\mu, \sigma_u^2)$ or $f(u) = \sigma_u \exp(-\sigma_u^2 u)$.

2.6.2.3.7 Stochastic Frontier Models with Heteroscedasticity

The original half normal model of Aigner et al. (1977) is based on the assumptions that the v_{it} and the pretruncated u_{it} are homoscedastic, that is, both parameter σ_v^2 and σ_u^2 are constant. However, there may be no reason to assume that this is so in reality. Heteroscedasticity can appear in either of the error components, and it affect inferences concerning production technology parameters, as well as the parameters of either error component. Wang and Schmidt (2002) posit that unlike a classical linear regression model in which heteroscedasticity affects only efficiency of the estimators and not their consistency, ignoring heteroscedasticity leads to inconsistent parameter estimates. The summary of the consequences of ignoring the heteroscedasticity as discussed in Kumbhakar and Lovell (2000, section 3.4) are as follows: (a) ignoring heteroscedasticity of the symmetric error term v_{it} gives consistent estimates of the frontier function parameters (β). Heteroscedasticity refers to models in which variances are functions of covariates that are both firm specific and time varying, except that the intercept (α) is downward biased. Estimates of technical efficiency will also be biased. (b) ignoring heteroscedasticity of the one-sided technical inefficiency error component u_{it} causes biased estimates of both the parameters of the frontier function and the estimates of technical efficiency. Moreover, the idiosyncratic error component might be heteroscedastic if the sources of noise vary with the size of the producers, and the inefficiency error component might be heteroscedastic, as expected, if the sources of the inefficiency vary with the size of producers. Thus, it is desirable to examine the sources of consequences of heteroscedasticity in either of the error component.

Extending the half normal model of Aigner et al. (1977) to allow for heteroscedasticity in both the one-sided technical inefficiency error component and in the symmetric noise term. This model is frequently termed the doubly heteroscedastic model in the literature. It is specified as;

$$y_{it} = \alpha + x'_{it}\beta + v_{it} - u_{it} \quad (2.45)$$

$$u_{it} \sim N^+(\mu, \sigma_{it}^2) = N^+(\mu, \exp(\omega_{u0} + \mathbf{z}'_{u,it} \boldsymbol{\omega}_u)) \quad (2.46)$$

$$v_{it} \sim N(0, \sigma_{v,it}^2) = N(0, \exp(\omega_{v0} + \mathbf{z}'_{v,it} \boldsymbol{\omega}_v)) \quad (2.47)$$

In the variance function ω_{u0} is a constant term, the $\mathbf{z}'_{u,it}$ vector includes exogenous variables associated with variability in the technical inefficiency function, and $\boldsymbol{\omega}_u$ is the corresponding coefficient vector. Similarly, ω_{v0} is the constant term, the vector $\mathbf{z}'_{v,it}$ includes exogenous variables (that can be time varying) associated with variability in the noise term, and $\boldsymbol{\omega}_v$ is the corresponding coefficient vector.

Caudill and Ford (1993); Caudill et al. (1995); Hadri (1999) propose that heteroscedasticity can be parameterised by a vector of observable variables and associated parameters. This involves using possible to use (2.45)–(2.47) and changing (2.46) to u_{it}

$$u_{it} \sim N^+(0, \sigma_{it}^2) = N^+(0, \exp(\omega_{u0} + \mathbf{z}'_{u,it} \boldsymbol{\omega}_u)) \quad (2.48)$$

Alternatively, we can consider a further generalization in which both the mean and variance of u are functions of z variables (Wang 2002)

$$u_{it} \sim N^+(\mu_{it}, \sigma_{it}^2) = N^+(\delta_0 + \mathbf{z}'_{it}\delta, (\exp(\omega_{u0} + \mathbf{z}'_{u,it} \boldsymbol{\omega}_u))) \quad (2.49)$$

Wang (2002) showed that parameterizing both the mean and variance of the one-sided technical inefficiency error component allows non-monotonic efficiency effects, which can be useful for understanding the relationships between the inefficiency and its exogenous determinants. The models of Huang and Liu (1994)

and Battese and Coelli (1995), in which variances are assumed to be constant, are special cases of the Wang model.

2.6.3 Distance Functions

The methodological review of the frontier techniques above is centred on the production technology specification with one output and multiple inputs. However, when there are many outputs, another approach that has proved useful to the multiple output production function is provided by the distance function. An advantage of using the distance function is that it does not require price data or explicit behavioural assumptions. This can be compared with another alternative approach where output prices and behavioural assumptions are used to estimate a multiple output production function by modelling both technical and allocative efficiency (Kumbhakar et al, 2015). The two approaches to modelling distance functions are the input distance function and output distance function, which are discussed below.

2.6.3.1 Input Distance Function

The input distance suggests the degree to which an input exceeds the input requirement for production of output. Shephard's (1953) input distance function can be algebraically expressed as:

$$D_I(\mathbf{y}, \mathbf{x}) = \max_{\rho} \{\rho \mid f(\mathbf{x}/\rho) \geq y\} \quad (2.50)$$

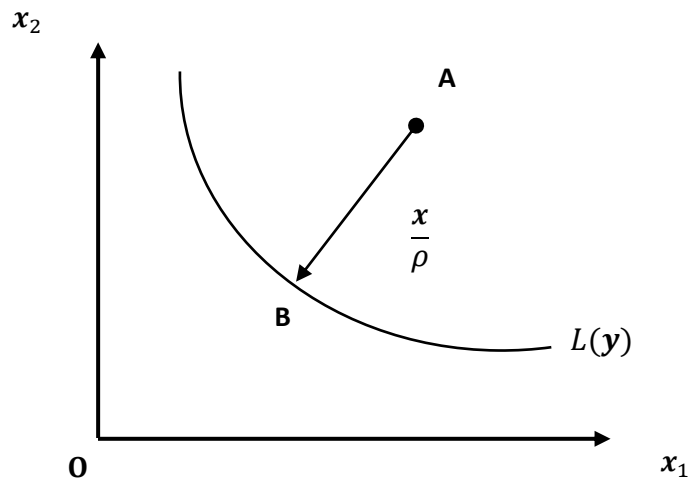
It is clear that $D_I(\cdot) \geq 1$. Also, $D_I(\cdot)$ is homogenous of degree 1 in \mathbf{x} , and concave in \mathbf{x} . If there are multiple output and input, the input distance function is defined as;

$$D_I(\mathbf{y}, \mathbf{x}) = \max_{\rho} \{\rho \mid f(\mathbf{x}/\rho) \in L(\mathbf{y})\} \quad (2.51)$$

Where $L(\mathbf{y})$ is the input requirement set. McFadden (1978) indicates that in order for the technology to qualify for an input-oriented distance frontier, the following regularity properties must ensure: $D_I(\cdot)$ must

be non-decreasing in \mathbf{x} , homogeneity of degree 1 in feasible input vector \mathbf{x} , concave in \mathbf{x} and non-increasing in \mathbf{y} . Figure 2.2 illustrates the case of two inputs and a single output.

Figure 2.2: Input Distance Function: Two Inputs and a Single Output



The input distance function is a function of x and y which can be only be separated by the imposing the homogeneity restriction. One way of imposing these restrictions is to normalize the function by one of the inputs Thus, for example, $D = f(\mathbf{y}, \mathbf{x})$ is an input distance function if it homogenous degree of one in \mathbf{x} . This can be written as;

$$\frac{D}{x_1} = f\left(\frac{x_2}{x_1}, \dots, \frac{x_k}{x_1}, \mathbf{y}\right) \quad (2.52)$$

Specifying input distance function in translog functional form we can write the distance function $D = (\mathbf{y}, \mathbf{x})$ as;

$$D_I x_1^{-1} = f(\tilde{\mathbf{x}}, \mathbf{y}) \quad \text{where } \tilde{\mathbf{x}} \left(\frac{x_2}{x_1}, \dots, \frac{x_k}{x_1}\right) \quad (2.53)$$

Taking the log of both sides give $\ln D_I - \ln x_1 = \ln f(\tilde{x}, y)$. Assuming a translog functional form on $f(\tilde{x}, y)$ yields

$$\begin{aligned} \ln D_I - \ln x_1 &= \alpha_0 + \sum_{k=2}^K \beta_k \ln \tilde{x}_k + \sum_{m=1}^M \alpha_m \ln y_m \\ &+ \frac{1}{2} \left[\sum_k \sum_l \beta_{kl} \ln \tilde{x}_k \ln \tilde{x}_l + \sum_m \sum_n \alpha_{mn} \ln y_m \ln y_n \right] \\ &+ \sum_k \sum_m \delta_{km} \ln \tilde{x}_k \ln y_m \end{aligned} \quad (2.54)$$

where $\tilde{x}_k = x_k/x_1$

The required symmetry restrictions for the translog function are.

$$\beta_{kl} = \beta_{lk}, \quad k, l = 1, 2, \dots, k, \quad \text{and} \quad y_{mn} = y_{nm}, \quad m, n = 1, 2, \dots, M$$

To make this distance function stochastic a random error term, v , is added. Furthermore, denoting $\ln D_I = u \geq 0$ and re-arranging it to the right-hand side of the equation yields an estimable equation in which the error term is $v - u$.

$$\begin{aligned} -\ln x_1 &= \alpha_0 + \sum_{k=2}^K \beta_k \ln \tilde{x}_k + \sum_{m=1}^M \alpha_m \ln y_m \\ &+ \frac{1}{2} \left[\sum_k \sum_l \beta_{kl} \ln \tilde{x}_k \ln \tilde{x}_l + \sum_m \sum_n \alpha_{mn} \ln y_m \ln y_n \right] \\ &+ \sum_k \sum_m \delta_{km} \ln \tilde{x}_k \ln y_m + v - u \end{aligned} \quad (2.55)$$

Having expressed $-\ln D_I = \varepsilon = v - u$ shows that the distance term may be interpreted as a traditional frontier disturbance term. Implying that the distances in a distance function (which are the radial distances between the data points and the frontier) could be due to either noise (v) or technical inefficiency (u). Therefore, this model can be estimated using the standard production function approach subject to the

imposing of symmetry restriction in the above translog function. The properties of the input distance function are non-decreasing in inputs ($\partial \ln D_I / \partial \ln x_1 \geq 0$) and non-increasing in outputs ($\partial \ln D_I / \partial \ln y_m \leq 0$). The inputs and outputs partial elasticities imply that the estimated distance function is increasing in input and decreasing in output respectively. Therefore, a marginal increase in outputs given all other variables unchanged implies an improvement in efficiency i.e. a decrease in distance.

2.6.3.2 Output Distance Function

The output distance function measures the distance between an observed level of output relative to the maximum attainable output (on the frontier), using a given input requirement set. In other words, the output distance suggests the degree to which output falls short of what can be produced with a given input vector.

Output distance function for a single output case can be algebraically defined as;

$$D_o(\mathbf{y}, \mathbf{x}) = \min_{\theta} \{ \theta \mid (\mathbf{y}/\theta) \leq f(\mathbf{x}) \}. \quad (2.56)$$

It is clear that $D_o(.) \leq 1$. For multiple outputs and multiple inputs, the output distance function is defined as;

$$D_o(\mathbf{y}, \mathbf{x}) = \min_{\theta} \{ \theta \mid (\mathbf{y}/\theta) \in V(\mathbf{x}) \}. \quad (2.57)$$

where $V(\mathbf{x})$ denotes the sets of output vectors that are feasible for each input vector \mathbf{x} .

The output distance function seeks the largest proportional increase in the observed output vector \mathbf{y} provided that the expanded vector (\mathbf{y}/θ) is still an element of the original output set (Grosskopf et al 1995). $D_o(\mathbf{y}, \mathbf{x})$ is homogeneous of degree 1 in outputs, and is a convex function in \mathbf{y} . The properties of $D_o(.)$ are as follows non-decreasing in \mathbf{y} , homogeneity of degree 1 in feasible input vector \mathbf{y} , concave in \mathbf{y} and non-increasing in \mathbf{x} .

Figure 2.3: Output Distance Function: Single Input and Two Outputs

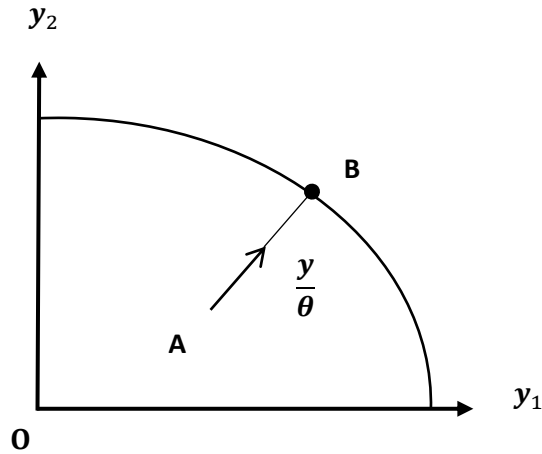


Figure 2.3 illustrates the case of a single input and two outputs \mathbf{y} , concave in \mathbf{y} and non-increasing in \mathbf{y} .

Like the input distance function, the output distance function of \mathbf{x} and \mathbf{y} , the only way to separate them is through the homogeneity restriction. One way of imposing these restrictions is to normalize the function by one of the outputs. Therefore, given $D = f(\mathbf{y}, \mathbf{x})$ is output distance if we impose linear homogeneity restriction on \mathbf{y} and it is written as;

$$\frac{D}{y_1} = f\left(\mathbf{x}, \frac{y_2}{y_1}, \dots, \frac{y_m}{y_1}\right), \quad (2.58)$$

Having imposed linear homogeneity conditions, we can re-write the distance function $D = (\mathbf{y}, \mathbf{x})$ as

$$D_0 y_1^{-1} = f(x, \tilde{\mathbf{y}}) \quad \text{where } \tilde{\mathbf{y}} = \left(\frac{y_2}{y_1}, \dots, \frac{y_m}{y_1}\right) \quad (2.59)$$

Taking the log of both sides gives $\ln D_0 - \ln y_1 = \ln f(x, \tilde{\mathbf{y}})$. Assuming a translog functional form on $f(x, \tilde{\mathbf{y}})$ yields

$$\begin{aligned}
\ln D_0 - \ln y_1 &= \alpha_0 + \sum_k \beta_k \ln x_k + \sum_m \alpha_m \ln \tilde{y}_m \\
&+ \frac{1}{2} \left[\sum_k \sum_l \beta_{kl} \ln x_k \ln x_l + \sum_m \sum_n \alpha_{mn} \ln \tilde{y}_m \ln \tilde{y}_n \right] \\
&+ \sum_k \sum_m \delta_{km} \ln x_k \ln \tilde{y}_m
\end{aligned} \tag{2.60}$$

where $\tilde{y}_m = y_m/y_1$

The required symmetry restrictions for the translog function are

$$\beta_{kl} = \beta_{lk}, \quad k, l = 1, 2, \dots, K, \quad \text{and} \quad \alpha_{mn} = \alpha_{nm}, \quad m, n = 1, 2, \dots, M$$

Like input distance function, we use the translog output distance function can be made stochastic by the idiosyncratic error term v . In addition, denoting $\ln D_0 \leq 0$ by $-u$ and moving it to the right-hand side of the equation results in an estimable equation in which the error term is $v + u$.

$$\begin{aligned}
-\ln y_1 &= \alpha_0 + \sum_k \beta_k \ln x_k + \sum_m \alpha_m \ln \tilde{y}_m \\
&+ \frac{1}{2} \left[\sum_k \sum_l \beta_{kl} \ln x_k \ln x_l + \sum_m \sum_n \alpha_{mn} \ln \tilde{y}_m \ln \tilde{y}_n \right] \\
&+ \sum_k \sum_m \delta_{km} \ln x_k \ln \tilde{y}_m + v + u
\end{aligned} \tag{2.61}$$

where the v is assumed to be independently and identically distributed (*iid*) as $N(0, \sigma^2)$, intended to capture statistical noise. $u = -\ln D_0$ is a non-negative random variable, intended to capture technical inefficiency. The output distance function is non-decreasing in output and non-increasing in input with an associated negative sign for the output elasticities and positive signs of input elasticities. These are interpreted to mean that the distance function is increasing in outputs and decreasing in inputs.

2.7 Conclusions

This chapter documents the literature review of the thesis under two broad categories; the overview of power sector reform and the methodological framework. The discussions on the overview of power sector reform cover theoretical descriptions, structures, as well as the review of empirical studies on electricity market reform. Specifically, the empirical review shows a wide range of studies based on econometric approach and efficiency and productivity analysis. The methodological framework touches on the concept of efficiency and the various efficiency measurement techniques. In particular, it focuses on the detail discussions of stochastic frontier models, especially the latest development in panel data stochastic frontier models which form the bedrock of the empirical study. Overall, it is revealed by a good number of studies on efficiency and productivity analysis that the impact of deregulation on efficiency has been largely mixed. Indeed, this may have been caused by how the models employed in the studies are structured to capture inefficiency. At any rate, in the next three chapters, we revisit the debate on the impact of power sector reform on production and cost efficiency.

Chapter 3: Efficiency and Productivity of Cross–Country Electricity Generation: A Distance Function Approach

3.1 Introduction

Electricity plays an essential role in the nation's economy. Its versatility is unparalleled enabling consumers to power homes, offices, and industries; it provides communications, entertainment, and medical services; powers computers, technology, and the internet; and it runs various forms of transportation. Not only is electricity the cleanest, most flexible, and most controllable form of energy, it's the only energy type that allows for easy and relatively cheap transportation over long distances and convertibility to other types of energy needed at the point of consumption: thermal or mechanical (Vaninsky, 2008). The reliability of electric power supply is one of the primary motivating factors for technical innovation and change in market organization (Chen & Yee, 2013).

The electricity sector is categorised based on the features of the constituent activities, namely generation, transmission, distribution and supply, and they are differentiated technologically and economically. Prior to the advent of power market reform, the power industry was characterised by vertical integration of these constituent segments within individual electric utilities, usually publicly owned and run by government. The firm that generates electricity also transmits it over high voltage lines and retails it to end users. These utilities in turn had, in actual fact, exclusive franchises to supply electricity to residential, commercial and industrial retail consumers within a defined geographic area (Delmas & Tokat, 2005; Joskow, 2008). The initial structural arrangement of the electric utility industry was hinged on the supposition that a central source of power supplied by efficient, low-cost utility generation, transmission, and distribution was a natural monopoly.

Electricity supply industry reform which began in Chile and UK in the earlier 1980s has gained international acceptance, and more than half the world's countries have introduced institutional policy reform agendas in their electricity sectors. These power sector policy reform instruments have included deregulation, restructuring, privatization and the introduction of incentive-based regulation by independent regulatory agencies (Newbery 2002). The market reform leads to an opening-up of certain segments such as generation and retail to competition which have been regarded as potentially competitive segments, whilst the transmission and distribution networks are viewed as natural monopoly activities that need to be regulated. Different compelling rationales have been widely recognized as driving the implementation of power sector reform in developed and developing countries. In developed economies the primary aim of electricity sector reform is to increase economic efficiency of a well-developed industry by competition. Conversely, the objectives for power policy reforms in developing countries typically extend beyond the concern for economic efficiency gains that characterises the developed countries to include, among other things, the poor performance of state-owned power companies, low service quality, low collection rate, the need to expand electrification, high network losses, the need to reduce or eliminate the fiscal stress from state involvement and the desire to increase mobile financing through the sale of power companies (Zhang et al., 2008, Ghanadan and Williams, 2006; Bacon and Besant-Jones, 2001).

According to economic theory, market oriented reforms will generate considerable efficiency gains for an economy as competition energizes firms to seek productive efficiency gains and produce at lowest unit costs. These arguments usually focus on allocative efficiency while the implications of competition for technical efficiency are less clear (Fabrizio et al, 2007) as the ex-post deregulation impacts have been contentious. X-inefficiency theory asserts that under conditions of less-than-perfect competition, firms will not operate on an outer-bound production possibility surface consistent with their resources because of workers' utility-maximizing trade-off between effort and leisure. However, under perfect competition firms can maximize efficiency and improve productivity (Leibenstein, 1966). This is also related to agency theory which recognises the interplay of asymmetric information and regulation with the tendency of inducing

inefficiency, whereas market competition makes firms residual claimants to cost-savings, thereby increasing incentives for efficiency-enhancing effort (Laffont and Tirole, 1993). The monopolistic utilities (the agents) have private information about their ability to transform inputs into outputs. As society (the principal) wants a guaranteed service at the lowest price possible, the utilities can extract information rents. Property rights theory equally argues that the ownership of assets matters as it provides decision-makers with different rights to the use of economic resources, thereby reducing transaction costs in exchange and production, and encouraging investment to promote overall economic growth (Alchian, 1965; Libecap, 1989). Thus a change in allocation of property rights will affect incentive structure, and hence, efficiency. However, whether power market reform guarantees a technical efficiency gain in the electricity industry still remains an empirical question. As noted by Bauer et al. (1998), policy makers are more particularly concerned about the potential impact of their decisions on performance of firms. Thus, an inefficient firm is viewed as wasting inputs as maximum attainable output is not produced at a given quantity of inputs used.

Given that electricity deregulation has evolved over the last three decades, there are still some mixed feelings regarding its impact on technical efficiency and productivity. Efficiency and productivity analyses of the industry which incorporates an analysis of deregulated and regulated countries is vitally important to help make informed and evidence-based decisions about reform impacts. We evaluate the performance of electricity generation and examine input requirement efficiency of 91 countries using stochastic input distance function. In addition, we investigate the impact of cross country specific characteristics to determine whether low efficiency countries can adopt deregulation policies of high efficiency countries by benchmarking their efficiency scores in order to improve their efficiency. We decompose the total productivity change in order to evaluate the impact of technical change, efficiency change and scale change. Efficiency measurement provides relevant information to the electricity supply industry and the policymakers. Therefore, it could serve strategic tool to identify best practices and success cases and to monitor performance.

The following section is a review of literature on the performance of electricity supply industry. Section 3.3 highlights the methodology and econometrics specification for the study. In Section 3.4 we present the overview of data used in the study. Section 3.5 gives the main findings of the empirical analysis. Section 3.6 discusses the conclusion and policy implications.

3.2 Literature Review

An attempt has been made by a good number of studies across the world to establish the benefits of market reform in the electricity sector. Several empirical studies have investigated the resulting impact on economic performance. Indeed, efficiency and productivity analysis as a measurement of firm performance has gained considerable traction in the literature. Different alternative approaches for estimating firm efficiency are stochastic frontier analysis (Hattori, 2002; Farsi and Filippini, 2004; Barros and Managi, 2009; Barros and Peypoch, 2007, 2008; Barros and Antunes, 2011; Kopsakangas-Savolainen and Svento, 2011; See and Coelli, 2012), data envelopment analysis, DEA, (Vaninsky, 2006; Nakano and Managi, 2008; Arocena, 2008; Zhou and Ang, 2008, Barros, 2008; Briec et al., 2011; Sueyoshi and Goto, 2011; Jaraite and Di Maria, 2012), and lately Stochastic Non-Smooth Data Envelopment, StoNED (Kuosmanen, 2012; Mekaroonreung and Johnson, 2012; Saastamoinen and Kuosmanen, 2015). Of course, there is a plethora of literature providing empirical analyses of firm efficiency based on parametric, non-parametric and semi parametric frontier approaches. A broad review of literature of these studies on firm performance and the SFA technique has been undertaken in Chapter 2. Here we will only focus on studies dealing with the performance of electricity generation sector.

Empirical analysis of efficiency performance within the electricity generation segment has been widely studied across the world. These studies include, among others, Arocena & Waddams-Price, 2002 on Spain, Barros (2008) on Portugal, Meibodi, 1998 on Iran; Coelli, 2002 on Australia, Coelli, 2012, See and Coelli (2012) on Malaysia, Vaninsky, 2006 on United State, Lam and Shiu (2004), Du et al. 2013 and Chen et al. 2015 on China, Domah, (2002) on 16 Small Island Economies; Jaraite and Di Maria (2012) on the European

Union and Chen et al 73 countries. While their findings have been mixed, most of these studies focus on investigating efficiency using plant level data. See and Coelli (2012) measure the technical efficiency levels of Malaysian thermal power plants and investigated the degree to which various factors influence efficiency levels in these plants using SFA from 1998 to 2005. The results indicate that ownership, plant size and energy type have a significant influence on technical efficiency levels. They also concluded that publicly-owned power plants obtain average technical efficiencies of 0.68, which is lower than privately-owned power plants, which achieve average technical efficiencies of 0.88. In the same vein, Du et al. (2013) evaluate the TFP of Chinese fossil-fired power plants using conventional SFA and conclude that the market reform in the electricity sector had significantly improved the efficiency. By contrast, Arocena & Waddams-Price (2002) examine generating efficiency of Spanish public and private electricity generators using data from 1984 – 1997. The research findings challenge some of the conventional wisdom on productive efficiency in the public and private sectors under both cost of service and incentive regulation as publicly owned generators were more efficient under cost of service regulation; private (but not public) firms responded to incentive regulation by increasing efficiency, bringing their productivity to similar levels.

Vaninsky (2006) estimated the efficiency of electric power generation in the United States for the period of 1991 through 2004 using Data Envelopment Analysis (DEA). Their results point to a relative stability in efficiency from 1994 through 2000 at levels of 99–100% with a sharp decline to 94–95% in the years following. Barros (2008) estimated changes in total productivity on the hydroelectric energy generating plants of Portugal Electricity Company by means of data envelopment analysis (DEA). He concluded that some plants experienced productivity growth while others experienced a decrease in productivity. Meibodi (1998) estimated technical efficiency in electricity generation using Iranian data and data from the World Bank and arrives at a similar conclusion. The study suggested that market reforms, such as privatisation were not a good choice to resolve their industry's problems and to reach the production frontier.

Focusing on cross country efficiency gains Jaraite and Di Maria (2012) measure the environmental efficiency and the productivity growth registered in public power generation across the EU over the 1996–2007 period using Data Envelopment Analysis methods. Their results suggest an increase in environmental efficiency and a shift outward of the technological frontier. More recently, Chen et al. (2013) find that Asia enjoys the highest and European countries suffer from the lowest technical efficiency among Europe, Asia, and America continents. However, Domah, (2002) conducts a comparative technical efficiency analysis of electricity generators in 16 small island economies using panel data, both DEA and SFA. The results indicate neither apparent differences in the production structure between islands and non-islands electric utilities, nor any evidence suggesting that they are less technically efficient.

It is commonplace to use samples of domestic utilities as efficiency analysis requires comparability of firms. However, international comparative analysis has been recognised as a veritable channel to evaluate the performance of national utilities within the larger context of international practice (See Jamasb, 2002). Therefore, regardless of the contribution of the recent efficiency studies of impact of deregulation electricity generation, there appears a scope for broader analysis at the level of a cross country. More specifically, it would also seem that there is potential for disentangling unobserved heterogeneity from technical efficiency so as to measure the efficiency of each country relative to the frontier country. For this reason, this study considers national electricity generation data of 91 countries which makes our estimation results more inclusive and reliable. In addition to the traditional SFA models (Battese and Coelli, 1992; Pit and Lee, 1981), the paper employs the Greene (2005a) ‘true fixed effect and true random effect model’ to estimate the efficiency of electricity generation. The models have the advantage of separating unobserved heterogeneity among sample countries from technical inefficiency. Estimating country level efficiency will serve as a policy guide to development institutions for policy formulation and efficiency benchmarking. More specifically, the significance of our research is that it allows us to find out whether deregulation is being measured by unobserved heterogeneity rather efficiency components, thus a compelling insight into the understanding of efficiency gains from electricity deregulation reforms.

3.3 Methodology

3.3.1 Modelling relative efficiency

First introduced by Aigner et al (1977) and Meesuen and van den Broeck (1977), stochastic frontier approach (SFA) has been widely used in the efficiency literature. These models allow for technical inefficiency, while acknowledging the fact that random shocks outside the control of producers can affect the output of the producer. By incorporating a composed error term, they separate the traditional two-sided error term which captures random noise from the one-sided error term which measures technical inefficiency. The performance of the electricity generation sector is given as the ability of the electricity generation plant to transform input resources into output. The efficiency measures are relative in nature, such that each efficiency measure reveals how well a country is performing as opposed to other countries. Using SFA allows the construction of a best-practice frontier and an evaluation of the degree to which a country could potentially reduce input resource use relative to the efficient frontier, holding output constant. Given that we are concerned with the potential input saving, we consider an input distance function¹¹. The choice of an input distance function rather than an output distance function is driven by the nature of production and regulation in the electricity generation industry¹².

A production technology may be defined using the input set, $L(y)$, denotes all those input vectors, x , that are technologically feasible which can produce the output vector y , i.e.

$$L(y) = \{x \in \mathfrak{R}_+^K: x \text{ can produce } y\} \quad (3.1)$$

¹¹ An output distance function measures efficiency by taking an output orientation where efficiency is improved by increasing output at a given level of exogenous inputs (see Saal et al., 2007)

¹² This modelling choice is consistent with Coelli et al (2003), which argue that input distance functions are the appropriate specification in network industries, where it is common for demand to be directly outside of the control of managers.

Suppose a country employs K input vector $\mathbf{x} \in \mathfrak{R}_+^K$ to produce M output vector $\mathbf{y} \in \mathfrak{R}_+^M$. We represent the production technology that satisfies the standard axiom such as convexity, strong disposability, closedness and boundedness in Fare and Primont (1995) at time t by the input distance function as,

$$D_{it}(\mathbf{y}, \mathbf{x}, t) = \max_{\rho} \{ \rho \mid f(\mathbf{x}/\rho) \in L(\mathbf{y}) \} \quad (3.2)$$

$D_I(\mathbf{y}, \mathbf{x}, t)$ is non-decreasing, positively linearly homogenous and concave in \mathbf{x} and increasing in \mathbf{y} (Coelli and Perelman 1999). ρ is the scalar distance by which the input vector can be deflated.

Since the value of the input distance function equals one if a country is on the efficient production frontier, and exceeds one where the country is inefficient, $D_I \geq 1$ and so,

$$\begin{aligned} \ln D_{it}(\mathbf{y}, \mathbf{x}, t) - u &= 0, \\ u &\geq 0, \end{aligned} \quad (3.3)$$

The inverse of the input distance function D_I is a measure of Farrell input based efficiency of the countries. The non-negative variable $u \geq 0$ corresponds to the inefficient slack in the use of inputs by the country relative to other countries; it is the feasible contraction in inputs which will project an inefficient producer on to the efficient frontier of the input requirement set.

Following McFadden (1978:32) and Kumbhakar and Lovell (2000:32), in order for the technology to qualify for an input-oriented distance frontier, the following regularity properties must be satisfied;

- (i). non-decreasing in \mathbf{x} , $\partial \ln D_I / \partial \ln x_k \equiv ex_k \geq 0$, $k = 1 \dots K$, where ex_k is the k th input elasticity
- (ii) homogeneity of degree one in \mathbf{x} , $D_I(\mathbf{y}, \mathbf{x}/x_k, t) = D_I(\mathbf{y}, \mathbf{x}, t)/x_k$
- (iii) concave in \mathbf{x}
- (iv) non-increasing in \mathbf{y} , $\partial \ln D_I / \partial \ln y_m \equiv ey_r \leq 0$, $r = 1 \dots R$, where ey_r is the m th output elasticity

(iv) scale elasticity of the production technology is at time t is

$$E_t = - \left(\sum_{k=1}^{k=M} \partial \ln D_i / \partial \ln y_m \right)^{-1} \equiv - \left(\sum_{k=1}^{k=M} e y_m \right)^{-1}$$

3.3.1.1 Translog Input Distance Function

Following Coelli and Perelman (1999), I use the translog functional form¹³ with M output (\mathbf{y}), K inputs (\mathbf{x}) and time t , $t = 1, 2, \dots, T$, and written as:

$$\begin{aligned} \ln D_{it} = & \alpha_0 + \sum_{m=1}^M \alpha_m \ln(y_{mit}) + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln(y_{mit}) \ln(y_{nit}) \\ & + \sum_{k=1}^K \beta_k \ln(x_{kit}) + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln(x_{kit}) \ln(x_{lit}) \\ & + \sum_{k=1}^K \sum_{m=1}^M \delta_{km} \ln(x_{kit}) \ln(y_{mit}) + \psi_t t + \frac{1}{2} \psi_t t^2 \\ & + \sum_{k=1}^K \varphi_{kt} \ln(x_{kit}) t + \sum_{m=1}^M \theta_{mt} \ln(y_{mit}) t + \sum_{j=1}^J \pi_j \mathbf{z}_{jit} \end{aligned} \quad (3.4)$$

Where D_{it} represents an input distance, ($i= 1, 2, \dots, N$). T is a time trend variable that captures the time varying effect across an individual country in a specified time period. \mathbf{z}_{it} denotes the exogenous characteristics which are assumed to have a direct linear influence on the production structure. In other words, each firm faces a different production frontier at each period given the effect of exogenous factors. The regularity properties as mentioned above require translog input distance function in equation (3.4) to be symmetric and homogeneous of degree +1 in input, viz.,

¹³ In order to provide a good approximation to the input distance function while preserving the availability of degrees of freedom, and to avoid multicollinearity problems, the choice of the functional form in which the input distance function is specified should obtain a balance between flexibility and parsimony. While the Cobb-Douglas specification is acknowledged to be too restrictive, the first-best option is to consider a translog flexible functional form, because it represents a second-order approximation of any arbitrarily chosen function, as well as being theoretically possible (See Berndt and Christensen, 1973).

$$\sum_{k=1}^K \beta_k = 1; \quad k, = 1, 2, \dots, K \quad (3.5a)$$

$$\sum_{k=1}^K \beta_{kl} = 0; \quad k, = 1, 2, \dots, K$$

$$\sum_{k=1}^K \beta_{km} = 0 \quad m, = 1, 2, \dots, M \quad (3.5b)$$

those required for symmetry are:

$$\alpha_{mn} = \alpha_{nm} \text{ and } \beta_{kl} = \beta_{lk} \quad (3.6)$$

The property of homogeneity of degree 1 in inputs restriction is empirically imposed by normalising all but one of the inputs in equation (3.4) by the remaining input which yield the following;

$$\begin{aligned} \ln(D_{li}/x_{Kit}) &= \alpha_0 + \sum_{m=1}^M \alpha_m \ln(y_{mit}) + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln(y_{mit}) \ln(y_{nit}) \\ &+ \sum_{k=1}^K \beta_k \ln(x_{kit}/x_{Kit}) + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln(x_{kit}/x_{Kit}) \ln(x_{lit}/x_{Kit}) \\ &+ \sum_{k=1}^K \sum_{m=1}^M \delta_{km} \ln(x_{kit}/x_{Kit}) \ln(y_{mit}) + \psi_t t + \frac{1}{2} \psi_{tt} t^2 \\ &+ \sum_{k=1}^K \varphi_{kt} \ln(x_{kit}/x_{Kit}) t + \sum_{m=1}^M \theta_{mt} \ln(y_{mit}) t + \sum_{j=1}^J \pi_j z_{jit} \end{aligned} \quad (3.7)$$

The equation above can be re-arranged by moving $\ln D_{li}$ the right-hand side of the equation yielding a dependent variable in the regression analysis of $-\ln x_{Kit}$

$$\begin{aligned}
-\ln x_{Kit} = & \alpha_0 + \sum_{m=1}^M \alpha_m \ln(y_{mit}) + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln(y_{mit}) \ln(y_{nit}) \\
& + \sum_{k=1}^K \beta_k \ln(x_{kit}/x_{Kit}) + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln(x_{kit}/x_{Kit}) \ln(x_{lit}/x_{Kit}) \\
& + \sum_{k=1}^K \sum_{m=1}^M \delta_{km} \ln(x_{kit}/x_{Kit}) \ln(y_{mit}) + \psi_t t + \frac{1}{2} \psi_{tt} t^2 \\
& + \sum_{k=1}^K \varphi_{kt} \ln(x_{kit}/x_{Kit}) t + \sum_{m=1}^M \theta_{mt} \ln(y_{mit}) t + \sum_{j=1}^J \pi_j \mathbf{z}_{jit} - \ln D_{li} \quad (3.8)
\end{aligned}$$

Thus, by appending a symmetric error term v_{it} to account for statistical noise, and rewriting $\ln D_{li}$ as u_{it} , the stochastic output distance function can be obtained as follows;

$$-\ln x_{Kit} = TL(y, x/x_K, t)_{it} + \pi' \mathbf{z}_{it} + v_{it} - u_{it} \quad (3.9)$$

where $TL(y, x/x_K, t)_{it}$ denotes the technology as the translog approximation to the distance function; $\pi' \mathbf{z}_{it}$ captures the cross-country heterogeneity, where \mathbf{z}_{jit} represents the exogenous factors; v_{it} denotes the conventional idiosyncratic error term incorporating sampling error, measurement error and specification error; and (u_{it}) is the inefficiency component of the disturbance error¹⁴.

3.3.1.2 Model Specification

In modelling inefficiency measurement, u is treated as a random variable distributed across producers with a known asymmetrical probability density function. However, there is a debate whether the distribution should be time-invariant or time-varying. Greene (2005a) argues that time-invariance may be a property of latent heterogeneity amongst the firms or countries, and that inefficiency should be time-varying. First, we

¹⁴ See Section "2.6.3.1 Input distance function" for the interpretation of input and output partial elasticities.

investigate the issue of observed heterogeneity and its impact on technical efficiency. To achieve this, we consider the Battese and Coelli (1992) time varying model which relaxes the time invariant assumption of the inefficiency i.e. the persistency of inefficiency is a function that is constant across firms. The inefficiency is firm-specific and is allowed to vary through time, which follows pattern of temporal variation in the one-sided error term u_{it} expressed as follows;

$$\begin{aligned}
 -\ln x_{Kit} &= TL(y, x/x_K, t)_{it} + \pi' z_{it} + v_{it} - u_{it} \\
 u_{it} &= u_i f(t) \\
 f(t) &= \exp(-\eta(t - T)) \\
 v_{it} &\sim N(0, \sigma_v^2)
 \end{aligned} \tag{3.10}$$

where u_i is assumed independently and identically distributed as $N^+(0, \sigma_u^2)$ distribution and η is a parameter to be estimated. If η is not statistically significant, it can be constrained to zero so as to maximize the degree of freedom by estimating more parameters than needed. However, the time-varying pattern of inefficiency is the same for all individuals, so the perennial problem of inseparable inefficiency and individual heterogeneity remains.

While Battese and Coelli (1992) addresses the issue of time invariant inefficiency, none of the two models could account for unobserved heterogeneity. Greene (2005b) pointed out that if latent heterogeneity exists and not is adequately accounted for, all time-invariant heterogeneities will be pushed into the intercept term α_0 and finally into the inefficiency term. Thus, the inefficiency is picking up latent cross-country variation that is not in any way related to inefficiency. The inability of these models to estimate individual effects in addition to the inefficiency effect would bias efficiency scores. This drawback is addressed by the ‘true’ fixed-effect model and the ‘true’ random-effects model proposed by Greene (2005b). The purpose of the model is to disentangle firm heterogeneity or firm effect from technical efficiency. The True-Fixed Effects

model specifies separate intercept dummy variables for each unit in the sample, and specifies the asymmetric half normal distribution for the inefficiency component of the random error and the normal distribution for the idiosyncratic error component. The True-Random Effects model does not use dummy variables at all, but treats the regression constant term as a random parameter comprising the usual intercept and a random component. Thus, these models can be written as;

$$\begin{aligned}
 -\ln x_{Kit} &= \alpha_i + TL(y, x/x_{Kit}, T)_{it} + \pi' z_{it} + v_{it} - u_{it} \\
 u_i &\sim N^+(0, \sigma_u^2) \\
 v_{it} &\sim N(0, \sigma_v^2)
 \end{aligned} \tag{3.11}$$

where u_{it} is the time-varying inefficiency. If one treats α_i , $i = 1, \dots, N$ as fixed parameters which are not part of inefficiency then the above model becomes the ‘true fixed-effect’ panel stochastic model (Greene, 2005a). The model is called the true random effects stochastic frontier model when α_i does not correlate with the regressors. Thus, the stochastic term α_i is expressed as follow:

$$\alpha_i \sim N(0, \sigma_\alpha^2)$$

The models are estimated by maximum likelihood. Within the framework of the normal-half normal model, Jondrow et. al.’s (1982) conditional estimator of u_{it} is often used for estimation of inefficiency, u_{it} ;

$$\hat{u}_{it} = E[u_{it} | \varepsilon_{it}] \tag{3.12}$$

The predictions of technical efficiency¹⁵ index of individual country in each period is calculated as:

$$TE = \exp(-u_{it}) \tag{3.13}$$

¹⁵ The predicted values of technical efficiency lie between zero and one. The value of one implies that the firm lies on the boundary of the production possibility set

3.3.2 Parametric Total Productivity Growth

Building on the specification of the input distance function, our study aims at investigating changes in productivity growth over time using generalized Malmquist productivity index. We compute returns to scale, technical inefficiency, and productivity change from the estimated parameters. Productivity change, when there are multiple inputs, is measured by total productivity change. Orea (2002) notes that a TFP index which is generalized from the case of one input and one output should satisfy four properties: (i) identity, (ii) monotonicity, (iii) separability and (iv) proportionality. Identity requires that if inputs and outputs do not change the TFP index is unity. Monotonicity requires that the weighted output growth rates and input growth rates are chosen so that higher output and lower input unambiguously improve TFP. Separability, which is a property of the chosen technology set, permits the generalization to the multiple-output multiple-input case. Proportionality requires that the weights in the output and input growth indices sum to unity. Using a quadratic identity lemma to the input distance function (see Caves et al. 1982) and setting the negative log of the input distance as the technical efficiency i.e. $-\ln D_I(t) = \ln TE_I$, we obtain the expression which decomposes the TFP change into a scale component, a technical change component and a technical efficiency change component.

$$\begin{aligned} \ln \text{TFPC} = & [\ln TE_{I,t+1} - \ln TE_{I,t}] + \frac{1}{2} [(\partial \ln D_{I,t+1} / \partial t) + (\partial \ln D_{I,t} / \partial t)] \\ & + \left[\frac{1}{2} \sum_{m=1}^{m=M} ((ey_{m,t+1} SF_{t+1}^I) + (ey_{m,t} SF_t^I) (\ln(y_{m,t+1}/y_{m,t})) \right] \end{aligned} \quad (3.14)$$

TFPC is total factor productivity change; $ey_{m,t}$ is the column vector of the m th output elasticities at time t ;

The first term; $[\ln TE_{I,t+1} - \ln TE_{I,t}]$ measures efficiency change, the second term; $\frac{1}{2} [(\partial \ln D_{I,t+1} / \partial t) + (\partial \ln D_{I,t} / \partial t)]$ captures the technical change and the last term represents scale change. The post estimation of technical change and scale change are based on the coefficients of estimated parameters of the input distance

function i.e. the first order and second order elasticities and scale parameter. The time derivatives of the translog distance function (3.9) for the computation of technical change is obtained as:

$$\frac{\partial \ln D_{I,t}}{\partial t} = \psi_t + \psi_{tt}t + \sum_{k=1}^K \varphi_{kt} \ln x_{kit}/x_{Kit} + \sum_{m=1}^M \theta_{mt} \ln y_{mit}$$

SF_t^I is the input scale factor at time and it is defined as

$$SF_t^I = \left(\sum_{m=1}^{m=M} ey_{m,t} + 1 \right) / \left(\sum_{m=1}^{m=M} ey_{m,t} \right) = 1 - E_t \quad (3.15)$$

In other words, the decomposition of the TFP change into components of technical efficiency change, EC , technical change, TC , and scale change, SC in the Eq (3.14) can be expressed as;

$$TFPC = EC + TC + SC \quad (3.16)$$

Equation (3.16) provides a meaningful decomposition of total factor productivity change into three independent factors. The term EC measures changes in the value of the input distance function from one period to the next i.e. the term measures changes in technical efficiency. The term TC captures the shift in technology between two periods evaluated at two different observed output and input vectors. The term SC measures the contribution of return to scale economies to productivity growth.

3.4 Data and Descriptive Statistics

Data used for the study were collected from different international databases for a period from 1980 to 2010. Years 1980 and 2010 represent, respectively, the earliest and the last year for which data are available at the time data obtained. The sample countries in the study covered 91 countries and are determined by data availability. Due to missing observations, our panel data is unbalanced. Pooled Ordinary Least Squares

(OLS) was carried out to remove the outliers in the data in order to avoid biased estimate¹⁶. The data was primarily extracted from the US Energy Information Agency, EIA, Euromonitor International, the International Energy Agency, IEA, and the World Development Indicators, WDI. As with most of the modelling work in stochastic frontier analysis which involves the use of software such as STATA, LIMDEP-NLOGIT, and Frontier, this study was undertaken using STATA to obtain the maximum likelihood estimates of the parameter of the models and efficiency measures. The data in the fitted regression are logged and mean-corrected for each variable, i.e. expressed as deviations from the sample mean so as to interpret the first order coefficients in the model as elasticities at the sample mean.

The importance of variable selection underscores any research findings as the reliability of the outcomes depend primarily on the input and output variables used in a model. Modelling of electricity generation of electrical power requires three basic inputs: capital, labour and energy. Building on Coelli et al., (2013), Jaraité & Di Maria (2012), among others, this paper considers three groups of input variables: net installed electrical capacity, labour and energy inputs. Output is the annual net electricity produced by each country unit, measured in gigawatt hours (GWh). Capital is measured in megawatts (MW) of installed capacity. Net installed capacity is used as a proxy for capital stock as electricity generation capital stock data are not available for electricity¹⁷ Installed capacity in this study is defined as the maximum amount of thermal electricity that a station can produce at any given point in time. It describes the maximum capacity that a system is designed to run at. The measurement of electrical generating capacity in units of maximum potential output is standard engineering practice and has been carried over to the economics literature from the early days of the peak load pricing theory.

¹⁶ The presence of outliers is critical for any efficiency analysis that compares individual firms/countries since most of efficiency analyses are based on the identification of the most efficient firm(s)/countries.

¹⁷ The net installed capacity is used as the measure of the services of capital input. The use of installed capital as a proxy for capital stock is consistent with literature (see Jaraité & Di Maria (2012)). Although, a potential issue is that some parts of the installed capital of a generator (conventionally measured as the electrical power rating of the capacity) may not in practice have been part of the 'used and useful' capital stock, as defined by US public service regulators. However, industry wide practice is to use installed capacity in the engineering sense as the comparable measure of the stock of capital services.

Labour data refers to the economically active population in utilities supply industry¹⁸, and is measured in thousands of employees. This is used as a proxy for labour since there is no available disaggregated data that represents precise number of employees in the electricity sector. Energy inputs are measured in kilotonnes of oil equivalent (ktoe), and include all varieties of energy utilised by the generation plants: coal, oil, gas, hydro, nuclear and biomass. As energy input data are available in the same measurement units, we aggregated them into one indicator. This allows for the different energy intensity of different generation technologies. Data for net electricity generation, installed capacity and energy are obtained from IEA. Labour input is obtained from Euromonitor International.

We include vector of cross-country variables that shift the production frontier. They include capacity factor which is an indicator for capacity utilisation which measures how often an electricity generator runs for a specific period. It compares how much electricity a generator actually produces with the maximum it could produce at continuous full power operation during the same period. Therefore, a higher load factor usually indicates more output and a lower cost per unit. Conversely, a lower load factor is often associated with higher unplanned and planned outages, which implies higher repairs and maintenance costs, thus resulting in a lower technical efficiency level (Hiebert, 2002; Khanna et al., 1999). Capacity factors vary greatly depending on the type of energy that is used and the design of the plant. Capacity factor is computed by taking the ratio of gross electricity generated divided by installed capacity multiply by the number of hours in a year. GDP per capita gives a measure of the general level of economic development and tends to influence electricity generation efficiency. An increase in GDP per capita is indicative of greater energy demand and this could encourage the country to be more efficient in electricity generation in order to bridge the energy demand gap via higher technology innovation and R&D effort in energy saving and energy efficiency improvement process. It is obtained from Penn World Table (PWT) 7.1.

¹⁸ In the Section “6.3 Limitations of the research”, we acknowledge the problem associated with using economically active population in the utility sector industry as a proxy for labour.

Electricity consumption per capita strongly correlates with the economic structure of a country. Countries with a high per capita electricity consumption are expected to have lower energy costs, thus resulting in a high technical efficiency level. Population density indicates the spatial presence of urban conurbation as measured in people per sq. km of land area. The rural urban shift will result in a move of energy use and consequently increases the demand for electricity consumption, thus inducing higher investment by utilities. Other control variables such as allows us to assess the impact of changing economic structure on production efficiency. It is defined as the industrial sector share of value added. Electricity consumption per capita, population density and industry value added are obtained from WDI.

To account for the degree of democracy, data on the ranking of political rights and civil liberty within the country are obtained from Freedom House. Political rights involve participation in the establishment or administration of a government and are usually held to entitle the adult citizen to exercise of the franchise, holding of public office, and engage in other political activities. Civil rights include the fundamental human rights enjoyed by every person regardless of sex or religion (such as freedoms of expression and belief, associational and organizational rights). Political rights and civil liberty variables are indicators for country institutional factors which measure political interference of government on the utility company and ability of the government to carry out an institutional restructuring reform in the power industry. Freedom House ranks countries on political rights and civil liberties on integers range from 1 (most freedom) to 7 (least freedom). From the Tyndall Centre for Climate Change Research and data market, we obtain data on Temperature which accounts for weather differentials across country. Nilsson and Pollitt (2010) found that more extreme climate factors have a negative impact on efficiency of utility firms. Given that market reform of the electricity sector is an on-going process that affects many dimensions of industry competition and structures, reform score is a potentially important variable although it only provides an indication of reform progress, rather than reform success. This variable is taken from a dataset in Erdogdu (2013)¹⁹. The score ranges from 1 to 8 (nonnegative integer values), and is assigned to countries based on their reform status. In other words, the data is constructed for countries which have introduced at least one of the following reform

¹⁹ See appendix 1 for the table on reform scores by country

step: (1) introduction of independent power producers, (2) corporatization of state-owned enterprises, (3) law for electricity sector liberalization, (4) introduction of unbundling, (5) establishment of electricity market regulator, (6) introduction of privatization, (7) establishment of wholesale electricity market, and (8) choice of supplier. The electricity market reform score assigns a score to each country based on the reform status of that country. A country with electricity market reform score of 8 has undertaken all the 8 reform steps while a country with score 1 has only implemented 1 reform step. For more details on this electricity market reform score see Erdogdu (2013). Table 3.1 gives the descriptive statistics of the variables used in the study.

Table 3.1: Descriptive Statistics

1786 Observations	Variable	Mean	SD	Min	Max
Output Variable					
Electricity generation (GWh)	y	155645.95	458782.4	62	4156745
Input Variables					
Installed capacity (MW)	x_1	37818	109132	130	1039062
Labour ('000 people)	x_2	141.21	376.32	0.93	3101.50
Energy (ktoe)	x_3	30969.38	99932.37	21	897292
Environmental Variables					
Capacity factor* (ratio)	z_1	0.05	0.01	0.01	0.18
GDP per capita (2005 US\$)	z_2	15551.77	14775.19	335.56	136248.10
Elect consumption per capita (kWh)	z_3	4525.23	5391.52	18.65	51439.91
Industrialisation (% of GDP)	z_4	25.21	9.15	4.43	68.497
Pop. density (ppl per sq. km of land)	z_5	167.88	613.10	1.47	7252.429
Temperature (Degree Celsius)	z_6	16.09	8.66	-8.74	32.73
Political rights (Index)	z_7	2.50	1.85	1	7
Civil liberty (Index)	z_8	2.70	1.60	1	7
Reform score (Index)	z_9	6.07	2.05	1	8

*the minimum value reveals the unused generating capacity which is out of service or operating at a reduced output for part of the time, possibly due to equipment failures or routine maintenance.

3.5 Empirical Analysis

3.5.1 Estimation results

The parameter estimates of the Battese and Coelli (1992), Greene (2005) True Fixed Effect and True Random Effect specifications, and their associated t-statistics allow us to determine the effect that the output and the inputs have on the distance functions, and also whether the magnitude corresponding to direct partial elasticity is statistically significant or otherwise. Since data are expressed as deviations from the overall sample mean, the elasticities can be evaluated at the mean by directly analysing the first order parameters. The elasticities in each one of these models are estimated as the information provided by the elasticity estimations are also a tool in order to check for the regularity conditions of the models, as well as a tool in order to estimate technical change and economies to scale. Therefore, to confirm monotonicity properties, the coefficient of output should be negative in relation to the input, capital and labour inputs are expected to show a positive sign in relation to energy input at the sample mean. The results show that the estimated input distance function is well behaved with all input coefficients positive and output coefficient negative.

Table 3.2: Monotonicity outside the sample mean

Variable	elasticity	BC (92)	TFE	TRE
Generation	ey	100	100	100
Capital	ex1	100	100	100
Labour	ex2	54.5	62.2	58.2

In addition, the percentages of elasticities outside the sample mean satisfy the regularity conditions of monotonic properties in Table 3.2. On the whole, we can say that the monotonicity condition is satisfied.

Table 3.3: Estimated input distance function parameters

Variable	Model 1 -BC (92)		Model 2-FTE		Model 3-TRE	
	Coef.	t-stat.	Coef.	Std. error	Coef.	Std. error
Generation	-0.919***	-118.00	-0.969***	-88.356	-0.963***	-294.968
Capital	0.974***	93.539	0.969***	131.230	0.997***	142.664
Labour	0.014**	3.038	0.008**	2.384	0.008*	2.290
Generation Squared	-0.014***	-9.050	-0.006***	-3.493	-0.007***	-8.521
Capital Squared	-0.087***	-21.818	-0.023***	-4.940	-0.036***	-9.021
Labour Squared	-0.004	-1.618	-0.001	-0.477	-0.004**	-2.321
Capital × Labour	-0.100***	18.381	-0.028***	4.642	-0.045***	9.277
Generation × Capital	0.085***	31.008	0.017***	3.920	0.029***	8.168
Generation × Labour	-0.006*	-2.286	-0.003	-1.293	-0.006***	-3.369
Time	-0.006***	-6.328	-0.001**	-2.718	-0.001***	-4.473
Time Squared	0.000**	1.969	0.000	0.108	0.000	-0.360
Generation × Time	0.000	-0.418	0.000	1.127	0.000	1.212
Capital × Time	-0.001*	1.948	0.000	0.314	0.000	0.129
Labour × Time	-0.001***	-4.448	0.000**	-2.745	-0.001**	-3.147
Capacity Factor	18.365***	60.859	20.13***	78.483	20.281***	83.012
GDP per capita	0.065***	6.053	0.026**	2.769	0.042***	5.563
Elect. Consumption	-0.071***	-6.774	-0.036**	-3.107	-0.056***	-8.503
Industrialisation	-0.016**	-2.099	-0.006	0.944	0.004	0.595
Pop. density	-0.012**	-2.223	0.015	-0.845	-0.019***	-6.720
Temperature	0.001	0.567	0.001	0.591	0.001	0.826
Political rights	0.003	1.543	0.005***	3.590	0.005***	3.706
Civil liberty	0.001	0.306	0.000	-0.002	-0.001	-0.314
Reform score	0.007	1.580	-0.003	0.574	-0.004	-1.082
Eta (η)	0.015***	6.060				
Mu (μ)	0.181***	5.260				
Sigma_u			0.033	24.31	0.032***	25.43
Sigma_v			0.018	20.91	0.020***	
Lambda (λ)	2.345***		1.845	939.25	1.627***	
Constant	0.266***	8.989			0.315***	4.27
Log Likelihood	2927.98		3485.73		3259.30	
AIC	-5799.96		-6741.47		-6466.70	

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

Table 3.3 presents the obtained maximum likelihood estimates of the alternative stochastic models. In the BC model, electricity generation elasticity is -0.919, capital elasticity is approximately 0.974, and labour elasticity is 0.014. The TFE and the TRE models show the electricity generation elasticities of -0.969 and -0.963 respectively with same magnitude of capital and labour capital elasticities. The apparent similarities in the parameter estimates of the TFE and TRE models are occasioned by the facts both models account for unobserved heterogeneity. A negative sign is associated with electricity generation parameters across all the models (a marginal increase in generation output given all other variables unchanged implies an improvement in efficiency i.e. a decrease in distance) while capital and labour elasticities are both positive. These estimates are all significantly different from zero in all the models specified. A negative effect corresponding to time variable implies an upward shift of the distance function, and ultimately a decline an increase in inefficiency. In other word, the statistically significant time parameter suggests that the annual technical change declines across the models. This finding may be due to low investment in technological capacity in driving growth in the generation sector, especially in the developing countries that constitute the major chunk of the sample. Overall, the capital elasticities are particularly large which is consistent with our expectations that increase in the volume of capital stock is the most significant driver of input requirement in the capital-intensive electricity generation industry.

Considering the impact of the exogenous variables on input requirements, the coefficients of capacity factor, GDP per capita, electricity consumption per capita and political rights are fundamental factors influencing technical efficiency of the country. The parameters literally show a comparable level of statistical significance and corresponding signs in the three models. For example, capacity factor is positive and significant in all the models which suggest that an increase in capacity factor will lower input requirements as higher capacity factors indicates larger scale economies and a lower cost per unit of electricity generation. This is in line with *a priori* expectation that the more efficient a plant is, the higher the capacity factor.

This result is largely consistent with those of Pollitt (1995) and Lam and Shiu (2004). Similarly, GDP per capita implies that as people become richer and improve on their standard of living, they will require more energy to fulfil their needs. Therefore, higher GDP per capita could potentially support an efficiency-inducing drive by bridging energy demand gap via higher technology innovation and R&D effort in energy saving and energy efficiency improvement process.

However, electricity consumption per capita is negative and significant in all the models which suggests that increased electricity consumption per capita results in higher input requirements to generate higher electricity. Moreover, population density reveals that population density is negative and significantly different from zero across three models with increased impact of input requirements on production technology. This implies that high population density as a consequence of urbanisation leads to increase in electricity usage and therefore results higher input requirements for electricity generation.

Our analysis also reveals that the estimated parameters of temperature and electricity market reform score respectively are not statistically significant in any of the models. One possible explanation to the apparent insignificance of the reform score variable may be due to the fact that deregulation has not been well measured as the electricity reform score data only considers reform progress and not reform success. Interestingly, political rights which controls for institutional factor of political freedom of individuals as allowed by incumbent government is positive and significant across two models i.e. true fixed effect and true random effect models. This suggests that an increase in political rights in a country results in reduced input requirements. Therefore, we consider this a robust evidence that democratic institutional endowments of a country which is accounted for by political rights adequately captures electricity deregulation's influence on technical efficiency.

The estimated coefficient of output for each model is less than one in absolute terms indicating increasing returns to scale at the sample mean which for the parametric stochastic input distance function is computed as the inverse of the negative of this value. The estimated returns to scale are 1.088, 1.032 and 1.044 for the

BC (92), TFE and TRE models respectively and t-statistics show they are statistically different from zero. Following the returns to scale estimation as shown in Table 3.4, it can be inferred that electricity production show mild increasing returns to scale at the sample mean.

Table 3.4: Scale elasticity

Variable	BC (92)	TFE	TRE
Parameter	1.088***	1.032***	1.044***
Standard error	0.008	0.011	0.002
t-ratio	246.39	179.51	872.69

*** *t*-statistics are shown in parenthesis.

3.5.1.1 Estimates of Technical Efficiency

An efficiency score of 100% for BC (92), for example, would indicate that a country is doing the best that it can to generate electricity using observed input quantities relative to other countries in the sample. The efficiency score estimates as shown in Table 3.5 reveals that efficiency estimates are sensitive to the choice of frontier models.

Table 3.5: Summary of the Efficiency Score

	BC (92)	TFE	TRE
Mean	0.806	0.968	0.964
Std. Dev	0.092	0.026	0.033
Min	0.624	0.775	0.788
Max	0.990	0.982	0.981

The average efficiency score for the BC (92) model across the 91 countries is 81% and the average efficiency the TFE & TRE models are 97% and 96% respectively. It is apparent that the distributions of

efficiency scores from model 1 and models 2–3 differ greatly. For TFE & TRE models effect that distinguishes between inefficiency and latent heterogeneities the average efficiency scores are relatively higher, whereas for model 1 has a lower average efficiency score as the individual-specific difference is considered as part of inefficiency. We measure reform effects by distance of each country from the frontier. Arguably, we expect deregulation to push the most efficient country close to the frontier with an efficiency score of 100% for electricity generation, which implies that the country is doing the best it can to reduce input requirements for electricity generation, relative to another country in the sample.

Table 3.6 shows the efficiency scores 91 for countries categorise as OECD and Non-OECD countries. The three highest efficiency scores for BC (92) model are Malta-99%, El Salvado-98% and Zambia-98%. For the True FE model, the best three efficient countries are Qatar -98%, Macedonia - 98% and Brazil -98%. Germany-98% ranks as the most efficient country in the True RE model, followed by Greece-98% and Turkey-98%. However, the least efficient countries in BC (92) model are Italy-62%, Nigeria -65% and Spain-66. For True FE model, the least efficient countries are Luxembourg -78%, Tanzania- 90% and Moldova-91%. Luxembourg -79% and Tanzania-79% also rank as the least efficient countries in the True RE model followed Bostwana-85%.

Interestingly, the efficiency score shows that most of the OECD European countries are among the top 20 most efficient countries in True FE and True RE as opposed to BC (92) model. This is not surprising as the result for True FE and True RE capture time invariant heterogeneities in each country's operating characteristics that are not otherwise controlled for in the model. Thus, the result is highly consistent with the statistically significant deregulation variable indicated by political rights in the True FE and True RE models where we detect the influence of market reform on the efficiency score.

Table 3.6: Efficiency Scores 91 for countries

Countries	BC (92)		True FE		True RE	
	Eff. Score	Rank	Eff. Score	Rank	Eff. Score	Rank
			OECD	Countries		
Australia	0.670	88	0.977	47	0.977	33
Austria	0.700	84	0.973	56	0.972	51
Belgium	0.746	63	0.981	20	0.980	11
Canada	0.727	69	0.981	25	0.979	16
Chile	0.783	47	0.972	58	0.965	69
China	0.862	30	0.979	34	0.978	27
Czech Republic	0.789	46	0.981	22	0.979	18
Denmark	0.713	76	0.969	68	0.969	61
Estonia	0.971	4	0.944	80	0.937	85
Finland	0.764	55	0.972	61	0.966	66
France	0.708	79	0.980	27	0.979	23
Germany	0.755	60	0.982	6	0.981	1
Greece	0.748	62	0.981	11	0.981	2
Hungary	0.796	44	0.982	9	0.980	10
Iceland	0.939	12	0.965	73	0.944	82
Ireland	0.735	66	0.970	66	0.971	56
Israel	0.779	50	0.981	12	0.980	8
Italy	0.624	91	0.978	42	0.977	36
Japan	0.727	68	0.979	33	0.978	28
Luxembourg	0.871	28	0.775	91	0.788	91
Mexico	0.726	71	0.981	17	0.980	12
Netherlands	0.718	75	0.981	15	0.980	7
New Zealand	0.842	33	0.980	28	0.976	42
Norway	0.829	34	0.980	31	0.969	63
Poland	0.823	35	0.958	77	0.955	74
Portugal	0.722	72	0.977	46	0.977	34
Slovakia	0.813	38	0.981	16	0.979	20
Slovenia	0.809	40	0.978	40	0.978	31
Spain	0.659	89	0.978	41	0.977	35
Sweden	0.770	51	0.981	13	0.980	6
Switzerland	0.768	52	0.981	23	0.980	5
Turkey	0.707	80	0.982	7	0.980	3
United Kingdom	0.720	73	0.981	14	0.980	13
USA	0.815	37	0.981	21	0.979	15

Table 3.6: Efficiency Scores 91 for countries (cond.)

Countries	BC (92)		True FE		True RE	
	Eff. Score	Rank	Eff. Score	Rank	Eff. Score	Rank
			Non-OECD	Countries		
Albania	0.953	8	0.938	85	0.919	87
Algeria	0.752	61	0.978	43	0.975	45
Argentina	0.690	86	0.938	86	0.944	83
Belarus	0.733	67	0.982	10	0.969	62
Bolivia	0.873	24	0.978	39	0.978	25
Bosnia-Herzegovina	0.877	21	0.973	55	0.971	54
Botswana	0.947	11	0.922	88	0.850	89
Brazil	0.683	87	0.982	3	0.980	9
Bulgaria	0.791	45	0.981	24	0.979	19
Colombia	0.697	85	0.977	44	0.977	39
Costa Rica	0.936	13	0.979	35	0.977	38
Croatia	0.815	36	0.977	45	0.976	40
Cuba	0.757	58	0.980	30	0.978	26
Cyprus	0.896	19	0.980	29	0.978	32
Dominican Republic	0.782	48	0.943	81	0.943	84
Ecuador	0.812	39	0.966	72	0.965	68
El Salvador	0.977	2	0.972	57	0.952	75
Ethiopia	0.908	18	0.962	76	0.960	71
Georgia	0.799	41	0.950	79	0.951	77
Ghana	0.867	29	0.972	60	0.972	53
Honduras	0.951	10	0.972	62	0.970	59
India	0.797	43	0.981	18	0.980	4
Indonesia	0.726	70	0.940	83	0.952	76
Iran	0.768	53	0.982	4	0.979	22
Jamaica	0.878	20	0.930	87	0.923	86
Jordan	0.873	25	0.978	38	0.977	37
Kenya	0.877	22	0.963	75	0.958	73
Latvia	0.846	32	0.939	84	0.945	81
Lithuania	0.746	64	0.966	71	0.967	65
Macedonia	0.954	7	0.982	2	0.978	30
Malaysia	0.743	65	0.975	50	0.976	43
Malta	0.990	1	0.981	19	0.968	64
Moldova	0.911	17	0.919	89	0.901	88
Mongolia	0.959	6	0.982	8	0.979	21
Morocco	0.780	49	0.971	63	0.971	55
Nicaragua	0.929	15	0.964	74	0.959	72
Nigeria	0.654	90	0.942	82	0.947	80
Pakistan	0.756	59	0.972	59	0.970	57
Panama	0.914	16	0.969	67	0.949	78

Table 3.6: Efficiency Scores 91 for countries (cond.)

Countries	BC (92)		True FE		True RE	
	Eff. Score	Rank	Eff. Score	Rank	Eff. Score	Rank
			Non-OECD	Countries		
Peru	0.766	54	0.975	51	0.974	49
Philippines	0.710	77	0.971	64	0.970	60
Qatar	0.952	9	0.982	1	0.980	14
Romania	0.702	83	0.978	37	0.976	41
Russia	0.703	82	0.979	32	0.978	29
Senegal	0.873	26	0.950	78	0.948	79
Serbia	0.871	27	0.982	5	0.979	24
Singapore	0.762	56	0.977	48	0.974	48
South Africa	0.762	57	0.976	49	0.976	44
Sri Lanka	0.860	31	0.974	52	0.972	50
Tanzania	0.965	5	0.901	90	0.792	90
Thailand	0.719	74	0.974	53	0.974	47
Trinidad and Tobago	0.875	23	0.979	36	0.975	46
United Arab Emirates	0.707	81	0.973	54	0.972	52
Uruguay	0.933	14	0.967	69	0.966	67
Venezuela	0.709	78	0.970	65	0.970	58
Vietnam	0.799	42	0.981	26	0.979	17
Zambia	0.976	3	0.967	70	0.961	70

This is not surprising as there is widespread knowledge that the European electricity market liberalisation which began in early 1990s has a central objective of increasing the efficiency in production, transportation and distribution of electricity. This liberalisation directive can be adduced to the widespread efficient score recorded from that region.

It is intriguing to note that Germany ranks as the most efficient European country in both models. Arguably, Germany has seen an impressive growth of electricity generation mix, especially from renewables during the 1990s due to a feed-in mechanism laid down in the first German feed-in system (Mitchell et al. 2006). This is aided by the liberalisation and deregulation of the German power market driven by the EU Electricity Directive, which has continuously increased the diversity within the group of energy producers coupled with the modification of the feed-in-tariff. However, Qatar is ranked the most efficient country in the True FE model, although the power sector was reformed in 2000 by separating power generation from transmission and distribution, with the entry some independent power producers (see KAPSARC, 2017).

Furthermore, contrary to expectation at the bottom end of the efficiency rank is Luxembourg, despite being an EU member, it doubly ranks as the least efficient country in both True FE and True RE models. Nevertheless, consistent with a capital-intensive industry, Luxembourg by itself does not have much installed capacity as the electricity wholesale market is highly interconnected with, and dependent on, foreign electricity supply. Most is power imported from its neighbouring countries (Al-Sunaidy and Green, 2006). Arguably, high electricity imports have a negative effect on power plant efficiency level. The inadequate power generation capacity and decrepit power plants in Nigeria also explain the country's inefficient score in BC (92) model as self-electricity generation is generally common in the country, which is projected to be between 4,000-8,000 MW (Eberhard and Gatwick, 2012). This has resulted in incessant blackouts and rationing; outrageous tariff increases and inadequate investments to realise a sustainable expansion in order to meet electricity demand. Finally, countries such as Italy and Spain are inefficient in BC (92) model electricity generation. The result is highly consistent with those of Chen & Yee (2013) which reported power plant inefficiency for most of these countries, potentially due to dwindling economic power and an associated reduction in electricity demand. It is not immediately clear why the ranking of efficiency scores across three models indicate that few regulated countries attain some level of efficiency in the models. Nevertheless, this finding shows the facts that efficiency scores are model specific to a large extent, as so me the countries are seen to be efficient in one model and otherwise in another model. In general, these efficiencies ranking results should be treated with some caution, especially given the large sampled countries with certain degree of diversity among them.

3.5.2 Intercept results

Our study further investigates whether deregulation is being measured by unobserved heterogeneity rather efficiency components, so we generated different intercepts by country for the fitted true fixed effect model. The choice of the model is based on the model selection test using Akaike's information criterion indicates The Akaike information criterion clearly confirms that the true fixed effect model best fits our data. The estimate of the intercept for each country for the true fixed effect is shown in Table 3.7

Table 3.7: Intercept by country - True Fixed Effects Model

Country	Model 1- All variables		Country	Model 2- Deregulation variable	
	Coefficient	t-statistic		Coefficient	t-statistic
Malta	0.167**	2.388	Botswana	0.822***	11.744
Tanzania	0.154***	2.948	Honduras	0.768***	18.891
El Salvador	0.148***	8.222	Jamaica	0.686***	20.343
Iceland	0.140**	2.341	Zambia	0.671***	28.411
Panama	0.117***	3.520	El Salvador	0.663***	19.801
Macedonia	0.117***	5.996	Ethiopia	0.660***	12.455
Albania	0.113***	6.053	Kenya	0.657***	18.545
Moldova	0.105***	3.778	Iceland	0.641***	14.331
Norway	0.104*	1.895	Senegal	0.640***	11.660
Cyprus	0.103***	3.444	Tanzania	0.637***	14.763
Jamaica	0.096***	3.919	Ghana	0.637***	24.761
New Zealand	0.094*	1.922	Qatar	0.617***	16.615
Singapore	0.093	1.492	Nicaragua	0.581***	12.799
Costa Rica	0.091***	3.896	Estonia	0.571***	12.625
Botswana	0.087	1.534	Costa Rica	0.563***	19.946
Honduras	0.081***	2.873	Panama	0.540***	17.291
Uruguay	0.081***	2.633	Uruguay	0.539***	22.365
Mongolia	0.079	0.881	Albania	0.535***	16.037
Zambia	0.077	1.454	Cyprus	0.483***	7.996
Slovenia	0.073***	5.211	Luxembourg	0.473***	6.199
Trinidad and Tobago	0.069	1.390	Malta	0.436***	7.502
Nicaragua	0.068	1.643	New Zealand	0.397***	22.760
Qatar	0.067***	2.594	Moldova	0.388***	10.008
Bosnia-Herzegovina	0.066***	2.804	Bolivia	0.363***	10.417
Kenya	0.066	1.481	Chile	0.345***	22.789
Finland	0.065	1.318	Latvia	0.340***	8.059
Sweden	0.063	1.339	Norway	0.330***	10.596
Ghana	0.0589***	1.734	Macedonia	0.295***	9.104
Hungary	0.056**	2.351	Ecuador	0.285***	13.405
Senegal	0.054	1.222	Dominican Republic	0.266***	7.949
Chile	0.053	1.056	Peru	0.216***	13.232
Ethiopia	0.053	0.929	Jordan	0.214***	7.642
Czech Republic	0.049**	2.061	Slovenia	0.202***	9.735
Jordan	0.048*	1.775	Cuba	0.200***	6.249
USA	0.046	0.518	Netherlands	0.157***	8.535
Japan	0.044	1.225	Croatia	0.150***	7.056
Slovak Republic	0.044***	2.651	Trinidad and Tobago	0.134***	3.850
Ecuador	0.043	1.290	Belarus	0.128***	3.413
Netherlands	0.043	2.353	Georgia	0.072**	1.961
Serbia	0.041*	1.660	Ireland	0.071***	4.295
Indonesia	0.040	0.788	Austria	0.066***	3.840
Estonia	0.039	1.888	Colombia	0.058***	3.512
Sri Lanka	0.038	1.004	Mongolia	0.055	1.123
Croatia	0.038**	2.089	Brazil	0.025	0.658
Bolivia	0.037	0.547	Nigeria	0.024	1.096
Bulgaria	0.035	1.055	Viet Nam	0.019	0.926
Switzerland	0.035**	2.264	Portugal	0.019	1.560
Dominican Republic	0.033*	1.695	Canada	0.008	0.214
Israel	0.029	0.756	Finland	0.008	0.433

Table 3.7: Intercept by country - True Fixed Effects Model (cond.)

Country	Model 1- All variables		Country	Model 2- Deregulation variable	
	Coefficient	t-statistic		Coefficient	t-statistic
Greece	0.029	1.085	Venezuela	0.001	0.069
Portugal	0.028	1.363	Switzerland	-0.003	-0.161
Poland	0.028	0.752	Denmark	-0.006	-0.295
Canada	0.027	0.273	Bosnia-Herzegovina	-0.017	-0.503
Denmark	0.025	1.262	Israel	-0.017	-1.024
France	0.025	0.568	Serbia	-0.048*	-1.737
Germany	0.025	0.671	Singapore	-0.053**	-1.967
Belgium	0.021	1.429	Sri Lanka	-0.055***	-0.768
Argentina	0.020	0.296	Morocco	-0.079***	-4.080
Peru	0.020	0.346	Malaysia	-0.082***	-5.826
Ireland	0.018	0.821	Turkey	-0.084***	-4.499
United Kingdom	0.017	0.547	Lithuania	-0.096***	-4.060
China	0.014	0.194	Philippines	-0.105***	-7.095
India	0.012	0.196	Sweden	-0.108***	-4.194
Malaysia	0.010	0.314	Hungary	-0.110***	-7.117
Austria	0.010	0.395	Greece	-0.115***	-7.475
Turkey	0.002	0.049	Belgium	-0.118***	-6.224
Morocco	0.002	0.056	Slovak Republic	-0.122***	-8.343
Philippines	0.000	-0.004	Pakistan	-0.124***	-4.763
Pakistan	-0.002	-0.049	Russia	-0.156***	-2.567
Viet Nam	-0.003	-0.081	Argentina	-0.158***	-8.704
Venezuela	-0.005	-0.093	Indonesia	-0.163***	-8.530
Brazil	-0.005	-0.064	Mexico	-0.174***	-7.522
Spain	-0.006	-0.144	Algeria	-0.186***	-9.599
Colombia	-0.009	-0.166	Thailand	-0.187***	-10.211
Lithuania	-0.015	-0.542	USA	-0.193***	-2.562
South Africa	-0.017	-0.356	South Africa	-0.206***	-7.904
Russia	-0.017	-0.179	Bulgaria	-0.211***	-9.484
Latvia	-0.018	-0.488	Japan	-0.212***	-4.405
Thailand	-0.025	-0.797	Czech Republic	-0.221***	-12.286
Mexico	-0.027	-0.648	United Arab Emirates	-0.232***	-7.973
United Arab Emirates	-0.028	-1.119	United Kingdom	-0.232***	-7.727
Romania	-0.028	-0.759	Germany	-0.251***	-6.797
Italy	-0.031	-0.993	Italy	-0.256***	-9.035
Australia	-0.036	-0.385	Poland	-0.267***	-10.949
Belarus	-0.046		Spain	-0.279***	-11.289
Algeria	-0.050	-0.826	Australia	-0.289***	-11.942
Cuba	-0.051*	-1.668	France	-0.299***	-8.537
Iran	-0.053	-1.254	China	-0.305***	-4.618
Nigeria	-0.066	-1.449	India	-0.323***	-7.770
Georgia	-0.085***	-2.712	Romania	-0.350***	-15.740
Luxembourg	-0.199***	-4.310	Iran	-0.355***	-12.225

We estimated the intercepts by controlling for all the exogenous variables as reported under model 1, while model 2 accounts for only the deregulation variable. The approach enables us to draw parallels between the rank order of the fixed effect for all variables and the rank order of the fixed effect for the deregulation variable. Intuitively, higher intercepts correspond to countries with lowest distance below the frontier. One striking result that emerges from this analysis is that almost 90% of the coefficients of the intercepts in model 2, after controlling for the deregulation impact, are statistically significant as against 33% for the model 1. This reinforces the important influence of political rights to reform measurement.

We find that the countries at the top 20 rank of the country intercepts after controlling for the deregulation variable are countries from Latin America and a few African countries. This is likely as a result of the marked liberalisation wave, especially for the Latin American countries, which has pushed them close to the frontier. Similarly, most of the African countries are democratic countries. For instance, Botswana is rated the country with the highest political rights index in Africa, although the country has undertaken little meaningful reform of its power sector. However, in 2007, the government of Botswana amended the energy supply act to facilitate the participation of independent power producers in the electricity sector and plans to restructure the electricity supply industry in accordance with Botswana's membership in the Southern Africa Power Pool (Vagliasindi and Besant-Jones, 2013). Iran ranks as the least efficient country after controlling for the deregulation variable. This finding confirms our expectation as the Iranian state owned vertically integrated utility is still responsible for electricity generation, transmission and distribution. Finally, most of the OECD countries gain less efficiency when controlled for political rights. Presumably, one plausible argument for this is that since these countries are already close to the frontier and politically advanced in their own right, the fixed effect is picking up some of the influence of the reform score on the Latin American and African countries which are increasingly becoming politically strong and reform oriented.

3.5.3 Productivity Change result

The indices for average productivity growth which is made up of the three aspects: efficiency, scale and technological change for the true fixed effect model over the period of 1981–2010 are shown in Table 3.8.

The estimate for average efficiency changes indicates the “catch up” of productivity, while technical change reveals the frontier shift at the input level and mix of each country.

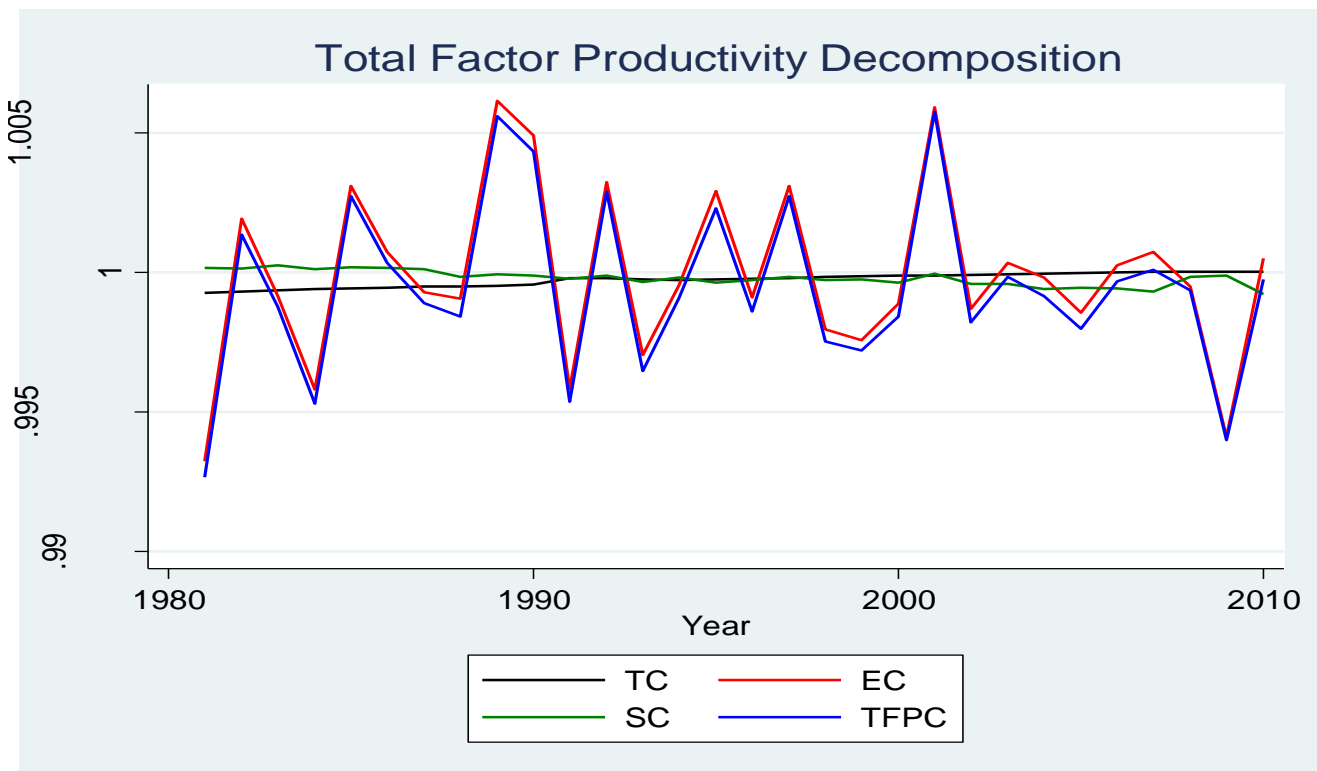
Table 3.8: Annual Average Generalised Malmquist Productivity Indices and its Components

Year*	Technical Change	Efficiency Change	Scale Change	Productivity Change
1981	0.999	0.993	1.000	0.993
1982	0.999	1.002	1.000	1.002
1983	0.999	0.999	1.000	0.999
1984	0.999	0.996	1.000	0.996
1985	0.999	1.003	1.000	1.003
1986	0.999	1.001	1.000	1.001
1987	0.999	0.999	1.000	0.999
1988	0.999	0.999	1.000	0.999
1989	1.000	1.006	1.000	1.006
1990	1.000	1.005	1.000	1.005
1991	1.000	0.996	1.000	0.996
1992	1.000	0.996	1.000	1.003
1993	1.000	1.003	1.000	0.997
1994	1.000	0.997	1.000	0.999
1995	1.000	1.003	1.000	1.002
1996	1.000	0.999	1.000	0.999
1997	1.000	1.003	1.000	1.003
1998	1.000	0.998	1.000	0.998
1999	1.000	0.998	1.000	0.997
2000	1.000	0.999	1.000	0.999
2001	1.000	1.006	1.000	1.006
2002	1.000	0.999	1.000	1.006
2003	1.000	1.000	1.000	1.000
2004	1.000	1.000	1.000	0.999
2005	1.000	0.999	1.000	0.998
2006	1.000	1.000	1.000	0.999
2007	1.000	1.001	0.999	0.999
2008	1.000	1.000	1.000	0.999
2009	1.000	0.994	1.000	0.994
2010	1.000	1.001	0.999	1.000

* Note that 1981 refers to the change between 1980 and 1981, etc.

The table reveals that over the whole sample period, there has been no technological deterioration except for 1981 which show evidence of technological regression. The table also reveals that the sample period is characterised by constant returns to scale of technology. Meanwhile the period experiences a mix of relatively small decline and a marginal increase in average efficiency changes. For the sake of brevity these results are summarised in Figure 3.1.

Figure 3.1: Total factor productivity decomposition 1980-2010



On the whole figure 3.1 reveals that productivity has been quite unstable through the sample period. A slight improvement occurred during 2001–2003. Tellingly, the decomposition shows that TFP wanders through the sample period. Efficiency change also meanders considerably mirroring the pattern of TFP change. The indices for average productivity growth show that average efficiency changes account for a large amount of the growth in productivity compared to technical change and scale change. Scale change is shown to have been generally stable through the sample period coupled with no significant frontier shift as revealed by

technical change. Moreover, the plotted scale change in the diagrams above appears consistent with the estimated returns to scale of 1.032 in our preferred model, the TFE model.

3.6 Conclusion and policy implications

This paper uses an extensive panel dataset of 91 countries in the electricity generation sector to measure the impact of deregulation in power sector efficiency and total productivity change. Three specific issues are addressed in the study: the relationship between deregulation and technical efficiency, the extent of the rank correlation of the country intercepts with deregulation via their position on the frontier ($\hat{\alpha}_j$) and the trend of total factor productivity and its components. The methodology relies on the traditional stochastic frontier Battese and Coelli (92) model, and the recently developed Greene (2005) True Fixed Effect and True Random Effect models which separate unobserved heterogeneity from the inefficiency.

A number of results follow. Firstly, we establish a positive impact of deregulation on efficiency as revealed by the statistically significant political rights variables in both True Fixed Effect and True Random Effect models. We also confirm the presence of mild increasing return to scale for electricity generation. Comparing the average efficiency scores of the countries in our sample, we gain a far-reaching understanding on the country performance with respect to electricity generation. The fitted models show different efficiency scores for each country at different levels. In both the true fixed effect and true random effect models, most OECD European countries are consistently ranked as highly efficient. This reinforces our a priori expectations that deregulation provides truly competitive markets which are efficiency-inducing among electricity generators in democratically developed countries.

Secondly, the estimates of the intercepts after controlling for the deregulation variable in our preferred model, TFE, show almost 90% of the coefficients of the intercepts in the model are statistically significant. This lends credence to the important influence of political rights on reform implementation. The result also shows that the deregulation variable has much higher impacts on countries intercepts from Latin America

and a few African countries. A plausible explanation for this result is that reform is gradually pushing these countries toward the frontier as a result of increasing democratic institution of the countries. It is notable that the World Bank and some other international organisations have, often, required that international aid and loans for electricity generation are conditional on market reform of the electricity sector. A notable example is Latin America (See Estache and Rossi, 2005). This finding underscores the policy conditionality as the imposed binding constraint has been empirically proven to be feasible and yields potential benefit. One possible policy recommendation is that policymakers should scale up more extensive electricity market reform in these countries in order to consolidate on the fledgling efficiency gains and create an independent regulatory body to prevent and mitigate against principle-agent problems.

Thirdly, the indices for average productivity growth decomposition shows that TFP wanders through the sample period with average efficiency changes accounting for a large amount of the growth in productivity compared to technical change during the sample period. We recommend technological innovation within a deregulation context as a possible power generation approach to improve productivity. This can be achieved through implementation of policies that allow independent power producers and generators to produce electricity from various sources such as PV, wind turbine or other energy sources which are technologically driven and more efficient. Policies intending to encourage commercialization of new energy technologies tend to enhance technological development and ultimately increase total productivity growth in the medium to long term. Moreover, policymakers should encourage adoption of cross national policy similarities in term of practices and technologies used in the high efficient countries through transnational communication, regulatory competition and technological innovation. This will enhance growth in technology and productivity such as the feed-in tariffs in Germany which has been adopted in France and the United Kingdom. This is evident from the result as these countries show no technological deterioration throughout the sample period. In conclusion, the results analysed hitherto support the assumption that there is a difference between countries in technical efficiency and productivity change. More specifically, adopting deregulation policy seems to confer performance advantage on deregulated countries.

Chapter 4: Cost Efficiency and Electricity Market Structure: A Case Study of OECD Countries²⁰

4.1 Introduction

Due to the liberalisation and deregulation wave in the electric power industry across most of the countries in the world, electricity generation companies, especially in the several OECD countries now act as unregulated companies that technically compete to sell power on an open market. An overview of experiences in several OECD countries where the generation segment has largely been deregulated while transmission and distribution continue to be regulated is provided by Al-Sunaidy & Green (2006); Joskow (2008). One compelling reason for the deregulation of electricity generation as against direct economic regulation is the lack of a natural monopoly in this segment²¹ which is the common feature of transmission and distribution. This policy choice, along with horizontal restructuring of the segment, has been accompanied by an increased number of competing generators which mitigate market power and ensure that wholesale markets are reasonably competitive.

The recent history of the electricity generation industry has been characterised in many countries by privatization, deregulation and liberalization. Although these changes are often given the convenient overall titles of deregulation or open markets, these can be misleading, and these changes can be significantly different in scope and meaning. It should be clear that while such policy induced changes can occur together, they do not mean the same thing. By privatization, we mean the conversion of state owned or publicly owned utilities into investor owned utilities. By deregulation, we mean the decision by government to step back from the day-to-day determination of pricing and investment decisions. One alternative to direct government control is to appoint a regulatory agency which is independent but accountable to government and which is responsible for regulating the natural monopoly aspects of the industry which arise from the

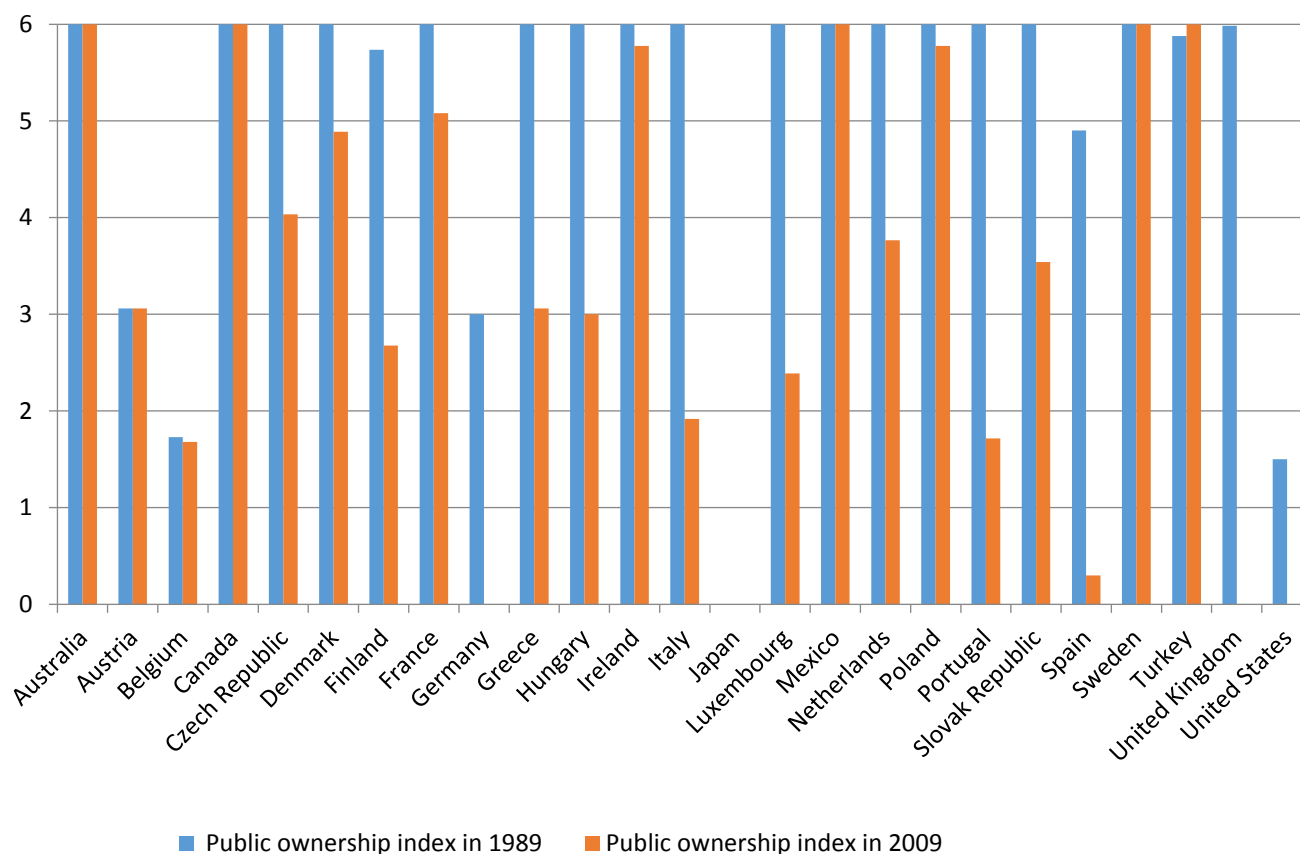
²⁰ An abridged version of this chapter has been published as: Ajayi, V., Weyman-Jones, T. and Glass, A., 2017. Cost efficiency and electricity market structure: A case study of OECD countries. *Energy Economics*, 65, pp.283-291.

²¹ Electricity production is conventionally segmented into generator, (HV) transmission, (LV) distribution and retail supply.

importance of economies of scale and scope. By liberalization, we mean the opening of the market to new entrants and the permission of incumbents to demerge into competing firms or alternatively to merge or even exit the industry. The model here is of a competitive industry where entry and exit are relatively free and of low cost, thereby reducing the need for extensive or intensive regulation by a national regulatory authority.

These forms are not synonymous with each other and may occur to varying degrees in the power generation industry at different times. In Scandinavian countries publicly-owned utilities exist within a deregulated and liberalised market and in Germany there are many municipal level publicly owned utilities within a deregulated and partly privatised market for power networks.

Figure 4.1: Public ownership index in OECD countries (1989, 2009)



Source: OECD Product Market Regulation (2015)

Figure 4.1 shows the degree of public ownership when electricity market reform was first introduced in 1989 compared with 2009 in our sample period. The index 0-6 measures the extent of public ownership, with 0 representing a fully open deregulated market in which public ownership is low and a score of 6 denotes a closed market and high state ownership. It is intriguing to note that virtually all the OECD countries were state-owned up until 1989. Essentially, this reflects cases where the market power arising from economies of scale has been addressed by state ownership rather than regulated investor ownership.

In a regulated environment, firms are often guaranteed a minimum profit as a function of the firm's capital stock. Hence, this often leads to unintended consequences in that a firm may have strong incentives to overinvest in capital, such as generation facilities which could potentially result in the electric plants operating at decreasing returns to scale owing to overcapitalisation²². However, power generation companies operating in a competitive market environment have incentives to reduce costs while maintaining the relevant cost savings as profits (Keith and Terrell, 2001). In effect, deregulation may stimulate firms to be more efficient in generating electricity, thereby reducing electricity cost with consumers receiving lower end-user prices of electricity.

The generation of electricity involves using a different range of technology and fuel. To a great extent, fossil-fuel-fired boilers producing steam for turbine generators remain the major electricity generation technology. These generation technologies are characterised by quasi-fixed inputs which implies that they cannot be immediately adjusted. Another important characteristic of electricity infrastructures is that its current technology is a consequence of investment decisions made in the past and whose effects resonate over various periods²³. Nelson (1985) argues that the nature of the generation facilities in the electric power industry could result in the firm not operating on the economic expansion path, since estimations of economic of scale in this industry have been based on long-run cost which implicitly or explicitly invoke the

²² This situation is known as the Averch Johnson effect. Averch and Johnson (1962) argue that when regulators tie profit to capital stock and a rate of return that exceeds actual cost of capital, this provides incentives for a profit maximizing firm to employ a capital to labour ratio that is too high to be on the efficient expansion path. See Averch and Johnson (1962)

²³ See Díaz-Hernández, et al. (2014) for a similar discussion on ports infrastructure

assumption of cost minimization, this assumption will be violated. The need to account for such quasi-fixed inputs is therefore important in estimating scale economies to avoid imprecise and biased cost function parameters.

Cost efficiency, economies of scale and scope, among other characteristics of multiproduct technologies, have important implications for industry structure, design and regulation. The estimation of scale economies plays a vital role in electricity sector policy formulation, and several studies (see Considine (2000), Keith and Terrell, (2001), Maloney (2001), Hiebert (2002) and Rungsuriyawiboon and Stefanou (2007) have favoured partial or complete deregulation of the electric utility industry as a means of achieving desirable competition between electric generating plants. This allows regulator and antitrust officials to utilise the information in achieving a balancing act between market power²⁴ and economies of scale, while inducing efficient performance. The reliability of efficiency scores and scale economies are crucial for effective policy decisions in order to determine the dimensions of industry competition and firm's operations in the generator segment, and how a firm can efficiently compete in a given market.

Analysis of electricity generation cost structure and efficiency is made more imperative in the understanding of the behaviour of power generators in relation to environmental and social welfare aspects. Electricity is a non-storable commodity which requires the balancing of power generated and consumed on an electric grid on a second by-second basis. The ability of these generators to adjust their generating capacity, and hence the output at will many times, is constrained and could be slowed down in the presence of suboptimal capacity factors like cost associated with such adjustments, administrative regulation, external factors and time. Therefore, cost structure analysis may help to reduce technical and economic inefficiency and enhance social benefit. This could perhaps necessitate mergers of power generators who are not operating optimally in order to reduce operation costs, since success of competition rests on the size and number of generators in the market.

²⁴ See Keith and Terrell, 2001 for a discussion of market power problem of deregulation

One of the major contributors to global greenhouse gas emissions is electric power generation, accounting for 42% of the global energy related CO₂ emissions and its associated externalities in 2011 (IEA, 2013). While focusing on how efficient power utilities are in generating electricity, it is also crucial to understand how well they manage to avoid unnecessarily large emission production levels (bad outputs). Carbon emissions produced by electricity generators are endogenous in the production process since they are considered a joint output of electric power plants alongside electricity generation output. Reducing these environmental costs is associated with decreasing generation output at existing input levels, or increases in input costs at desired output levels. Power utilities are concerned that commitment to reducing these bad outputs would eliminate their profit margins and impede their competitiveness with other generators.

More often than not, charges and levies associated with carbon emissions in the generation process pales into insignificance when compared with the cost of technologies for carbon abatement. Hence, these charges are usually not sufficient to motivate plant operators to reduce emissions and instead induce output effects as they often rationalise their optimal decisions at the expense of environmental optimality, which results in a trade-off between electric power output and carbon emission. This variation in costs of mitigation and technological investment is central to economies of scope and cost complementarities in the process of joint production of the electricity output and undesirable products. Understanding utility cost structure dynamics is fundamental to setting relevant environmental policy interventions and regulations.

To this end, this paper attempts to contribute to the sparse empirical literature by assessing the cost efficiency and industry structure of OECD power generation sectors. Although deregulation is regarded as a flagship of electricity market reform policies, to our knowledge, no empirical study has explicitly investigated cost inefficiency, economies of scale and scope, cost complementarity of generation and emissions associated with this segment for OECD electricity countries. The remainder of the paper proceeds as follows. Section 4.2 presents the brief literature review and section 4.3 details the methodology used in this paper in order to estimate cost functions and efficiency. Section 4.4 presents the data description and

section 4.5 provides the results and discussion. Section 4.6 presents the concluding remarks and policy recommendation.

4.2 Literature review

A large number of studies have attempted to investigate cost structure and efficiency in electricity industry, as evidenced by the proliferation of the methodology. This underscores the growing discourse regarding deregulation of power sector and its attendant gains as advanced by proponents of market reform. Nevertheless, recent empirical findings have shown that cost function parameter estimates in the electricity sector differ across many study dimensions such as methodology, data type, model specification, sample size etc. While most of these studies have been dominated by the conventional long run cost minimisation assumption, little attention has been given to sub optimality of capacity as a result of costly adjustment to the time profile of electricity demand. For the handful that have considered cost estimation of the industry by taking into account the quasi-fixed input, there is no recognition of the multiproduct nature of the power industry where harmful emissions are assumed to be jointly produced with electric power. Most existing empirical applications of the short run cost which allows one to relax the assumption of cost minimization with respect to all inputs in electricity sector have used different functional forms, with translog functional forms being the most common specification.

A search in the literature shows that cost function empirical analyses have been carried out for the different stages of the industry, as each of these stages are marked by different levels of competition and regulation in varying degrees across countries (See Nelson and Wohar, 1983; Kaserman and Mayo, 1991; Nemoto et al., 1993). Most of the articles on the generation stage of the industry are in the context of the electricity industry in the U.S. which dates back to the work of Christensen and Greene (1976), using a translog total cost function to estimate scale economies of electric power generating firms. Other such as Nelson (1985, 1989), Kraustmaan and Solow (1988), and Hovde et al (1996) employ a variable cost function to estimate scale economies. Rhine (2001) estimates economies of scale for fossil fuel and nuclear fuel electricity

generation using a variable cost function. The result shows that electric utilities are operating on the negatively sloped portion of the long-run average cost curve, indicating either slight economies of scale or no economies of scale. Nemoto et al (1993) also specify the variable cost function as a translog form using panel data of nine Japanese electric utility firms during the period 1981 to 1985. They find most firms experienced scale economies in the short run but diseconomies in the long run, and a certain degree of over-capitalization.

Some studies, which include Considine (2000), Keith and Terrell, (2001), Maloney (2001), Hiebert (2002) and Rungsuriyawiboon and Stefanou (2007), use data on the steam electric power generation source to estimate cost structures and the possible savings in the production costs for major investor owned utilities. Considine (2000) estimates short-and long-run marginal production cost and returns to scale and finds substantial short-run diseconomies of scale at high output levels. Keith and Terrell (2001) use a Bayesian stochastic frontier model to measure cost efficiency, price elasticities, and returns to scale of 78 steam plants. Their results indicate that plants, on average, could reduce costs by up to 13% by eliminating production inefficiency. They show that most plants operate at increasing returns to scale, suggesting further cost savings could be achieved through increasing output. Maloney (2001) applied a translog variable cost function to study electricity generation in the United States. The cost function is estimated using a two dimensional definition of capacity utilization and the result shows that both dimensions affect average cost, which generally declines as capacity utilization increases. Hiebert (2002) finds increasing scale economies in both coal-fired plants and natural gas-fired plants with 20% and 12% scale economies respectively. Rungsuriyawiboon and Stefanou (2007) show that most electric utilities underutilized fuel and overutilized capital in production. They conclude that states adopting a deregulation plan could improve the performance of utilities in terms of the technical efficiency of variable inputs.

More recent studies such as Wang, Xie, Shang & Li (2013) identify measures to improve the performance of China's thermal power industry in view of cost efficiency. Assaf, Barros, Managi (2010) analyse and

compare the cost efficiency of electricity generation in Japanese steam power generation utilities using the fixed and random effect Bayesian frontier models. The results show that total cost increases significantly with input prices and outputs, with the exception of the price of labour and restricting CO₂ emissions can lead to a decrease in total cost. Akkemik (2009) estimates cost functions and investigates the degree of scale economies, overinvestment, and technological progress in the Turkish electricity generation sector for the period 1984–2006 using long-run and short-run translog cost functions. Estimations were done for six groups of firms, public and private. The results indicate the existence of scale economies throughout the period of analysis, hence declining long-run average costs.

Empirical studies on the cost structure for the transmission and distribution stages include the work of Kwoka (2005) which use quadratic cost functions to examine whether mergers in the US distribution sector which appeared as a consequence of the reforms could enhance cost efficiencies. The findings reveal significant economies at low output levels, holding system size and customer density constant, but the cost gradient is otherwise modest. It also shows that the scale properties of the wires function are significantly stronger than those for the supply function performed by distribution utilities. Yatchew (2000) estimates the costs of distributing electricity using data on municipal electric utilities in Ontario, Canada. Their specifications comprise semiparametric variants of the translog cost function where output enters non-parametrically and remaining variables (including their interactions with output) are parametric. The study reveals substantial evidence of increasing returns to scale with minimum efficient scale being achieved by firms with about 20,000 customers while the large firms exhibit constant or decreasing returns. Giles and Wyatt (1993) estimate a total cost function from a sample of 60 New Zealand electricity distributors, reporting an efficient scale for a sales range of 500 to 3500 GWh.

Burns and Weyman-Jones (1996) use cost frontier models to estimate the efficiency change for 12 regional electricity distributors in the UK. They enumerate factors which determine costs such the maximum demand on the system, the number of customers served (the main determinants of distribution operating costs), the

type of consumer, the dispersion of the consumers, the size of the distribution area, the total kWh sold system security, the length of distribution line and the transformer capacity. Their results indicate significant evidence of economies of scale. Kopsakangas-Savolainen and Svento, (2008) examine the cost-effectiveness of Finnish electricity distribution utilities employing several panel data stochastic frontier specifications of Cobb–Douglas and Translog model. The study points out the importance of the efficient use of the existing distribution network with the economies of scale results suggesting that firms could reduce their operating costs by using networks more efficiently.

In two different studies of Swiss electricity distribution utilities, Filippini (1996) and Filippini and Wild (2001) use a flexible translog by introducing a quasi-fixed cost, representing the impacts of quasi-fixed distribution equipment and a linear average cost function, and find evidence of increasing scale economies throughout their sample of 39 and 59 utilities respectively. Filippini (1998) also shows the existence of economies of density for most output levels for 39 Swiss municipal distribution utilities, while economies of scale appear for small and medium-sized utilities. A policy recommendation for mergers among the utilities follows. Pollitt et al (2005) examine the relative performance of electricity distribution systems in the UK and Japan between 1985 and 1998 using cost-based benchmarking with data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods and suggest that the productivity gain in UK electricity distribution has been larger than in the Japanese sector.

Some studies also provide empirical evidence for the whole industry. Arcos and De Toledo (2009) examine eleven vertically integrated Spanish utilities and find the presence of economies of scale, the effect of technological progress and differences in the efficiency of the different firms within the market. They conclude that the Spanish electrical utility industry was not, in fact, characterized by economies of scale, but witnessed a great improvement in efficiency within that period. Fraquelli and Vannoni (2005) investigate cost savings from generation and distribution of Italian electric utilities. The study finds evidence of both

multi-stage economies of scale and vertical economies and suggests that a complete divestiture policy would entail efficiency losses.

Considering the theoretical supposition of deregulation which assumes the exhaustion of economies of scale for generation²⁵, there is a need to further investigate this argument from the point of view of cross country analysis. Thus, the present study contributes to existing literature in threefold. First, unlike previous studies which are centred on country level analysis, the present study focuses exclusively on cost estimates at the generation segments in OECD countries. The broader geographical coverage enhances a better understanding of the cost structures among these estimates in OECD countries electricity generation. Second, we investigate the impact of electricity market structure on cost efficiency by incorporating electricity reform regulatory indexes in our analysis. Third, unlike previous studies, we extend our model to include a multiproduct function by including carbon emissions as part of the outputs of electricity generation in order to estimate and provide reliable information on some cost characteristics of generation such as cost complementarity, non-jointness etc.

4.3 Methodology

4.3.1 Theoretical Framework-Cost Function

An electricity utility produces a vector of outputs $\mathbf{y} = (y_r, y_s)'$ ≥ 0 , with y_r the desirable output generated in the production process, and y_s the part of production that constitutes environmental pollution. The output of electricity during the production process is dependent upon inputs such as stock of capital from generating capacity (K), labour (L) and primary fuels (F). Our analysis is described as follows;

Let $\mathbf{y} \in \mathfrak{R}_+^m$ represents an m -dimensional vector of outputs produced from an n -dimensional input vector $\mathbf{x} \in \mathfrak{R}_+^n$. Outputs are determined exogenously in order to meet market demand. The production process can be characterised as $f(\mathbf{y}, \mathbf{x}, t) = 0$ where $\mathbf{x} = (x_K, x_L, x_F)'$ is the vector of inputs and $\mathbf{y} = (y_r, y_s)'$ is the

²⁵ See Landon (1983) and Joskow (1996) for a discussion of the assumption of technology and cost structures of different segments of the power sector.

vector of output and t denotes the level of technology which uses time as a proxy. Duality theory demonstrates a complete reconstruction of the associated minimum cost function for a good from the original production function²⁶. Cost minimization assumes that, given the input costs, firms choose the mix of inputs that minimizes the costs of producing a given level of output. Given that the factors are purchased competitively at price $\mathbf{w} \in \mathfrak{R}_+^n$, we assume the power plant chooses the inputs so as to minimize the long-run cost of production, such that:

$$\min_{\mathbf{x} \geq 0} \sum_{i=K,L,F} w_i x_i \quad \text{such that } f(\mathbf{y}, \mathbf{x}, t) = 0 \quad (4.1)$$

Where $\mathbf{w} = (w_K, w_L, w_F)'$ is the vector of factor prices. This yields the long-run cost function $C(\mathbf{y}, \mathbf{w}, t) = \sum_i w_i x_i(\mathbf{y}, \mathbf{w}, t)$.

The long-run cost function has to satisfy the following regularity conditions:

- $C(\mathbf{y}, \mathbf{w}, t)$ is nonnegative and a real valued function, non-decreasing in $y \geq 0$ and $w \gg 0$, strictly positive and for nonzero y , twice continuously differentiable and concave in factor prices and linear homogenous of degree 1 in input prices for each y .

Linear homogeneity in factor prices is an important precondition for the existence of the duality relationship between cost and production²⁷. Estimating the structure of a cost function requires an explicit assumption regarding the state of equilibrium (long run and short run). While the cost function presented above implies that electricity utility firms are operating on their long-run expansion paths where all factor inputs can be adjusted instantaneously to desired levels during the production process, there is no evidence to support this assumption. For instance, there are a number of reasons why power utilities may be non-optimal²⁸. First, adjustments in the capital stock are relatively costly and thus the size of the main power utilities

²⁶ See Varian (1992, pg 83) for a discussion on duality theory

²⁷ See Caves, Christensen and Tretheway (1980) for a discussion on the regularity conditions and model specification.

²⁸ See Faust and Baranzini (2014) for similar reasons for water utilities infrastructures.

infrastructures is typically based on demographic and economic forecasts. Second, power utilities are obliged to respond to all the demand, and thus they typically dispose of excess capacities to account for seasonal and unexpected demand variations. Thirdly, power utilities can be affected by investment constraints, regulation or indivisibilities which could make immediate adjustment difficult in the short run. These situations reflect the quasi-fixity of capital stock which does not allow for alteration in the short-run, but is available at increasing marginal costs in the long-run. Faced with this situation, the economic decision of the firm in the industry will, at any given moment, be to minimise cost by only employing the optimal quantities of the easily adjustable variables inputs (i.e. labour and fuel) given the existing, possible non optimal levels of the fixed input (i.e. capital stock). Therefore, it is important to recognise this fact and differentiate between variables and quasi-fixed inputs when evaluating the cost efficiency of electric power utility. To account for this peculiar quasi-fixity characteristic of capital stock, we employ a short-run equilibrium model which assumes capital as a quasi-fixed input while the utility uses the most efficient level of other variable inputs. Moreover, since the adjustment path of capital is unspecified, the model is compatible with whatever path capital is adjusted along²⁹.

Therefore, we proceed by differentiating capital stock as an input which is a fixed input in the short run and variable in the long run, and symbolise it with z_0 , with input price: w_0 . We denote $\mathbf{x} = (x_L, x_F)'$ as vector of variable inputs and $\mathbf{w} = (w_L, w_F)'$ as the vector of variable factor prices.

Following the arguments in Friedlander and Spady (1981) and Braeutigam and Daughety (1984), we can rewrite the long run cost function, with all inputs including capital stock treated as variable, in the form

$$C(\mathbf{y}, \mathbf{w}, w_0, t) = \min_{z_0, \mathbf{x}} \{w_0 z_0 + \mathbf{w}' \mathbf{x} : f(\mathbf{y}, \mathbf{x}, z_0, t) = 1\} \quad (4.2)$$

²⁹ This assumption is employed by Nelson (1985, 1989), Krautmarm and Solow (1988), and Nemoto et al. (1993).

In the short-run, capital input available to the firm is generally assumed to be fixed, implying that the firm attempts to minimize cost conditional on a given plant size. The short run cost function is:

$$C^S(\mathbf{y}, \mathbf{w}, \mathbf{z}_0, t) = \min_{\mathbf{x}} \{w_0 z_0 + \mathbf{w}'\mathbf{x} : f(\mathbf{y}, \mathbf{x}, z_0, t) = 1\}$$

(4.3)

If z_0 is the same as the optimal input z^* that would be chosen in the long run, then

$$C(\mathbf{y}, \mathbf{w}_0, \mathbf{w}, t) = C^S(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t) \tag{4.4}$$

The envelope theorem confirms that the long run total cost defines the envelope of short run total cost expressed in as the sum of variable cost and fixed cost. If the firm minimizes the variable cost of producing a given output, subject to a fixed stock of capital, \mathbf{z}_0 , the variable cost function could be enveloped to determine the long run total cost function.

$$\begin{aligned} C(\mathbf{y}, \mathbf{w}_0, \mathbf{w}, t) &= \min_{\mathbf{z}_0} C^V(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t) + w_0 z_0 \\ &= \min_{\mathbf{z}_0} C^S(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t) \end{aligned} \tag{4.5}$$

Where $C^V(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t)$ is the variable cost function³⁰

Equation (4.5) above is the tangency condition between the short and long run total cost curve. Thus, the envelope theorem implies that for any slight deviation of the level of the fixed input above or below the optimal level, there will be no reduction in total cost.

³⁰ The variable cost function includes the stock of capital as explanatory variable instead of the price of capital

The short run cost function $C^S(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t)$, differs from the more commonly used long run cost function in two ways. First, the dependent variable in the long run cost function is total cost, while the dependent variable in the short run cost function is short run total cost. Second, the price of capital stock appears as an explanatory variable in the long run cost function, while the stock of capital appears as an explanatory variable in the short run cost function. The short run cost function, $C^S(\cdot)$ for electric power generation depends upon two variable factor prices: fuel prices and labour prices, conditional upon predetermined levels of capital stocks \mathbf{z}_0 , electricity generation, \mathbf{y} and the state of technology t . $C^S(\cdot)$ is non-negative and non-decreasing in \mathbf{y} , homogenous of degree one, non-decreasing, and concave in the variable factor input prices, and non-increasing and convex in the levels of quasi-fixed factors \mathbf{z}_0 .

If z^* represents the optimal value of fixed inputs which minimises the short run total cost, then

$$\left(\frac{\partial C(\mathbf{y}, \mathbf{w}_0, \mathbf{w}, t)}{\partial \mathbf{z}_0} \right)_{\mathbf{z}_0 = z^*} = 0 = \left(\frac{\partial C^V(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t)}{\partial \mathbf{z}_0} \right)_{\mathbf{z}_0 = z^*} + w_o \quad (4.6)$$

where w_o is the price of capital and z^* is the equilibrium stock of capital

Rearranging Equation (4.6) gives the important interpretation of the shadow price of the capital input

$$\left(\frac{\partial C^V(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t)}{\partial \mathbf{z}_0} \right)_{\mathbf{z}_0 = z^*} = -w_o \quad (4.7)$$

Equation (4.7) above implies that, in the long run equilibrium, cost minimisation is accompanied when variable cost is saved by substituting the last unit of capital for variable inputs is equal to the price, w_o . This allows us to interpret the derivative on the left-hand-side of (4.7), i.e. the effect on the variable cost function of a change in the quasi-fixed input of capital as the negative of the shadow price of capital. If the derivative is expressed in log or elasticity terms, then it corresponds to the negative of the shadow rate of return on capital. This is the core argument of Breatigam and Doherty (1984).

If $\frac{\partial C^V(y, z_0, w, t)}{\partial z_0}$ is less than $-w_0$ i.e. negative and greater in absolute value magnitude, it implies suboptimal capital whereas if $\frac{\partial C^V(y, z_0, w, t)}{\partial z_0}$ is larger than $-w_0$, it means excess capital. There is a possibility of $\frac{\partial C^V(y, z_0, w, t)}{\partial z_0}$ being positive, implying over-investment in capacity generation and could potentially result in a situation where electric power utility does not operate at a long run efficiency position³¹.

4.3.2 Cost structure

The cost structure of the electric utility industries has been studied extensively using a single product cost function. Since we are interested in the multiproduct cost function as a determinant of power generation utility cost, the model allows us to measure both short-run and long-run economies of scale, as well as cost complementarity.

4.3.2.1 Economies of Scale

Traditionally, scale economies are defined in terms of the relative increase in output resulting from a proportionate increase in all inputs. According to Hanoch (1975) and Brown and Chachere (1980), it is more appropriate to represent scale economies by the relationship between cost and output along the expansion path where input prices are held fixed and cost is minimised at every level of outputs. Although conventional measures of economies of scale are hinged on the single-product firm, the analysis of scale economies for the multiproduct firm is more involved. The shadow price of the quasi-fixed input is important for estimating the degree of scale economies, which is a long run parameter by definition. Panzar and Willig (1977) show the measure of degree ray (or overall) scale economies, r , at output vector y from the multi-product firm is derived from the long run cost function as;

$$r = \frac{C(y, w_0, w, t)}{\sum_{i=1}^n y_i MC_i} = \frac{1}{\sum_{i=1}^n \epsilon_{C y_i}} \quad (4.8)$$

³¹ For a discussion of the interpretation of the enveloped conditions, see Cowing and Holtmann (1983).

where $C(y, w_0, w, t)$ is the long run total cost, $y_i (i = 1 \dots n)$ are the single products of vector y , MC_i is the marginal cost³² with respect to the individual output which is obtained as $\partial C(w, y, X) / \partial y_r$ and \mathcal{E}_{Cy_i} are cost elasticities of the individual outputs.

Therefore, ray scale economies are expressed as the proportional increase in total costs that would result from a proportional increase in all outputs. As shown above, the degree of overall scale economies for the multiproduct firm is obtained as the inverse of the sum of the cost elasticities of single products.

However, studies have shown that there are two distinct methods of deducing the degree of ray scale economies (in the presence of quasi-fixed inputs) to determine whether or not scale economies prevail at efficient expansion points. The more appealing approach, which is in tandem with our motivation and theoretical framework, is the proposition by Friedlander and Spady (1981) and Oum et al. (1991). They suggested evaluation at the equilibrium stock of capital, which involves estimating returns to scale by first enveloping the short run variable cost function using the prices of fixed factors, to determine the corresponding long-run cost function. Therefore, in the presence of a quasi-fixed input, Braeutigam and Daughety, (1983) show that scale economies can be calculated from the short run cost function at efficient expansion points by adjusting the Panzar and Willig measure by the shadow price of the quasi-fixed input:

$$r^* = 1 - \sum_{i=1}^m \frac{\partial \ln C^s(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t)}{\partial \ln z_0} \Big|_{\mathbf{z}_0 = z^*} / \sum_{i=1}^n \frac{\partial \ln C^s(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, t)}{\partial \ln y_i} \Big|_{\mathbf{z}_0 = z^*} \quad (4.9)$$

where $\mathbf{z}_0 = z^*$ is the optimal level of capital stock in for a given output produced. Ray scale economies are present when the calculated value of r exceeds one, while if r equals one there are long run constant returns to scale and decreasing returns to scale if r is less than one.

³² If the marginal costs are identical for all outputs, the overall measure of scale economies collapse into the conventional single output measure of scale economies, see Kim (1987).

Caves et al. (1981) also proposed an alternative approach of inferring economies of scale based on the direct estimation of the variable cost function, without reference to prices of fixed capital input³³ using the following derivation;

$$\begin{aligned}
 r &= 1 - \frac{\sum_{i=1}^n \frac{\partial \ln C^V(\cdot)}{\partial \ln z_0}}{\sum_{i=1}^n \frac{\partial \ln C^V(\cdot)}{\partial \ln y_i}} \\
 &= C^V(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, \mathbf{t}) - \sum_{i=1}^n \frac{\partial C^V(\cdot)}{\partial \ln z_0} z_0 \Big|_{\mathbf{z}_0 = z^*} / \sum_{i=1}^n \frac{\partial C^V(\cdot)}{\partial \ln y_i} y_i \Big|_{\mathbf{z}_0 = z^*} \quad (4.10)
 \end{aligned}$$

The scale economies are calculated using equation (4.10) above and is based on the actual capital stock, rather than the optimal value of the fixed capital input. The method makes no attempts to envelop the variable cost function to reach the efficient expansion point. In actual fact, this alternative approach measures economies of scale at the actual point of operation. However, Braeutigam and Daughety (1983), Nelson (1985) and Oum et al. (1991) showed that the two methods are not equivalent and each produce different economies of scale values which could potentially lead to conflicting policy recommendations. Since the motivation for adopting the variable cost framework is the belief that the firm being studied is not necessarily operating on their efficient expansion path, scale economy estimates computed using the second method would rarely be expected to coincide with those derived using the first (Vita, 1990). The key point is that if the unadjusted Panzar-Willig estimator is applied in variable cost estimation, the result will indicate only the curvature of the short run total cost function, which is likely in a capital-intensive industry such as electricity generation to be much steeper than the curvature of the long run cost function. Consequently, evaluating scale economies is it critical that we make the adjustment for the shadow price of the quasi-fixed input.

³³ Cowing and Holtmann (1983) also proposed a similar approach to Caves et al. (1981) for evaluating scale economies from a variable cost function without reference to the price of the fixed factor, see Vita (1990) for a detailed discussion

4.3.2.2 Cost complementarity

Baumol et al, (1982) state that cost complementarity implies that the marginal cost of producing one good changes when production of the other goods within the product set N increases, indicating economies of scope at a given output y . Cost complementarity in products r and s exist, if the following condition holds:

$$\frac{\partial^2 C}{\partial y_r \partial y_s} < 0 \quad (4.11)$$

Clark (1988) shows the twice-differentiable cost functions, expressing the translog form in equation (4.13) with the following condition as follows;

$$\frac{\partial^2 C}{\partial y_r \partial y_s} = \left(\frac{C}{y_r y_s} \right) \left[\frac{\partial^2 \ln C}{\partial \ln y_r \partial \ln y_s} + \left(\frac{\partial^2 \ln C}{\partial \ln y_r} \right) \left(\frac{\partial^2 \ln C}{\partial \ln y_s} \right) \right] < 0 \quad (4.12)$$

This implies that an increase in the level of production of product y_r reduces the marginal cost of producing y_s . Thus $\frac{\partial^2 C}{\partial y_r \partial y_s} < 0$ indicates product specific-economies of scope between products y_r and y_s . However, if

$\frac{\partial^2 C}{\partial y_r \partial y_s} > 0$, it means diseconomies of scope between products y_r and y_s .

Cost complementarities at the sample mean can be tested because with log mean corrected data, they are regression coefficients using the non-jointness test. Cost complementarity is a feature of the off-diagonal elements³⁴. Applying the estimated translog equation

$$\frac{\partial^2 (C/w_K)}{\partial y_r \partial y_s} = \left(\frac{C/w_K}{y_r y_s} \right) (\alpha_{rs} + \alpha_r \alpha_s) \quad (4.13)$$

The non-jointness test is expressed as follows;

³⁴ Only the sign of the second bracketed term matters since the first must be positive.

$$H_0: \alpha_{rS} + \alpha_r \alpha_s = 0 \text{ versus } H_1: \alpha_{rS} + \alpha_r \alpha_s \neq 0$$

4.3.3 Econometrics Model

The studies on stochastic frontier cost (production) decomposes deviations from these frontiers into random noise and inefficiency terms while estimating efficiency based on the independent proposition of Aigner et al. (1977) and Meeusen and van den Broeck (1977). In order to investigate empirically cost inefficiency in electricity generation in OECD countries, we employ a multi-product cost function model. We have the following stochastic frontier cost models with:

$$C_{it} = f(\mathbf{y}, \mathbf{z}_0, \mathbf{w}, \mathbf{t})_{it} + u_{it} + v_{it} \quad (4.14)$$

where C_{it} = is the cost for the i th OECD country national generation at the time t , $i = 1, \dots, 25$ and $t = 1, \dots, 30$, \mathbf{y}_{it} is a vector for the outputs, \mathbf{w}_{it} is a vector for the factor prices, \mathbf{z}_{0it} is a quasi-fixed input. Since the mean of the variables are regarded as the expansion point, costs as well as outputs and factor prices are normalised by dividing the variables by their corresponding means. u_{it} represents one-side technical inefficiency, whereas v_{it} denotes a two-sided conventional idiosyncratic error term with zero means and variance σ_v^2 .

4.3.3.1 Translog Cost Function

Several flexible functional forms have been proposed, which help to address the drawback associated with previous inflexible functional forms such as Cobb-Douglas based on constant elasticities of substitution as criticized by Uzawa (1962)³⁵. It is worth noting that these functional forms are not parsimonious (in terms of the number of parameters) and are more cumbersome to implement empirically³⁶. The most popular and widely used specification of these flexible functional forms in stochastic frontier cost literatures has been the

³⁵ Uzawa (1962) proved that it is impossible for any functional form that exhibits constant elasticities of substitution to provide simultaneously the capability to attain an arbitrary set of elasticities.

³⁶ A functional form is parsimonious if it provides a second order approximation using a minimal number of parameters. See Fuss, McFadden, and Mundlak (1978) which argue that a growing number of variables leads to more parameter estimates which exacerbate problems of multicollinearity. Also, when the sample is small, excess parameters mean a loss of freedom and hence a loss in the precision of estimation.

translog form³⁷. Using the transcendental logarithm functional form as an arbitrary second order approximation to the multi-product cost function, we fit variable cost functions (i.e. a function for the minimum cost required to produce outputs given the input prices), $C(y, z_0, w, t)$ for N country over T periods as follows;

$$\begin{aligned}
\ln C_{it} = & \alpha_0 + \sum_m \alpha_m \ln y_{mit} + \sum_j \beta_j \ln w_{jit} + \sum_m \sum_j \gamma_{mj} \ln y_{mit} \ln w_{jit} \\
& + \frac{1}{2} \sum_m \sum_n \alpha_{mn} \ln y_{mit} \ln y_{nit} + \frac{1}{2} \sum_j \sum_k \beta_{jk} \ln w_{jit} \ln w_{kit} + \pi_1 \ln z_{0it} \\
& + \sum_m \rho_m \ln y_{mit} \ln z_{0it} + \sum_j \sigma_j \ln w_{jit} \ln z_{0it} + \frac{1}{2} \pi_2 (\ln z_{0it})^2 \\
& + \delta_1 t + \frac{1}{2} \delta_2 t^2 + \sum_m \theta_m \ln y_{mit} t + \sum_j \mu_j \ln w_{jit} t + \varepsilon_{it}
\end{aligned} \tag{4.15}$$

Where $\ln C_{it}$ is the natural logarithm of cost, $\ln y_{mit}$ is the natural logarithm of m th output ($m=1, 2$); $\ln w_{mit}$ is the natural logarithm of the j th input price ($j=1, 2$), $\ln z_{0it}$ is the natural logarithm of the quantity of the fixed input, and $\varepsilon_{it} = v_{it} + u_{it}$. We impose the usual symmetry restrictions on the above cost function, viz., $\alpha_{ml} = \alpha_{lm}$ for all l and m , and $\beta_{jk} = \beta_{kj}$ for all j and k . Moreover, to ensure linear homogeneity of the variable cost function, $C^V(\cdot)$ in the input prices (i.e. doubling of all factor prices leading to doubling of costs), the following restrictions are imposed;

$$\sum_j \beta_j = 1; \sum_j \beta_{jk} = 0 \quad \forall k; \sum_j \gamma_{mj} = 0 \quad \forall k; \sum_j \psi_{jt} = 0 \tag{4.16}$$

³⁷ See Christensen, Jorgenson and Lau (1971, 1973) for a discussion on the rationale for preference towards the translog functional form.

The condition that the cost function is homogenous of degree one in input prices is imposed by normalising cost and labour price by fuel price. The estimated cost function is specified as follows;

$$\begin{aligned}
\ln \frac{C_{it}}{w_s} = & \alpha_0 + \sum_{m=1}^M \alpha_m \ln(y_{mit}) + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} (\ln(y_{mit}) \ln(y_{nit})) + \sum_{j=1}^J \beta_j \ln \left(\frac{w_{jit}}{w_s} \right) \\
& + \frac{1}{2} \sum_{j=1}^J \sum_{k=1}^J \beta_{jk} \left(\ln \left(\frac{w_{jit}}{w_s} \right) \ln \left(\frac{w_{kit}}{w_s} \right) \right) + \sum_{m=1}^M \sum_{j=1}^J \gamma_{mj} \left(\ln(y_{mit}) \ln \left(\ln \frac{w_{jit}}{w_s} \right) \right) \\
& + \sum_{j=1}^J \sigma_j \left(\ln \left(\frac{w_{jit}}{w_s} \right) \ln(z_{oit}) \right) + \sum_{m=1}^M \rho_m (\ln(y_{mit}) \ln(z_{oit})) + \pi_1 \ln(z_{oit}) + \frac{1}{2} \pi_2 (\ln(z_{oit}))^2 \\
& + \sum_{m=1}^M \theta_m \ln(y_{mit}) t + \sum_{j=1}^J \mu_j \ln \left(\frac{w_{jit}}{w_s} \right) t \quad \delta_1 t + \frac{1}{2} \delta_2 t^2 + \varepsilon_{it}
\end{aligned} \tag{4.17}$$

4.3.3.2 Cost Efficiency Estimation

The cost function in equations (4.17) is estimated using three different stochastic frontier estimation models based on the assumptions imposed on the error term (ε_{it}), inefficiency and error term. These models are the fixed effects model by Schmidt and Sickles (1984), Greene's true fixed effects model and the four-way error component model (FWEC hereafter) proposed by Kumbhakar, Lien and Hardaker (2014). They are summarised in Table 4.1. Model I: TI is the time-invariant fixed effects model proposed by Schmidt and Sickles (1984). The model specifies a firm-specific effect u_i , an independent randomly distributed intercept and a random noise term v_{it} which is assumed to be identically and independently distributed (*iid*). The advantage of this model is that it avoids making any distributional assumption about the inefficiency term, and it permits the inefficiency term to be correlated with the regressors. The disadvantage is the inability to distinguish between time-invariant unobserved heterogeneity and cost inefficiency as all time-invariant firm-specific effects are incorporated into inefficiency.

Table 4.1: Econometric specifications of the cost frontier models

Specification	Model 1 (TI)	Model 2 (TFE)	Model 3 (FWEC)
	Schmidt-Sickles (1984)	Greene (2005)	Kumbhakar-Lien-Hardaker (2014)
Error-component model	$\varepsilon_{it} = v_{it} + u_i$	$\varepsilon_{it} = v_{it} + \alpha_i + u_{it}$	$\varepsilon_{it} = v_{it} + \eta_i + \gamma_i + u_{it}$
Idiosyncratic error	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$	$v_{it} \sim N(0, \sigma_v^2)$
Time-invariant (persistent) inefficiency	Yes Fixed Effects, u_i	No	Yes $\eta_i \sim N^+(0, \sigma_\eta^2)$
Country-specific latent heterogeneity	No	Yes Fixed Effects, α_i	Yes Random Effects, γ_i
Time-varying (residual) inefficiency	No	Yes $u_{it} \sim N^+(0, \sigma_u^2)$ or $u_{it} \sim iid - exponential$	Yes $u_{it} \sim N^+(0, \sigma_u^2)$
<i>Inefficiency measure</i>			
Persistent (time-invariant)	$\hat{u}_i - \text{Min}\{\hat{u}_j\}$	<i>None</i>	$E(\eta_i \varepsilon_{it})$
Residual (time-varying)	<i>None</i>	$E(u_{it} \varepsilon_{it})$	$E(u_{it} \varepsilon_{it})$

A country i 's inefficiency is assumed to be the interval between its estimated fixed effect and that of the country on the frontier namely, the minimum estimated fixed effect ($\min \{ u_i \}$). Furthermore, the time invariant nature of the inefficiency term assumption is considered restrictive, especially in the presence of empirical applications based on long panel data sets.

Model II relaxes the restrictive assumption in model I by allowing time variation in the inefficiency term while enabling investigation of the impact of observed heterogeneity on cost and efficiency. If latent

heterogeneity exists (such as factors that beyond the firms' control but may affect their costs) then all the time invariant heterogeneity will be pushed to the intercepts and, finally, into the inefficiency term leading to a biased efficiency estimate. The unobserved firm-specific heterogeneity can be taken into account with conventional fixed or random effects in a panel data model. In order to distinguish external heterogeneities from cost efficiency, Greene (2005a) proposed the "true" fixed effect that incorporates an additional stochastic term representing inefficiency in both fixed and random effects models. Model II addresses the time invariant heterogeneity by specifying separate intercept dummy variables for each unit in the sample and follows the asymmetric half normal distribution for the cost inefficiency component and the normal distribution for the error term. This model is estimated using the Simulated Maximum Likelihood (SML) method.

In model II, the time-invariant component of the inefficiency might be picked up other than through the effect of pure heterogeneity. Model III proposed by Kumbhakar, Lien and Hardbaker (2014) deals with the time-invariant inefficiency by separating time-invariant (persistent) inefficiency from time-invariant heterogeneity. The model is a modified and extended version of a model proposed by Kumbhakar and Heshmati (1995) where technical inefficiency is assumed to have a persistent firm-specific (time-invariant) component and a time-varying residual component. Although firm effects are treated as persistent inefficiency by Kumbhakar and Heshmati (1995), a random firm effect is included in the Kumbhakar, Lien and Hardbaker (2014) model. The extended model includes separate four components; two of which are stochastic inefficiency terms (residual and persistent inefficiencies) and the other two are time invariant heterogeneity and the idiosyncratic error term. This model is specified as follows;

$$C_{it} = \alpha_o + f(\mathbf{y}_{it}', \mathbf{w}_{it}') + \pi(\mathbf{z}_{it}) + \gamma_i + \eta_i + v_{it} + u_{it} \quad (4.18)$$

Where γ_i are the random firm effects that capture unobserved time-invariant heterogeneities, η_i time-invariant (persistent) inefficiency v_{it} is an idiosyncratic error term and u_{it} is the time-varying (residual) inefficiency. The overall cost efficiency is given as the product of time-invariant (persistent) efficiency and

time-varying (residual) efficiency. The consideration for model III becomes more relevant in the context of a quasi-fixed input to the extent that the inefficiency associated with this input may not be eliminated in the short run and tends to remain with the firm over time. This model is estimated using the Pseudo-Maximum Likelihood method originally suggested by Fan et al (1996) which involves a four step KLH modelling procedure.³⁸

Inclusion of observed heterogeneity in the models is usually done through a variety of ways, either by allowing observed heterogeneity to affect the cost frontier or to influence the distribution of the inefficiency term³⁹. An alternative approach to analyse the effect of observed heterogeneity on inefficiency is obtained by scaling its distribution⁴⁰. The observed heterogeneity in the inefficiency model is expected to include any factors that help explain the extent to which the cost observations exceed the corresponding stochastic frontier cost values. These variables include the electricity consumption per capita, industry value added, overall electricity market closeness, entry barriers, vertical integration and public ownership.

The cost efficiency score for each country can be estimated from the point estimates of the cost inefficiency (u_{it})⁴¹ as the ratio of observed cost C_{it} to frontier or minimum cost C_{it}^F :

$$CE_{it} = \frac{C_{it}}{C_{it}^F} = \exp(-u_{it}) \quad (4.19)$$

The cost efficiency measure lies between 0 and 1. A score of one indicates a country is on the frontier, while non-frontier firms receive scores below one. This approach is based on conditional expectations which generalize the estimators proposed by Jondrow et al. (1982).

³⁸ Kumbhakar, Lien and Hardbaker (2014) demonstrate the procedures for estimating the model which includes fitting a one-way random effect model in order to predict the random effect and the error term components. The errors are then used in the following steps to estimate the time-invariant (persistent) inefficiency and time-varying (residual) inefficiency. See Kumbhakar, Lien and Hardbaker (2014) for a detailed discussion of the estimation procedure.

³⁹ Kumbhakar et al. (1991), Huang and Liu (1994) and Battese and Coelli (1995) proposed an approach of parameterizing the mean of a pre-truncated truncated normal distribution as a way to analyze the exogenous influence on inefficiency. See Wang (2002).

⁴⁰ Caudill and Ford (1993), Caudill et al. (1995) and Hadri (1999) proposed to parametrize the variance of the pre-truncated inefficiency distribution. See Wang (2002).

⁴¹ Cost inefficiency takes a value between one and infinity with a value of one indicating a country on the frontier while a value above one means non-frontier country

4.4 Data description

The analysis of cost structure and efficiency of electricity generation in OECD is hampered by the paucity of data for the entire OECD countries. Data collected from different international databases for a period from 1980 to 2009 covers only 25 countries. Years 1980 through to 2009 are respectively the years for which data are available for all the variables. The data necessary for the cost estimation include the variable cost, the price of two variable factors i.e. labour (L) and fuel (F); a quasi-fixed capital input (K) together with the quantity of electricity generated. Others include carbon emissions, electricity reform indicators i.e entry barrier, vertical integration, public ownership and overall market reform, as well as the country-specific heterogeneous variables.

The input prices and variable cost were calculated as follows. The price of labour (w_1) is computed as the ratio of labour compensation⁴² and the number of people engaged obtained from EU KLEMS. This is obtained in each country's currency at current price, and converted to constant price by using a value-added price index (1995=100). These real local currency measures are then normalised into international units using purchasing power parity exchange rate from the Penn World Table (PWT7.1). Fuel price (w_2) represents the price of fuel used for electricity generation measured in dollars at current prices. It is obtained from the energy, prices and taxes folder of International Energy Agency (IEA). The price is converted to constant price by normalising using the price index (1995=100) from the World Development Indicators. Data on operating cost was calculated as the sum of labour and fuel expenditures. The number of people represents labour while fuel consumption inputs measured in kilotonnes of oil equivalent (ktoe) includes all varieties of fuel utilised by the generation plants: coal, oil, gas, hydro, nuclear and biomass. As fuel input data are available in the same measurement units, we aggregated them into one indicator. This allows for the different fuel intensity of different generation technologies. The fuel consumption data is collected from the International Energy Agency (IEA).

⁴² The data represents labour compensation for utility i.e. water, gas and electricity as there is no available disaggregated data for the electricity sector. It is reasonable to assume that a substantial portion of the employment in the utility industry is actually attributable to electricity sector.

As for the choice of the outputs, we consider both desirable and undesirable outputs that are jointly produced during electricity and heat production. The outputs are electricity generation (y_1), which represents the annual net electricity output generated by each country measured in gigawatt-hours, and carbon emissions (y_2) measured in million metric tons. Capital stock is measured in megawatt (MW) of installed capacity. Installed capacity is used as a proxy for the quasi-fixed stock of capital in our cost model. This is a consistent proxy of capital stock in line with relevant papers (See Jaraitė & Di Maria, 2012). Electricity generation and installed capacity are also obtained from International Energy Agency (IEA) while carbon emission is sourced from the World Bank Development Indicators.

Besides the standard variables of proper cost estimation, we added electricity sector regulatory reform indicators in the model. These include the sub indicators of the reform process; namely entry barriers, public ownership, and vertical integration, and overall electricity market reform. They extracted from the OECD market regulatory OECD Product Market Regulation database. The OECD's PMR database contains a large amount of information on regulatory structures and policies that is obtained through a questionnaire sent to governments in OECD and non-OECD countries. The database covers all OECD countries and 21 non-OECD countries. These indicators range from 0 to 6, with 0 representing the fully open market in which entry barriers, public ownership and vertical integration are minimized and a score of 6 is given to a closed market. Or, as the OECD expresses it: "Scores vary from 0 (the most effective governance structure) to 6 (the least effective governance structure)". Incorporating the variable into the cost frontier, costs are expected to increase with increasing restriction of the electricity market. A positive sign on the market reform variable means that cost rises as index rises from 0 to 6. Moreover, we added country-specific heterogeneous variables in our analysis to account for possible shifts of frontier cost level. We also control for the degree of industrialisation of each country, which is measured by the industrial output percentage share of GDP. We expect a large proportion of industrial customers to increase operating costs in order to a balance industrial electricity demand with energy supply as customers can increase their power demand anytime.

Table 4.2: Descriptive Statistics

520 Observations	Units	Mean	SD	Min	Max
Cost	US \$ (1995=100)	1.69E+07	4.31E+07	7497.12	4.31E+07
Outputs					
Electricity generation	GWh	370562.20	762132.50	903.00	4190541
Carbon emission	MMT	226.59	532.18	1.03	2732.80
Input prices					
Price of labour	US \$ (1995=100)	52.36	46.51	0.65	540.48
Price of fuel	US \$ (1995=100)	274.70	331.53	5.40	2643.20
Quasi-Fixed input					
Capital	MW	90173.52	183543.00	1235.00	1026869.00
Environmental Variables					
Industrialisation	% of GDP	24.37	4.10	13.78	32.70
Entry barriers	(0-6)	4.10	2.46	0.00	6.00
Public ownership	(0-6)	4.28	2.17	0.00	6.00
Vertical integration	(0-6)	5.45	0.80	3.00	6.00
Overall elect. mkt. reform	(0-6)	4.47	1.60	1.17	6.00

Finally, we included a time trend in the model, measured in years, so as to account for the possible effects of Hicks neutral technological change, with the expectation that costs are expected to diminish over time, all things being equal. For the estimation, we mean-adjusted and logged each variable by taking the means (in order for the cost order coefficient in the model to be interpreted as elasticities at the sample mean). The descriptive statistics on the variables used in the empirical estimation are provided in Table 4.2.

4.5 Result and discussions

We begin our analysis by checking the validity of our stochastic frontier specifications. This involves running a pooled OLS based on the test proposed by Schmidt and Lin (1984) in order to confirm the presence of technical inefficiency. In the case there were no technical inefficiency, the error term would be distributed symmetrically around zero i.e. $u_{it} = 0$ then $\varepsilon_{it} = v_{it}$, thereby invalidating the inefficiency

assumption. The estimated skewness and kurtosis test for normality from the pooled OLS regression has the expected sign and confidently rejects the null hypothesis of the normal residual⁴³. Thus, the test result provides evidence for the presence of the one-sided error⁴⁴. Furthermore, a series of hypothesis tests were conducted using log likelihood ratio tests. Table 4.3 presents the results of hypothesis tests that examined a number of restrictions.

Table 4.3: Likelihood ratio test

Null Hypothesis	Test statistics	Critical value (0.05 level)	Decision
Cobb-Douglas			
H_0 : all cross effects null	269.073	$\chi_{13}^2 = 22.362$	Reject H_0
Hicks neutral technical change $H_0: \theta_1 = \theta_2 = \mu_j = 0$	36.845	$\chi_3^2 = 7.815$	Reject H_0
Homotheticity $H_0: \gamma_{1j} = \gamma_{2j} = 0$	46.842	$\chi_2^2 = 5.991$	Reject H_0

The hypotheses tests were obtained using the generalized likelihood statistic. This is defined by $\lambda = -2[\ln(LH_0) - \ln(LH_1)]$. If the null hypothesis is true, λ has a chi-square distribution χ_p^2 where p is the degrees of freedom equal to the difference between the number of parameters estimated under H_0 and H_1 . We test the translog specification against a Cobb–Douglas specification in a bid to confirm if the translog gives adequate representation of the cost structure. The Cobb–Douglas frontier is rejected at 1% significance level. The chi-square statistic for the restrictions is 269.07, while the critical value at 5% is 22.36. Second, we test the hypothesis of Hick-neutral technological progress that technology change has no effect on factor augmenting and input demand. The hypothesis of technical bias in the translog cost function is also rejected. The homotheticity assumption which emphasises that the level of output has no effect on the demand for input is also tested. We impose restrictions on the parameters associated with interactions between input

⁴³ Since our model is a cost frontier function with a composed error term, the distribution of the OLS residual skew to the right (positive) as against left (negative) for production function regardless of any distributional assumption

⁴⁴ The normality result is available.

price and outputs. We reject homotheticity of the technology implying that input prices have significant impact on the scale economies.

4.5.1 Model results

The cost frontier in equation 4.17 is estimated using the fixed effects for time-invariant inefficiency without heterogeneity, FE – Schmidt & Sickles (1984), the true fixed effects for heterogeneity with time varying inefficiency, FTE – Greene (2005a) and the four-way component model with heterogeneity, residual and persistent inefficiency, FWEC – Kumbhakar et al. (2014), models. Table 4.4 shows the estimated parameters from the different specifications of the stochastic cost frontier. The first and third columns of results correspond to the fixed and random effects one-way panel model respectively, while the second column corresponds to the true fixed effects model, TFE. On grounds of the likelihood function values and the significance of the coefficients, the TFE model is clearly preferable.

The results in the third column permit derivation of both time-varying and time invariant inefficiency components with latent heterogeneity as well, but only the first step estimates are shown here, which correspond to the random effects version of the fixed effects model in column 1. Again, the precision of the coefficients is less convincing than the true fixed effects model in the second column and, moreover, the additional time-invariant inefficiency component is minimal. On all these grounds, the TFE model in the second column clearly performs best, and we focus our interpretation on these TFE results.

Table 4.4: Estimated results of different Frontier models

Variable	Model I- FE		Model II-TFE		Model III- FWEC (RE)	
	Coeff	Std error	Coeff	Std error	Coeff	Std error
Generation	1.1538***	(0.0616)	1.1567***	(0.0488)	1.1871***	(0.0650)
Emissions	0.0362	(0.0308)	0.0986***	(0.0259)	0.0346	(0.0332)
Input price ratio	1.0279***	(0.0064)	1.0163***	(0.0052)	1.0232***	(0.0070)
Generation squared	0.2769**	(0.1404)	0.4572***	(0.1171)	-0.2680*	(0.0142)
Emissions squared	0.0301	(0.0252)	0.0635***	(0.0207)	0.0349	(0.0273)
Generation × Emissions	-0.1367	(0.1012)	-0.3719***	(0.0830)	-0.1141	(0.1120)
Input price ratio squared	0.0004	(0.0025)	-0.0001	(0.0020)	-0.0007	(0.0027)
Generation × Input price	-0.0682**	(0.0331)	-0.0408	(0.0261)	-0.0985***	(0.0362)
Emissions × Input price	0.0084	(0.0105)	0.0012	(0.0081)	0.0120	(0.0116)
Time	0.0020	(0.0015)	0.002	(0.0013)	0.0005	(0.0015)
Generation × Time	-0.0046***	(0.0016)	-0.0057***	(0.0014)	-0.0003	(0.0017)
Emissions × Time	-0.0019	(0.0013)	0.0009	(0.0011)	-0.0028*	(0.0015)
Input price × Time	-0.0004	(0.0005)	-0.0005	(0.0004)	-0.0009*	(0.0005)
Capital	-0.3201***	(0.0521)	-0.3219***	(0.0429)	-0.2877***	(0.0560)
Capital squared	0.2390*	(0.1238)	0.2081*	(0.1116)	-0.2299	(0.1275)
Generation × capital	-0.3264	(0.0250)	-0.4496**	(0.2160)	0.6034**	(0.2543)
Emissions × capital	0.0775	(0.0917)	0.2062***	(0.0726)	0.0616	(0.1020)
Input price × capital	0.0424	(0.0333)	0.0299	(0.0270)	0.0627*	(0.0364)
Increased industrialization	-0.0007	(0.0020)	0.0004	(0.0016)	-0.0014	(0.0022)

Increased entry barriers	0.0092	(0.0064)	0.0024	(0.0052)	0.0188***	(0.0070)
Increased vertical integration	0.0351***	(0.0068)	0.0270***	(0.0057)	0.0421***	(0.0075)
Increased public ownership	0.0486***	(0.1163)	0.0334***	(0.0091)	0.0717***	(0.0127)
Reduced overall market reform	-0.0370**	(0.0162)	-0.0101	(0.0143)	-0.0655***	(0.0176)
Constant	-0.5325***	(0.0710)	All FE***		-0.4908***	(0.0954)
Est. SE time invariant heterogeneity					0.3080***	
Est. SE time invariant inefficiency	0.9352				0.0002	
Est. SE idiosyncratic error	0.0617		0.0275***		0.0607***	
Est. SE time varying inefficiency	-0.001		0.0556***		0.0281	
$\lambda = \sigma_u/\sigma_v$			2.0223***		0.4636***	
Log of likelihood function	705.481		739.814		n/a	

Notes: *, **, *** denote statistically significant at 10%, 5% and 1% respectively. Standard error in parenthesis

We discuss several aspects of these results. First, the monotonicity conditions for the translog cost function are clearly satisfied with significant coefficients on the generation, emissions and input price terms. Generation and the input price are the dominant drivers of total costs with a statistically significant but low elasticity of cost arising from emissions handling. The direct impact of neutral technical progress is not significant but there is a significant interaction of technical progress and generation output. This reflects a common finding amongst international panels that it is input accumulation and output expansion that drives productivity over time rather than pure technical progress – see Adetutu et al (2016) for a similar finding for the BRIIC economies. The negative sign of the parameter of the quasi-fixed input also show expected sign indicating clearly that cost is non-increasing in the quasi-fixed input. This result is consistent with economic theory and satisfies the regularity condition of non-increasing variable costs with respect to capital stock at the mean of the data (See Chamber, 1988; Filippini, 2005). The presence of generation capital stock as a quasi-fixed input enables us to estimate the rate of return on capital from the negative of the reported cost elasticity. We see that at a statistically significant sample mean value of 0.3129 the return on capital in generation has been high over the sample period suggesting that producers have been undercapitalised and that expansion of generation investment was warranted given the cost of capital that has prevailed in most of the sample countries over this period.

Looking at the measurement of the impact of exogenous variables, particularly the variables of interest- electricity market reform indicator variables on cost efficiency, most of the results are consistent with a priori expectation. The coefficient of per capita electricity consumption is negative. However, we were unable to establish a statistically significant relationship between per capita electricity consumption and variable cost in all the models, at least within the sample period. On the other hand, industry value added i.e. industry share of percentage of GDP influences variable cost negatively. This result indicates that a marginal increase in industry share of value added does lower variable costs. This finding is reasonable because where the market has a higher share of industrial consumers it can be less costly to plan for variations in

load throughout the year. Thus, utility can efficiently manage generation constraints to keep future reinforcement costs down for the benefit of both the utilities and customers.

Of primary interest has been the role of regulatory reform and the progress in the product market regulation indicators computed by the OECD. In the first and third columns there is an indication that overall market reform has not reduced cost, but this appears to be a spurious finding related simply to the country specific differences across the sample. When country specific latent heterogeneity is allowed for in the TFE results in the second column, which are already preferred for reasons of goodness of fit, it becomes clear that the overall market reform indicator is not statistically significant. In other words, the overall reform effort is picked up by the heterogeneity of the countries in the sample; this should not surprise us because each of these countries has pursued different strategies in designing the regulatory oversight and ownership of the generation industry.

On the other hand, two of the OECD's product market regulation indicators are statistically significant even when country-specific heterogeneity is taken into account. These are vertical integration and public ownership. Greater vertical integration and a greater degree of public ownership are statistically significant in raising generation costs in each of the estimated models. In the random effects model in the third column barriers to entry are also significant in raising generation costs. We can speculate on the reasons for these findings. Strong vertical integration means that the generation companies are closely allied to the providers of transmission and distribution services. These are invariably in a natural monopoly position of market power so that some protection of market power from competitive forces could be transmitted back up the electrical power supply chain leading to the higher generation costs found in these data. Turning to the impact of public ownership, there is a wide acknowledgement in the literature that public and state-owned corporations have a mixed range of objectives that can lead to weaker incentives for cost reduction, and this hypothesis is confirmed by the data.

There are some lessons for the reform process in electricity generation from this research. First, countries have approached the market reform process differently. Inter-country heterogeneity is an important ingredient of the determination of generation costs, and therefore in reviewing lessons from international sample data, significant country differences must be expected. Second, leaving vertically integrated industries intact in the reform process reduces the ability to save generation costs – possibly because of the natural monopoly aspects of the downstream activities. Therefore, unbundling of the industry to create a separate generation sector is likely to enhance efficiency. Third, public and state ownership hinders the reduction in generation costs that can be achieved during periods of market reform. Privatisation appears to be a more efficient policy to pursue. The findings on scale economies in generation alone tell us that taking the quasi-fixed input into consideration, the cost elasticity of scale is 1.05 confirming that a competitive equilibrium in generation without the market power impact of economies of scale is feasible and will permit the unbundling of generation from transmission and distribution.

4.5.2 Economies of Scale and cost complementarity

Scale economies in power generation utilities are a measure of how costs change as the utilities expands all of its productive resources proportionately to provide increased generation. We compute short run elasticity of scale in line with the unadjusted Panzar-Willig measure while long run returns to scale was estimated according to adjusted Braeutigam-Daughety measure. The elasticity of scale is reported in table 4.5 with ε_1 denoting the cost elasticity with respect to electricity generation, ε_2 is the cost elasticity with respect to emissions and ε_k represents the cost elasticity with respect to quasi-fixed capital. Standard errors and significance tests were constructed using the delta method. We are interested in the difference between the unadjusted measure of scale economies r and the measure adjusted for the quasi-fixed input r^* . Traditionally, economies of scale have been a main characteristic of power generation. Interestingly, our scale economies estimates provide additional insight into existing studies.

Table 4.5: Economies of Scale: Inverse of cost elasticity of output vector

Model	Unadjusted Panzar-Willig measure, r [$1/(\varepsilon_1 + \varepsilon_2)$]	Standard error	Adjusted Braeutigam-Daughety measure r^* [$(1 - \varepsilon_k)/(\varepsilon_1 + \varepsilon_2)$]	Standard error	Test: unadjusted $r =$ adjusted r^* p-value	Test: adjusted $r^* = 1$ p-value
TFE	0.797	0.031	1.053	0.031	0.000	0.082

Our findings show that input-augmenting scale effects in power generation are not observed in the short run leading to increasing costs, but the analysis reveals the presence of mild scale economies in the long-run when the return on capital is included in the calculation.

Interestingly, our scale economies estimates provide additional insight into existing studies. Our findings show that input-augmenting scale effects in power generation are not observed in the short run leading to increasing costs. In other words, the estimated economies of output expansion for the models in the short run is about 0.8, indicating the existence of sharply rising costs when capacity is fixed. In the generation stage, the exhaustion of scale economies is usually related to market size which allows competition among power generators (Landon, 1983; Joskow, 1996). Effectively, OECD generation utilities do not benefit from economies of scale in an attempt to expand their generation operations as they lie in the range at which average costs are considered to be on upward steep. However, economies of scale in the long run are measured at 1.05 – and are not significantly different from 1, implying constant returns to scale when adjustment is made for the quasi-fixed input.

Table 4.6: Cost complementarity and non-jointness test⁴⁵

Model	Cost complementarity	Non-jointness Test statistics	P-value
TFE	-0.258	11.83	0.001

⁴⁵ The test is a nonlinear Wald test which can be implemented by the `testnl` command in STATA which uses the delta method. We only reported the p-value, the test estimate is available upon request.

Table 4.6 provides cost complementarity estimates and non-jointness test statistics. The cost complementarity estimates are based on the expressions in Equation 4.13. The point estimates for the output combination is negative in our model, indicating that the marginal cost in production of a bad output decreases as electricity output generation production expands. The test for cost complementarity between the two outputs as shown above gives the chi-square values of each model and their associate p-values which are less than the generally used criterion of 0.05. Thus, we are able to reject the null hypothesis of non-jointness of the outputs indicating therefore that there is a possibility to reduce emissions without reducing generation. Therefore, the findings provide evidence of economies of scope as a result of cost complementarity.

4.5.3 Cost efficiencies

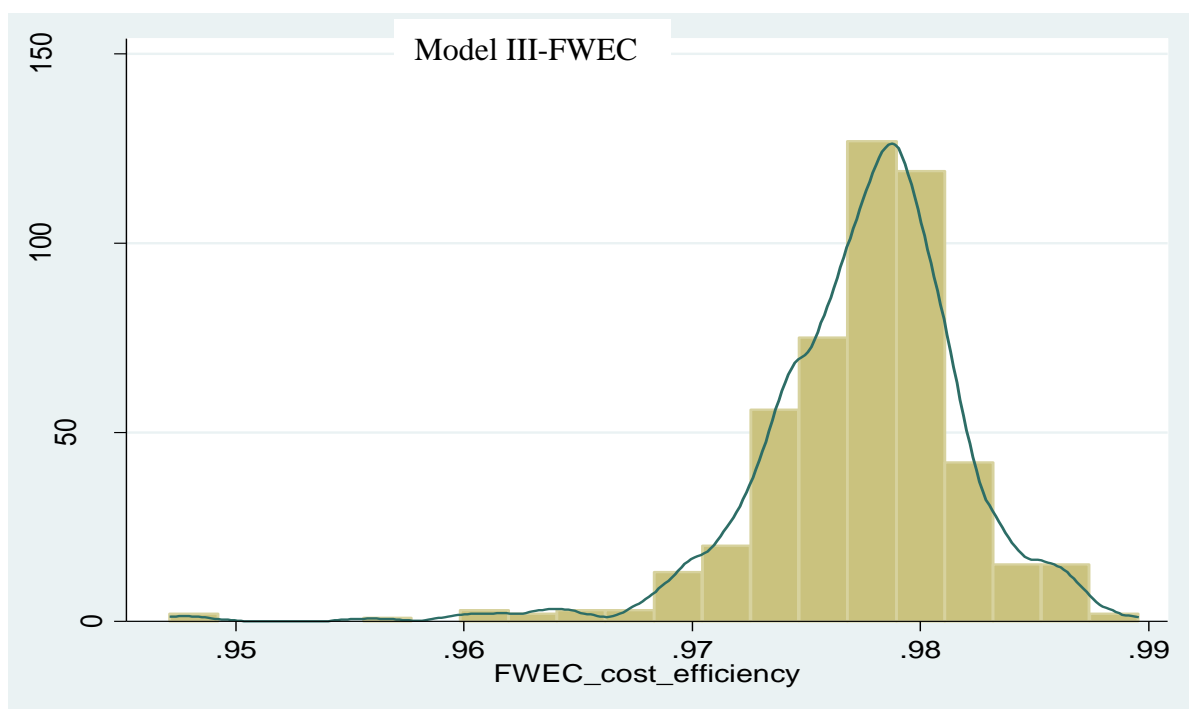
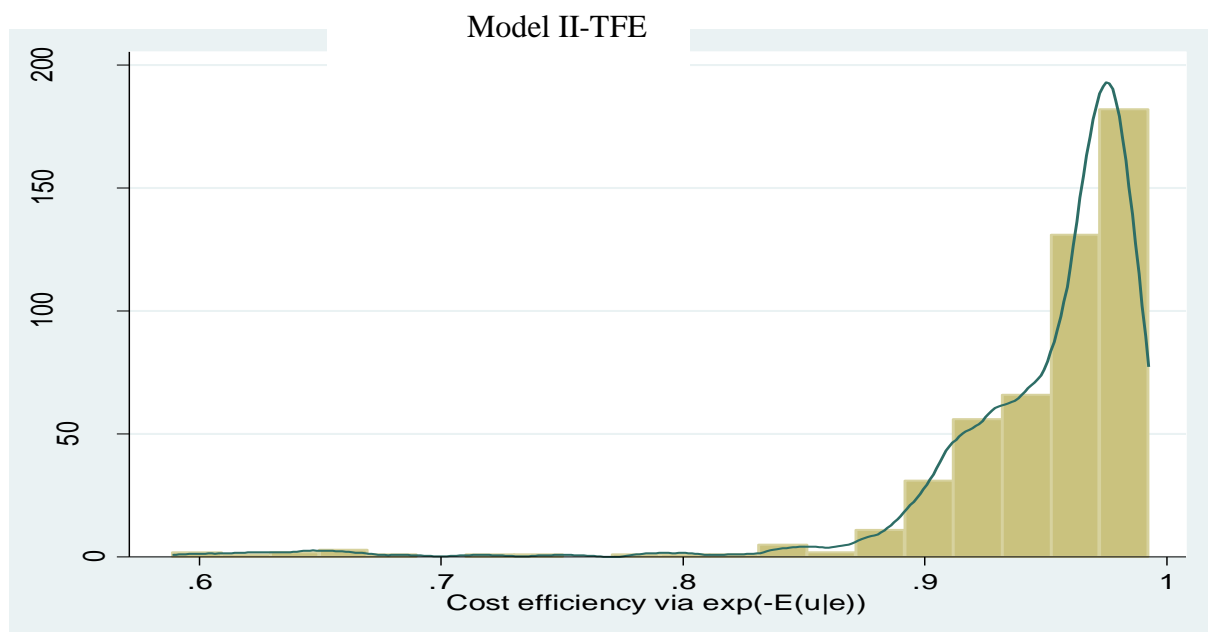
Using the Jondrow et al. (1982) decomposition of the error term, we assess the cost efficiency for each model. The efficiency score estimates lie between 0 and 1 as shown by descriptive statistic for the cost efficiency. Efficiency estimates are sensitive to the choice of frontier model specification. For comparison, the descriptive statistic for the cost efficiency of the true fixed effect and the four-way error component models is given in Table 4.7. The cost reduction potential of each country is given by one less its efficiency score. With regards to model II (TFE), that separates only the idiosyncratic error and inefficiency, this has a relatively lower average efficiency score of 0.948 against model III (FWEC) which has an average overall efficiency score of 0.978.

Table 4. 7: Estimate cost efficiency scores

Model	Mean	SD	Min	Max
Model I- TFE	0.948	0.055	0.589	0.993
Model II-FWEC	0.978	0.005	0.947	0.990

This result is not surprising due to the fact that the four-way error component model not only separates the idiosyncratic error from the inefficiency but also divides stochastic inefficiency terms into two residual and persistent inefficiencies, hence the relatively larger average efficiency score. Figure 4.2 shows two histograms each overlaid with kernel density plot for the true fixed effect model and four-way error component model respectively.

Figure 4.2: Histograms and Kernel densities for Model II and Model III



Nevertheless, the result of our preferred model implies that OECD countries are, on average, 94.8% cost efficient in generating electricity. Figure 4.2 reveals that the TFE model which treats time invariant unobserved heterogeneity separately from inefficiency is right-skewed which further reinforces the results under discussion. Finally, we present a broad check of the link between market structure variables⁴⁶ and the measured efficiency scores in Table 4.8

Table 4.8: Pairwise correlations

	Industrialization	Increased entry barriers	Increased vertical integration	Increased public ownership	Efficiency
Industrialization	1				
Increased entry barriers	0.2636*	1			
Increased vertical integration	0.1619*	0.3969*	1		
Increased public ownership	0.2501*	0.8495*	0.2971*	1	
Efficiency	0.0948*	-0.1439*	-0.0895*	-0.1278*	1

*Note: * means statistically significant at the 5 per cent level*

We see that market reform indicators are themselves positively correlated – so that countries that score poorly on entry barriers or vertical integration for example also score poorly on the other market reform indicators. In terms of the efficiency scores, more industrialized economies have a weak but significant correlation with stochastic efficiency, and countries that have worse (i.e. numerically higher) scores on market reform indicators have lower stochastic efficiency scores although this time the strongest effect is from entry barriers.

⁴⁶ We exclude the overall market reform indicator from this table because the efficiency scores are from the TFE model where its effect is submerged in the country-specific latent heterogeneity fixed effects

4.6 Conclusion and policy implication

This study employs different stochastic frontier methods to estimate a short-run equilibrium model of electricity generation variable cost functions in which capital stock is treated as a quasi-fixed input. This is applied to OECD electricity generation sectors while accounting for the impact of electricity market structures by using the published OECD product market reform indicators. Empirical models are developed for the variable cost function as a translog form and analysed using panel data for 25 countries during the period 1980 to 2009. We use three main estimation models: Schmidt-Sickles' (1984) fixed effects, Greene's (2005) True fixed effects which include country specific latent heterogeneity and Kumbhakar, Lien and Hardakar' (2014) four-way error component effects which accounts for time-invariant inefficiency by disentangling time-invariant (persistent) inefficiency from time-invariant heterogeneity. Our results show that cost efficiency scores, as well as, their ranking are sensitive to the choice of model specification. We find the efficiency score from the Schmidt-Sickles fixed effects model to be much lower than in other models as a result of treating unobserved country effects as inefficiency. The true fixed effects model is most successful since the additional time-invariant inefficiency component of the four-way model is negligible. The results reveal the underlying importance of accounting for unobserved heterogeneity, and distinguishing it from inefficiency.

Our results show the significant influence of the electricity market regulatory reform index on the cost of electricity generation. On one hand, public ownership and vertical integration are found to be associated with a high efficiency loss while no statistically significant relationship is established for entry barriers. This result reiterates the benefits of privatisation of generation assets and private ownership in the power sector. Our results have important policy implications for the electricity market reform agenda. The nature of the deregulation matters since unbundling and privatization are the factors which encourage the generation utility to make maximum use of least cost options for efficiency gain. On the other hand, overall electricity market reform shows evidence of cost reduction only when unobserved heterogeneity is not treated separately from inefficiency.

The estimated economies of output expansion for the models in the short run is about 0.8, indicating the existence of sharply rising costs when capacity is fixed. However, economies scale in the long run are measured at 1.05 – and are not significantly different from 1, implying constant returns to scale when adjustment is made for the quasi-fixed input. Thus, policymakers can create conditions that encourage more competition among generators in order to encourage investment in the industry since we find a high return to capital investment when we model the shadow price of the quasi-fixed capital input. Finally, we find that market reforms are positively correlated – a country pursuing one type of reform often pursues others as well – and that these market structure reforms as measured by the OECD product market reform indicators produce more cost-efficient electricity generation.

Chapter 5: US Electricity Generation Efficiency: Does Restructuring Matter?

5.1 Introduction

The United States electricity sector has been historically dominated by large, vertically integrated, and heavily regulated utilities, with firms exercising monopoly in their local service area while firms are subject to control in the form of rate of return regulation. However, a strand of literature on US power sector reform starting with the works of Palmer and Burtraw (1995), Joskow (1997) and Ando and Palmer (1998) argue that since the late 1990s, due to structural transformation and advances in technology which has changed the production characteristics of the industry, a series of significant restructuring policies have been implemented. The policies are aimed at promoting competition to enhance more efficient electricity supply, lower electricity prices and more innovation by suppliers among wholesale and retail customers. Although, the extant literature has no evidence of a mandatory and comprehensive federal electricity restructuring program, restructuring activities vary considerably from state to state, with many states introducing only limited reform without a fundamental electricity sector restructuring.

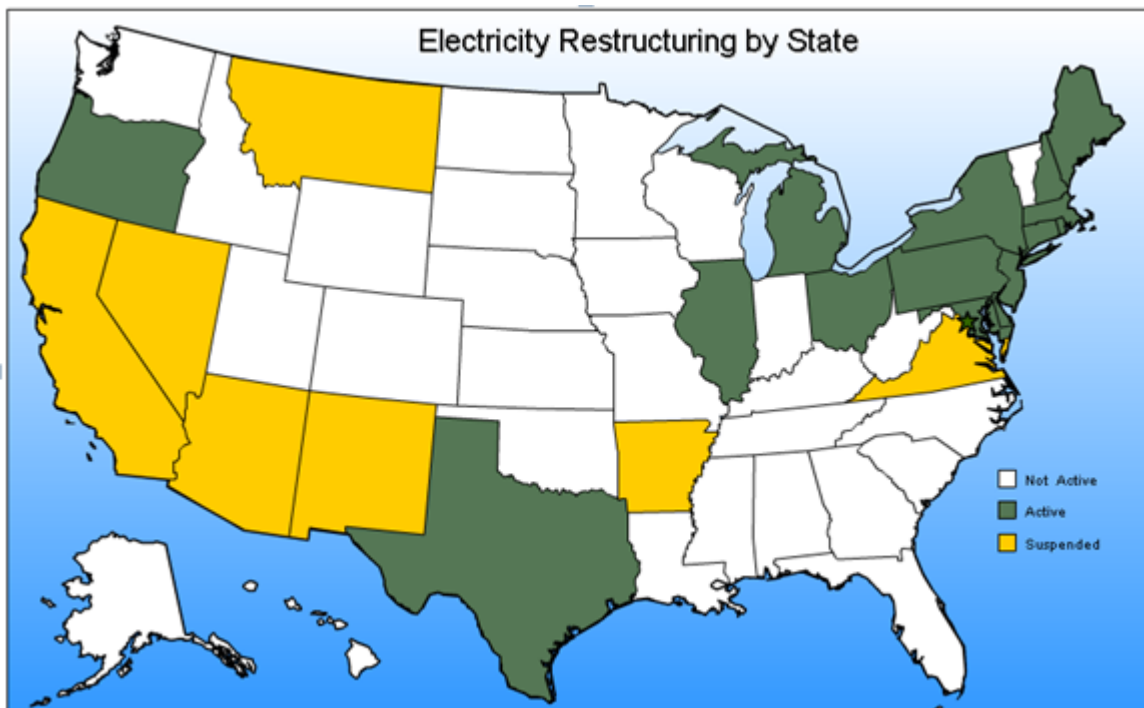
Electricity market restructuring began with the enactment of the Federal Energy Policy Act of 1992 and FERC Order No. 888 in 1996⁴⁷. On one hand, the former legislation allowed some categories of generators to build or purchase electricity generation sources to sell electricity at the wholesale market and required transmitting utilities to allow open access to their transmission capacities for wholesale electricity sale to any electric utility, federal power marketing agencies and any person generating electric energy (FERC, 2006, p. 24). On the other hand, the later act facilitates the restructuring process by permitting independent private and other participants entry into the wholesale market. In both cases, restructuring was mainly intended to induce competition in the wholesale market as the starting point of the restructuring program.

⁴⁷The precursor to restructuring legislations is the Public Utility Regulatory Policy Act of 1978 (PURPA) which offered the first organisational departure from the legitimate monopoly franchise of electricity generation by regulated utilities. The main objective is to promote greater use of alternative renewable energy.

Competition among independent generators was supposed to create a framework for wholesale power transactions so that retail customers and local distribution utilities could purchase power from a wide range of alternative suppliers in order to lower wholesale costs and thus lower retail prices (Kwoka, 2008).

At the state level, the wave of restructuring in the US was driven mainly by the regional disparity in electricity prices. Prices for both residential electricity customers and large industrial electricity consumers were shown to be much higher in most of the Northeastern states and California with price variation up as high as 130% across states (See Joskow, 1997 p 126). Indeed, the quest for retail competition was seen as way of lowering prices (Palmer and Burtraw, 1995). Thus in 1996, California became the first state to enact market restructuring legislation that introduced competition into the retail market. Today, some states have active on-going restructuring activities, some have maintained their original structure while some failed to achieve the expected outcome of deregulation and suspended further restructuring a few years afterwards.

Figure 5.1: Electricity restructuring by US states as of 2012



Source: United States Energy Information Administration (EIA, 2016)

Figure 1 shows patterns of restructuring across the U.S., with seventeen states together with the District of Columbia having active restructuring as of 2012⁴⁸ while other states have suspended and are not active restructuring according to the Department of Energy's (DOE) of the US Energy Information Administration (EIA)

Over all, the key dimension of restructuring in the United States has implications for ownership arrangements, resulting in the conversion of some generation capacity from utility status to independent power producer status⁴⁹. Essentially, this impacted on the generation asset remuneration swiftly from a rate of return regulation model (in which generators were guaranteed a positive return on their capital costs), to a market-based pricing model, under which these assets earned a market price for the output they were able to produce. The aftermath of the restructuring witnessed an unprecedented investment in new generation, especially renewables, with the share of nuclear generation owned by IPP increasing from zero in 1997 to almost 50% in 2012, as utilities sold off their nuclear assets (see Borenstein and Bushnell, 2015).

Since the implementation of market reform, there has been proliferation of empirical studies on the effects of restructuring in the electric power industry. One aspect that has attracted much attention is the investigation of the efficiency gains from restructuring. Obviously, the debate has been more intense about how reform has potentially impacted on the operational efficiency of the investor –owned electric utilities. Protagonists of restructuring have earlier advocated that it offers incentives to electricity producers to improve their efficiency; however, controversies remain going by the mixed pictures of the findings from these studies. Previous studies which have established efficiency gains from restructuring in the US electricity sector include Kleit and Terrell (2001), Knittel (2002), Hiebert (2002), Wolfram (2005), Zhang (2007) and Craig and Savage (2013). Empirical studies that confirmed the negative efficiency impact of

⁴⁸ These states are Connecticut, District of Columbia, Delaware, Illinois, Maine, Maryland, Massachusetts, Michigan, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island and Texas.

⁴⁹ The extent one considers the electric sector to be deregulated," in the United State, it is due to this fundamental shift in the paradigm for compensating owners of generation.

deregulation on the electric power industry include Delma and Tokat (2005) and Goto and Tsutsui (2008), while Fabzrio et al. (2007) confirms both negative and positive impacts of deregulation on efficiency.

Using a Bayesian stochastic frontier model, Kleit and Terrell (2001) examine the potential efficiency gains in electric power generation for 78 steam plants in the year 1996. They find that plants, on average, could reduce production costs by up to 13% by eliminating production inefficiency. Knittel (2002) reveals an increase in efficiency by about two per cent for coal and natural gas fuelled plant. Hiebert (2002) investigates the impact of restructuring on cost efficiency for 633 fossil-fuelled plants from 1988 to 1997 and finds a mean efficiency increase in the states implementing retail competition to about 50 per cent. Craig and Savage (2013) examine the effects of market restructuring initiatives that introduced competition into the US electricity industry on the thermal efficiency of electricity generation for 950 plants from 1996 to 2006. Their results indicate that found access to wholesale electricity markets and retail choice together increased the efficiency of investor-owned plants by about nine percent and that these gains stem from organizational and technological changes within the plant.

In contrast, Delmas and Tokat (2005) using data envelopment analysis (DEA) on 177 U.S. electric utilities from 1998 to 2001 show that the process of retail deregulation had a negative impact on firms' productive efficiency. Goto and Tsutsui (2008) investigate the impact on technical efficiency change in electric utilities in their generation, transmission/distribution, and general administration functions using the input distance function and stochastic frontier approach. They examine technical efficiency change using annual data for 22 U.S. electric utilities firms from 1992-2000, and find that firms located in states that have enforced deregulation are less efficient. However, Fabzrio et al (2007) shows both negative and positive impacts of deregulation by estimating the input demand functions for 769 fossil fuelled plants from 1981 to 1999. They indicate that the labour and non-fuel expenses of plants in the states that implemented restructuring legislation were about 3 to 5 percent lower than plants in non- restructured states while concluding that restructuring yields substantial medium-run efficiency for the investor owned utilities.

Our paper contributes to the literature by analysing electric power industry's performance using consistent state-level electricity generation dataset for the contiguous state from 1998-2014. The empirical analysis of the production technology and inefficiency builds on the estimation of several specifications of stochastic frontier models. As a clear departure from the existing papers, the estimation of different heteroscedastic models allows us to address the twofold objectives of this study; investigating the determinants of the inefficiency, and an evaluation of the non-monotonic margin effects. To achieve these objectives, we adopt the Wang (2002, 2003) approach that allows both mean and variance of the pre-truncated normal to depend on the exogenous variables. To date, this study represents the first empirical work that captures the impact of restructuring on efficiency using this robust and flexible approach. An insight into our finding reveals that deregulation significantly reduces inefficiency across the models estimated. However, retail choice is found to increase inefficiency. Furthermore, the result from the preferred model shows that deregulated states are more efficient in electricity generation than non-deregulated states.

The remainder of the paper is organised as follows. Section 2 provides the methodological approach. Specifically, we present the specification for the estimated models and describes the non-monotonic marginal effects. In section 3, we explain in detail the data and variables used. Section 4 presents the empirical results from models and the marginal effects. Section 5 presents the concluding remarks and recommendations.

5.2. Methodology

In this paper, we explore the impact of restructuring by estimating a stochastic production frontier model. We adopt this approach in order to unravel the extent of the contribution of restructuring to electricity generation in the United State as well as its influence in shaping production efficiency. The stochastic frontier analysis (SFA) independently proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) SFA is centred on the concept that deviations from the production frontier defined by the “best practice” technology might not be entirely under the control of the firm and might be due to measurement errors and other noise upon the frontier. The approach decomposes the error term into two

components, a traditional two-sided error term which captures the effects of measurement error and a one-sided error term to measure technical inefficiency. The general stochastic production function (ALS, hereafter) is specified as follows:

$$y_{it} = \alpha + x'_{it}\beta + v_{it} - u_{it} \quad (5.1)$$

$$v_{it} \sim N(0, \sigma_v^2) \quad (5.2)$$

$$u_{it} \sim N^+(0, \sigma_u^2) \quad (5.3)$$

The cross-sectional units are indexed $i = 1, \dots, N$ and the time periods are indexed $t = 1, \dots, T$, where N is appreciably large (47) and T is 17. y_{it} is the output of each state, α is the intercept, x'_{it} is the vector of inputs of the production process and β the vector of coefficients to be estimated. The v_{it} denotes a two-sided conventional idiosyncratic error term which is assumed to follow an *i.i.d.* $N(0, \sigma_v^2)$ distribution and accounts for measurement sampling and specification error, as well as for the effect of other random shocks. The u_{it} represents a one-sided and non-negative random variable which measures technical inefficiency and has an identically and independent half normal distribution. This model was originally developed for cross-sectional data but was later extended to accommodate panel data by the inclusion of a time trend or time dummy in order to capture technical progress. The nexus between inefficiency and exogenous effects has been investigated sequentially using a two-step approach⁵⁰ (See Kumbhakar and Lovell, 2000). Lately, the approach has been considered biased due to the misspecification inherent in the first model (Battese and Coelli, 1995, Schmidt and Wang, 2002).

⁵⁰ The approach estimates the observation-specific inefficiency measure in the first step, and goes further to regress the efficiency index on exogenous variables in the second step. The shortcoming of the procedure is that if the input variables and the exogenous are correlated, the first step of the two-step procedure is considered biased. In the event that input variables and the exogenous factors are uncorrelated, ignoring the dependence of the inefficiency on the exogenous variable will lead the first step technical efficiency to be underdispersed such that the results of the second stage regression are likely to be biased downward (See Kumbhakar et al, 2015)

Modelling of exogenous effects on inefficiency has always followed two flexible approaches. First, Kumbhakar, et al. (1991), Huang and Liu (1994), and Battese and Coelli (1995) (KGMHLBC hereafter) proposed parametrising the mean of the pre-truncated inefficiency distribution.

$$u_{it} \sim N^+(\mu_{it}, \sigma_{it}^2) \tag{5.4}$$

$$\mu_{it} = \mathbf{z}'_{it}\delta$$

where \mathbf{z}_{it} is the vector of exogenous variables. Second, Reifschneider and Stevenson, Caudill and Ford (1993) and Caudill et al. (1995) assume μ_{it} to be constant but parameterize the variance of the pre-truncated distribution as a function of the exogenous variables;

$$u_{it} \sim N^+(\mu_{it}, \sigma_{it}^2) \tag{5.5}$$

$$\sigma_{it}^2 = \exp(\mathbf{z}'_{it}\gamma)$$

Hadri (1999) generalise the second approach by allowing the variance of the two-sided error term to be heteroscedastic, parameterizing the variance of the noise component. This second approach is jointly classed as the Caudill and Ford (1993) and Caudill et al (1995) and Hadri (1999) approach (RSCFGH hereafter)⁵¹. Given that u_{it} has a truncated normal distribution, its variance is a function of both μ_{it} and σ_{it}^2 . Wang (2002) proposed another model that combines the features of KGMHLBC and RSCFGH and allows both μ_{it} and σ_{it}^2 to be observational specific.

The WANG truncated normal distribution model, with double heteroscedasticity is which parameterised as follows:

⁵¹ The ALS half normal distribution suffers some drawbacks as it assumes that u_{it} and the pre-truncated u_{it} are homoscedastic i.e. both σ_u^2 and σ_{it}^2 parameters are constants. This drawback is addressed by this approach. Ignoring the heteroscedasticity of v_{it} would not affect the consistency of a frontier's function parameters estimates but could bias the intercept downward and also bias technical efficiency. Whereas if heteroscedasticity of u_{it} is ignored both the estimates of the frontier parameters as well as the technical efficiency are biased (See Wang et al. 2015)

$$\begin{aligned}
u_{it} &\sim N^+(\mu, \sigma_{it}^2) \\
\mu_{it} &= \mathbf{z}'_{it}\delta \\
\sigma_{it}^2 &= \exp(\mathbf{z}'_{it}\gamma) \\
\sigma_{vit}^2 &= \exp(\mathbf{z}'_{it}\lambda)
\end{aligned} \tag{5.6}$$

The determinants vector \mathbf{z}'_{it} includes a constant and other exogenous variables associated with the inefficiency. The δ and γ are the corresponding coefficient vectors. All other notations remain as defined above. It is instructive to note that whether we allow the mean, the variance, or both the mean and the variance of the pre-truncated normal to depend on exogenous factors, both the mean and the variance of the truncated half normal will always depend on the exogenous factors. Failure to model the exogenous factors appropriately leads to biased estimation of the production frontier model and of the level of technical inefficiency, hence leading to poor policy conclusions (see Liu and Mayer, 2008).

In this paper, we adopt a general-to-specific estimation approach involving five different models which is based on a number of variable restrictions in the specific models against the general model. First, we begin by assuming the general model is the WANG model in which δ and γ are both estimated using the maximum likelihood method as parameterised in equation (5.6). Second, we consider the KGMHLBC model in which $\gamma = 0$. The model treats exogenous variables as a function of the mean of the pre-truncated normal while assuming homoscedastic variance of the pre-truncated normal variable as specified in the Eq (5.5). Third, we look at the pre-truncated normal distribution RSCFG model in which $\mu = 0$. This model addresses heteroscedasticity by treating exogenous variables as determinants of the variance of the pre-truncated normal variable. This is followed by the RSCFG- μ in which $\delta = 0$ proposed by Alvarez et al. (2006) where the mean of the distribution is allowed to be different from zero⁵². Lastly, we estimate the half homoscedastic half normal ALS in which $\mu = \gamma = 0$. We nest the four other restricted models into the general model and select the appropriate model that provides the best fit for our data using diagnostics tests

⁵²Alvarez et al. (2006) gives a technical discussion on the desirability of the scaling property arising from the non- zero mean assumption of the model which parametrises the inefficiency term as a deterministic function of a set of efficiency covariates, i.e. $h(\cdot) = \exp(\mathbf{z}'_{it}\gamma)$ times a one-sided random variable that does not depend on any efficiency determinant, $u_{it}^* \sim N^+(0, \sigma_u^2)$.

such as the Likelihood ratio (LR) and the Akaike information criterion (AIC). The summary of the general model together with the restrictions of the other competing models is presented in Table 5.1.

Table 5.1: List of the estimated models

Variable	Restrictions	$N^+ (\mu_{it}, \sigma_{it}^2)$	
		Mean	Std Deviation
WANG Model		$\mu_{it} = z'_{it}\delta$	$\sigma_{it}^2 = \exp(z'_{it}\gamma)$
KGMHLBC Model	$\gamma = 0$	$\mu_{it} = z'_{it}\delta$	$\sigma_{it}^2 = \sigma_u^2$
RSCFG- μ Model	$\delta = 0$	$\mu_{it} = \mu$	$\sigma_{it}^2 = \exp(z'_{it}\gamma)$
RSCFG Model	$\mu = 0$	$\mu_{it} = 0$	$\sigma_{it}^2 = \exp(z'_{it}\gamma)$
ALS Model	$\mu = \gamma = 0$	$\mu_{it} = 0$	$\sigma_{it}^2 = \sigma_u^2$

Given that the composed error term $\varepsilon_{it} = u_{it} + v_{it}$, u_{it} is estimated as the conditional expectation of the one-sided error term, $\exp(u)$, given the composed error, $v + u$:

$$\hat{u}_{it} = E[u_{it}|v_{it} + u_{it}] \quad (5.7)$$

The maximum likelihood residuals are used to replace $\varepsilon_{it} = v_{it} + u_{it}$

The measurement of technical efficiency is obtained by deriving the probability density function for u , conditional on every numerical realization of the composed error term ε_{it} . This approach is based on conditional expectations which generalize the estimators proposed by Battese and Coelli (1988). The technical efficiency index for each state can be estimated from the point estimates of the technical inefficiency (u_{it}) as the ratio of observed output to corresponding frontier output.

$$TE_{it} = E[\exp(-(u_{it}|\varepsilon_{it}))] \quad (5.8)$$

The technical efficiency index lies between 0 and 1. Scores of one indicates a fully efficient state is on the frontier, while non-frontier firms receive scores below one.

5.2.1 Marginal effect

We proceed to derive the marginal effect of the $z[j]$, the j th variable of the \mathbf{z}_{it} vector in (5.6). Wang's (2002) model has the advantage of allowing for the estimation of non-monotonic efficiency impacts which implies that \mathbf{z}_{it} can have, within the sample, both increasing and decreasing effects on the production efficiency. The conventional stochastic frontier model is built on the implicit assumption that the exogenous variables' impact on inefficiency are monotonic i.e. the exogenous factors are either strictly efficiency-enhancing or efficiency –impeding in the sample, but not both. However, Wang (2002) demonstrates exogenous variables can positively (negatively) affect the mean and variance efficiency when the values of the \mathbf{z}_{it} vector are within certain range, and then the impacts turn negative (positive) for values of \mathbf{z}_{it} outside the range.

The non-monotonicity marginal effects of on $E(u_{it})$ of the j th element of \mathbf{z}_{it} can written as;

$$\frac{\partial E(u_{it})}{\partial z[j]} = \delta[j] \left[1 - \Lambda \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] - \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]^2 \right] + \gamma[j] \frac{\sigma_{it}}{2} \left[(1 + \Lambda^2) \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] + \Lambda \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]^2 \right] \quad (5.9)$$

where $\Lambda = \mu_{it}/\sigma_{it}$, ϕ and Φ are the probability and cumulative density functions of a standard normal distribution. $z[j]$ is the j th element of \mathbf{z}_{it} , and δ and γ are associated coefficients of the determinants of mean and variance inefficiency. In the event that the variance σ_{it}^2 is non- parameterised, $\gamma[j]$ is assumed to be zero and constant for all j and equation (10) would imply a monotonic \mathbf{z}_{it} on (u_{it}) . The marginal effect takes the sign of $\delta[j]$ which is the same for all values of \mathbf{z}_{it} .

The marginal effects of \mathbf{z}_{it} on $V(u_{it})$ can be expressed as follows:

$$\begin{aligned} \frac{\partial V(u_{it})}{\partial z[j]} = & \frac{\delta[j]}{\sigma_{it}} \left[\Lambda + \frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] (m_1^2 - m_2) \\ & + \gamma[j] \sigma_{it}^2 \left\{ 1 - \frac{1}{2} \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] \left((\Lambda + \Lambda^3 + (2 + 3\Lambda^2) \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]) \right) + 2\Lambda \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]^2 \right\} \end{aligned} \quad (5.10)$$

where m_1 and m_2 are the first two moments of u_{it} represented as

$$m_1 = f(\mu_{it}, \sigma_{it}) = \sigma_{it} \left[\Lambda + \frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] \quad (5.11)$$

$$m_2 = g(\mu_{it}, \sigma_{it}) = \sigma_{it}^2 \left[1 - \Lambda \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] - \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]^2 \right] \quad (5.12)$$

Equations (5.9) and (5.10) reveal that the marginal effects of the non-monotonic inefficiency effects consist of two terms, indicating the impact of the variables on the mean and variance of the inefficiency components.

5.3 Data and descriptive statistics

This section discusses the data used to implement the stochastic production frontier model. The study is based on a US state level electricity panel data set for a sample of 47 states ($i=1, \dots, 47$) over the period 1998 to 2014. The sample period covers the era of the implementation of major electric industry restructuring policy, especially the Electricity Generation Customer Choice and Competition Act which introduces retail competition into the electricity industry in most states between 1998 and 2002. For our purposes, we limit the analysis to the contiguous states (i.e. Alaska and Hawaii are excluded)⁵³. The data set is based on information from the U.S. Department of Energy's (DOE) US Energy Information Administration (EIA) database, the Bureau of Economic Analysis of US Department of Commerce, and the US Census Bureau. Our choice of inputs and output is consistent with the literature such as Coelli et al. (2013), Jaraitė & Di Maria (2012), among others.

⁵³ The District of Columbia and Vermont were initially considered in the analysis but were later filtered out as outliers after running a pooled OLS for the whole sample.

The capital input is measured in megawatts (MW) of installed capacity. Installed capacity is commonly used as a standard measure of capital stock of electricity generation in the literature⁵⁴. Installed capacity in this study is defined as the maximum amount of electricity that a thermal electricity station can produce at any given point in time. It describes the maximum capacity that a system is designed to run at. Installed capacity is collected from Form EIA-860 of the US Energy Information Agency (EIA). The labour input refers to the economically active population in electricity generation for each state measured in thousands of employees. Information on the number of people employed for electricity generation is taken from the US Bureau of Labour Statistics. The quantity of energy input is measured as the total heat content in billions of British thermal unit (billion BTUs) for each state, and includes all varieties of energy consumed from different energy sources by the generation plants such coal, petroleum, natural gas, nuclear, geothermal and other gases. Energy consumption at the state level from coal, petroleum and natural gas are reported on physical quantity units in EIA-906, EIA-920 and EIA-923 Forms (tons of coal, barrels of oil and mcf of natural gas). The reported heat content information for individual fuels is taken from the EIA so as to convert energy consumption into billion BTU. After converting the energy consumption into the same measurement units, we aggregated them into total heat content in billion British thermal units. The output variable is each state's aggregate electric power industry net generation of electricity for each year from various energy sources (coal, hydro, natural gas, petroleum). Electricity generation is measured in consumption in megawatt hours. Total electric power industry net generation derives from the summation of generation by different type of producers such as electric utilities generator, Combined Heat and Power and independent power producers. The data is extracted from Forms EIA-906, EIA-920 and EIA-923 of the US Energy Information Administration (EIA) database. Input variables are capital, labour and energy.

Previous studies have identified factors that could shape the operating environment but are not directly related to the performance of the generation plants. These exogenous factors are categorised into political and economic variables that could influence the mean of the inefficiency. First, we consider the market

⁵⁴ Installed capital is used as the measure of the services of capital input. The use of installed capital as proxy for capital stock is consistent with the literature. Although, a potential issue is that some parts of the installed capital of a generator (conventionally measured as the electrical power rating of the capacity) may not in practice have been part of the 'used and useful' capital stock, as defined by US public service regulators. However, industry wide practice is to use installed capacity in the engineering sense as a comparable measure of the stock of capital services.

restructuring variables encompasses the different levels of deregulation which utilities face in each state and the degree of competition allowed in the electricity market. Of course, several studies in the literature propose broader indicators of market restructuring as follows; (a) plant access to wholesale electricity market places through a regional transmission organisation (b) the date at which formal hearings on restructuring began; (b) the date at which formal hearings on restructuring legislation enacted; (d) the implementation of retail choice under legislation; and (e) complementary aspects of restructuring, such as access to wholesale markets, permit capacity trading, the mandatory divestiture of generation assets and the type of rate of regulation (Fabrizio et al, 2007; Zhang, 2007; Craig & Salvage 2013; Davie and Wolfram, 2012).

For our purpose, we rely on the current restructuring classification originally developed by the Energy Information Administration (EIA) of the US Department of Energy (EIA, 2010). The Energy Information Administration defines restructuring as when a monopoly system of electric utilities has been replaced with competing sellers and classifies electricity restructuring into active, not active and suspended. According to the restructuring information update only seventeen states and the District of Columbia are active in restructuring activities. It is interesting to observe the spatial clustering. Most restructured states are predominantly the Northeastern region and East North Central, barring Maryland, District of Columbia, Oregon and Texas. In addition, the EIA further breaks down the restructuring activities by state into deregulation and retail choice – either yes, no or suspended. Therefore, considering this classification, we employ two indicators, deregulation and retail choice to construct dummy variables for restructured and non-restructured states. For deregulation and retail choice variables, states where deregulation/retail choice is ‘yes’ are assigned the value of one and zero if they are ‘no’ or ‘suspended’. We also control for political variables that might likely influence the state restructuring process by including a dummy variable REP GOV which is equal to one when the state has Republicans who control both the governorship and the legislature. PUC is a dummy variable that equals one if the majority of the state’s PUC commissioners are Republican and zero if otherwise. Republican PUC members are more likely to promote retail competition.

A negative coefficient on the restructuring variables would mean positive impacts on technical efficiency.

The data is constructed using the National Association of Regulatory Utility Commissioner (NARUC).

Finally, we also control for state specific heterogeneity captured using two major observable exogenous variables, which are all obtained as follows. Population density measures the number of people in an area relative to its size. It is computed as the ratio of thousands of people per square kilometre of land area. Data on population is obtained from the Bureau of Economic Analysis of the US Department of Commerce while land area information is extracted from the US Census Bureau. The real GDP per capita for each state allows us to assess the impact of economic structure on the mean of inefficiency. The real GDP is measured for each year in thousand US in chained 2009 dollars and obtained from the Bureau of Economic Analysis of the US Department of Commerce. The summary statistics on the variables used in the empirical estimation are provided in Table 5.2.

Table 5.2: Descriptive Statistics

Variable	Mean	Sd. Dev.	Min	Max
Net electricity generation (MWh)	8.89e+07	7.24e+07	5971545	4.38e+09
Installed Capacity (MW)	23442.53	19903.80	1385	124214.9
Energy (million BTU)	6.16e+08	5.90e+08	3430158	3.93e+09
Labour ('000 people)	5713.24	6569.51	10	37599
Deregulation (1= yes , 0 = no)	0.3134	0.4642	0	1
Retail Choice (1= yes , 0 = no)	0.2479	0.4321	0	1
PUC (1= yes , 0 = no)	0.6546	0.4758	0	1
REP GOV (1= yes ,0 = no)	0.6811	0.4664	0	1
GDP (million U.S2009\$)	44574.71	7864.20	28764	69787
POP (ppl/sq.km of land area)	0.1720	0.2258	0.0051	1.2154

5.4 Empirical Result and Analysis

5.4.1 Model results

We estimate the translog production function, with inputs of capital, fuel consumption and labour and the exogenous variables, a flexible functional form which assumes that the output of a firm can be written as a quadratic function of the logarithms of the factor inputs⁵⁵. Our empirical analysis is programmed in Stata using the maximum likelihood code written by Wang (2005). Indexing each input by j or k , j or $k = 1, 3$, and time dummies by DT_t , the estimated equation can be written as follows:

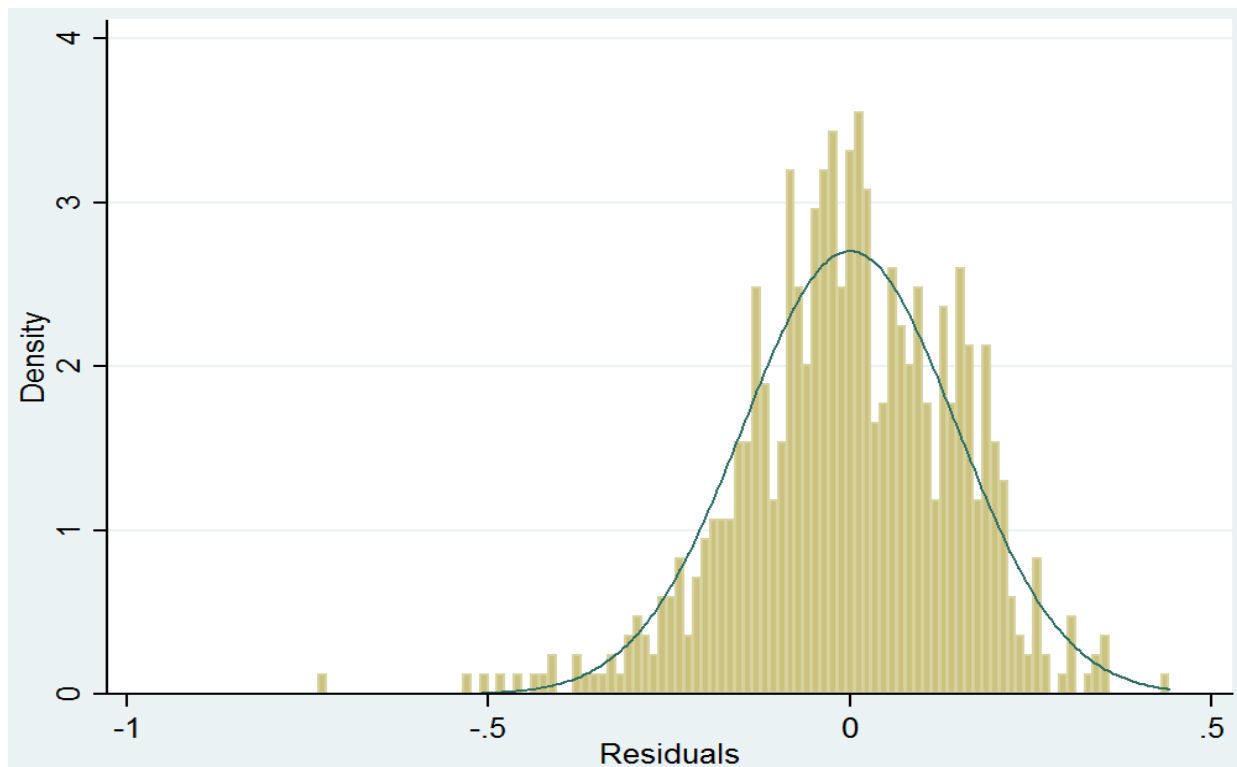
$$\ln y_{it} = \alpha_0 + \sum_{k=1}^3 \beta_k \ln(x_{ikt}) + \frac{1}{2} \sum_{k=1}^3 \sum_{j=1}^3 \beta_{kj} \ln(x_{ijt}) \ln(x_{ikt}) + \sum_{t=2}^T \alpha_t DT_t + v_{it} - u_{it} \quad (5.13)$$

As a preliminary step to our analysis, we estimated a pooled OLS regression of the stochastic production frontier in order to ascertain statistically whether the data contains inefficiency effects. If there were no technical inefficiency, the error term will be symmetric i.e. $u_{it} = 0$, the model reduces to the standard regression model and the composed error term collapses to the two-sided error, i.e. $\varepsilon_{it} = v_{it}$. Thus, the data will not support the technical inefficiency analysis. Figure 1 displays the histogram of the residuals following the OLS estimation. Compared with a normal density distribution, the residual shows a skewed distribution to the right, indicating the presence of inefficiency in the model. In order to demonstrate the skewness more empirically, a skewness test for normality proposed by Coelli (1995) rejects the null hypothesis of normal residual⁵⁶. The computed statistic equals -4.807. Because it a normal distribution, the critical value is 1.96, therefore, the result confirms the rejection of the null hypothesis of no skewness in the OLS residual.

⁵⁵ The translog function can be approximated by the second order Taylor series (Christensen, et al. 1973).

⁵⁶ Coelli (1995) notes that under the null hypothesis of normal residual, the third moment of the OLS residual is asymptotically distributed as a normal random variable with mean 0 and variance $6m_2^3/N$. The statistic is given as $M3T = m_3 / \sqrt{6m_2^3/N}$.

Figure 5.2: Histogram chart of the OLS residual



In this paper we propose to study the impact of restructuring on electricity generation efficiency. Therefore, we have included in all the competing models deregulation and retail choice indicators for restructuring. We include PUC and REP GOV so as to control for political influence on restructuring while the real GDP per capita and population density act as control variables for economic structure and spatial diversity respectively. We opine that our findings might be dependent on the empirical models in relation to the inefficiency determinants. We implemented several model selection tests while imposing restrictions on the translog production function in order to obtain the preferred model. Since the WANG model is nested to the other models, we carried out the standard likelihood ratio LR test suggested by Alvarez et al (2006). The LR test is given by $\lambda = -2(\ln L_0 - \ln L_1)$ where $\ln L_0$ and $\ln L_1$ represents the maximum log-likelihood value under the null hypothesis H_0 and the alternative H_1 respectively. If λ of the hypothesis is greater than the critical value of chi-square, then this null hypothesis is rejected. However, Lia and Huang (2010) pointed out that the standard LR test may have the tendency of favouring the model with a greater number of parameters since there is no penalty on imposing extra parameters. Therefore, we estimate the Akaike

information criterion (AIC) to further justify our selection decision. The Akaike information criterion is defined as: $AIC = -2 (\ln (\text{likelihood})) + 2K$, where the likelihood is the probability of the data given the model, and K is the number of free parameters in the model. Thus, a model with the smaller value of AIC fits the data better than one with the larger AIC.

The LR test shows the four other competing models nested in the WANG model. Considering the WANG model as the baseline model, we proceed to test the restrictions that would best fit our data. We set the null hypotheses that each restricted model is more appropriate for our data against the alternative hypotheses of the unrestricted model. The results of the model selection tests are given table 3 below. The likelihood-ratio test shows that the KGMHLBC ($\gamma = 0$), RSCFG- μ ($\delta = 0$), RSCFG ($\delta = 0$) and ALS ($\mu = \gamma = 0$) models are all rejected in favour of the WANG model at a one per cent significance level due to the inclusion of exogenous variables in the mean and variance of the heteroscedastic inefficiency term. The table also reports the WANG model as the best frontier specification with the smallest AIC = -874.701. Undoubtedly, the data favours the WANG model over other simpler alternative models.

Table 5.3: Model selection tests

Model	WANG	KGMHLBC	RSCFG- μ	RSCFG	ALS
Log-likelihood	478.350	419.148	400.945	398.799	369.650
AIC	-874.701	-768.297	-731.889	-729.600	-705.300
LR test ^a	GM	118.403	154.812	159.101	213.643
# Restrictions	-	6	6	7	13
1% critical value ^b	-	16.704	16.704	17.755	27.026

^aIn the LR test, GM denotes the general model. All other competing models are nested in the general model.

^bThe critical value of the chi-square is taken from the table in Kodde and Palm (1986, Econometrica)

The empirical model for the analysis is based on five different frontier models to investigate the impact of restructuring on technical inefficiency. Table 5.4 reports the maximum likelihood estimates of the technological parameters which seem to be very similar in magnitude. The production input variables are log

mean corrected prior to estimation which enables the estimated coefficients to be directly interpreted as elasticities. As expected, the estimated values of the output elasticities for all the inputs are positive, suggesting that the estimated translog production function is a well-behaved function. Specifically, in our preferred model (in the first column), the estimated output elasticities with respect to capital, energy and labour are 0.629, 0.268 and 0.011 respectively. The elasticities indicate that, *ceteris paribus*, a one percentage increase in capital will, on average, result in a 0.63% increase in electricity generation. Similarly, a one percentage increase in energy use will result in a corresponding increase in electricity generation by 0.27%. The estimated parameter associated with labour is not statistically significant. Arguably, this finding might be due to the fact workers have little scope to influence the performance of the electricity industry, particularly true of the generation sector of the industry, where costs are dominated by the capital required to build plants and the fuel required to operate them (see Bushnell and Wolfram, 2009). The capital input has the highest impact on production technology. This is consistent with the capital-intensive characteristic of the electricity generation industry. The second-order coefficient of both capital and energy inputs are positive and statistically significant indicating the effect on production is positively increasing. In addition, Table 5.5 reports the coefficient estimate for the time dummies across the models of the frontier model. The positive coefficients on the time dummy variables indicate a steady upward shift of the production function over time, demonstrating technical progress. This is more significant in the earlier part of the sample period since in the later years - after the start of the global financial crisis - the whole US economy including the electricity sector experienced a slowing down in demand growth while the economy recovered.

Table 5.4: Estimated results of the Frontier models

Variable	WANG Model		KGMHLBC Model		RSCFG- μ Model		RSCFG Model		ALS Model	
	Coeff	Std error	Coeff	Std error	Coeff	Std error	Coeff	Std error	Coeff	Std error
Capital	0.629***	(0.023)	0.771***	(0.023)	0.722***	(0.019)	0.721***	(0.019)	0.715***	(0.020)
Energy	0.268***	(0.015)	0.225***	(0.017)	0.211***	(0.015)	0.212***	(0.015)	0.216***	(0.015)
Labour	0.011	(0.007)	0.023**	(0.008)	0.020**	(0.007)	0.021**	(0.007)	0.018*	(0.007)
Capital Squared	0.188***	(0.019)	0.076***	(0.014)	0.083***	(0.016)	0.079***	(0.015)	0.089***	(0.016)
Energy Squared	0.154***	(0.009)	0.099***	(0.010)	0.086***	(0.008)	0.085***	(0.008)	0.085***	(0.008)
Labour Squared	-0.005***	(0.001)	-0.004***	(0.001)	-0.004***	(0.001)	-0.004***	(0.001)	-0.004***	(0.001)
Capital \times Energy	-0.341***	(0.023)	-0.204***	(0.023)	-0.191***	(0.019)	-0.188***	(0.020)	-0.184***	(0.020)
Capital \times Labour	0.094***	(0.011)	0.040***	(0.007)	0.052***	(0.008)	0.052***	(0.008)	0.044***	(0.010)
Energy \times Labour	-0.055***	(0.007)	-0.022**	(0.006)	0.023**	(0.006)	-0.022***	(0.006)	-0.019**	(0.006)
Time dummies	Yes		Yes		Yes		Yes		Yes	
Constant	-0.023***	(0.024)	0.179***	(0.040)	0.032	(0.026)	0.051***	(0.025)	0.052***	(0.025)
Sigma v	-4.472***	(0.090)	-4.679***	(0.525)	-4.679***	(0.161)	-4.755***	(0.196)	-4.844***	(0.211)
σ_v^2	0.011***	(0.001)	0.009*	(0.005)	0.009***	(0.001)	0.009***	(0.002)	0.008***	(0.002)

Notes: *, **, *** denote statistically significant at 10%, 5% and 1% respectively. Standard error in parenthesis

Table 5.5: Time dummy estimates

Variable	WANG Model		KGMHLBC Model		RSCFG- μ Model		RSCFG Model		ALS Model	
	Coeff	Std error	Coeff	Std error	Coeff	Std error	Coeff	Std error	Coeff	Std error
DT_{1998}	0.201***	(0.028)	0.199***	(0.031)	0.189***	(0.030)	0.189***	(0.030)	0.198***	(0.031)
DT_{1999}	0.201***	(0.028)	0.206***	(0.031)	0.204***	(0.031)	0.204***	(0.030)	0.211***	(0.031)
DT_{2000}	0.172***	(0.028)	0.186**	(0.031)	0.174***	(0.030)	0.173***	(0.030)	0.181***	(0.031)
DT_{2001}	0.132***	(0.028)	0.141***	(0.031)	0.123***	(0.030)	0.122***	(0.030)	0.129***	(0.031)
DT_{2002}	0.099***	(0.027)	0.118***	(0.030)	0.105**	(0.030)	0.104**	(0.030)	0.110***	(0.031)
DT_{2003}	0.067*	(0.027)	0.090**	(0.030)	0.076*	(0.030)	0.075**	(0.030)	0.078**	(0.030)
DT_{2004}	0.063*	(0.027)	0.089**	(0.030)	0.073*	(0.030)	0.072**	(0.030)	0.073**	(0.030)
DT_{2005}	0.069*	(0.027)	0.099**	(0.030)	0.083**	(0.030)	0.083**	(0.030)	0.080**	(0.031)
DT_{2006}	0.034	(0.027)	0.077*	(0.030)	0.060**	(0.030)	0.058*	(0.030)	0.058*	(0.031)
DT_{2007}	0.052**	(0.027)	0.086**	(0.029)	0.074**	(0.030)	0.072**	(0.030)	0.071**	(0.030)
DT_{2008}	0.047*	(0.027)	0.078**	(0.029)	0.069*	(0.030)	0.069**	(0.030)	0.067**	(0.030)
DT_{2009}	0.007	(0.027)	0.017	(0.029)	0.007	(0.030)	0.006	(0.030)	0.010	(0.030)
DT_{2010}	0.035	(0.026)	0.052*	(0.029)	0.043	(0.030)	0.044	(0.030)	0.045	(0.030)
DT_{2011}	0.016	(0.028)	0.021	(0.029)	0.027	(0.030)	0.025	(0.030)	0.024	(0.030)
DT_{2013}	0.012	(0.007)	0.022	(0.029)	0.025	(0.006)	0.026	(0.030)	0.026	(0.030)
DT_{2014}	0.009	(0.026)	0.021	(0.029)	0.022	(0.030)	0.022	(0.030)	0.021	(0.030)

Notes: *, **, *** denote statistically significant at 10%, 5% and 1% respectively. Standard error in parenthesis

We now turn our attention to the impact of restructuring on electricity production across states. We incorporated several exogenous variables into the heteroscedastic alternative models by allowing the variables to affect the mean and variance of the inefficiency. This also includes estimating the general homoscedastic ASL model. The result of the inefficiency determinants is reported in Table 5.6. Since the AIC and LR tests have support the WANG model, our discussion is centred on the model that allows both the mean and the variance of the pre-truncated distribution of the inefficiency to depend on the exogenous factors. Tellingly, our preferred model points to the reliability of the variance of the inefficiency to appreciably capture the impacts of the exogenous variables on production inefficiency, as most of the restructuring variables are insignificant. The preferred model also shows that the estimated restructuring coefficients on the variance of the inefficiency have the expected signs (with the exception of retail choice) and are statistically significant.

Focusing on the variance of the inefficiency, overall, our finding shows the importance of restructuring in the electricity generation industry. The coefficient of deregulation is statistically significant at 1% and negatively correlated with inefficiency, while retail choice is positively correlated with inefficiency. The sign of the coefficient of the deregulation variable means a negative impact on technical inefficiency, thus a positive effect on efficiency in the production of electricity due to the impact of restructuring. This particularly holds true for the a priori expectation that deregulation represents a key factor in improving electricity production efficiency. This finding is largely consistent with previous studies such as Kleit and Terrell (2001), Knittel (2002), Hiebert (2002), Zhang (2007) and Craig and Savage (2013). The sign on retail choice is quite surprising as it appears states that have implemented retail competition in the generation segment seem less efficient. The result is contrary to the findings of Joskwo (2006) that wholesale and retail restructuring has led to lower prices. A plausible interpretation arising from this finding could be that retail choice market reform might not be a sufficient condition for restructuring as only a few number of deregulated states have permitted consumers access to competitive suppliers of generation.

Table 5.6: Estimate for the inefficiency components

Variable	WANG Model		KGMHLBC Model		RSCFG- μ Model		RSCFG Model		ALS Model	
	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
<i>Mean function</i>										
δ_0	-0.606***	(0.135)	0.287***	(0.036)	-0.199***	(0.184)	0		0	
Deregulation	-0.049	(0.084)	-0.181***	(0.023)	0		0		0	
Retail choice	0.011	(0.084)	0.066**	(0.022)	0		0		0	
PUC	0.369	(0.028)	-0.055**	(0.017)	0		0		0	
REP GOV	0.470***	(0.103)	0.090***	(0.018)	0		0		0	
GDP	-0.812***	(0.116)	0.112**	(0.040)	0		0		0	
POP	-0.200***	(0.023)	0.049***	(0.008)	0		0		0	
<i>Variance function</i>										
γ_0	-3.156***	(0.336)	-4.679***	(0.525)	-2.978***	(0.413)	-3.470***	(0.209)	-3.263***	(0.158)
Deregulation	-2.135***	(0.440)	0		-1.015***	(0.267)	-1.113***	(0.314)	0	
Retail choice	0.558*	(0.300)	0		0.246	(0.234)	0.221	(0.271)	0	
PUC	-0.489	(0.321)	0		-0.775***	(0.207)	-0.908***	(0.226)	0	
REP GOV	-0.955**	(0.337)	0		1.056***	(0.235)	1.218***	(0.250)	0	
GDP	6.224***	(0.886)	0		1.477**	(0.449)	1.663**	(0.504)	0	
POP	1.180***	(0.233)	0		0.213**	(0.085)	0.260**	(0.101)	0	
# Observations	718		718		718		718		718	
Log-likelihood	478.350		419.148		400.944		398.800		371.529	

Notes: *, **, *** denote statistically significant at 10%, 5% and 1% respectively. Standard error in parenthesis

It is noteworthy to exercise some caveat with respect to the interpretation of the retail choice coefficient as it is only slightly significant at 10%. From these result, we can conclude that electricity deregulation has significant potential benefits in enhancing technical efficiency.

The inclusion of PUC and REP GOV enables us to get better intuition into the political dynamics of restructuring on inefficiency. Interestingly, the coefficients of PUC and REP GOV are negatively correlated with inefficiency. These findings imply an increase in technical efficiency as the majority of the state commissioners on public utility commission are Republicans and when the state has Republicans control both the governorship and the legislature. Intuitively, a plausible explanation to these findings is the tendency of these states controlled by Republicans to influence some political decisions that support restructuring policy in order to promote competition among the electric power generators. In contrast, we found real per capita gross domestic product and population density to be positive and statistically significant.

Table 5.7: Estimate technical efficiency scores

Model	Mean	SD	Min	Max
WANG	0.897	0.096	0.283	0.998
KGMHLBC	0.763	0.074	0.568	0.963
RSCFG- μ	0.885	0.075	0.527	0.987
RSCFG	0.871	0.076	0.540	0.975
ALS	0.861	0.077	0.476	0.971

Besides the determinants of the inefficiency, we are also interested in the unit-specific inefficiency so as to ascertain the distribution of the efficiency. In doing so, we computed the Battese and Coelli efficiency estimates for each observation in all the models. The summary

statistics of the efficiency index across competing models are reported for comparison in Table 5.7. The efficiency index summary statistics shows that our preferred model has the highest average efficiency of 0.897. This finding means that, on average, states electricity generation is 89.7 per cent of the maximum output. Better still, it implies that the states lost about 10.3 per cent of the potential generation output to technical inefficiency.

Figure 5.2: Kernel densities of efficiency scores of the estimated models

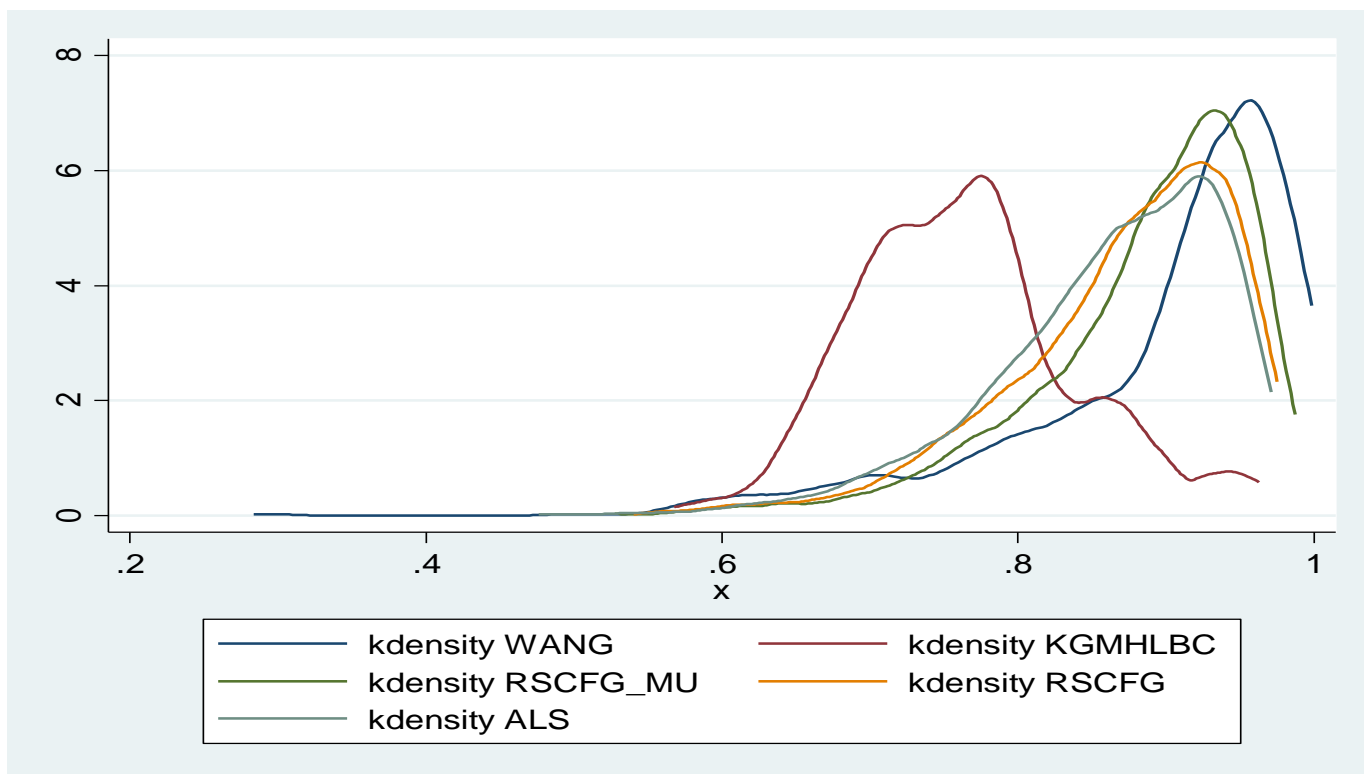


Figure 5.2 plots the kernel density estimates of the efficiency scores for the five models. The kernel density reveals the WANG mode as the most rightly skewed distribution, which further reinforces WANG as our preferred model. dc

In order to draw further distinctions on the impacts of deregulation on the states' technical efficiency in electricity generation, we categorise the efficiency index into states in which

deregulation has been implemented and is currently on-going and their counterparts (which have not implemented or suspended deregulation activities). Instead of reporting all the results from the alternative models, we use our preferred model, the WANG model, to evaluate the efficiency impact of deregulation as shown in Table 5.8. Comparing the efficiency result, we found out that, on average, deregulated states are more efficient in the electricity generation with a mean efficiency score of 0.928 compared with the non-deregulated states. According to the result, the non-deregulated states can potentially close their average electricity generation inefficiency gap by 4.5 per cent with the implementation of a restructuring market reform. Furthermore, it is intriguing to observe that the average technical efficiency of deregulated states surpasses that of the whole sample average efficiency index. The result further strengthens our earlier finding that deregulation constitutes a major factor at improving electricity production efficiency due to its negative impact on the variance of inefficiency.

Table 5.8: WANG model efficiency scores

	# Observations	Mean	SD	Min	Max
Deregulated States	225	0.928	0.092	0.283	0.998
Non-deregulated States	493	0.883	0.095	0.563	0.988
Whole Sample	718	0.897	0.096	0.283	0.998

5.4.2 Marginal Effects results

Having discussed the slope parameters of the exogenous variables, we now focus on the marginal effect. The marginal effect indicates by how much the technical inefficiency will change if each of the exogenous variables changes, *ceteris paribus*. The estimation of marginal effect is important to our analysis as the estimated slope parameters of the

inefficiency determinants are only indicative of the direction and not the magnitude. Therefore, marginal effects are evaluated for both the mean and the variance of the technical inefficiency i.e. $E(u_{it})$ and $V(u_{it})$ as explained in equation (5.9) and (5.10).

Table 5.9: Marginal effects on inefficiency using WANG Model

Variable	Marginal effects on $E(u_{it})$		Marginal effects on $V(u_{it})$	
		Coeff		Coeff
Deregulation	Average	-0.119		-0.027
	25 th percentile	-0.115		-0.011
	50 th percentile	-0.074		-0.005
	75 th percentile	-0.049		-0.002
Retail choice	Average	0.024		-0.006
	25 th percentile	-0.003		-0.002
	50 th percentile	0.014		-0.001
	75 th percentile	0.028		-0.000
PUC	Average	-0.010		-0.012
	25 th percentile	-0.020		-0.016
	50 th percentile	-0.008		-0.011
	75 th percentile	0.024		-0.007
REP GOV	Average	0.013		-0.006
	25 th percentile	-0.011		-0.002
	50 th percentile	0.022		-0.000
	75 th percentile	0.379		0.021
GDP	Average	-0.005		0.003
	25 th percentile	-0.604		0.002
	50 th percentile	0.071		0.003
	75 th percentile	0.220		0.005
POP	Average	-0.014		0.012
	25 th percentile	-0.144		0.000
	50 th percentile	0.011		0.002
	75 th percentile	0.038		0.004

The mean function marginal effects demonstrate how a change in an exogenous variable affects the expected inefficiency. On the other hand, the marginal effects of the variance function reveal the partial effect of the exogenous variable on production uncertainty in the electricity generation industry. Following Wang's (2002, 2003) approach, the computed non-monotonic marginal effects of the exogenous factors on technical inefficiency at the average, 25th, 50th and 75th per centile levels are presented in Table 5.9.

Not surprisingly, the marginal effects on $E(u_{it})$ and $V(u_{it})$ of the deregulation variable quantifies how an increase in the degree of deregulation changes the expected inefficiency and the production uncertainty. We find that deregulation overall has a negative partial effect, i.e. a monotonic impact on the mean and variances of the inefficiency. Indeed, as shown on the third column, the partial effect impact on the mean indicates that an increase in deregulation reduces production inefficiency by 12 per cent for the whole sample, hence an increased electricity generation output by the same size⁵⁷. This negative pattern is the same for the non-linear first, second and third quartiles of the sample. However, we notice a decreasing trend in the partial effect from first to third quartiles. This implies that states with a low degree of deregulation could restructure market reform activities as they would benefit more from deregulation. This explanation is also valid for the marginal effects impact on the variance of inefficiency, as increases in deregulation appear to reduce production uncertainty (probably because generators were guaranteed returns on their investment, thereby expanding their generation capacity). Conversely, for retail choice, the mean marginal effect of the sample is positive, while in the first-quartiles it is negative and in the third-quartile positive. The opposite marginal effects in these two quartiles means that retail choice affects efficiency non-monotonically in the sample. In other word, when there is partial retail choice, a higher

⁵⁷ The percentage change in output due to changes in exogenous factors is derived from the partial effect of the mean of inefficiency as $\partial E(\ln y) / \partial(z_{it}) = -\partial E(u) / \partial(z_{it})$.

retail choice reduces the production inefficiency. However, retail choice tends to decrease production uncertainty, possibly due to large number of consumers depending directly on demand for generation outputs.

The marginal effects of PUC, REP GOV, GDP and POP variables provide other interesting insights into the non-monotonic marginal effect. PUC, on the average, has a negative marginal effect of -0.010 in the mean inefficiency function, which represents an increase in efficiency by 1 per cent. The first-quartiles and second-quartiles are also negative while the non-monotonic third quartile is positive (0.024). This finding for the first and second quartiles suggest that states represented by few numbers of republican commissioners on public utility commission could potentially improve on their technical efficiency. The positive sign for the third 75th percentile indicates that states with a high number of republican commissioners on the public utility commission do not experience a further increase in technical efficiency by increasing the number of their republican commissioners. For these variables, the marginal effects also differ with respect to production uncertainty. In particular, increased GDP and POP seem to increase production uncertainty, probably because of excess demand over supply, occasioned by higher income and population.

5.5 Conclusions

One area that has attracted much attention in the industrial organisation literature is the debate on the efficiency gains from restructuring. Controversies remain going by the mixed findings from past studies. This paper attempts to analyse the electric power industry's performance using a consistent state-level electricity generation dataset for the contiguous US states from 1998-2014. First, we estimate several specifications of stochastic production frontier models to investigate the impacts of restructuring on technical efficiency in order to find a channel for policy adjustment. More specifically, we adopt the Wang (2002, 2003)

approach that allows both mean and variance of the pre-truncated normal to depend on the exogenous variables. Second, we examine the non-monotonic marginal effects of exogenous factors on technical efficiency.

Our results indicate a positive impact of deregulation on technical efficiency across all the estimated models. The finding is largely consistent with previous studies on deregulation's impact on efficiency. In particular, our preferred model reveals that states where deregulation is active are more efficient. More importantly, the result shows that non-deregulated states can increase their technical efficiency by 4.5 per cent if they implement deregulation. Despite the influence of positive deregulation, retail choice is found to reduce technical efficiency at 10 per cent significant level. The results of marginal effects show that deregulation has a reducing impact on production inefficiency by 12 per cent, and a 2.7 per cent decrease in production uncertainty for the whole sample, hence an increase electricity generation output by same size. Conversely, retail choice exhibits non-monotonic marginal effects impact on production inefficiency and overall reducing in the variance of the inefficiency.

Finally, we found that political institutions and structure within the state affects the level of technical efficiency. Performance seems to improve as Republicans control both the governorship and the legislature, as well as when the majority of the state commissioners on public utility commissions are Republican, as they have a high propensity to influence some political decisions that could potentially support restructuring policy in order to promote competition among the electric power generators. However, increased GDP per capita and population density seems to increase production uncertainty probably because of the inability to accurately forecast future electricity demand because of occasional excess demand over supply arising from higher income and population.

Chapter 6 Conclusions and future research

6.1 Summary

This thesis consists of three independent but related essays which quantitatively examine the impact of power sector market reform on efficiency of the electricity generation. The long-lasting debates on the efficiency gain from power sector reforms remains largely unresolved, at best controversial, which underscores the need for more comprehensive studies of this kind. This thesis contributes to the existing empirical literature by extending the methodological dimension of measuring cost and technical efficiency from electricity market reforms with an application to both macro level cross-country and US state level data. The thesis demonstrates that countries which are advanced in their level of reform attain a higher efficiency in generating electricity compared to their counterparties in the rest of the world. This objective was further generalised for the developed economies of the OECD countries, in order to delve into the cost efficiency and other cost characteristics of electricity generation while recognising the production of undesirable output in the generation process. In addition, the dynamics of the marginal effect of restructuring activities in the US states electricity generation efficiency was analysed. The aforementioned issues were addressed via the three papers in Chapters 3, 4 and 5.

6.2 Empirical Findings and Policy Implications

Stemming from the research questions set out in chapter 1, we discuss our empirical findings around these questions and ascertain whether we have provided answers to them. The first essay tries to provide answers to these three questions; “*do countries with significant reform progress attain higher efficiency in generating electricity compared to their counterparties?*”, “*do unobserved heterogeneities measure the influence of deregulation?*”

and “*what is the key driver of total productivity growth?*”. This paper estimates technical efficiency of 91 countries by specifying three different models; the time varying model, the true fixed effect and true random effect models. Although, the analysis in the first paper shows that our findings are sensitive to the choice of model specified, we establish that the degree of democratic freedom (as shown by political rights of a country) positively influences electricity generation. Results show increasing efficiency in electricity generation across sampled countries over the period under consideration, with Germany being the most efficient in electricity generation whereas Tanzania, a seemingly socialist country, is consistently ranked the least efficient country.

Another emerging debate which this study touches on is the potential ability of unobserved heterogeneities to capture deregulation in addition to efficiency measurement. Findings from the estimates of the intercept reveal that countries with marked deregulation, especially for the Latin American countries and Africa, are being pushed close to the frontier. A major contributing factor for these countries to be located on the frontier is that they are increasingly becoming more democratic and reform oriented. The thesis also shows that mean efficiency changes serve as the main driver of total factor productivity growth which implies movement towards the frontier.

The following policy implications derive from chapter 3. It is evident that political rights, a necessary condition for electricity reform, substantially increase electricity generation efficiency. Nonetheless, reform variable, proxy by reform stage in each country, does not significantly impact electricity generation due to the simultaneity of reform steps. However, regardless of the stage of electricity reform, democracy in a country is the right ingredient for the implementation of electricity market reform. The pushing towards the frontier of these

countries explains the potential influence of politically driven electricity reform. Therefore, reform policies designs in these countries must consider the country-specific level of democracy. In particular, policy that conditions development loans and aid on the democratisation and deregulation of the electricity segment is a veritable avenue to scale up efficiency in the electricity generation segments, especially in developing countries. Governance improvements are crucial in these countries so as to control corruption and consolidate the nascent efficiency gains. Improvements in governance are also necessary in order to have independent regulation in place as the electricity reforms progress.

The second essay concerns these three questions; “*what are the impacts of the electricity regulatory reform indicators on cost efficiency?*” “*does the cost complementarity exist between generation and carbon emission?*” and “*is there any difference between scale economies in the long run and the short run?*”. Given the substantial level of reform witnessed so far in the OECD countries, this paper looks at the impact of different market regulatory indicators on the cost of electricity generation. Employing the short-run cost function in which capital stock is treated as a quasi-fixed factor input, frontier models, including the four-way error component model, are developed for the cost function for a panel dataset of 25 countries during the period 1980 to 2009. Findings show that public ownership and vertical integration appear to have significant and sizable increasing impacts on cost. This result reiterates the benefit of privatisation of generation assets and private ownership in the power sector. Our results have important policy implications for the electricity market reform agenda. The nature of the deregulation matters since unbundling and privatization are the factors which encourage the generation utility to make maximum use of least cost options for efficiency gain. Cost complementarity between generation and emissions is investigated and found to be significant. This suggests an important policy signal

for a carbon emission strategy in the power sector given the potential of lowering emission while increasing electricity generation. By incorporating quasi-capital input into the cost function, the estimated economies of output expansion for the models in the short run indicates the existence of sharply rising costs when capacity is fixed. However, economies scale in the long run shows constant returns to scale when adjustment is made for the quasi-fixed input. Finally, we find that market reforms are positively correlated – a country pursuing one type of reform often pursues others as well – and that these market structure reforms as measured by the OECD product market reform indicators produce more cost-efficient electricity generation.

Given the increasing cost implication of the estimated parameter of public ownership and vertical integration, Chapter 4 proffers policy recommendations which suggests that the ownership of unbundling represents the key aspect of electricity market reform in these countries as it may help to leverage additional financial and human resources, diversify technology and managerial approaches, and spread risk. Arguably, the prospects of competition and innovation in the electricity sector are hinged on implementation of a policy for that allows private ownership and participation. Hence, privatisation of state owned utility assets through property rights reallocation should be encouraged as it helps to reduce associated cost inefficiency. Obviously, investment adequacy too is increasingly essential given the need to make substantial investments in generation capacity from different technology sources. Thus, policymakers should create conditions that encourage more competition among generators in order to encourage investment in the industry since we find a high return to capital investment when we model the shadow price of the quasi-fixed capital input. This will bolster investment for expansion and replacement of existing assets as they become obsolete, with the possibilities to accommodate large amounts of renewables.

While Europe has sought to move away vertical integration given its successive directives, however it still in a de facto operation in some countries. Institutional arrangements of complete separation of the constituent segments should be implemented and completed followed by an effective regulatory oversight (where none previously existed or are not in existence). Moreover, due to the presence of cost complementarity, there is a possibility of reducing emissions without necessarily reducing generation with the existing technologies. Therefore, the use of emission control instruments can cause generators to internalize the cost of environmental pollution without significant effects on electricity generation output. Hence, environmental policy that creates incentives for investment in new technologies-, especially low carbon technologies- for emission abatement would be yield desirable outcome for combating environmental pollutions in generation.

Finally, the third essay considers two main research questions; “*Does restructuring shape the mean and variance of electricity generation inefficiency?*” and “*what is dynamic of the marginal effect of restructuring?*”. This paper examines the performance of the electric power industry using consistent state-level electricity generation dataset for the 47 US contiguous states from 1998-2014. The stochastic production frontier for five competing models was estimated in order to identify the determinants of technical inefficiency and the marginal effects. The positive impact of deregulation on technical efficiency across the models estimated was established. More specifically, deregulated states are more efficient in electricity generation than the non-deregulated states. One would have expected retail choice to equally increase production efficiency but our result shows otherwise. Findings also show that inter political affiliation explains technical efficiency. Again, another vital issue on the debate of electricity reform which this essay addresses is the dynamic nature of the marginal effect of restructuring. Some critics of reform have argued that restructuring policy could

potentially have a positive impact on inefficiency at certain ranges and then turn negative outside these ranges. Therefore, the findings reveal that both deregulation and retail choice have an overall monotonic impact on the mean and variances of the inefficiency, although the marginal effect of retail choice reduces technical efficiency.

The main policy implications arising from chapter 5 are as follows. First, deregulation has consistently had an increasing influence on production efficiency. Thus, statutory measures that facilitate full deregulation on states which have not yet implemented deregulation could drive production efficiency as well as reduce the large electricity price disparity in the retail market among utilities in different state. In addition, states which have suspended deregulation could consider rolling back as research reveals compelling evidence that non-deregulated states can potentially increase their technical efficiency by 4.5 percent if they implement deregulation. Second, implementation of this measure could be fast tracked using political institutions and instruments as our finding suggests that electricity generation performance appears improved when Republicans control both the governorship and the legislature, as well as when the majority of the state commissioners on the public utility commission are Republican. It may be argued that this relates to the political ideology of this party which supports market oriented restructuring policy that potentially promotes competition among the electric power generator.

6.3 Limitations of the research

Every research study, regardless of how well conducted or constructed, suffers some limitations. Hence, this study acknowledges a number of limitations which by no means undermine our analyses or the findings thereof. The major limitations recognised in the research work pertain to the issue of data. First, the study was constrained by the lack of data

that accurately captures electricity market reform variables for each country. A case in point is the reform scores employed in chapter 3 in which electricity market reform scores are assigned to each country based on the reform status of that country. Of course, this approach of measuring reform might not be the most appropriate indicator to reflect all characteristics and intensity of the reforms in various countries. However, we believe it is an indicator of reform progress, rather than reform success and it does help to satisfactorily categorise countries in term of reform steps⁵⁸. Moreover, the estimation of different models that account for unobserved heterogeneities would reasonably pick up some cross-country differences in reforms that are not accounted for in the models. Second, following a similar study (See Jaraitė, and Di Maria, 2012), we use economically active population data in the utility supply industry as a proxy for labour due to paucity of data for cross-country disaggregated labour for electricity generation in chapters 3 and 4. There is a caveat here given the unlikely implementation of deregulation policy in all the industries across countries at the same time. Besides, there might be large differences in the distribution of workers across the various utilities in sampled countries which might not be sufficiently captured by different intercepts. At any rate, the potential drawback is lessened by the fact electricity sector accounts for the largest of share of utility labour. Lack of data also explains the exclusion of other OECD countries from the sample in chapter 4 which could have made the sample more representative and our findings more robust and generic.

Lastly, given that market reform is an on-gong process, we cannot claim that we have covered all aspects of the reform process and then generalised our findings of the positive impact of reform on electricity generation efficiency. Infact, retail choice in chapter 5 shows

⁵⁸ The electricity market reform score variable ranges from 0 to 8. It is constructed using reform steps that have been taken in each country; (1) introduction of independent power producers, (2) corporatization of state-owned enterprises, (3) law for electricity sector liberalization, (4) introduction of unbundling, (5) establishment of electricity market regulator, (6) introduction of privatization, (7) establishment of wholesale electricity market, and (8) choice of supplier (See Erdogdu , 2013).

some unintended negative consequences on reform. On the whole, the estimated models have revealed, to a certain extent, that the methodological application of recent developments regarding efficiency and productivity analysis has adequately mitigated the potential bias in our analysis of the impact of electricity market reform.

6.4 Directions for future research

This thesis analysed the impact of market driven electricity reforms on efficiency in three separate essays. In the first essay, we used the stochastic input distance function to explain the impact of reform on technical efficiency in 91 countries across the world. In the second essay, we investigated the impact OECD product market regulation indicators on cost efficiency in the face of quasi capital input. While in the third essay, we examined the influence of restructuring on US state electricity generation and technical efficiency. Essentially, our findings demonstrated the mixed evidence of market-based reforms in improving efficiency. For this reason, there is a need for further research on electricity reform within the context of efficiency analysis.

Since market driven electricity reform is still in progress and gradually evolving, especially in the developing and transition economies, more interesting findings could potentially arise from the analysis of the reform impact on efficiency (with the application of more appropriate reform variables as opposed to the use of reform scores employed in chapter 3). This could serve as a basis for establishing concrete economics justification for policy reform recommendation and adoption to these countries.

The results of the impact of restructuring on the mean and the variance of inefficiency reveals negative impact of retail choice on production efficiency and the marginal effect. Although the findings lend more credence to the positive impact of deregulation on efficiency, the

ensuing findings on the estimates of retail choice as reported in the third essay is shrouded with suspicions as to the benefit of retail competition arising from implementing market restructuring. Needless to say, further research is required to assess the actual degree of competition in the electricity market. This research can be situated in the context of the US electricity utility-level analysis using the application of Boone indicators as a measure of competition. Boone explains that firms are punished more harshly (in term of profit) for losing efficiency as well as when there are more firms in the market owing to a fall in entry barriers due to competition.

Chapter 5 also offers another prospect for spatial stochastic frontier analysis in order to report some underlying negative externalities from deregulation. Fossil-fuel-fired plants for generating electricity produce environmental pollution in the form of carbon dioxide, nitrogen oxides and sulphur dioxide emissions. The emission rate could vary considerably depending on the stage of deregulation in each state, with the possibility of a spillover effect. Therefore, a study on the environmental efficiency of deregulation by incorporating at least one pollutant as an undesirable output is vitally important. This might provide ample evidence for discouraging fossil-based generation towards achieving objectives of decarbonisation the power sector.

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Appendix 1: Reform scores by country

8	7	6	5	4	3	2	1
Australia	Argentina	Albania	Algeria	Bosnia-Herzegovina	Costa Rica	Serbia	Belarus
Austria	Belgium	Ecuador	China	Honduras	Cyprus	Tanzania	Botswana
Bulgaria	Bolivia	Estonia	Ethiopia	Switzerland	Malta	Uruguay	Cuba
Canada	Brazil	Indonesia	Ghana	Vietnam	Mexico		Iran
Czech Rep.	Chile	Jordan	Jamaica		Zambia		Israel
Denmark	Colombia	Luxembourg	Kenya				Paraguay
El Salvador	Croatia	Macedonia	Morocco				Trinidad and Tobago
Finland	Dominican Rep.	Malaysia	Qatar				
France	Georgia	Mongolia	Senegal				
Germany	Iceland	Nigeria	South Africa				
Greece	India	Pakistan	Sri Lanka				
Hungary	Ireland	UAE	Thailand				
Italy	Japan	Venezuela					
Latvia	Lithuania						
New Zealand	Moldova						
Norway	Netherlands						
Panama	Nicaragua						
Poland	Peru						
Portugal	Philippines						
Romania	Russia						
Singapore	Slovakia						
Spain	Slovenia						
Turkey	Sweden						
USA							
United Kingdom							

Source: Erdogdu, 2013

Appendix 2: Cost Complementarities and Non-jointness

The translog cost function;

$$\ln c(\mathbf{y}, \tilde{\mathbf{w}}, t) = \alpha_0 + \boldsymbol{\alpha}' \mathbf{ly} + \boldsymbol{\beta}' \mathbf{l}\tilde{\mathbf{w}} + \frac{1}{2} \mathbf{ly}' \mathbf{A} \mathbf{ly} + \frac{1}{2} \mathbf{l}\tilde{\mathbf{w}}' \mathbf{B} \mathbf{l}\tilde{\mathbf{w}} + \mathbf{ly}' \boldsymbol{\Gamma} \mathbf{l}\tilde{\mathbf{w}} + \delta_1 t + \frac{1}{2} \delta_2 t^2 + \boldsymbol{\mu}' \mathbf{ly} t + \boldsymbol{\eta}' \mathbf{l}\tilde{\mathbf{w}} t$$

[1]

In this equation,

$$\mathbf{l}\tilde{\mathbf{w}} = (\ln(w_1/w_K) \quad \dots \quad \ln(w_{K-1}/w_K))$$

$$\mathbf{ly} = (\ln y_1 \quad \dots \quad \ln y_R)$$

and homogeneity of degree +1 in \mathbf{w} has been imposed by dividing each of the input prices by w_K . We write the vector of optimal share weights as: \mathbf{s} and write $\hat{\mathbf{s}}$ to represent the diagonal matrix with the shares on the leading diagonal. Concavity with respect to input prices requires that the sub-matrix of the Hessian:

$$\mathbf{B} - \hat{\mathbf{s}} + \mathbf{s}\mathbf{s}'$$

[2]

is negative definite, throughout the sample. If mean corrected data are used, then the concavity condition at the sample mean is negative definiteness of:

$$\mathbf{B} - \hat{\boldsymbol{\beta}} + \boldsymbol{\beta}\boldsymbol{\beta}'$$

[3]

Cost complementarities are derived from the sub-matrix of the Hessian that refers to output effects. Output elasticities are in the vector: $\boldsymbol{\varepsilon}_y$ and $\hat{\boldsymbol{\varepsilon}}_y$ is the diagonal matrix with output elasticities on the leading diagonal.

In general cost complementarities are given by:

$$\mathbf{A} - \hat{\boldsymbol{\varepsilon}}_y + \boldsymbol{\varepsilon}_y \boldsymbol{\varepsilon}_y' \quad [4]$$

At the sample mean with log mean corrected data these become:

$$\mathbf{A} - \hat{\boldsymbol{\alpha}} + \boldsymbol{\alpha} \boldsymbol{\alpha}' \quad [5]$$

The cost complementarities can be numerically evaluated throughout the sample using [4] but they cannot be statistically tested in this form since each is a nonlinear function of the variables. However the cost complementarities at the sample mean using [5] can be tested because with log mean corrected data they are regression coefficients. Cost complementarity is a feature of the off-diagonal elements, typically

$$\frac{\partial^2(C/w_K)}{\partial y_r \partial y_s} = \left(\frac{C/w_K}{y_r y_s} \right) (\alpha_{rs} + \alpha_r \alpha_s)$$

Only the sign of the second bracketed term matters since the first must be positive. The test is:

$$H_0: \alpha_{rs} + \alpha_r \alpha_s = 0 \text{ versus } H_1: \alpha_{rs} + \alpha_r \alpha_s \neq 0$$

This is a nonlinear Wald test which is implemented by the `testnl` command in STATA which uses the delta method. The data include `ly1`, `ly2` and `ly12` to which represent log of output 1,

log of output 2 and log of output 1 X log of output 2, the test for cost complementarity between outputs 1 and 2 is:

$$\text{testnl } (_b[\text{ly12}] + (_b[\text{ly1}] * _b[\text{ly2}]) = 0$$

Appendix 3: Four Ways Error Component Model

The FWEC model is written

$$y_{it} = \alpha_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \mu_i + v_{it} + \eta_i + u_{it}$$

There are four components to the error term:

Inter-firm heterogeneity, μ_i , which is a time-invariant random error assumed to be a zero mean, constant variance normally distributed random variable, $\mu_i \sim Nid(0, \sigma_\mu^2)$

Idiosyncratic error, v_{it} , which is a time-varying random error assumed to be a zero mean, constant variance normally distributed random variable, $v_{it} \sim Nid(0, \sigma_v^2)$

Time-invariant inefficiency, which is a time-invariant random error assumed to be a zero mean, constant variance normally or exponentially distributed random variable truncated below at zero, $\eta_i \sim Nid^+(\mu, \sigma_\eta^2)$ or $f(\eta) = \sigma_\eta \exp(-\sigma_\eta^2 \eta)$. Referred to by KLH as persistent inefficiency.

Time-varying inefficiency, which is a time-varying random error assumed to be a zero mean, constant variance normally or exponentially distributed random variable truncated below at zero, $u_{it} \sim Nid^+(\mu, \sigma_u^2)$ or $f(u) = \sigma_u \exp(-\sigma_u^2 u)$. Referred to by KLH as residual inefficiency

There are potentially four error component variances which can give rise to a number of different models. The relationship between the KLH model and four other panel models considered is demonstrated in table A1, from which it can be seen that the Pitt-Lee (1981) model adopted by BLANK is both the oldest vintage model and the most restrictive in its assumptions. None of the restrictions has been tested by BLANK and the BLANK response simply rejected model (2) (which was suggested by Frontier Economics (FE)) without commenting on the estimated results on the grounds that it was inappropriate to specify inefficiency as time-varying rather than time-invariant. BLANK failed to report that even though model (2) specifies inefficiency as time varying, there is nothing in the specification to stop the estimated inefficiencies bblankng relatively stable over time, so that the BLANK theoretical objection is unfounded.

Table A2: Alternative models

Error component included	Error variance component	(1) Pitt-Lee (1981) adopted by BLANK	(2) Greene (2005) (TFE/TRUE models) suggested by FE	(3) Kumbhakar and Heshmati (1995)	(4) Separate the time-invariant effects, FE	(5) Kumbhakar, Lien and Hardaker (2014) suggested by FE
Time-invariant inter-firm heterogeneity	σ_{μ}^2	= 0	> 0	= 0	> 0	> 0
Idiosyncratic error	σ_v^2	> 0	> 0	> 0	> 0	> 0
Time-invariant/persistent inefficiency	σ_{η}^2	> 0	= 0	> 0	> 0	> 0
Time-varying/residual inefficiency	σ_u^2	= 0	> 0	> 0	= 0	> 0

It is clear from Table A3 that the BLANK model is a special case of the other models, in particular all of the models (1)–(4) are special cases of model (5), with the BLANK version bblankng the most restrictive. In principle therefore it may be possible to carry out comparative testing.

Estimation is a multi-step procedure in the case of models (3)-(5) using pseudo-likelihood estimation as suggested by Fan et al (1996), therefore care must be exercised. Maximum likelihood estimation (MLE) is used for all the parameters including both frontier cost function parameters and variance components in models (1) and (2), but, invoking the assumptions in the Fan et al paper, MLE is used only for the variance components in models (3)-(5). However, since our interest is in the error variance components, this allows the availability of two types of test for the null hypothesis: $H_0: \sigma_p^2 = 0, P \in \{v, \mu, \eta, u\}$

- (i) a generalised likelihood ratio test of the error variance component with corrected degrees of freedom
- (ii) use of the asymptotic normality property of the MLE estimators of the error variance components to apply a test based on $(\hat{\sigma}_p/SE(\hat{\sigma}_p)) \sim N(0,1)$

Models (1) and (2): use the STATA options for xtfrontier and spanel. Models (3)-(5) use the multi-step procedure described in Kumbhakar, Lien and Hardaker (2014), and variants of this.

Step 1

Begin by converting the truncated-error components to zero-mean constant-variance errors as follows

$$y_{it} = \alpha_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \mu_i + v_{it} + \eta_i + E(\eta_i) - E(\eta_i) + u_{it} + E(u_{it}) - E(u_{it})$$

Then

$$y_{it} = [\alpha_0 + E(\eta_i) + E(u_{it})] + \mathbf{x}'_{it}\boldsymbol{\beta} + \mu_i + v_{it} + (\eta_i - E(\eta_i)) + (u_{it} - E(u_{it}))$$

That is

$$y_{it} = \beta_0 + \mathbf{x}'_{it}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it}$$

This now has the form of a one-way panel model with time-invariant and time-varying components, each of satisfies by construction the zero-mean condition

In this case:

$$\beta_0 = [\alpha_0 + E(\eta_i) + E(u_{it})]$$

This is a constant intercept term, with $E(\eta_i) = (\sqrt{2/\pi})\sigma_\eta$ in the half-normal case and

$E(\eta_i) = \sigma_\eta$ in the exponential case, and $E(u_{it}) = (\sqrt{2/\pi})\sigma_u$

$$\alpha_i = \mu_i + (\eta_i - E(\eta_i))$$

This is a zero mean time-invariant random error with constant variance

$$\varepsilon_{it} = v_{it} + (u_{it} - E(u_{it}))$$

This is a zero mean time-varying random error with constant variance

This equation is now in the form of the standard zero-mean one-way panel random effects model – very similar to the Pitt-Lee (1981) modelled utilised by BLANK, except for the zero-mean conversion.

Fit this model and retain the results: $\hat{\boldsymbol{\beta}}$, β_0 , $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$

Step 2

Use the predicted residuals from the one-way random effects panel estimated in step 1

$$\hat{\varepsilon}_{it} = v_{it} + (u_{it} - E(u_{it})) + (\hat{\varepsilon}_{it} - \varepsilon_{it})$$

Therefore

$$\hat{\varepsilon}_{it} = -E(u_{it}) + [v_{it} + (\hat{\varepsilon}_{it} - \varepsilon_{it})] + (u_{it})$$

These are the usual time-varying residual components of the one-way panel composed error without the random effects component. The first term on the RHS is a constant, the second term in square brackets is a zero mean constant variance idiosyncratic error if $(\hat{\varepsilon}_{it} - \varepsilon_{it})$ is treated as asymptotically zero (by the Law of Large Numbers). The third term is the time-varying inefficiency component, assumed to be half-normally distributed. Therefore, this step can be solved by fitting the standard basic stochastic frontier analysis model with pooled data using $\hat{\varepsilon}_{it}$ as the dependent variable and regressing this against a constant term and the composed normal and half-normal error components model.

Kuosmanen, Johnson and Saastamoinen (2014) show that this procedure implements the Fan et al (1996) pseudo-likelihood method for semi-parametric stochastic frontier analysis.

Hence in step 2, the parameters of the time-varying inefficiency component combined with time-varying idiosyncratic error are obtained: $\hat{\sigma}_u, \hat{\sigma}_v$ and the JLMS or BC procedures for deriving estimated time-varying efficiency can be implemented. We are also able to test the hypothesis common to models (2), (3) and (5):

$$H_0: \sigma_u^2 = 0 \text{ against } H_1: \sigma_u^2 > 0$$

KLH refer to this component as Residual Efficiency, RE:

$$RE = \exp(-\hat{u}_{it})$$

Step 3

Use the predicted random error effects from the one-way random effects panel estimated in step 1

$$\hat{\alpha}_i = [\mu_i + (\eta_i - E(\eta_i))] + (\hat{\alpha}_i - \alpha_i)$$

Therefore

$$\hat{\alpha}_i = -E(\eta_i) + [\mu_i + (\hat{\alpha}_i - \alpha_i)] + \eta_i$$

Applying arguments similar to those already used in step 2, the pseudo-likelihood procedure can be invoked. The first term on the RHS is a constant, the second term in square brackets is a zero mean constant variance idiosyncratic error representing heterogeneity if $(\hat{\alpha}_i - \alpha_i)$ is treated as asymptotically zero. The third term is the time-invariant inefficiency component, assumed to be half-normally distributed. Therefore, this step can be solved by fitting the standard basic stochastic frontier analysis model with pooled data using $\hat{\alpha}_i$ as the dependent variable and regressing this against a constant term and the composed normal and half-normal error components model.

Hence in step 3, the parameters of the time-invariant inefficiency component combined heterogeneity treated as a random effect are obtained: $\hat{\sigma}_\eta, \hat{\sigma}_\mu$ and the JLMS or BC procedures for deriving estimated time-invariant efficiency can be implemented. We are also able to test the hypothesis common to models (1), (3), (4) and (5):

$$H_0: \sigma_\eta^2 = 0 \text{ against } H_1: \sigma_\eta^2 > 0$$

The tests can then be combined to distinguish model (5) from the others.

KLH refer to this component as Persistent Efficiency, PE:

$$PE = \exp(-\hat{\eta}_i)$$

Overall efficiency is then calculated as

$$OE = PE * RE$$