Energy Efficiency: A Sectoral Analysis for Kerala

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ENERGY EFFICIENCY:
A SECTORAL ANALYSIS FOR KERALA

A Study Report

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Acknowledgement

"What do you suggest, sir?" Alice asked.

"That depends on what you want," the caterpillar said wisely.

Lewis Carroll might not have raised Alice in an *energy efficient* wonderland. But the present study is about the light and shades of such a wonderland, about the significance of energy efficiency. The study also unravels another extreme of a sluggish terrain of imperfect information, precisely a vacuum of information.

This Report is about such a wonderland, unfortunately embedded in imperfect information. The study was made possible by a research grant from the Energy Management Centre (EMC), Government of Kerala, Trivandrum, sanctioned in late 2018. We are grateful at the outset to all those at EMC and its Director, K. M. Dhareshan Unnithan, who recognized the significance of such a study.

A number of in-house workshops at EMC that we had opportunity to attend in the context of the progress of the study have greatly contributed towards the better fruition of this Project. The first of such workshops on the project proposal ("Sectoral Energy Intensity (Electricity) Kerala"), presented by N. Vijayamohanan Pillai, Centre for Development Studies, took place on 26th September 2018 at EMC Conference Hall, Thiruvananthapuram. We are thankful to V. K Damodaran, Executive Committee member, EMC; Sankaranarayanan, Former Director of National Productivity Council; N. R. Joy, Chief of Industry and Infrastructure Division, State Planning Board; Jayashankar, Senior Economist Analyst, Kerala State Electricity Regulatory Commission; R Jayaraman, Executive, and Arjun. O, Assistant Manager, both of Kannan Devan Hills Plantation (P) Ltd; Ajaya Krishnan and Omega, Assistant Engineers (Electrical Division), from Electrical Inspectorate, as well as the officials of the EMC, K. M. Dhareshan Unnithan, Director, R. Harikumar, Joint Director ; Johnson Daniel, ET- E1; Dinesh Kumar A. N, ET- E II; Sandeep K, ET – B; Sarath Krishnan S, ET – B; Beena T.A, PRO; Rakesh V J, Project Engineer, Arya V A, Project Engineer, and Rahul Raj, Project Engineer for their support and insightful comments.

This kick-off workshop was followed by a number of in-house workshops on the progress of the project work, and the final review workshop on the draft report of the "Research Study on Energy Productivity: A Sectoral Analysis for Kerala", presented by N. Vijayamohanan Pillai, Centre for Development Studies, took place on 28 November 2019 at the conference hall of EMC. We are highly indebted to P.S. Chandramohan, Principal (Retd.) Govt Engineering College Barton Hill, V. K. Damodaran, Executive Committee Member, EMC; K. Damodaran, Joint Director, Directorate of Economics & Statistics, Govt. of Kerala; Roy Pius, Joint Director, Factories and Boilers; Rejin, Inspector, Factories and Boilers; Rahul J.S, Assistant Electrical Inspector, Electrical Inspectorate; Suresh Kumar, Additional Director, Petroleum Conservation Research Association; Suresh Babu, Accredited Energy Auditor, Ottotractions; and from Energy management Centre, K. M. Dharesan Unnithan, Director; R. Harikumar, Joint Director ; Johnson Daniel, ET- E1; Dinesh Kumar A. N, ET- E II; Sandeep K, ET – B; Sarath Krishnan S, ET – B; Beena T.A, PRO; and Rakesh V J, Arya V A, and Rahul Raj, Project Engineers for their valuable comments. Gratefully we acknowledge that the forum appreciated and formally approved the research work and suggested to identify areas for further research study and to present data formats required for disaggregated level studies, which we have incorporated in the last chapter of this report.

At CDS, we have, as usual, had all the full support and cooperation from all the concerned that have gone a long way towards the completion of this Report. We would like to record our thanks to the Director, Sunil Mani, Registrar, Suresh Kumar S., and his colleagues in the administration, library and computer centre, especially, Suresh S., Finance Officer; Venukumar V., Accounts Officer cum Internal Auditor; Sarath V., Systems Officer; Sriram V., Chief Librarian and his colleague-Librarians, Ansamma Joseph, Anitha GP, Ameer Ali, Gopakumar S., and Sivakumar P.; Emmanuel TJ., Ajikumar AR, Shareef HS, Anandh NR, Anoopkumar PP, Satheesh SS, Sumesh CS, Vineeth and others. Thanks are also due to Kuriachan Jose, who worked as an associate in the project for a while.

The day-to-day management of the Project, including the whole data analysis and Report writing, was carried out by N. Vijayamohanan Pillai as the Principal Investigator at Centre for Development Studies**.**

The empirical work for this project would not have been possible but for the cooperation and contribution from a number of officials in respect of data collection; we are immensely indebted to Rajeeve L., Finance Officer, Kerala State Electricity Board, Trivandrum, and Suresh Kumar, Additional Director, Petroleum Conservation Research Association, Kochi and their colleagues in the respective institutions.

It goes without saying that behind every work of this dimension and objective (of energy efficiency), there surely lie an ardent concern and care for the future generation; to that future generation this Report we dedicate.

N. Vijayamohanan Pillai
AM Narayanan

Thiruvananthapuram,
17 December 2019.

Abstract

One positive impact of the 1973 oil crises has been the concerted effort across the world to reduce energy consumption through energy use efficiency improvements. Improving energy efficiency ensures the objective of conserving energy and thus promoting sustainable development. Recognition of this fact has now appeared in terms of including the aim of improving efficiency as an important component of electrical energy policy in all the countries across the globe. Conserving electrical energy through energy efficiency measures can meet the high challenge of increasing energy demands at reasonable costs in a sustainable manner. Moreover, improving energy efficiency also has the potential of reducing the environmental and health threats associated with the use of hydrocarbons and of encouraging clean energy systems.

In this study, our focus is on electrical energy conservation by means of efficiency improvements. A large number of studies have demonstrated that the aggregate energy efficiency inherently encompasses a number of factors that affect energy intensity, viz., a structural effect, representing the effect of changes in economic structure, an activity effect, representing the changes in the levels of aggregate activity, a wealth effect, representing changes in GDP, and an underlying energy efficiency effect, including a technical effect and an energy quality effect. This new light has in turn led to the development of the techniques of factorization or decomposition.

Energy efficiency research in general has opened up three avenues of enquiry, namely, the measurement of energy productivity, the identification of impact elements (such as the three factors mentioned above) and the energy efficiency assessment. The traditional interest in energy efficiency has centred on a single energy input factor in terms of productivity that has become famous through an index method proposed by Patterson (1996). The enquiry that has proceeded from the problems associated with this method has led to identifying the effect source of variation, in terms of some decomposition analysis. Almost all the earlier studies have in general employed the method of indicators pyramid, based on which energy efficiency changes have been decomposed from other factors at each level of disaggregation using factorization method. Factorization has been conducted either on the energy-GDP ratio or almost equivalently on total consumer energy use and carried on to the finest level of subsector, subject to data availability.

The Laspeyres index decomposition approach was in vogue earlier that has now been replaced with methodologically superior Divisia approach, in terms of Logarithmic Mean Divisia index (LMDI). Finally, a new energy efficiency estimation method, criticizing the single factor energy efficiency method, has come up utilizing a multi-variate structure. Here we have a parametric (econometric) approach, in terms of frontier production function analysis, and a non-parametric approach, in terms of data envelopment analysis (DEA).

Following the introductory chapter, the next chapter presents a detailed discussion of a techno-economic approach to conceptualizing energy efficiency. Chapter three discusses all the traditional analytical methods and the index decomposition approach to measuring energy efficiency. The next three chapters constitute the core of the study: Chapter four takes up the analytical and empirical exercises based on Logarithmic Mean Divisia index for the State of Kerala with the available data. The next two chapters present the theoretical and empirical analyses in terms of the multi-variate energy efficiency approaches: Chapter five with stochastic frontier production function and Chapter six with data envelopment analysis.

A major problem that we experienced during the execution of this project was availability and suitability of the required data for Kerala. Finally we had to satisfy ourselves mostly with the available time series data on electricity supply only. In Chapter four on decomposition analysis, we use along with the power sector data, petroleum consumption data also available only for a limited number of recent years.

Chapter 1
Introduction

1.1 Introduction

One positive impact of the 1973 oil crises has been the concerted effort across the world to reduce energy consumption through energy use efficiency improvements. Improving energy efficiency ensures the objective of conserving energy and thus promoting sustainable development. Recognition of this fact has now appeared in terms of including the aim of improving efficiency as an important component of electrical energy policy in all the countries across the globe. Conserving electrical energy through energy efficiency measures can meet the high challenge of increasing energy demands at reasonable costs in a sustainable manner. Moreover, improving energy efficiency also has the potential of reducing the environmental and health threats associated with the use of hydrocarbons and of encouraging clean energy systems.

Energy conservation is usually defined as a deliberate reduction in using energy below a certain level of current state of affairs (Munasinghe and Schramm 1983). This may be achieved at both the ends of supply and demand, and works through load management of electricity usage, including direct (mechanical) controls on end-use equipments and power cuts on supply side and time-differential tariffs and other management measures on the demand side. “Load management meets the dual objectives i) of reducing growth in peak load, thus nipping the need for capacity expansion, and ii) of shifting a portion of the load from the peak to the base-load plants, thereby securing some savings in peaking fuels. By moving toward achieving these objectives electric utilities stand to win a cut in operating and capacity costs, share the gain with the consumers and provide a partial solution to the country's energy dilemma." (Pillai 2002: 4-5).

In this study, our focus is on electrical energy conservation by means of efficiency improvements. Improving energy efficiency is expected to reduce energy demand through its rational use in the end-use devices; every unit of energy input consumed will bring in greater amount of useful energy output. The energy efficiency of most of the end-use appliances that we use is pretty low, with consequent losses and higher demand for inputs, leading to environmental damages. This in turn suggests that improving energy efficiency can manage energy demand in better ways and contribute highly to a better environment. It is estimated that higher energy efficiency standards for residential and commercial appliances in the US could result in a cumulative total energy savings of nearly 26 quads for the period 2010–2030 (1 quad ≈ 293,071,000,000 kilowatt-hours) (Rosenquist et al., 2004).

The International Energy Agency (IEA, 2018) estimates that the primary energy demand has grown by 39% since 2000, whereas the global economy, by nearly 85%. "The forces driving energy demand, led by strong economic growth, outpaced progress on energy efficiency. As a result energy intensity – primary energy use per unit of gross domestic product (GDP) – fell by just 1.7% in 2017, the slowest rate of improvement since 2010" (IEA, 2018: 17). IEA points out that in fact the higher economic activity would have led to a much higher energy demand, without energy efficiency progress. "Efficiency improvements made since 2000 prevented 12% additional energy use in 2017" (ibid).

The International Energy Agency generally traces three types of energy efficiency policy: mandatory codes and standards; market-based instruments; and incentives (ibid). "In 2017, 34% of global energy use was covered by mandatory energy efficiency policies, but progress implementing new policies was slow for a second year running. Utility obligation programmes remained largely unchanged in 2017. Spending on energy efficiency incentives in 16 major economies was estimated to be around USD 27 billion" (ibid).

Energy efficiency has become essential to the environment and economic growth. The global energy-related carbon dioxide (CO_2) emissions rose by 1.6% in 2017, with a grim prospect of continued growth, far from the climate goals (International Energy Agency, 2018). Energy efficiency is accepted as the cheapest way to reduce global emission of greenhouse gases (such as carbon dioxide, methane, nitrous oxide and sulfur hexafluoride) (Enkvist, Nauclér, and Rosander, 2007). They have developed a cost curves approach to measure abatement cost of avoided greenhouse gases emissions (by subtracting potential cost savings (for example, from reduced energy consumption) from the annual additional operating cost (with depreciation) and dividing it by the amount of avoided emissions; note that this formula implies negative costs if there are considerable cost savings). "The abatement cost for wind power, for example, should be understood as the additional cost of producing electricity with this zero-emission technology instead of the cheaper fossil fuel-based power production it would replace. The abatement potential of wind power is our estimate of the feasible volume of emissions it could eliminate at a cost of 40 euros a ton or less." (ibid.)

According to the International Energy Agency (IEA: *World Energy Outlook 2006*), the global energy-related CO_2 emissions, under the current situation, would increase by 55% between 2004 and 2030, or 1.7% per year; and that power generation would contribute half of the increase in global emissions over this period with developing countries accounting for over three-quarters of the increase. Indian contribution also was found to be very high (IEA, 2006: 41). The Report states that "[p]olicies that encourage the more efficient production and use of energy contribute almost 80% of the avoided CO_2 emissions. …. More efficient use of fuels, mainly through more efficient cars and trucks, accounts for almost 36% of the emissions saved. More efficient use of electricity in a wide range of applications, including lighting, air-conditioning, appliances and industrial motors, accounts for another 30%. More efficient energy production contributes 13%. Renewables and biofuels together yield another

12% and nuclear the remaining 10%." (IEA, 2006: 42). According to the Report, "the new policies and measures analysed yield financial savings that far exceed the initial extra investment cost for consumers ….. On average, an additional dollar invested in more efficient electrical equipment, appliances and buildings avoids more than two dollars in investment in electricity supply. This ratio is highest in non-OECD countries. ….. The payback periods of the additional demand-side investments are very short, ranging from one to eight years. They are shortest in developing countries …." (IEA, 2006: 43).

It is estimated that efficiency gains made since 2000 have "prevented 12% more greenhouse gas emissions and 20% more fossil fuel imports, including over USD 30 billion (United States dollars) in avoided oil imports in IEA countries" (IEA, 2018: 17).

What follows is divided into four sections. The next part of the chapter discusses the concept and empirical methods of energy efficiency and introduces decomposition of energy consumption change in terms of Divisia index. Part 3 presents the initiatives of the central Government of India and the State Government of Kerala in energy efficiency policies and programmes. And the empirical exercise of indicator decomposition of energy efficiency in Kerala is given in the fourth section; the temporal trends of the indicators and their Divisia indices are presented. The final section concludes the study.

1.2 Energy Efficiency: Indian Background

Energy efficiency policy framework in India comes under the purview of the Energy Conservation Act, enacted in 2001 and amended in 2010. This Act in turn is reinforced through the National Mission on Energy Efficiency, one of the eight missions under the 2008 National Action Plan on Climate Change. The Act led to the formation of the Bureau of Energy Efficiency (BEE) under the Ministry of Power, and the State Designated Agencies (SDA) in the States in order to realise the institutional framework for formulating energy efficiency policies and implementing them. The SDAs, being the State counterparts of the

BEE, “have contributed significantly towards creating awareness on efficient use of energy among consumers and manufacturers, implementing demonstration projects, and supporting execution of BEE’s programmes in States” (Government of India, 2018a: v). The Act also put in place the much-needed institutional framework for formulating energy efficiency policies and implementing them. The BEE was instrumental in developing and implementing a number of initiatives such as the Energy Conservation Building Code, an expansion of the Standards and Labelling programme for the most energy-intensive cooling appliances like room air conditioners, fans and refrigerators, an innovative industrial energy efficiency programme called Perform Achieve and Trade (PAT), and the extension of fuel efficiency standards to commercial heavy-duty vehicles. “India has recently implemented performance standards for electric motors at the IE2 level. Unlike in other major economies, however, these standards are not mandatory” (IEA, 2018: 151). Another milestone is NITI Aayog’s energy scenario modelling tool, viz., India Energy Security Scenarios (IESS) 2047, which offers a platform to facilitate academic and policy discourse about potential pathways for the Indian energy sector. According to this modeling exercise, there is substantial potential to impact energy efficiency and reduce energy demand by 2047.

The IEA Report (2018) has also highlighted an Indian initiative towards energy efficiency; acknowledging the supremacy of light emitting diode (LED) bulb in efficiency, as it consumes less electricity, lasts longer, and does not contain harmful mercury, the Government of India launched a programme in 2014, called UJALA (Unnat Jyoti by Affordable LEDs for All), to promote LED bulbs in Indian households. “Energy Efficiency Services Limited (EESL), an Indian state-owned “super” energy services company (ESCO) [under Ministry of Power], has radically pushed down the price of LEDs available in the market and helped to create local manufacturing jobs to meet the need for energy efficient lighting. LEDs now cost less than USD 1 (around INR 60), down 80% from the first round of procurement in 2014. Through its Unnati Jyoti by Affordable LEDs for ALL (UJALA) programme, EESL has replaced over 308 million lamps with LEDs, without the need for any subsidies." (IEA, 2018: 152, Box 6.4.). Similarly, EESL has undertaken a bulk procurement of 100,000 super-efficient air conditioners as a demand aggregation strategy that successfully brought down the cost of high-efficiency equipment (Government of India, 2018b: 3). "Mission Innovation (MI) launched on 30 November 2015, during COP21 in Paris in the presence of the Prime Minister of India, is a global platform to foster and promote R&D for accelerated and affordable clean energy innovation. India is a key member of this global initiative and is a member of all seven Innovation Challenges" (ibid).

According to the IEA, energy efficiency improvements in India in the residential buildings and industry and service sectors since 2000 have helped to avoid an additional 6% more energy use in 2017 (IEA, 2018: 149). "Efficiency improvements also prevented nearly 145 Mt CO_2-eq in emissions and 5% more imports of fossil fuels in 2017" (ibid; Mt CO_2-eq = metric tons carbon dioxide equivalent, a standard unit for measuring carbon footprints, based on the global warming potential of greenhouse gases). Nearly 70% of this gain came from the industry and service sectors, where the gross value added more than tripled during the period from 2000, and structural changes were responsible for avoiding 1% more energy use. The latter is explained in terms of the shifts in "economic activity from energy-intensive industry sectors to less-intensive manufacturing and service sectors"; however, the "impact of these changes was almost completely offset by structural changes that boosted energy use, specifically increases in residential building floor area and appliance ownership, shifts to less efficient modes of transport, and decreasing vehicle occupancy rates" (ibid).

Another milestone was the first edition of the State Energy Efficiency Preparedness Index, brought out by the Alliance for an Energy Efficient Economy (AEEE) under the leadership of the Bureau of Energy Efficiency (BEE) aligned with NITI Aayog, that assesses State policies and programmes aimed at improving energy efficiency in buildings, industries, municipalities, transportation, agriculture and electricity distribution companies (DISCOMs). Energy efficiency indicators in each sector in each State are developed to measure the impact of State-level energy efficiency initiatives. Both qualitative and quantitative indicators, including outcome-based indicators, are used. The indicators include information on sector-wise energy consumption, energy saving potential and the States' influence in implementing energy efficiency in terms of their policies and regulations, financing mechanisms, and institutional capacity. The Index is formed from 63 indicators, with 59 across the sectors of buildings, industry, municipalities, transport, agriculture and DISCOMs; and 4 cross-cutting indicators.

The study finds that most of the States have implemented one or more national programmes of BEE and EESL, while a few have their own (State-level) initiatives as well. For example, even though most of the States have implemented UJALA for energy efficient lighting in the building sector, only less than half of them have notified the Energy Conservation Building Code (ECBC) and incorporated ECBC in municipal building bye-laws. In terms of energy efficiency preparedness, it is found that Kerala, with 77 points, leads among the States and union territories, followed by Rajasthan (68) and Andhra Pradesh (66.5).

1.3 Energy Efficiency: Kerala Background

Fuel wood, petroleum products and electric power are the conventional sources of energy in Kerala. Power sector of Kerala is comparatively small (her installed capacity is less than one percent of all-India capacity), and is heavily dependent on hydro-power, capacity expansion of which is limited in terms of unavailability of technically favourable sites and of unfavourable ecological impacts. High population density and fragile ecology have already precluded the nuclear option from Kerala. The only other alternative, fossil-fuel-fired thermal stations, itself is again limited, such that Kerala at present is heavily dependent on power import; thus in 2016-17, import accounted for about 84% of the total energy available in the State. It is worth noting at the same time that Kerala was declared a fully electrified State on May 29, 2017 (Government of Kerala, 2018: Box 5.12).

Considering the limited availability of fossil fuels and their unlimited contribution to global warming, Government of Kerala has turned to alternative sources of power generation, especially from environment friendly non-conventional energy sources, such as municipal waste, agro waste, industrial waste, sewage and other biomass, small-hydel units, solar photo voltaic, wind, tide, wave, geothermal etc. Agency for Non-conventional Energy and Rural Technology (ANERT), an autonomous body under the Power Department of Kerala Government, is the nodal agency for the implementation and propagation of non-conventional sources of energy in the State. It is also the nodal agency in the State for the Ministry of New and Renewable Energy Sources (MNRE) of Government of India.

Energy Management Centre (EMC) is the State designated agency of the Bureau of Energy Efficiency for promoting energy conservation and energy efficiency through enforcing Energy Conservation Act, 2001 in Kerala.

As already stated, Kerala has ranked first among the Indian States in the first edition of the energy efficiency preparedness index of the Alliance for an Energy Efficient Economy (AEEE). The index has 21 indicators in the buildings sector "to capture the States' initiatives and progress on energy efficiency in buildings, covering various aspects such as Energy Conservation Building Code (ECBC), programmes and incentives for ECBC construction and energy efficient appliances, institutional capacity for supporting energy efficiency in buildings, energy savings and energy intensity" (Government of India, 2018a: 11). Kerala has got the highest 29 out of 30 scores in the buildings sector energy efficiency preparedness. In the industrial sector with 13 indicators for energy efficiency preparedness, Kerala has bagged again the highest 21 out of 25 scores. In the municipalities sector with 9 indicators, primarily focussed on public infrastructure such as street lighting and water pumping, Kerala has come third (with 7 out of 10 scores) after Maharashtra (with a score of 8) and Tamil Nadu (with 7.5). In the transport sector with 5 indicators, with 3 indicators for energy efficiency of State Road Transport Corporations (SRTC) and 2 for electric and hybrid vehicles, Kerala has lagged behind a number of States, with a score of only 6 out of 15. In the agriculture and DISCOMs sector with 11 indicators, related to demand side management (DSM) regulations, programmes and savings, and transmission and distribution (T&D) losses for DISCOMs in the State, Kerala has come third with 10 out of 15 scores.

1.4 Significance of the study

The linkage between energy intensity and energy efficiency with productivity is expected to impart valuable knowledge to evolve policies in the State's power sector for the socio-economic growth and development. Returns from enhancing energy productivity and in turn from lowering energy intensity of the economic activities significantly contribute in general to the economy as a whole, and in particular to energy security and mitigation of carbon foot print.

This in turn requires an examination into the extent to which aggregate energy intensity trends are attributable to shifts in the underlying sectoral structure and efficiency improvements within individual sectors. The present study proposes to undertake such an exploration into the economy of the State of Kerala. To our knowledge, such a study is unique in India.

The energy productivity and economic prosperity index can quantifiably measure the effectiveness with which energy resources are being used; and this can give signals to policy makers to plan for a high energy-productivity growth and sustainable development scenario. The State can achieve higher economic output per unit of energy input either by changes in economic structure or through technical energy efficiency gains.

1.5 Objectives of the Study

The main objective of the study is to examine the extent to which aggregate energy intensity trends are attributable to shifts in the underlying sectoral structure, activity, and efficiency improvements within individual power consuming sectors, viz., domestic, commercial, industrial, agricultural, and buildings sectors, of Kerala. In particular, the study seeks to

a) establish sector wise energy intensity;
b) identify the sector wise energy-productivity ratios;
c) estimate the energy savings from efficiency improvements; and
d) set up a simulation for energy intensity reduction both in a business-as-usual and in a revised policy scenario, factoring in energy efficiency and the renewable.

1.6 Data and Methods

The study is designed to rely mainly on secondary data, available from various departments of the State Government. In respect of the case studies some field survey also is required.

An analytical framework required to identify the driving forces behind changes in energy efficiency is structured in terms of the interaction between the human and environmental systems, in which the dynamic nature of the interactive system is assessed within a driving forces pressure - state - impact - response framework; this was originally used as the stress - response framework in the context of ecosystem response as an anthropocentric issue (Friend and Rapport, 1979). The former model (for example, Niessen et al., 1995) starts with the premises that the social and economic developments tend to exert pressure on the environment, causing environmental changes that in turn impact on the social and economic functions of the environment; these impacts then elicit a social response that in turn feeds back to the driving forces. The present study also makes use of this framework, as energy efficiency is indeed an anthropocentric issue with interactions among its driving forces, state and social response.

Almost all the earlier studies have in general employed the method of indicators pyramid, based on which energy efficiency changes have been decomposed from other factors at each level of disaggregation using factorization method. Factorization has been conducted either on the energy-GDP ratio or almost equivalently on total consumer energy use and carried on to the finest level of subsector, subject to data availability. The Laspeyres index decomposition approach was in vogue earlier that has now been replaced with methodologically superior Divisia approach. The present study also follows suite.

1.7 Project Deliverables (models/papers/case studies /report)

a) Classified data bank
b) White papers and Research publications in peer reviewed journals and conferences with Case studies

c) Models establishing interrelations between energy, energy efficiency and productivity, sector-wise and for the whole State's economy
d) Organisation of presentations in front of invited audience as suggested by EMC to discuss and disseminate the knowledge
e) Final research project report with information on survey, analysis, design and development of the algorithms, models and policy recommendations for implementations.

1.8 Motivation

EMC, an autonomous body under Department of Power, Government of Kerala, since its inception in 1996 is actively involved in efficient use of energy and its conservation and development of Small Hydro Power. In the capacity of State Designated Agency since 2003, EMC is responsible in enforcing the Energy Conservation Act, 2001(Central Act 52 of 2001) in the State.

The Centre for Development Studies (CDS) is an internationally reputed institution known for its research in applied economics and topics germane to socio-economic development. The CDS is financially supported by the Government of Kerala and the Indian Council of Social Science Research (ICSSR). The Reserve Bank of India and the Planning Commission has instituted endowment units for research in selected areas at CDS. The Union Ministry of Overseas Indian Affairs has set up a migration unit to study issues relating to international migration from India.

This research, first of its kind Study in Indian States, is expected to bridge an important gap in the power sector and the report of the study is expected to serve as a well-researched knowledge base and input to policy formulation.

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1.9 Structure of the Report

Following this introductory chapter, the next chapter presents a detailed discussion of a techno-economic approach to conceptualizing energy efficiency. Chapter three discusses all the traditional analytical methods and the index decomposition approach to measuring energy efficiency. The next three chapters constitute the core of the study: Chapter four takes up the analytical and empirical exercises based on Logarithmic Mean Divisia index for the State of Kerala with the available data. The next two chapters present the theoretical and empirical analyses in terms of the multi-variate energy efficiency approaches: Chapter five with stochastic frontier production function and Chapter six with data envelopment analysis.

1.10 Merits

The merits of this study may be summarized as follows:

(i) A comprehensive documentation of conceptualization of energy productivity.

(ii) A comprehensive documentation of analytical methods of measuring energy productivity.

(iii) First study in the Indian context, utilizing all the three important methods of measuring energy productivity.

(iv) Utilizing energy efficiency decomposition method for simulation purposes.

1.11 Limitations

A major problem that we experienced during the execution of this project was availability and suitability of the required data for Kerala. Finally we had to satisfy ourselves mostly with the available time series data on electricity supply only. In Chapter four on decomposition analysis, we use along with the power sector data, petroleum consumption data also available only for a limited number of recent years.

Chapter 2

Conceptualizing Energy Efficiency: A Techno-Economic Approach

2.1 Introduction

A comprehensive documentation of a techno-economic conceptualization of energy productivity and its analytical methods of measurement is an essential prerequisite for a study like this. The former, the techno-economic conceptualization, is important because it constitutes the basis on which the entire study is erected; it delineates significantly the approach to defining the concept under study and the definition itself in its subtle structure, which in turn determines the way towards discovering and deconstructing the measurement methods. The present chapter is an attempt at the first of the tasks, the documentation of the techno-economic conceptualization of energy productivity, which we complete in the following seven sections. The next part of the paper discusses the energy efficiency indicators in terms of its conceptual definition. Part three differentiates in this light between energy efficiency and energy conservation. Following this background, a brief discussion of the laws of conservation of mass and thermodynamics is given in part four and the next section turns light onto energy efficiency indicators at different aggregation levels. Section six deals with the determinants of energy efficiency indicators, and is followed by a conceptual framework for energy efficiency in Kerala, given in part seven. The final section concludes the study.

2.2 Energy Efficiency Indicators

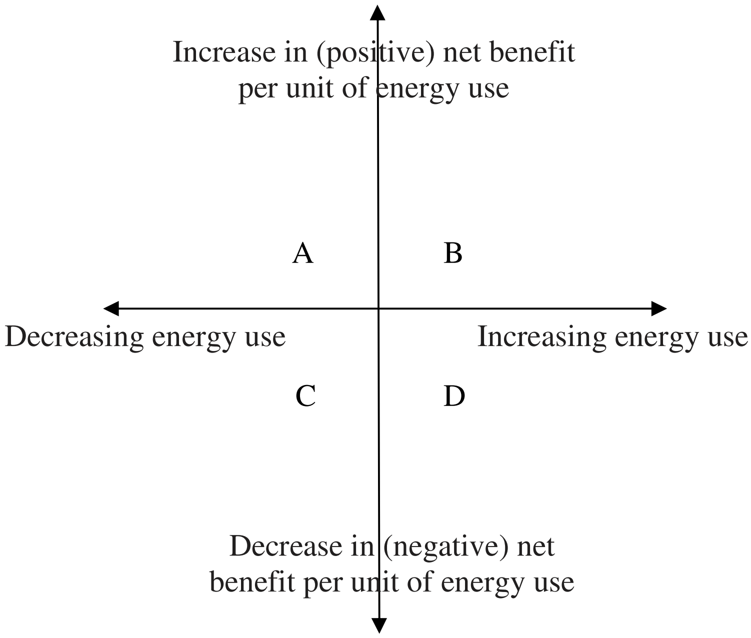
Traditionally, there are two basically reciprocal Energy Efficiency Indicators: one, in terms of energy intensity, that is, energy use per unit of activity output, and the other, in terms of energy productivity, that is, activity output per unit of energy use. As a general concept, "energy efficiency refers to using less energy to produce the same amount of services or useful output. For example, in the industrial sector, energy efficiency can be measured by the amount of energy required to produce a tonne of product." (Patterson, 1996: 377). Thus Patterson defines energy efficiency broadly by the simple ratio of the useful output of a process in terms of any good produced that is enumerated in market process, to energy input into that process (ibid.).

Defining energy efficiency in this sense (of useful output per unit of input) also helps us to define energy efficiency as "a change to energy use that results in an increase in net benefits per unit of energy" (section 3 of the Energy Efficiency and Conservation Act 2000 of New Zealand), where net benefits represent useful output.

2.3 Differentiating between Energy Efficiency and Energy Conservation

The concept of energy efficiency thus defined also clarifies the differences among the concepts of energy efficiency, energy conservation and energy saving. These differences may be better explained using Figure 1. The quadrants A and B represent energy efficiency, defined in terms of net benefits per unit of input. They also capture the idea of energy efficiency improvement, "defined [by Energy Efficiency and Conservation Authority, 1997] as any change in energy use that results in increased net benefits per unit of energy, whether or not total energy use increases or decreases" (Lermit and Jollands (2001, p. 7). Thus, quadrant B represents energy efficiency improvement, by increasing net benefits per unit of energy use through increasing energy use and quadrant A, on the other hand, represents energy efficiency improvement, by increasing net benefits per unit of energy use through decreasing energy use (for example, by installing double-glazing windows that can reduce heating energy bill costs during winter).

Figure 2.1: The energy efficiency and conservation quadrants



Source: Adapted from Lermit and Jollands (2001, p. 7).

Cases like quadrant B simply show that energy efficiency improvement need not imply energy savings and render monitoring energy efficiency difficult. "If energy efficiency were the same as energy savings, then all that would be required would be to estimate the amount of energy saved compared to some base year and add up energy savings across sectors. However, this does not necessarily equate to energy efficiency." (Lermit and Jollands (2001, p. 8).

As already explained in the earlier Chapter, energy conservation, as an important complement to energy efficiency, is defined in terms of reduction in total energy use, and is thus represented by quadrants A and C. Thus, this can happen in two ways: quadrant A represents efficiency-improving energy conservation, where energy savings lead to an increase in net benefits per unit of energy use; and quadrant C represents efficiency-reducing energy conservation, where energy savings lead to a decrease in net benefits per unit of energy use, "as is the case with the proverbial "cold bath in the dark"" (ibid.).

In short, the above discussion reminds us that energy efficiency is a context-specific concept, not necessarily equivalent to energy savings, and is usually defined as net benefits (useful output) per unit of energy input, but without an unequivocal operationally useful quantitative measure. This necessitates construction of a series of indicators specific to the context (or level of sectoral disaggregation, as discussed below).

2.4 The Laws of Conservation of Mass and Thermodynamics

It goes without saying that an economic system is bound to operate within the immutable constraints set by the law of conservation of mass and the laws of thermodynamics (Boulding 1966; Ayres and Kneese 1969; Daly and Umana 1981). The conservation law states that mass cannot be created or destroyed and hence the total mass of all materials entering any process (input) must equal the total mass of all materials leaving (output) plus the mass of any materials accumulating or left in the process. That is, input = output + accumulation. When there is no accumulation of materials in a process, "what goes in just comes out", and such a process is called a steady-state process. This mass-balance principle (Ayres and Kneese, 1969) thus implies that, for a given material output, equal or greater quantities of material must be used as inputs, leaving a residual in terms of a pollutant or waste product, if any. This in turn means that any production process, involving material input-output relationships, is subject to some minimal material input requirements.

The first law of thermodynamics is a specialized version of the law of conservation of energy, reformulated for thermodynamic systems. It states that energy cannot be created or destroyed: it can only be transformed from one form of energy to another. Thus work (which is a form of energy) can be transformed completely into heat. The second law of thermodynamics, on the other hand, relates to the reverse transformation of heat into work, and states that it is not possible to completely transform heat into work; this means that no energy-conversion process is 100% efficient. Thus this law in its simplest form becomes useful in assessing the thermal efficiency of heat engines, and in a more general form introduces the concept of the 'quality' of energy.

As all activities involve work and thus energy, so do all economic activities; all economic production processes must require a minimum quantity of energy (Baumgärtner, 2004); this in turn implies that there is a limit to the substitution of other factors of production for energy, and this makes energy always an essential factor of production (Stern, 1997).

As we know, the production function helps in defining marginal products of inputs and in distinguishing between allocative efficiency and technical efficiency. In addition to the marginal productivities, we can also have average productivities of the inputs, the partial factor productivity, in terms of the output divided by the input. Thus, taking energy as one of the inputs in a production function yields marginal and partial (average) energy productivity, the inverse of the latter being energy intensity.

One of the first detailed empirical analyses of consumption of fuels and water power in the United States economy was by F. G. Tryon in 1927, who stated that "Anything as important in industrial life as power deserves more attention than it has yet received from economists

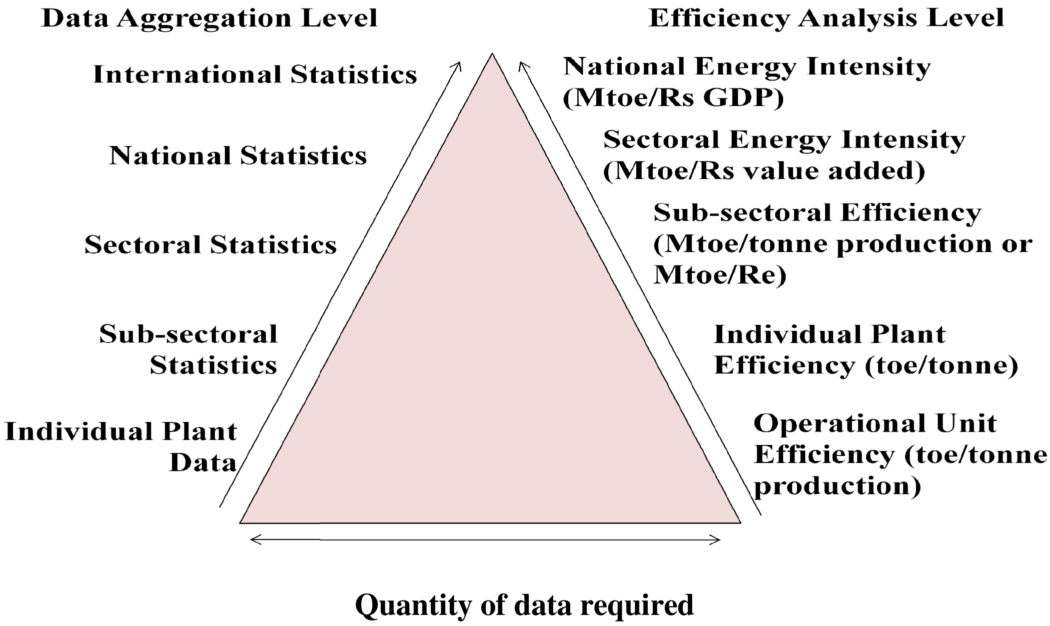
.... A theory of production that will really explain how wealth is produced must analyze the contribution of this element energy.” (Tryon, 1927: 271).

However, the significance of energy in economic growth started to attract the researchers’ curiosity only by the start of the 1950s. In October 1950, Harold J. Barnett came out with an Information Circular for the U.S. Bureau of Mines, entitled *Energy Uses and Supplies, 1939, 1947, 1965*. In it he documented for the first time that the consumption of energy relative to GNP (i.e., energy intensity) had been declining persistently over a long period of time following World War I. This led to an interest among the researchers to analyze the role of energy in economic growth, and the prime importance of energy in economic productivity growth was first established in a classic study *Energy and the American Economy, 1850-1975* by Sam H. Schurr and Bruce C. Netschert (along with their associates Vera F. Eliasberg, Joseph Lerner and Hans H. Landsberg) in 1960. They noted that both energy intensity and labour intensity of production had fallen from 1920 to 1955, and the total factor productivity had risen. The simultaneous decline of both energy and labor intensity of production left the factor substitution possibility a puzzle and pointed towards technical change as a possible critical explanatory factor. Schurr and his associates found that the electricity consumption had increased by a factor of more than ten during the period from 1920 to 1955, while utilization of all other forms of energy only doubled. It was also noticed that the thermal efficiency of conversion of fuels into electricity during this period increased by a factor of three, and the electrification of industrial processes had led to much greater flexibility in the application of energy to industrial production. Significant fall in energy intensity was found in many developed and developing countries in the recent decades also (Gales *et al*., 2007, Stern, 2010a).

2.5 Energy Efficiency Indicators at Different Aggregation Levels

It is possible to design and devise energy efficiency indicators at different levels of aggregation, using the corresponding statistics. Thus at the highest level of aggregation, we can use the international statistics for national level indicators, and from there we can come down to different disaggregated levels of a national economy; for instance, using national economic statistics, we can have various macro-sectoral indicators, and coming down to the most disaggregated micro level data on individual plant, we can construct energy efficiency indicators of the corresponding operational units. This is illustrated in Figure 1 below in a pyramid framework.

Figure 2.2: Energy Efficiency Indicator Pyramid



Note: Mtoe = Million Tonnes of Oil Equivalent; the tonne of oil equivalent (toe) = a unit of energy = the amount of energy released by burning one tonne of crude oil; approximately 42 gigajoules or 11,630 kilowatt hours.

As we know, higher levels of aggregation conceal many relationships and effects, functioning at the micro levels. As we move down the pyramid to micro levels, these relationships and effects appear more clearly, providing better understanding of the ground reality that throws more light on the macro-level reality. However, the quantity and quality of data required at the bottom of the pyramid increases substantially, and the data availability becomes more and more difficult.

2.6 Determinants of Energy Efficiency Indicators

It is generally believed (for example, Schipper, et al., 1992; Phylipsen et al., 1998) that energy consumption is essentially determined by the following effects:

(i) Activity (Ai) – economic or human activity level (output/income produced, population/households supported, passenger-km travelled, etc)

(ii) Structure (Si) – the composition of activity (shares of different sectors or subsectors of human/economic activities)

(iii) Energy intensity (Ii =Ei/Ai) – quantum of energy required to deliver one unit of economic/human activity.

Thus the total energy consumption across all the sectors

$$E = \sum_i E_i = \sum_i A \frac{A_i}{A} \frac{E_i}{A_i} = \sum_i A\, S_i I_i$$

where E is the total energy consumption, A (= $\sum_i A_i$) is the activity level, S_i (= S_i/S) is the ith sector's activity share and I_i (= E_i /A_i) is that sector's energy intensity.

Recent contributions have included two additional parameters; climate and behaviour. However, in practice, we can find that they are only part of the basic factors given above, as climate is a structural factor, for example, for heating applications, and behaviour is a part of energy intensity.

The level of aggregation, as outlined above in the pyramid structure, determines the exact definitions and units of these factors. Thus at the highest aggregation level of the macro economy, the activity is measured in economic terms (GDP or value-added, VA), and hence energy intensity, in terms of energy consumption (Giga Joule per unit of GDP (GJ/GDP) or per unit of value-added (GJ/VA); similarly, structure is defined as the share of the different sectors (primary, secondary and tertiary). At a lower level of aggregation, for instance, the steel industry within the industry sector, activity may be measured in either value-added or tonnes of steel produced, energy intensity in either GJ/VA or GJ/tonne steel, and structure in terms of the share of primary and secondary steel in total or in some other shares.

A detailed illustration of this for the bottom micro-level sectors is given in Table 2.1 below. For example, the residential or domestic sector consists of a number of subsectors such as space heating/cooling, water heating, cooking, lighting, appliances, etc. Activity in each subsector is measured in terms of the corresponding population or number of households, structure in the case of space heating/cooling and lighting is defined in terms of floor area per capita and intensity in terms of energy per square feet floor area. In transport sector, passenger and freight transport are the two subsectors, with passenger-km and ton-km as respective activities. The other two factors are similarly defined. Both in services and manufacturing, value-added measures the activity with corresponding shares and intensity factors.

Table 2.1: Micro-level Determinants of Energy Efficiency Indicators

Sector (i)	Subsector (j)	Activity (Aj)	Structure (Sj)	Intensity (Ij = Ej/Aj)
Residential or domestic	Space heating/cooling	Population, Number of Households and Floor area (sq. ft.)	Floor area/capita	Energy/floor area
	Water heating		Person/HH	Energy/capita
	Cooking		Person/HH	Energy/capita
	Lighting		Floor area/capita	Energy/floor area
	Appliances		Ownership/capita	Energy/appliance
Transport	Passenger	Passenger-km	Share in total Passenger-km	Energy per passenger-km
	Car Bus Rail Domestic air			
	Freight	Ton-km	Share in total Ton-km	Energy per Ton-km
	Trucking Pipelines (Natural gas Petroleum) Air Water			
Services	Any sector	Value-added	Share in total VA	Energy/VA
Manufacturing	Any sector	Value-added	Share in total VA	Energy/VA

Source: Adapted from Schipper, et al. 2001; and https://www.energy.gov/sites/prod/files/2015/06/f24/index_methodology.pdf

A number of different formulations are used to generate energy efficiency indicators such as those given in the Table 2.2 below.

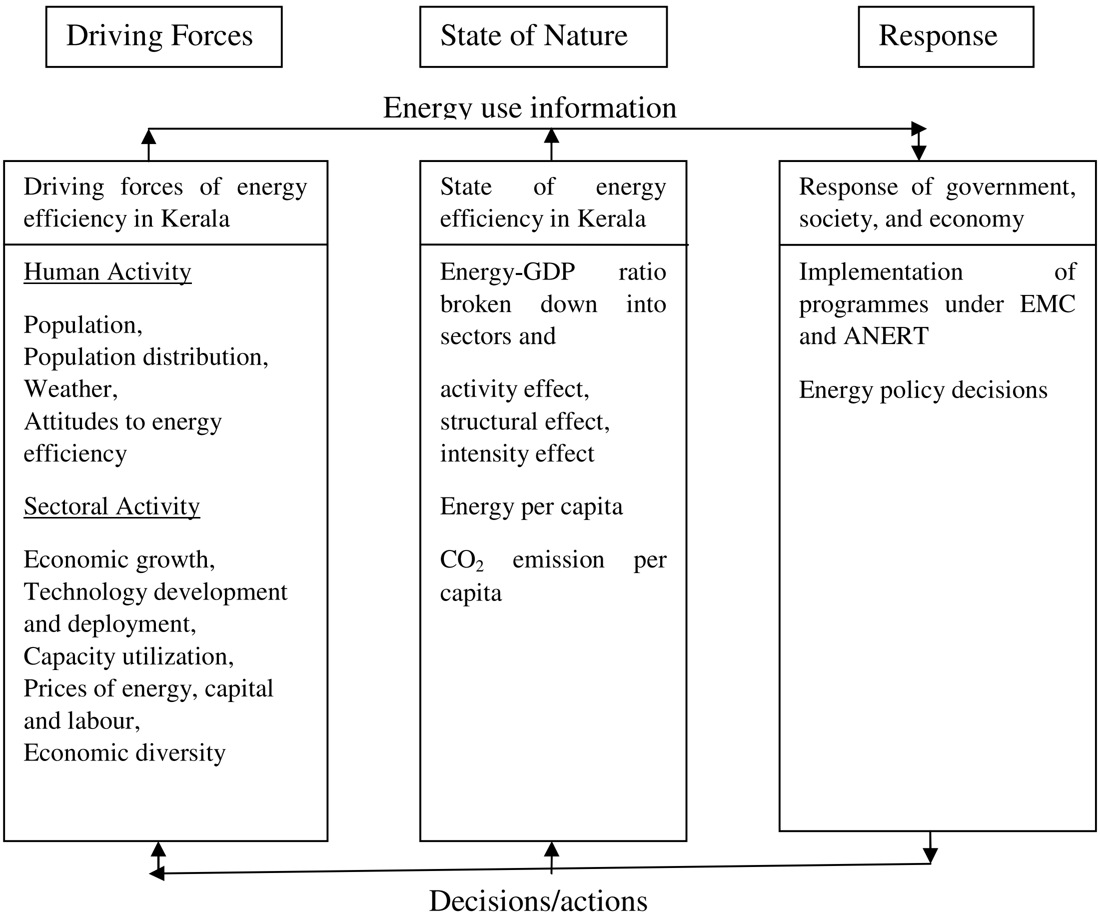
Table 2.2: Determinants of Energy Efficiency Indicators

Aggregation level	Indicator	Combines effects of	The indicator can assess	The indicator cannot assess
Economy as a whole	Energy per GDP	Share of different sector and subsectors, energy intensity of each of the (sub-) sectors, costs of the production factors (energy, material, labour) and value of products and services delivered, share of sectors that do not generate (account for) value	Energy required to produce an amount of GDP	Energy efficiency, level of development, future trends, improvement potentials
Sectoral intensity				
Industry	Energy per VA	Share of different types of subsectors, energy intensity of each of the sub-sectors, costs of the production factors (energy, material, labor) and value of products delivered	Final energy required to produce an amount of VA in this sector	Share of primary resources to generate VA; Future trend in energy consumption; Energy efficiency; Improvement potential
Residential	Energy per capita	Dwelling size (square feet/house), household size (number of people/house), type of dwellings, number of appliances, usage of appliances (number of hours), climate, efficiency of dwelling and appliances, behaviour		Energy required for a certain level of welfare or services provided; Energy efficiency; Energy efficiency improvement potential
Transport	Energy per passenger-km or per ton-km	Share of passenger transport and freight transport, share of various modes (car, bus, truck, train, boat, plane), occupancy load (number of passengers or ton per vehicle), distance travelled by each of the modes, energy intensity of each of the modes		

Source: Adapted from G.J.M. Phylipsen, Energy Efficiency Indicators: Best practice and potential use in developing country policy making. 30 June 2010 Phylipsen Climate Change Consulting, Commissioned by the World Bank. P. 19.

2.7 A Conceptual Framework for Energy Efficiency in Kerala

A conceptual framework for monitoring energy efficiency of Kerala may be summarized as follows (Fig. 2.3):



Source: Adapted from Lermit and Jollands (2001, p. 17).

The illustration is self-explanatory, and hence we do not venture for a tautology. However, it is essential to note that we follow this framework in our empirical exercise in the following chapters: we consider both the human and sectoral activity as the driving forces of energy efficiency in Kerala, and accept the state of nature of energy efficiency in terms of energy-GDP ratio, broken down into different sectors and effects, such as activity effect, structural effect, and intensity effect.

2.8 Conclusion

The present chapter has attempted at a comprehensive documentation of the techno-economic conceptualization of energy productivity as a prelude to a comprehensive documentation of the analytical methods of its measurement, which we take up in the next chapter.

We have in this chapter started with a discussion of the energy efficiency indicators in terms of its conceptual definition. Defining energy efficiency in the Patterson's sense of useful output per unit of input leads us to define energy efficiency also as an increase in net benefits per unit of energy. This helps us differentiate between energy efficiency and energy conservation, which is an important complement to the former. Energy conservation is defined in terms of reduction in total energy use, which can happen in two ways: one representing efficiency-improving energy conservation, where energy savings go along with an increase in net benefits per unit of energy use; and the other representing efficiency-reducing energy conservation, where energy savings results in a decrease in net benefits per unit of energy use.

Following this background is a brief discussion of the laws of conservation of mass and thermodynamics and of some of the important earlier studies on energy-economic growth relationship. Then we have turned the light onto energy efficiency indicators at different aggregation levels, presented in a pyramidal structure, and onto the determinants of energy efficiency indicators. It is generally believed energy consumption is essentially determined by three effects, viz., activity, structure and intensity. A detailed illustration of this for the bottom micro-level sectors also is provided thereafter. For example, the residential or domestic sector consists of a number of subsectors such as space heating/cooling, water heating, cooking, lighting, appliances, etc. Activity in each subsector is measured in terms of the corresponding population or number of households; structure in the case of space heating/cooling and lighting is defined in terms of floor area per capita and intensity in terms of energy per square feet floor area. The chapter concludes with a conceptual framework that we follow in our empirical exercise in the later chapters.

Chapter 3
Measuring Energy efficiency: The Techno-Economic Empirical Methods

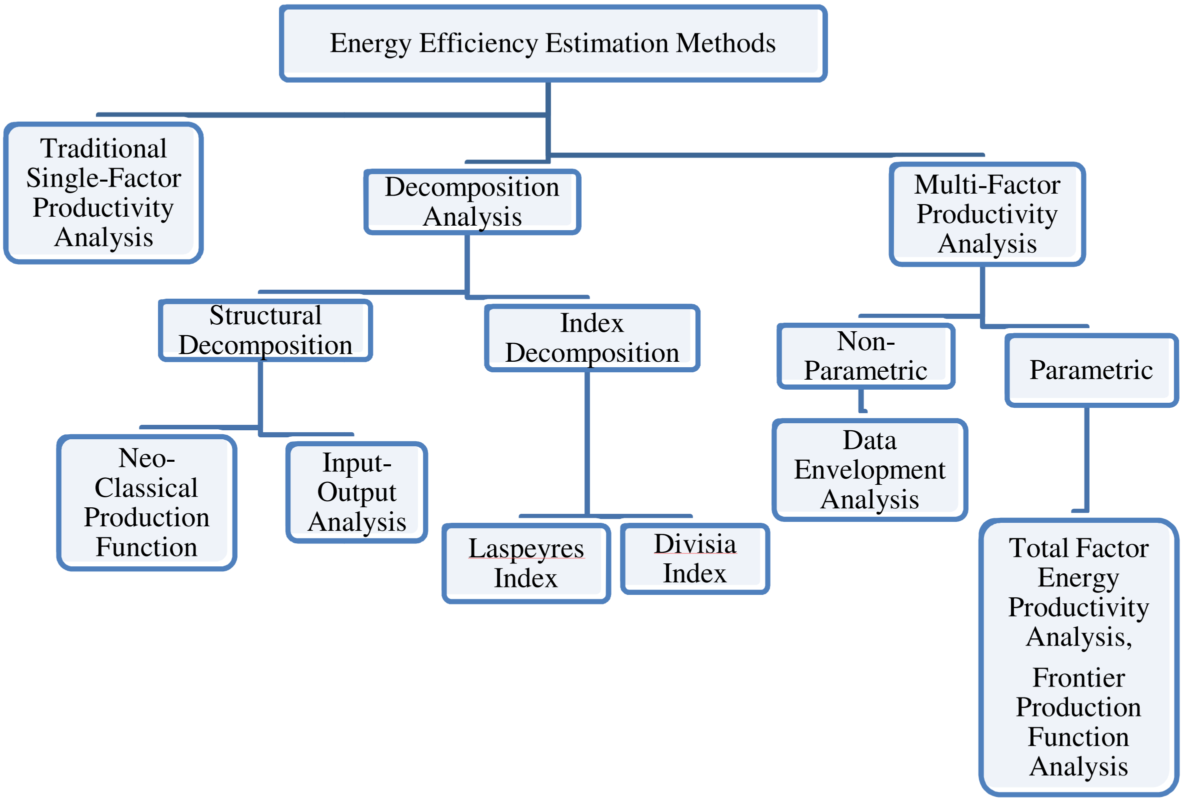
3.1 Introduction

Given the documentation of the techno-economic conceptualization of energy productivity in the last chapter, the present chapter, structured into six sections, seeks for a comprehensive documentation of some of the analytical methods of its measurement. The next section of this chapter presents an introduction to a comprehensive list of the estimation methods of energy productivity indicators. Note that the methods fall under three heads: traditional single factor productivity analysis, decomposition analysis and multi-factor productivity analysis. The present chapter documents the first two approaches, while the theoretical framework of the multi-factor productivity analysis is given in the later chapters. Part three of this chapter starts with the traditional indicators identified by Patterson to monitor changes in energy efficiency in terms of thermodynamic, physical-thermodynamic, economic-thermodynamic and economic indicators. When we analyze the indicator in terms of energy intensity changes, the corresponding index falls under two major decomposition methods, namely, structural decomposition analysis and index decomposition analysis. Section four discusses the structural decomposition analysis in terms of its two approaches, viz., input-output method and neo-classical production function method; and the next section presents the index decomposition analysis in terms of Laspeyres' and Divisia indices. The last section concludes the documentation.

3.2 Energy Efficiency Indicators: Estimation Methods

Energy efficiency research in general has opened up three avenues of enquiry, namely, the measurement of energy productivity, the identification of impact elements (such as the three factors mentioned above) and the energy efficiency assessment. The traditional interest in energy efficiency has centred on a single energy input factor in terms of productivity that has become famous through an index method proposed by Patterson (1996). The enquiry that has proceeded from the problems associated with this method has led to identifying the effect source of variation, in terms of some decomposition analysis. Finally, a new energy efficiency estimation method, criticizing the single factor energy efficiency method, has come up utilizing a multi-variate structure. This trajectory is explained in detail in the following Figure 2.3 and Table 2.3.

Figure 3.1: Energy Efficiency Indicators: Estimation Methods



Source: Adapted from Ou (2014)

Table 3.1: Energy Efficiency Indicators: Estimation Methods

Indicator	Estimation method	Problems and applicability
Energy productivity (reciprocal of energy intensity)	Ratio between useful output and energy input	Easy for data acquisition and calculation Productivity does not equate to efficiency Calculation commonly using GDP and energy use, and unable to remove other impacts on GDP Unable to reflect individual elements of efficiency Unable to reflect the differences between resource allocation efficiency and technical efficiency
Energy productivity after factor decomposition	Laspeyres Index Divisia Index	Driven by energy productivity changes analysis, the relation between energy consumption and economy being purified Limited by decomposition method, and difficulty to get empirical support
Comprehensive energy efficiency index	Technical efficiency Allocative efficiency Economic efficiency (Commonly used estimation methods include: stochastic frontier analysis, DEA)	Can be used to compare efficiency differences between manufacturers, can also estimate efficiency changes trend over time Can be applied to the comparisons in the levels of manufacturer, industry, region, and nation Unable to evaluate the efficiency of individual elements, (Hu and Wang (2006) further proposed TFEE method for the relative analyses)

Source: Adapted from Yang(2012); Ou(2014).

3.3 Traditional Energy Productivity Indicator

Recognizing that the actual measure of energy efficiency varies with the context in which the concept is used with different numerators and denominators, Patterson (1996) has identified four indicators to monitor changes in energy efficiency: thermodynamic, physical-thermodynamic, economic-thermodynamic and economic.

First we have thermodynamic indicators, the 'most natural and obvious way to measure energy efficiency' as thermodynamics is the 'science of energy and energy processes' (Ibid.). Traditionally, it measures the heat content, or work potential. The thermodynamic indicators are a measure of the thermal, or enthalpic, efficiency, the sum of the ratio of useful energy output of a process to input into a process. As a thermodynamic indicator, Patterson uses the example of a light bulb: it has an enthalpic efficiency of around six percent. This means that six percent of the input of energy (electricity) is converted to the desired output (light energy) and 94 percent is converted to 'waste' heat (Patterson, 1996, 378). One flaw with this straightforward measurement of energy is that it does not differentiate between energy quality. This means that thermodynamic indicators are unsatisfactory indicators in general in a policy context as they are related to a process and do not allow for a comparison across different processes with different energy input and output. They are thus less suited for macro-level use (Patterson, 1996, 386).

Second, physical-thermodynamic indicators: Unlike in thermodynamic efficiency ratios, numerator in this indicator is not heat content or work potential, but output measured in physical units rather than in thermodynamic units. Physical units specifically reflect the end use service that consumers require. For instance, in relation to transport, the output is given as distance. That is, the energy efficiency is the sum of the ratio between output in a physical unit (kilometers) and the change in energy input.

Third, economic-thermodynamic indicators: these are hybrid indicators in which energy input is measured in thermodynamic units and output is measured in terms of market prices (Rs). The most commonly used aggregate measure of a nation's 'energy efficiency' is the GDP (Gross Domestic Product)-energy ratio, being reported annually by international organisations (for example, European Environment Agency, 2016; International Energy Agency, 2017); this ratio is also used in its inverse form as energy intensity (Patterson, 1996: 377, footnote). Even though this concept is of utmost importance in national energy policies, "there are [many] critical methodological problems that stand in the way of the establishment of such operational indicators of energy efficiency." (Patterson, 1996: 386). However, he argues that "indicators such as energy-GDP ratio are more useful for macro-level policy analysis" that however, "encounter problems with separating the structural effects from the underlying technical energy efficiency trends." (Patterson, 1996: 387; Wilson et al. 1994). There are many other factors such as changes in the sectoral mix in the economy, energy for labour substitution, and changes in the energy input mix that can influence changes in energy-GDP ratio, though they have nothing to do with technical energy efficiency (Patterson 1996). Note that the other measure, energy productivity ratio, is the reciprocal of energy-GDP ratio, suffering from the same problems.

Last, we have economic indicators, in which output is measured in terms of economic value (Rs) and energy input is still measured in thermodynamic terms. Some critics argue that both the input and output measurements be in terms of economic value (Rs), using monetary values of input and output. The most widely advocated pure economic indicator of energy efficiency (intensity) is the ratio of national energy input (Rs) to national output (GDP in Rs), or its reciprocal, productivity measure. The greatest advantage of this measure is its ease of applicability regarding data acquisition and calculation, using GDP and energy use. However, it also suffers from a number of problems: productivity in general cannot be equated to efficiency, as it is highly unable to remove the other impacts on GDP, and thus to reflect individual elements of efficiency; it is again difficult to reflect the differences between resource allocation efficiency and technical efficiency

The following Table summarizes the four indicators:

Table 3.2: Energy Efficiency Indicators

Indicators	**Numerator (Energy)**	**Denominator (Activity)**
Thermodynamic indicator	Thermodynamic units	Thermodynamic units
Physical-thermodynamic	Thermodynamic units	Physical units
Economic-thermodynamic	Thermodynamic units	Economic/monetary units
Economic indicator	Economic/monetary	Economic/monetary units

3.4 Factor Decomposition Analysis

As we know, energy intensity is obtained by dividing energy consumption by GDP, which implies the quantum of energy consumption that must be input in order to increase one unit of GDP. Analyzed in terms of energy intensity changes, the index falls under two major decomposition methods, namely, Structural Decomposition Analysis and Index Decomposition Analysis.

Structural Decomposition Analysis (SDA)

SDA has both inputs and outputs as its theoretical foundation, and is hence also known as equilibrium analysis. There are two approaches here: input-output method and neo-classical production function method.

Input–output model is a quantitative representation of the interdependence among various sectors of a national economy. It was Wassily Leontief (1906–1999; a Russian-American economist) who developed this method, for which he earned the Nobel Prize in Economics in 1973. The model development was highly influenced by the work of the classical economist Karl Marx (1818–1883; German), who had represented an economy as consisting of two interdependent departments. Even before Marx, a cruder version of this model of sectoral interdependence of an economy had been provided by Francois Quesnay (1694–1774; a French economist and physician of the Physiocratic school) in terms of *Tableau économique*. The general equilibrium theory of Léon Walras (1834–1910; a French mathematical economist) in his *Elements of Pure Economics* also was a forerunner and a generalization of Leontief's seminal model.

Input-output model functions under three assumptions: (1) fixed coefficient; (2) fixed proportion; and (3) single product (Miller and Blair, 2009). The first assumption stipulates that the technical relation between input and output be constant; this is possible when the production function of each industry exhibits constant returns to scale; that is, when all the inputs simultaneously increase n times, its output also increases n times. The second assumption requires that each industry uses the same fixed input proportion to the product, implying an irreplaceable nature among the inputs of production. And the third assumption is that each industry produces only one kind of product.

The second approach is in terms of a production function. A production function of a firm is a mathematical expression of the technological relationship between the quantities of inputs and quantities of outputs that the firm produces with those inputs. One of the key concepts of orthodox neoclassical economics, the production function helps in defining marginal products of inputs and in distinguishing between allocative efficiency and technical efficiency, the two components of economic efficiency, which is the main focus of orthodox economics. In the neoclassical economics, allocative efficiency in the use of inputs in production is very significant in the resulting process of distribution of income to those factor inputs, based on their marginal products.

The Cobb–Douglas production function is the first specific functional form, widely used in empirical studies on the technological relationship between two or more inputs (physical capital, labor and energy, for example) and the corresponding output. This function was developed and empirically tested with data by Charles Cobb ((1875–1949; an American mathematician and economist) and Paul Douglas (189 –1976; an American politician and economist) during 1927–1947. A few other more flexible production functions, such as the constant elasticity of substitution (CES and its variant versions) and transcendental logarithmic (translog) production functions, have also appeared in a large number of empirical studies. However, the Cobb–Douglas production function is generally preferred to these more complex forms as the use of the latter has in general yielded nothing better in many cases and the former has got a lot of empirical justification for its use in the light of the fact that the factor shares are roughly constant (Felipe and McCombie 2013, pp. 1-2).
For example, Hoover (2012, p. 330) says: "The approximate constancy of the labor share confirms the prediction of our model and provides a good reason to take the Cobb–Douglas production function as a reasonable approximation of aggregate supply in the U.S. economy." Moreover, the other functions, though more flexible, suffer from a number of problems: the CES function is non-linear and is thus more difficult to estimate

econometrically; the translog function, on the other hand, is often beset by severe multicollinearity in its estimation (Felipe and McCombie 2013, p. 2).

However, the wider popularity of the Cobb–Douglas production function does not mean that it is free from errors, especially when its aggregate form is used at the national economy level. “Most notably, there are the problems posed by both the Cambridge capital theory controversies and what may be generically termed the ‘aggregation problems.’” (Felipe and McCombie 2013, p. 3).

The Cambridge capital theory controversy was a dispute between two groups of economists, one including the ‘post-Keynesians’ such as Joan Robinson and Piero Sraffa at the University of Cambridge in England and the other with the ‘neoclassicals’ such as Paul Samuelson and Robert Solow at the Massachusetts Institute of Technology, in Cambridge, Massachusetts, during the 1950s and the 1960s. The debate was concerned with the theoretical problems of aggregating heterogeneous individual capital goods into a single variable to represent ‘capital’ as an input at the aggregate economy level. The debate in general led to the conclusion that no such aggregate variable could be constructed (Harcourt, 1972; Cohen and Harcourt, 2003, 2005).

The second criticism runs in terms of the ‘aggregation problem’. This is concerned with the attempts to aggregate several micro variables (relationships) into one macro variable (relationship). It is generally accepted that the conditions under which micro- production functions are summed to get an aggregate relationship are severely restrictive such that the concept of the aggregate production function becomes untenable (Brown, 1980; Fisher, 1992; Felipe and Fisher, 2003). Both these problems may be summed up in terms of the fallacy of composition: what is true of some parts of the whole may not be true of the whole. In passing, note that the paradox of thrift in Keynesian economics is a good example for fallacy of composition: while individual thrift is good, collective thrift may be bad for the economy.

3.5 Index Decomposition Analysis (IDA)

As already mentioned, the 1973 oil crisis opened the eyes of the world countries to the prime need for energy consumption reduction through energy use efficiency improvements; this in turn essentially required complete evaluation of energy consumption patterns and identifying the driving factors of changes in energy consumption.

Second of all, the growing awareness of environmental issues and especially of the need to reduce carbon dioxide (CO2) and other greenhouse gases (GHG) in order to prevent global warming also created a demand for effective tools to decompose aggregate indicators. As the ultimate objective of the Kyoto protocol is to achieve stabilization of GHG in the atmosphere (UNFCCC 1992), emission level targets are given to every committed country. Since energy consumption is the main cause of GHG emissions, there is a need to understand the patterns of energy use and how they affect GHG emissions. Information on the factors contributing to emission growth becomes therefore more and more important.

This need led to the development of the Index Decomposition Methodology in the late 1970s in the United States (Myers and Nakamura 1978) and in the United Kingdom (Bossanyi 1979). These pioneering studies then spurred a number of different decomposition methods, most of which were derived from the index number theory, initially developed in economics to study the respective contributions of price and quantity effects to final aggregate consumption. A variant of factor decomposition analysis, IDA takes energy as a single factor of production, and explores various effects on energy intensity changes, by decomposing these changes into pure intensity changes effect and industrial structure changes effect. The first component (pure intensity changes effect) implies that when the industrial structure remains unchanged, the energy intensity change may be taken as the result of energy use efficiency changes in some sector, and the second implies that given the fixed energy efficiencies of various industries and their different energy intensity levels, the total energy intensity changes effect may be taken as the result of the dynamic changes of the yield of each industry.

IDA, as applied to time series data of a specific period, involves results which are very sensitive to the choice of the base period during the study period. In terms of the selection of base period, the approach usually considers Laspeyres Index of fixed weights and Divisia Index of variable weights.

Laspeyres Index

The Laspeyres Index was developed by the German economist Etienne Laspeyres (Ernst Louis Étienne Laspeyres; 1834 – 1913) in 1871 as a price index for measuring inflation (price rise), and is a base year quantity weighted method. This index has the advantage of being mathematically simple and easy to understand. If P_{i0} and P_{it} are the prices and q_{i0} and q_{it}, the quantities of the ith good in the base year and current year respectively, then the Laspeyres price index is given by

$$L = \frac{\sum_i P_{it} q_{io}}{\sum_i P_{io} q_{io}}.$$

Here the numerator is the total expenditures on all the goods in the current period (t) using base (0) quantities, and the denominator is the total expenditures on all the goods in the base period using base quantities. A Laspeyres index of unity (when the numerator = the denominator) means that a consumer is able to afford the same basket of goods in the current period as he was in the base period. The quantities remaining the same, it is only the price that varies; and this simple method helps determine inflation rate. This situation gives rise to the economic concept of compensating variation: by how much do we need to raise a consumer's income in order to meet a price rise (inflation)?

Later on the German economist Hermann Paasche (1851–1925) developed a new index, taking current period as fixed base period weights. Thus the Paasche price index is a current period quantity weighted method and is given by

$$P = \frac{\sum_i p_{it} q_{it}}{\sum_i p_{io} q_{it}}.$$

In Laspeyres' index number, the money value in exchange of the goods consumed in the base year at base year prices is taken as the weights and in Paasche's index number, the money value of the goods consumed in the current year at base year prices is taken as weights. The former has an upward bias and the latter, a downward bias. To reduce the bias, it is suggested to take the average of the two types of weights as the weight. Thus the Marshall and Edgeworth's index number is based on a weight in terms of the arithmetic mean of these weights.

Fisher in 1972 further proposed the geometric mean of Laspeyres Index and Paasche Index as an Ideal Index Number.

Laspeyres Index of Energy Efficiency

As already explained, factorization approach helps decompose the changes in energy consumption into three main factors: changes in production or output (activity, A), changes in the mix of sub-sectors (structure, S), and changes in the amount of energy required for each unit of output in each subsector (intensity, I). That is,

$$\Delta E = \Delta E_{ACT} + \Delta E_{STR} + \Delta E_{INT} + E_{RSD}$$

where $\Delta E = E^{Year\ T} - E^{Year\ 0}$, is the change in energy consumption, and ACT = Activity, STR = Structure, INT = Intensity, RSD = Residual. In estimation, the residual term is usually ignored, and the other terms are estimated as follows:

$$\Delta E_{Act} = E_0 \left(\frac{A^T}{A_0} - 1 \right)$$

$$\Delta E_{Str} = E_0 \left(\frac{S^T}{S_0} - 1 \right)$$

$$\Delta E_{Int} = E_0 \left(\frac{I^T}{I_0} - 1 \right)$$

An example of the use of Laspeyres Index of fixed weights for energy efficiency estimation is Jenne and Cattell (1983), in the case of the energy use trends of the UK's industries during 1968-1980. Other studies are Sun (1998) in the case of China's energy consumption efficiency during 1980-1994, and Reddy and Ray (2010) in a study on the final energy consumption and energy intensity of Indian manufacturing industries. This study has found that the decline in energy intensity is purely due to structural effect change, rather than to the improvement of actual energy efficiency.

Divisia Index of variable weights

Divisia Index was proposed by Francois Divisia (1889–1964), a French economist, in 1925 for continuous-time data on prices and quantities of goods consumed. The biggest advantage of this index is that it can almost fully explain the changes effect of energy intensity in terms of those of its components, as the residual effect involved is much less compared with other indices; moreover, the Divisia Index gives the weights of each effect as functions of time (varying with time). An important property of this index is that a Divisia price (quantity) index has a rate of growth equal to a weighted average of rates of growth of its component prices (quantities).

In productivity measurement studies, Divisia index was first employed by Solow (1957) with two important innovations: he used Divisia index method to obtain the rate of growth of total factor input by weighting rates of growth of capital and labour; and interpreted the resulting Divisia index of total factor productivity as shifts in an aggregate production function. Later on, Denison (1962, 1967) followed Solow by measuring growth in the U.S. total factor productivity and making international comparisons of productivity growth using Divisia index. He obtained Divisia index of rate of growth of total factor input by weighting rates of growth of capital and labor, which were in turn measured using Divisia indexes obtained from weighted rates of growth of individual components of labor and capital.

Divisia factor decomposition analysis of Energy Efficiency

Divisia index decomposition approach has become very popular these days in the context of analysis of energy intensity changes (see Ang and Zhang (2000), and Ang (2004) for a survey of index decomposition analysis in this field). There are two common Divisia index decomposition methods: Arithmetic mean (AMDI) and Logarithmic Mean Divisia index (LMDI). The AMDI method was first used by Gale Boyd, John McDonald, M. Ross and D. A. Hansont in 1987, for “separating the changing composition of the US manufacturing production from energy efficiency improvements” using Divisia index approach (as the title shows). This was followed by a number of studies, some attempts being directed towards modifying the index. These efforts were finally culminated in Ang and Choi

(1997), who used logarithmic mean function as weights for aggregation with the attractive property that the decomposition leaves no residuals at all. Ang et al. (1998) called this model "Logarithmic Mean Divisia index (LMDI)". There are two LMDI measures: LMDI-I and LMDI-II. Both the indices have a number of desirable properties that make them very popular (Ang 2004). A practical guide to these measures is available in Ang (2005). For both the measures, decomposition can be done either additively or multiplicatively. In additive decomposition method, we decompose the aggregate indicator (total energy consumption) in terms of its arithmetic change (or difference), with both the aggregate and decomposed changes given in physical unit. In multiplicative model, the aggregate indicator is decomposed in terms of its ratio change, with both the aggregate and decomposed changes given in indexes.

Two important studies using this method are: (i) Sheinbaum-Pardo, Mora-Pérez and Robles-Morales (2012) to assess the relative contributions of fuel switching to activity, structure and intensity in different industrial sub-sectors in Mexico; and (ii) Wang, Liu, Zhang and Song (2014), to analyze the main drivers of energy consumption in China in 1991-2011, using a Cobb-Douglas production function and LMDI method.

In this study, we use the multiplicative model of LMDI-I, which we denote simply by LMDI.

3.6 Conclusion

Following the documentation of the conceptualization of energy productivity in the last chapter, we have attempted in this chapter at a comprehensive documentation of the analytical methods of its measurement. We have started with an introduction to a comprehensive list of the estimation methods of energy productivity indicators. In general these methods can be grouped under three heads: traditional single factor productivity analysis, decomposition analysis and multi-factor productivity analysis. In the present chapter we have documented the first two approaches, leaving the theoretical framework of the multi-factor productivity analysis to the later chapters.

The traditional indicators as identified by Patterson to monitor changes in energy efficiency are in terms of thermodynamic, physical-thermodynamic, economic-thermodynamic and economic indicators. The last one, in which output is measured in terms of economic value (Rs) and energy input in thermodynamic terms, is the commonly used indicator. When we analyze the indicator in terms of energy intensity changes, the corresponding index falls under two major decomposition methods, namely, structural decomposition analysis and index decomposition analysis. We have discussed in detail the structural decomposition analysis in terms of its two approaches, viz., input-output method and neo-classical production function method; the problems and limitations of these approaches are also considered. We have then turned to the index decomposition analysis in terms of Laspeyres' and Divisia indices. The discussion is finally zeroed in on the Logarithmic Mean Divisia index (LMDI), the recently developed method that has captured wider popularity in applied studies. We measure energy efficiency in Kerala using this method in the next chapter.

Chapter 4
Measuring Energy Efficiency in Kerala: Index Decomposition Analysis

4.1 Introduction

The first of the core chapters of this Report, this Chapter seeks to measure energy productivity in Kerala in terms of index decomposition analysis. As already indicated, this we carry out using the Logarithmic Mean Divisia Index (LMDI) method. The Chapter is structured in five sections; the next part details the method of decomposing the changes in energy consumption over time into three different effects of activity, structure and intensity in the framework of the LMDI approach. In section three, we present the results from the decomposition exercise; first we analyse the two sectors of power and petroleum separately, and then the combined sector is analysed for decomposition. Section four then turns to a simulation analysis for energy consumption in Kerala under different scenarios and the final section concludes the study.

4.2 Decomposition of Energy Consumption Change: Method

As already explained, the changes in energy consumption over time (E) may be attributed to three different effects:

(i) an activity effect that refers to the overall level of activity (Q) in an economy; in general different units are used for different sectors of the economy to measure activity (for example, for the residential (or commercial) sector, we use either square footage of floor space or number of households (or commercial units), for the industrial sector, we use the money value of output produced, for the transport sector, we have passenger-miles, and so on);

(ii) a structural effect which refers to changes in the structure of activities in terms of their inter-sectoral or intra-sectoral shares (S_i); this reflects the impact on energy use emanating from the changes in the relative importance of sectors or sub-sectors with different absolute energy intensities; and

(iii) an intensity effect that represents the effect of changing energy intensity for sectors or sub-sectors (I_i).

Thus the decomposition identity may be written as

$$E = \sum_i E_i = \sum_i Q \frac{Q_i}{Q}\frac{E_i}{Q_i} = \sum_i Q\, S_i I_i$$

where E is the total energy consumption, Q (= $\sum_i Q_i$) is the activity level, S_i (= Q_i/Q) is the ith sector's activity share and I_i (= E_i/Q_i) is that sector's energy intensity.

Assuming from period 0 to T, the aggregate (E) changes from E^0 to E^T, our objective is to find out the contributions of the components to the change in the aggregate. Thus, the change in energy use in multiplicative decomposition model is given by

$$D_{total} \equiv E^T/E^0 = D_{activity}\, D_{structure}\, D_{intensity}$$

And in the additive decomposition model by

$$\Delta E_{total} \equiv E^T - E^0 = \Delta E_{activity} + \Delta E_{structure} + \Delta E_{intensity}$$

These equations simply indicate that change in total energy consumption is due to changes in activity level, Q (activity effect), sectoral shares, S_i (structural effect) and sectoral energy intensities, I_i (energy intensity effect).

These effects evaluated for the multiplicative model of the LMDI-I are:

$$D_{activity} = \exp\left(\sum_i \widetilde{w_i} \ln\left(\frac{Q^T}{Q^0}\right)\right)$$

$$D_{structure} = \exp\left(\sum_i \widetilde{w_i} \ln\left(\frac{S_i^T}{S_i^0}\right)\right)$$

$$D_{intensity} = \exp\left(\sum_i \widetilde{w_i} \ln\left(\frac{I_i^T}{I_i^0}\right)\right)$$

$$\text{where } \widetilde{w_i} = \frac{(E_i^T - E_i^0)/(\ln E_i^T - \ln E_i^0)}{(E^T - E^0)/(\ln E^T - \ln E^0)}$$

The effects evaluated for the additive model of the LMDI-I are:

$$\Delta E_{activity} = \sum_i w_i \ln\left(\frac{Q^T}{Q^0}\right)$$

$$\Delta E_{structure} = \sum_i w_i \ln\left(\frac{S_i^T}{S_i^0}\right)$$

$$\Delta E_{intensity} = \sum_i w_i \ln\left(\frac{I_i^T}{I_i^0}\right)$$

where $w_i = (E_i^T - E_i^0)/(\ln E_i^T - \ln E_i^0)$

4.3 Decomposition of Energy Consumption Change: Empirical Analysis

For the empirical exercise of decomposition, we consider two energy sectors of Kerala: power sector and petroleum sector. Since the petroleum consumption data is available only for the period from 2007-08 to 2016-17, we take this as our study period for the analysis. As the measure of activity, we have the usual real gross State domestic product (GSDP at 2011-12 prices), available in the *Economic Review* of the Government of Kerala. First we analyse the two sectors separately, and then the combined sector is analysed for decomposition. Corresponding to the three broad sectors of primary, secondary and tertiary of the GSDP, we consider the sub-sectors of agriculture, industry and others of the power sector, data on which are available from the Kerala State Electricity Board's publications (*Power System Statistics*, *System Operations*), and unpublished records. The petroleum data are from *Monthly Petroleum Products Sale data*, compiled by SLC, Kerala; and *Monthly data of Petroleum*, Planning and Analysis Cell, Ministry of Petroleum and Natural gas. For the LMDI exercise, we have utilized the "LMDI Program for Stata module" by Kerry Du (2017).

For our analysis, first we consider the power sector of Kerala. Table 4.1 presents electricity consumption and real GSDP in Kerala (sector-wise and total) for the study period (from 2007-08 to 2016-17).

From this basic data, we estimate the sectoral energy intensity of electricity (unit (or kWh) of electricity used per Rupee of real GSDP) and the sectoral shares of GSDP, which are given in Table 4.2. These are then input into the LMDI decomposition exercise, and the results therefrom are given in Table 4.3.

Table 4.1: Electricity Consumption and Real GSDP in Kerala

	Electricity Consumption MU				Real GSDP, Rs Lakh			
	Agriculture	Industry	Others	Total	Primary	Secondary	Tertiary	Total
2007-08	230.55	4123.68	9042.38	13396.61	4341828	4571935	12819755	21733518
2008-09	225.22	4002.37	8650.06	12877.65	4643108	4576364	13841297	23060769
2009-10	257	4481.09	9286.9	14024.99	4504923	4854334	15522423	24881679
2010-11	231.56	4616.59	9829.99	14678.14	4131565	5576848	16503211	26211624
2011-12	286.18	4926.43	10969.02	16181.63	4266424	8369967	17390244	30026635
2012-13	306.08	5007.11	11526.02	16839.21	4104417	8580866	19042425	31727708
2013-14	310.25	5132.05	13426.35	18868.65	4052624	8865392	20439675	33357691
2014-15	298.28	5236.64	13249.43	18784.35	4263300	9033930	21507602	34804832
2015-16	279.48	5209.23	13889.87	19378.58	3636758	9825120	22933704	36395582
2016-17	321.98	5260.116	14505.44	20087.54	3794551	10164829	24640455	38599835

Table 4.2: Sectoral Energy Intensity and Sectoral Share of GSDP

	Sectoral Intensity, Electricity, kWh/Re			Sectoral Share of GSDP		
	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
2007-08	0.00053	0.00902	0.00705	0.2	0.21	0.59
2008-09	0.00049	0.00875	0.00625	0.201	0.198	0.6
2009-10	0.00057	0.00923	0.00598	0.181	0.195	0.624
2010-11	0.00056	0.00828	0.00596	0.158	0.213	0.63
2011-12	0.00067	0.00589	0.00631	0.142	0.279	0.579
2012-13	0.00075	0.00584	0.00605	0.129	0.27	0.6
2013-14	0.00077	0.00579	0.00657	0.121	0.266	0.613
2014-15	0.0007	0.0058	0.00616	0.122	0.26	0.618
2015-16	0.00077	0.0053	0.00606	0.1	0.27	0.63
2016-17	0.00085	0.00517	0.00589	0.098	0.263	0.638

Table 4.3: LMDI Decomposition Result

From	Energy Consumption Change	Intensity Effect	Structure Effect	Activity Effect
2007-08 to 2008-09	0.961	0.912	0.994	1.061
2008-09 to 2009-10	1.089	0.991	1.019	1.079
2009-10 to 2010-11	1.047	0.963	1.032	1.053
2010-11 to 2011-12	1.102	0.938	1.026	1.146
2011-12 to 2012-13	1.041	0.972	1.014	1.057
2012-13 to 2013-14	1.121	1.057	1.008	1.051
2013-14 to 2014-15	0.996	0.955	1	1.043
2014-15 to 2015-16	1.032	0.966	1.022	1.046
2015-16 to 2016-17	1.037	0.975	1.003	1.061

The results show that the electrical energy consumption increased in all but two years: 2008-09 and 2014-15 over the respective previous years. It is significant to note that energy efficiency improvement contributed to energy intensity reduction in all but one year: 2013-14 over 2012-13. Energy efficiency improvement reduced energy use by about 9% in 2008-09 over 2007-08 and nearly 5% in 2013-14 over the previous year; no energy efficiency improvement means that consumption would have increased. Note that these two years correspond to quadrant A in Fig. 2.1 on energy efficiency and conservation quadrants, given above.

On the other hand, the activity structure change led to increase in energy use in all but one year (2008-09 over 2007-08) and the activity effect was always greater than unity. The latter is so expected, as unity minus activity effect represents the growth rate of the economic activity (here the real GSDP), and higher the growth rate, greater the social benefit. Hence, we have to take the activity effect as given. Note that according to the LMDI decomposition, energy consumption change is the product of these three effects, intensity, structure and activity effects; for example, for 2008-09 over 2007-08, energy consumption change = 0.961 = 0.912 x 0.994 x 1.061. Thus, given the activity effect, the combined effect of structure and intensity must more than compensate the activity effect in order for an effective energy conservation. That is, the combined effect of structure and intensity must be sufficiently smaller.

Energy conservation means that the energy consumption change is less than unity; this in turn requires the combined effect of activity (ΔA), structure (ΔS) and intensity (ΔI) be less than unity (ΔA x ΔS x ΔI < 1); that is, the given activity effect be less than the reciprocal of the combined effect of the other two ($\Delta\mathrm{A} < \frac{1}{\Delta\mathrm{S}\Delta\mathrm{I}}$); for example, for 2008-09 over 2007-08, an energy consumption change of 0.961 implies $\Delta\mathrm{A} = 1.061 < \frac{1}{\Delta\mathrm{S}\Delta\mathrm{I}} = \frac{1}{(0.994)(0.912)} = 1.1031$. Note that this also means that the combined effect of structure and intensity must be sufficiently smaller, as already stated ($\Delta\mathrm{S}\Delta\mathrm{I} < \frac{1}{\Delta\mathrm{A}}$).

Note that an energy consumption change of 0.961 for 2008-09 over 2007-08 implies a 3.9% fall in energy use in that year. An approximate decomposition of this energy saving as obtained from the three effects is as follows:

Energy saved in efficiency improvement = 1 – 0.912 = 0.088

Energy saved in structural change = 1 – 0.994 = 0.006

Total energy saved = 0.088 + 0.006 = 0.094.

Surplus energy used for activity change = 1 – 1.061 = (–) 0.061

Therefore, Net energy saved = 0.094 – 0.061 = 0.033

Energy saved in consumption = 1- 0.961 = 0.039

Next we turn to the petroleum sector of Kerala; Table 4.4 presents the sector-wise a product-wise petroleum consumption in Kerala for the study period (from 2007-08 to 2016-17) and the next Table (4.5) provides the combined data for two sectors, industry (secondary) and others (tertiary) to correspond to the National Income Accounts classification that we followed in the last part (for the power sector). The activity measure that we use is the same, real GSDP (2011-12 prices) for the same period, from 2007-08 to 2016-17.

As earlier, from this basic data, we estimate the sectoral energy intensity of petroleum (MT/lakh Rupees of real GSDP) and the sectoral shares of GSDP, which are given in Table 4.6. The corresponding LMDI decomposition results are given in Table 4.7.

The results show that the petroleum energy consumption increased in all the years over the respective previous years, without any exception. At the same time, it is significant to note that energy efficiency improvement contributed to energy intensity reduction in all but two years: 2008-09 over 2007-08 and 2016-17 over 2015-16. In 2011-12, energy efficiency improvement reduced energy intensity by about 10% over 2010-11. However, the structure effect was less than unity only for three years (2010-11, 2011-12 and 2015-16 over the respective previous years) and the activity effect was always greater than unity. That no year witnessed energy conservation effort in this sector implies that the combined effect of intensity and structure was not sufficient to cover the growth in the economic activity. Note that the activity effect is temporally different in this sector compared with the earlier model, because here we considered only two sectors, secondary and tertiary.

Table 4.4: Consumption of Petroleum Products in Kerala, TMT

Product	LPG	Naphtha	Auto LPG	MS	HSD - For Automobiles	HSD- Industrial	HSD- Commercial DG Sets etc	SKO*- PDS	SKO- Fishing	LDO	FO/LSHS	Bitumen	Lubes	ATF	Natural Gas	All Products
2007-08	517.53	397.92	0	555.95	1403	84.8	169.4	134.47	89.65	0.55	297.7	111.72	41.19	202.9	0	4006.73
2008-09	514.5	609.31	10.79	619.12	1496.4	87.86	164.18	131.87	87.92	1.96	380.1	143.26	37.75	228.7	0	4513.73
2009-10	559.49	646.67	15.24	705.81	1575.3	96.54	179.3	135.65	90.43	1.36	408	148.52	44.72	271	0	4877.98
2010-11	627.4	487.8	12.6	757.7	1726.5	101.4	188.3	110.7	73.8	0.5	347.5	178.7	42.6	297.8	0	4953.1
2011-12	647.9	272.7	11.7	800.4	1887.2	110.9	205.9	93.4	62.3	0.1	322.8	222.5	42.5	302	0	4982.3
2012-13	662.5	403.3	11	846	2111.1	110.6	205.4	59.4	39.6	0.1	338.7	170.9	40.6	314.9	0	5314
2013-14	662.6	269.3	8.9	917.2	2331.9	72.8	135.2	56.9	38	0.1	264.3	221.5	42	337.9	0.1	5358.6
2014-15	715.6	181.1	8.5	1024	2325.8	86	159.7	56.9	37.9	0.1	263.7	178.4	42.1	358.1	0.1	5437.9
2015-16	769.2	23.5	6.5	1129.8	2317.6	111.2	206.5	58.8	39.2	0.1	322.6	193.4	43.7	382.1	0.2	5604.4
2016-17	848.1	0	5.5	1259.6	2329.5	109.6	203.5	48.5	32.3	0.3	314.9	173.3	42.8	428.1	287.7	6083.8
2017-18	933.3	4	5.7	1404	2372.2	114.2	212.2	37.3	30	0.8	243.7	234	41	473.7	291	6397.1
Sector	Domestic	Industrial	Transport	Transport	Transport	Industrial	Commercial	Domestic	Transport	Industrial	Industrial	Infrastructure	Transport	Transport	Industrial	

Source: (i) Monthly Petroleum Products Sale data, compiled by SLC, Kerala; (ii) Monthly data of Petroleum Planning and Analysis Cell, Ministry of Petroleum and Natural gas.

Table 4.5: Sectoral Consumption of Petroleum Products and Real GSDP in Kerala

	Petroleum, TMT			Real GSDP, Rs Lakh		
	Industrial	Others	Total	Secondary	Tertiary	Total
2007-08	780.96	3225.77	4006.733	4571935	12819755	17391690
2008-09	1079.2	3434.51	4513.729	4576364	13841297	18417661
2009-10	1152.6	3725.39	4877.977	4854334	15522423	20376756
2010-11	937.17	4015.98	4953.144	5576848	16503211	22080059
2011-12	706.47	4275.79	4982.261	8369967	17390244	25760211
2012-13	852.6	4461.35	5313.95	8580866	19042425	27623291
2013-14	606.56	4752.06	5358.619	8865392	20439675	29305067
2014-15	530.98	4906.96	5437.9371	9033930	21507602	30541532
2015-16	457.52	5146.86	5604.3813	9825120	22933704	32758824
2016-17	712.51	5371.27	6083.779	10164829	24640455	34805284

Table 4.6: Sectoral Energy Intensity and Sectoral Share of GSDP

	Sectoral Intensity, Petroleum, MT/lakh Rs		Sectoral Shares of GSDP	
	Secondary	Tertiary	Secondary	Tertiary
2007-08	0.171	0.252	0.263	0.737
2008-09	0.236	0.248	0.248	0.752
2009-10	0.237	0.24	0.238	0.762
2010-11	0.168	0.243	0.253	0.747
2011-12	0.084	0.246	0.325	0.675
2012-13	0.099	0.234	0.311	0.689
2013-14	0.068	0.232	0.303	0.697
2014-15	0.059	0.228	0.296	0.704
2015-16	0.047	0.224	0.3	0.7
2016-17	0.07	0.218	0.292	0.708

Table 4.7: LMDI Decomposition Result

From	Energy Consumption Change	Intensity Effect	Structure Effect	Activity Effect
2007-08 to 2008-09	1.127	1.061	1.003	1.059
2008-09 to 2009-10	1.081	0.976	1	1.106
2009-10 to 2010-11	1.015	0.94	0.997	1.083
2010-11 to 2011-12	1.006	0.901	0.957	1.166
2011-12 to 2012-13	1.067	0.984	1.011	1.072
2012-13 to 2013-14	1.008	0.944	1.007	1.061
2013-14 to 2014-15	1.015	0.968	1.006	1.042
2014-15 to 2015-16	1.031	0.965	0.996	1.073
2015-16 to 2016-17	1.086	1.014	1.007	1.062

Finally we turn to the decomposition analysis for the combined energy sector of Kerala (electricity and petroleum sectors taken together); as conversion factor for petroleum, we take one metric ton oil equivalent = 11630 kwh and thus one thousand metric ton (TMT) oil equivalent = 11.63 MU. The converted petroleum data in MU is given in Table 4.8. For the combined energy sector, we consider the three usual economic activity sectors: agriculture (primary), industry (secondary) and others (tertiary), and real GSDP (at 2011-12 prices) for activity measure for the period from 2007-08 to 2016-17; the corresponding data are reported in Table 4.9. The information required for decomposition analysis (that is, the sectoral intensities and shares) is given in Table 4.10. The decomposition results are presented in the next Table (4.11).

Table 4.8: Sectoral Consumption of Petroleum Products in Kerala

Petroleum Mu			
	Industrial	Others	Total
2007-08	9082.58	37515.7	46598.3
2008-09	12551.36	39943.3	52494.67
2009-10	13404.63	43326.2	56730.87
2010-11	10899.23	46705.8	57605.06
2011-12	8216.23	49727.5	57943.7
2012-13	9915.77	51885.5	61801.24
2013-14	7054.3	55266.4	62320.74
2014-15	6175.3	57067.9	63243.21
2015-16	5321.01	59858	65178.95
2016-17	8286.52	62467.8	70754.35
2017-18	7603.29	66795.3	74398.56

Table 4.9: Sectoral Energy Consumption (Electricity and Petroleum) and Real GSDP in Kerala

	Energy Consumption, MU				Real GSDP, Rs Lakh			
	Agriculture	Industry	Others	Total	Primary	Secondary	Tertiary	Total
2007-08	230.55	13206.26	46558.11	59994.91	4341828	4571935	12819755	21733518
2008-09	225.22	16553.73	48593.36	65372.32	4643108	4576364	13841297	23060769
2009-10	257	17885.72	52613.14	70755.86	4504923	4854334	15522423	24881679
2010-11	231.56	15515.82	56535.82	72283.2	4131565	5576848	16503211	26211624
2011-12	286.18	13142.66	60696.49	74125.33	4266424	8369967	17390244	30026635
2012-13	306.08	14922.88	63411.49	78640.45	4104417	8580866	19042425	31727708
2013-14	310.25	12186.35	68692.79	81189.39	4052624	8865392	20439675	33357691
2014-15	298.28	11411.94	70317.34	82027.56	4263300	9033930	21507602	34804832
2015-16	279.48	10530.24	73747.82	84557.53	3636758	9825120	22933704	36395582
2016-17	321.98	13546.63	76973.28	90841.89	3794551	10164829	24640455	38599835

Table 4.10: Sectoral Energy Intensity and Sectoral Share of GSDP

	Sectoral Intensity , units/Rs			Sectoral Share		
	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
2007-08	0.00053	0.029	0.036	0.2	0.21	0.59
2008-09	0.00049	0.036	0.035	0.201	0.198	0.6
2009-10	0.00057	0.037	0.034	0.181	0.195	0.624
2010-11	0.00056	0.028	0.034	0.158	0.213	0.63
2011-12	0.00067	0.016	0.035	0.142	0.279	0.579
2012-13	0.00075	0.017	0.033	0.129	0.27	0.6
2013-14	0.00077	0.014	0.034	0.121	0.266	0.613
2014-15	0.0007	0.013	0.033	0.122	0.26	0.618
2015-16	0.00077	0.011	0.032	0.1	0.27	0.63
2016-17	0.00085	0.013	0.031	0.098	0.263	0.638

Table 4.11: LMDI Decomposition Result

From	Energy Consumption Change	Intensity Effect	Structure Effect	Activity Effect
2007-08 to 2008-09	1.09	1.028	0.999	1.061
2008-09 to 2009-10	1.082	0.979	1.024	1.079
2009-10 to 2010-11	1.022	0.944	1.027	1.053
2010-11 to 2011-12	1.025	0.908	0.986	1.145
2011-12 to 2012-13	1.061	0.981	1.023	1.057
2012-13 to 2013-14	1.032	0.968	1.014	1.051
2013-14 to 2014-15	1.01	0.965	1.004	1.043
2014-15 to 2015-16	1.031	0.965	1.022	1.046
2015-16 to 2016-17	1.074	1.005	1.008	1.061

Fig. 4.1: Energy Consumption Change

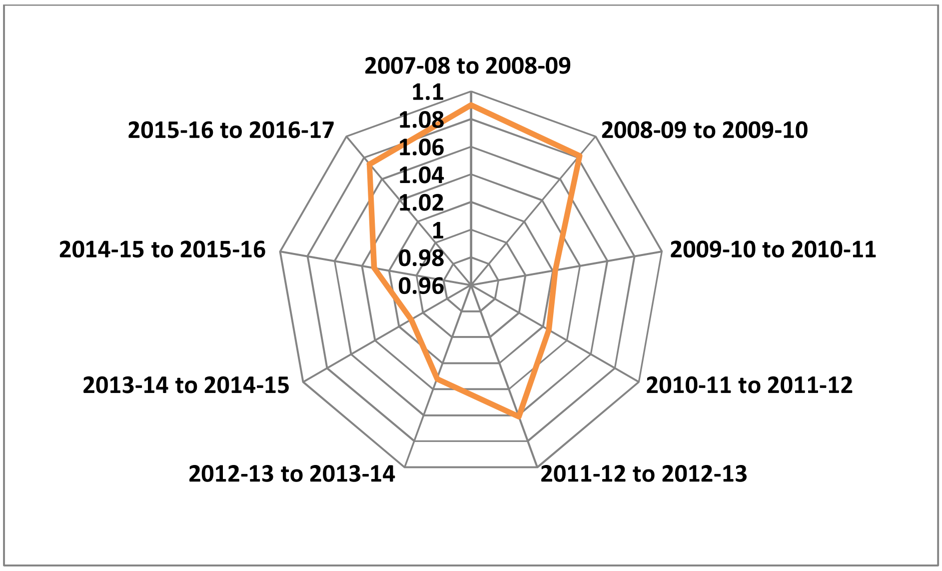


Fig. 4.2: Structure Effect

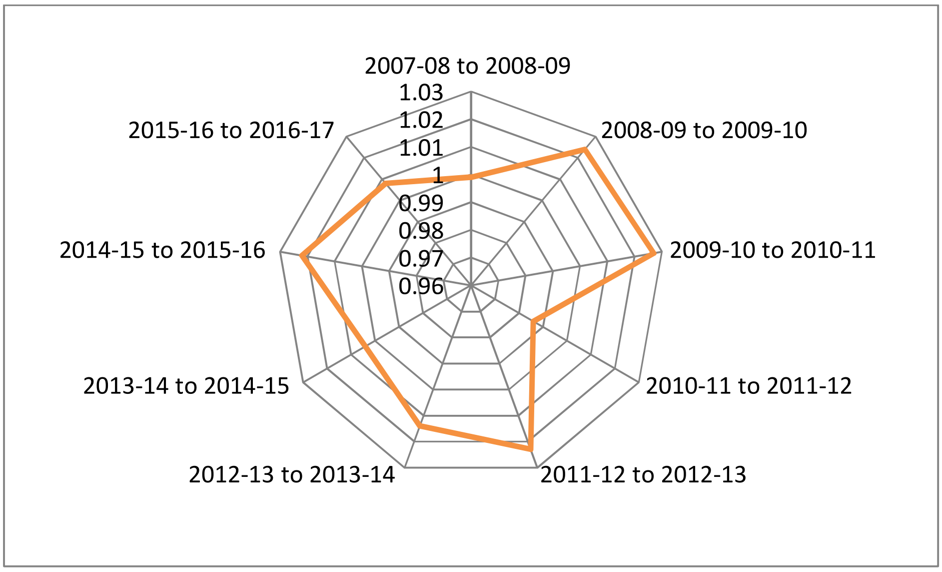


Fig.4.3: Activity Effect

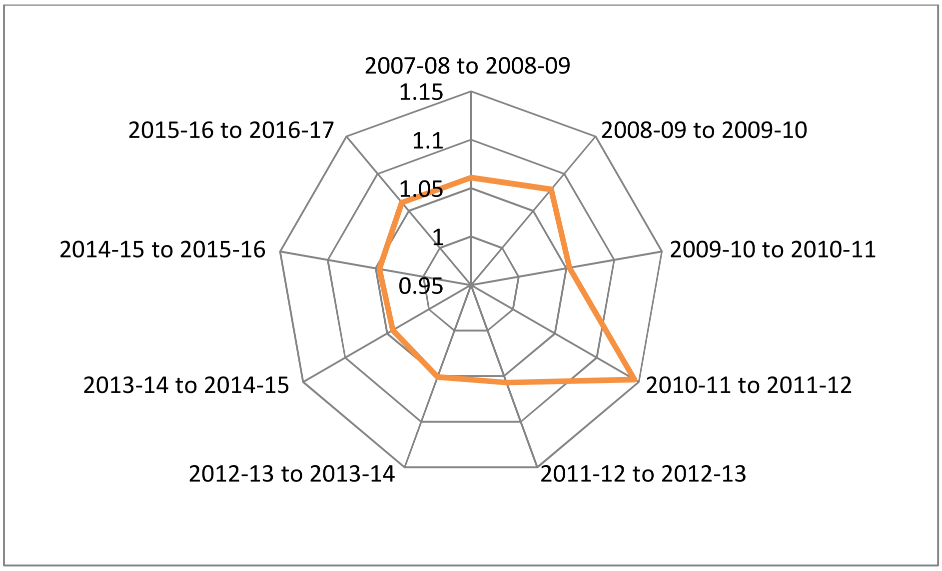
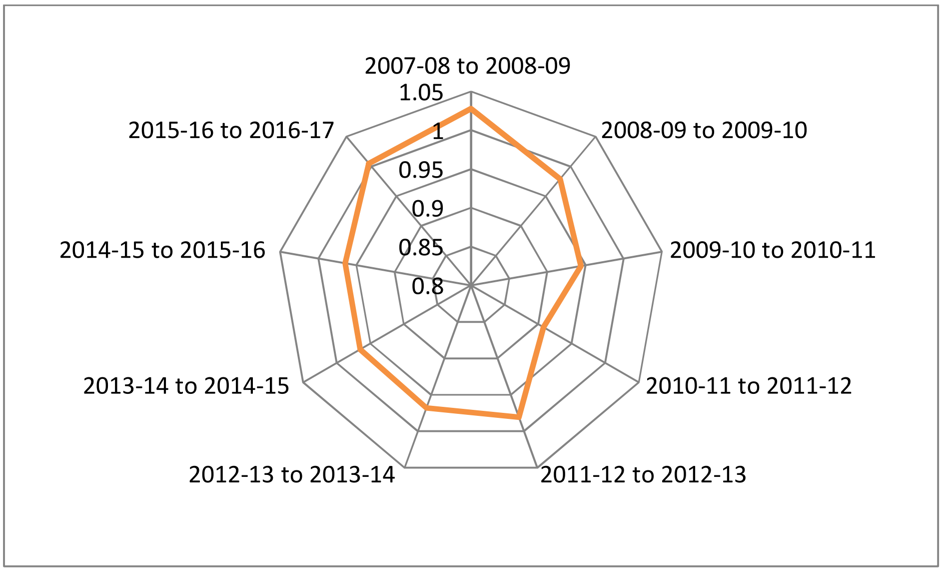


Fig. 4.4: Intensity effect



We have the same results as for the petroleum sector: increase in total energy consumption for all the years compared with the respective previous years; contribution of energy efficiency improvement to energy intensity reduction in all but two years: 2008-09 and 2016-17 over the respective previous years. In 2011-12, energy efficiency improvement reduced energy intensity by about 10% over 2010-11 as in the petroleum sector case. However, the structure effect was less than unity only for two years (2008-09 and 2011-12 over the respective previous years) and the activity effect was always greater than unity. The net result of all these is that the energy consumption did increase in all the years under consideration. It is significant to note that the energy efficiency achieved in the power sector, though in a limited way, got melted away in the combined sector under the flames from the petroleum sector performance.

4.4 Simulation for Energy Consumption Under Different Scenarios

We have already seen that the decomposition identity may be written as

$$E = \sum_i E_i = \sum_i \frac{E_i}{Q_i}\frac{Q_i}{Q} \mathrm{Q}$$

where E is the total energy consumption, Q (= $\sum_i Q_i$) is the activity level (in our case, real GSDP), Q_i /Q is the ith sector's activity share (S_i) and E_i /Q_i is that sector's energy intensity (I_i). We can make use of this identity to simulate energy consumption under different scenarios.

The following Table reports the annual growth rate of real GSDP of Kerala for the last few years:

Real GSDP Annual Growth Rate (%)								
2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
6.11	7.9	5.35	14.55	5.67	5.14	4.34	4.57	6.06

Based on this, for simulation purposes, we assume an annual growth rate of real GSDP of 6%; thus, given the real GSDP of Rs 38599835 lakh of 2016-17 and 6% annual growth rate, the first year of simulation will have a real GSDP of Rs. 40915825 lakh. We also assume that the energy efficiency improvement leads to annual 10% fall in energy intensity in all sectors and also the real GSDP sectoral shares remain the same. Given this information, we estimate the total energy for the next four years after 2016-17; we find that the annual energy conservation in this scenario amounts to 4.6%. Also note that these assumptions imply an activity effect of 1.06, structure effect of unity, and intensity effect of 0.9; and yield an annual change in energy consumption of 0.954 (= 1.06 x 1 x 0.9), with an energy conservation of 4.6%.

Table 4.12: Simulation for Energy Consumption under Scenario 1

	Intensity, kWh/Re			Sectoral shares			Real GSDP Rs Lakh	Energy consumption	
Year	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary		MU	Fall %
2016-17	0.00085	0.013	0.031	0.098	0.263	0.638	38599835	90841.89	
Year 1	0.00076	0.012	0.028	0.098	0.263	0.638	40915825	86663.16	-4.6
Year 2	0.00069	0.011	0.025	0.098	0.263	0.638	43370775	82676.66	-4.6
Year 3	0.00062	0.01	0.023	0.098	0.263	0.638	45973021	78873.53	-4.6
Year 4	0.00056	0.009	0.02	0.098	0.263	0.638	48731402	75245.35	-4.6

Assumptions: (i) Annual growth rate of real GSDP = 6%; (ii) Energy efficiency improvement leads to annual 10% fall in energy intensity in all sectors; and (iii) Real GSDP sectoral shares remain the same.

The following Tables represent different scenarios of simulation.

Table 4.13 assumes (i) 5% annual growth rate of real GSDP; (ii) annual 10% fall in energy intensity in all sectors thanks to energy efficiency improvement; and (iii) real GSDP sectoral shares remain the same. This scenario involves an annual energy conservation of 5.5%.

Table 4.13: Simulation for Energy Consumption under Scenario 2

	Intensity, kWh/Re			Sectoral shares			Real GSDP Rs Lakh	Energy consumption	
Year	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary		MU	Fall %
2016-17	0.00085	0.013	0.031	0.098	0.263	0.638	38599835	90841.89	
Year 1	0.00076	0.012	0.028	0.098	0.263	0.638	40529827	85845.59	-5.5
Year 2	0.00069	0.011	0.025	0.098	0.263	0.638	42556318	81124.08	-5.5
Year 3	0.00062	0.01	0.023	0.098	0.263	0.638	44684134	76662.25	-5.5
Year 4	0.00056	0.009	0.02	0.098	0.263	0.638	46918341	72445.83	-5.5

Assumptions: (i) Annual growth rate of real GSDP = 5%; (ii) Energy efficiency improvement leads to annual 10% fall in energy intensity in all sectors; (iii) Real GSDP sectoral shares remain the same.

Table 4.14: Simulation for Energy Consumption under Scenario 3

	Intensity, kWh/Re			Sectoral shares			Real GSDP Rs Lakh	Energy consumption	
Year	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary		MU	Fall %
2016-17	0.00085	0.013	0.031	0.098	0.263	0.638	38599835	90841.89	
Year 1	0.00081	0.013	0.03	0.098	0.263	0.638	40529827	90614.79	-0.25
Year 2	0.00077	0.012	0.028	0.098	0.263	0.638	42556318	90388.25	-0.25
Year 3	0.00073	0.011	0.027	0.098	0.263	0.638	44684134	90162.28	-0.25
Year 4	0.00069	0.011	0.025	0.098	0.263	0.638	46918341	89936.87	-0.25

Assumptions: (i) Annual growth rate of real GSDP = 5%; (ii) Energy efficiency improvement leads to annual 5% fall in energy intensity in all sectors; (iii) Real GSDP sectoral shares remain the same.

Table 4.15: Simulation for Energy Consumption under Scenario 4

	Intensity, kWh/Re			Sectoral shares			Real GSDP Rs Lakh	Energy consumption	
Year	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary		MU	Fall %
2016-17	0.00085	0.01333	0.03124	0.0983	0.2633	0.6384	38599835	90841.89	
Year 1	0.00076	0.01199	0.02811	0.0893	0.2660	0.6447	40915825	87498.55	-3.68
Year 2	0.00069	0.01079	0.02530	0.0802	0.2686	0.6512	43370775	84278.54	-3.68
Year 3	0.00062	0.00972	0.02277	0.0710	0.2713	0.6577	45973021	81177.31	-3.68
Year 4	0.00056	0.00874	0.02050	0.0617	0.2740	0.6643	48731402	78190.45	-3.68

Assumptions: (i) Annual growth rate of real GSDP = 6%; (ii) Energy efficiency improvement leads to annual 10% fall in energy intensity in all sectors; (iii) Real GSDP shares of secondary and tertiary sectors increase by 1% per annum and the primary sector share correspondingly decreases.

Table 4.16: Simulation for Energy Consumption under Scenario 5

Year	Intensity, kWh/Re			Sectoral shares			Real GSDP Rs Lakh	Energy consumption	
	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary		MU	Fall %
2016-17	0.00085	0.0133	0.0312	0.0983	0.2633	0.6384	38599835	90841.89	
Year 1	0.00076	0.0120	0.0281	0.1163	0.2581	0.6256	40915825	84992.39	-6.44
Year 2	0.00069	0.0108	0.0253	0.1340	0.2529	0.6131	43370775	79520.71	-6.44
Year 3	0.00062	0.0097	0.0228	0.1513	0.2479	0.6008	45973021	74402.37	-6.44
Year 4	0.00056	0.0087	0.0205	0.1683	0.2429	0.5888	48731402	69614.53	-6.44

Assumptions: (i) Annual growth rate of real GSDP = 6%; (ii) Energy efficiency improvement leads to annual 10% fall in energy intensity in all sectors; (iii) Real GSDP shares of secondary and tertiary sectors decrease by 2% per annum and the primary sector share correspondingly increases.

Table 4.14 assumes (i) annual growth rate of real GSDP of 5%; (ii) annual 5% fall in energy intensity in all sectors owing to energy efficiency improvement; and (iii) real GSDP sectoral shares remain the same. This results in 0.25% energy saving per annum.

Table 4.15 assumes (i) 6% annual growth rate of real GSDP; (ii) annual 10% fall in energy intensity in all sectors energy following efficiency improvement; and (iii) an increase in the real GSDP shares of secondary and tertiary sectors by 1% per annum and a corresponding decrease in the primary sector share. This yields 3.68% energy saving per year.

Table 4.16 assumes (i) 6% annual growth rate of real GSDP; (ii) annual 10% fall in energy intensity in all sectors from energy efficiency improvement; and (iii) a decrease in the real GSDP shares of secondary and tertiary sectors by 2% per annum with a corresponding increase in the primary sector share. Strangely this leads to greater energy conservation; this evidently can be due to the predominance of energy-inefficient petroleum sector through the secondary and tertiary sectors. The real contributions of these two sectors (secondary and tertiary) can come out of this mask only when this sector becomes energy-efficient.

4.5 Conclusion

In this first core chapter of the Report, we have applied the index decomposition analysis to measure energy productivity in Kerala in terms of the Logarithmic Mean Divisia Index (LMDI) method. This method helps us to decompose the changes in energy consumption over time into three different effects of activity, structure and intensity. As already indicated, non-availability of suitable time-series data for Kerala has forced us to limit our ambition down to an empirical decomposition exercise for Kerala in terms of only two sectors, power and petroleum, that too, for a limited period (from 2007-08 to 2016-17); first we have analysed the two sectors of power and petroleum separately, and then the combined sector has been analysed for decomposition.

Note that energy conservation means the energy consumption change be less than unity; this in turn requires the combined effect of activity, structure and intensity be less than unity. The activity effect is expected to be greater than unity; since unity minus activity effect represents the growth rate of the economic activity (here the real GSDP), and higher the growth rate, greater the social benefit. Hence, we have to take the activity effect as given. This in turn requires that given the activity effect, the combined effect of structure and intensity must more than compensate the activity effect in order for an effective energy conservation. That is, the combined effect of structure and intensity must be sufficiently smaller. The empirical exercise for Kerala power sector shows that this was possible only for two years during the study period (from 2007-08 to 2016-17). Energy consumption reduced by about 9% in 2008-09 over 2007-08 and nearly 5% in 2013-14 over the previous year.

It is significant to note that energy intensity in the power sector reduced in all but one year: 2013-14 over 2012-13, thanks to energy efficiency improvements; and this lies behind the energy use reduction in the two years of 2008-09 and 2013-14; no energy efficiency improvement means that consumption would have increased. Thus in these two years, social benefit increased along with positive energy conservation. That this occurred only for two years is explained by the performance of the other component, structure effect, that was greater than unity in all but one year (2008-09 over 2007-08). In short, despite energy intensity reduction thanks to energy efficiency improvement in the power sector of Kerala for a number of recent years, energy conservation along with increased social benefit (real GSDP) could not be achieved because of the anomaly in the real GSDP structure (composition of sectoral shares). If the current state of nature dictates this activity structure as given, then the only recourse for energy conservation is through higher levels of energy efficiency improvement for greater reduction in intensity.

The results for the petroleum sector (with only two sectors, secondary and tertiary), however, show that no year witnessed energy conservation effort in this sector. This is despite energy intensity reduction (thanks to energy efficiency improvement) in all but two years: 2008-09 over 2007-08 and 2016-17 over 2015-16. The structure effect was less than unity only for three years (2010-11, 2011-12 and 2015-16 over the respective previous years). Their combined effect was incapable of containing the activity effects of the secondary and tertiary sectors for occasioning any energy conservation. Such performance of the petroleum sector has overshadowed that of the power sector, and the combined sector of energy in Kerala has shown almost similar results as the petroleum sector, with the net result that the energy consumption increased in all the years under consideration.

Following this, we have then turned to a simulation analysis for energy consumption in Kerala under different scenarios that offer energy savings. This exercise shows some strange results, emanating from the peculiar characteristics of the petroleum sector in Kerala. As already remarked earlier, the petroleum consumption data relating only to the secondary and tertiary sub-sectors, the less-efficient petroleum sector overweighs the combined energy sector of Kerala to such an extent that the energy-efficiency potential of these two sub-sectors gets clouded. In this situation, the simulation with an assumption of a small reduction in the real GSDP shares of secondary and tertiary sectors yields greater energy conservation. A sufficiently high degree of energy efficiency in the petroleum sector can indeed reverse this anomaly.

Chapter 5

Measuring Energy Efficiency in Kerala: Stochastic Frontier Production Function Analysis

5.1 Introduction

The present chapter starts our multi-factor productivity analysis, with the stochastic frontier production function method. The chapter is structured in six parts. The next section discusses the theoretical framework of frontier production function in general; section 3 continues the discussion with frontier approach and introduces both the deterministic and stochastic frontiers. A detailed presentation of the panel data stochastic frontier model that we utilize in our empirical exercise for the Kerala power sector also follows in the same section. Part four discusses the regression results from the empirical study. For a comparative purpose, we also present the regression results from a pooled data stochastic frontier approach in section five. The last section concludes the chapter.

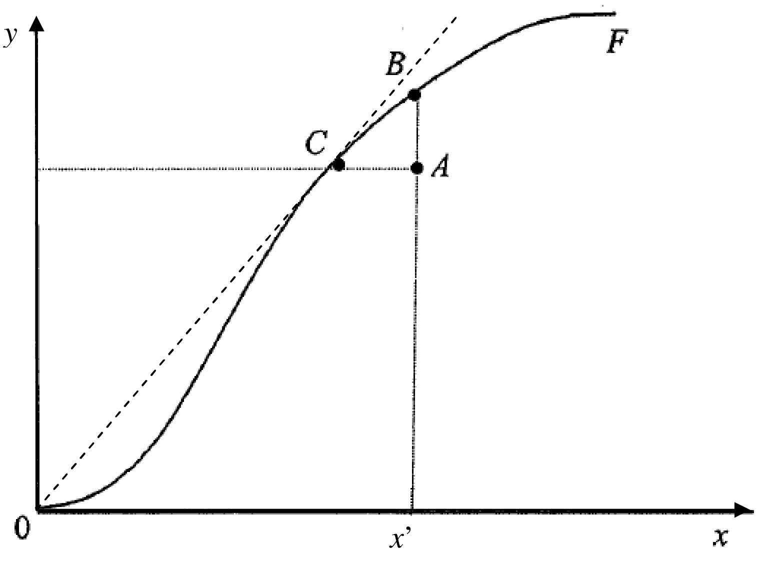
5.2 Frontier Production Function

A production function in microeconomic theory is defined as yielding maximum output (y) from a specified set of inputs (x), given the existing technology, and is given as

$$y = f(x; \beta), \qquad (1)$$

where β represents the production parameters. The function is assumed to be single-valued continuous one, with continuous first- and second-order partial derivatives. "The production function differs from the technology in that it presupposes technical efficiency and states the *maximum* output obtainable from every possible input combination." (Henderson and Quandt 1971; 54). Thus, the production function determines a production frontier, points on which represent technically efficient input combinations. Points such as B and C in Fig. 5.1 are thus technically efficient, but point A is not. The technical efficiency of the firm at point A with an input level of x' is given by $x'A \,/\, x'B$, where the denominator is the 'frontier output' and the numerator, the actual output of the firm, both associated with that input level; that is, the distance between the points A (actual output) and B (frontier output) represents its technical inefficiency at that input level.

Fig. 5.1: Technical Efficiency with a Frontier Production Function



It was the seminal paper of Farrell (1957) that stimulated econometric modeling of production functions as frontiers. According to him, the overall efficiency (now called economic efficiency) of a production unit is composed of two components, viz., technical efficiency and price efficiency (now called allocative efficiency); the former refers to the capability of the unit to produce maximum output from a given bundle of inputs, and the latter to the capability of the unit to utilize the inputs in an optimum proportion subject to the given input prices. In this chapter, we are considering the technical efficiency only (represented in Fig. 5.1 by points B and C).

However, there is a difference between the two efficient points B and C. We know that a ray through the origin as in Fig. 5.1 has a slope equal to *y/x* (that is, output/input) and is thus a measure of productivity. The ray from the origin has the maximum slope when it is at tangent to the production frontier and the point of tangency thus defines the point of maximum possible productivity. In Fig. 5.1, the point C represents optimum productivity, in addition to technical efficiency. Note that in this Report, we consider only technical efficiency.

Remember the efficiency of a production unit is measured in relation to an efficient production function (representing an efficient firm), which is in fact unknown and must be estimated using the sample data. For estimation, Farrell suggested (i) a parametric frontier function, such as the Cobb-Douglas production function, estimated from the data in such a way that no actual data point should lie to the right or above it, or (ii) a non-parametric piecewise-linear convex isoquant, estimated from the data in such a way that no actual data point should lie to the left or below it. Farrell used his models with agricultural data for the 48 states of the US.

5.3 Frontier Production Function Analysis

There are two types of production frontiers: (i) deterministic and (ii) stochastic frontiers.

Deterministic frontiers

The econometric model of the deterministic production frontier is obtained from the above equation (1) by adding an inefficiency term to the right side frontier and indexing the model for each of the n firms under study, as follows:

$$y_i = f(x_i; \beta)\exp(-u_i), \quad i = 1, 2, \dots, n \qquad (2)$$

where y_i is the actual production level of the ith firm in the sample;

$f(x_i; \beta)$ models the frontier, represented by a suitable functional form, such as Cobb-Douglas or Translog, of the of inputs x_i and production parameters β of the ith firm;

u_i is a non-negative random variable representing the technical inefficiency of the ith firm;

n is the number of firms in the cross-sectional sample of the industry, and

exp represents exponential.

Remember that the technical efficiency of a firm is defined in terms of the ratio of the actual level of production of the firm to its frontier output. In the case of the above deterministic frontier model, the actual output for the ith firm is given by $f(x_i; \beta)\exp(-u_i)$, and the frontier output is $f(x_i; \beta)$ such that the technical efficiency of the ith firm (TE_i) is given by

$$\begin{aligned} TE_i &= \text{actual output/frontier output} \\ &= f(x_i;\beta)\exp(-u_i)\,/\,f(x_i;\beta) \\ &= \exp(-u_i). \qquad (3) \end{aligned}$$

Using appropriate estimation methods, we can have the frontier parameter estimates, which, along with the given sample input levels of individual firms, will yield the corresponding frontier output estimates; a comparison of the actual level of output with this will reveal the technical efficiency of each of the firms in the sample. It was Aigner and Chu (1968) who first estimated such a model by considering Cobb-Douglas production frontier and using linear programming technique. Taking natural log of (2), we obtain the technical inefficiency of the ith firm as the difference between the log of its actual and frontier output levels. Aigner and Chu (1968) sought to minimize the sum of the inefficiency subject to the constraint that u_i is non-negative; they also suggested quadratic programming as another solution method. The first econometric estimation came with Afriat (1972), who assumed gamma distribution for the u_i random variables and used the maximum likelihood method. Then Richmond (1974) followed, using a modified least squares method, known as *modified* (or *corrected*) ordinary least squares (MOLS or COLS), making the estimates unbiased and consistent. Schmidt (1976) assumed exponential and half-normal distributions for the random variable and estimated the model by the maximum likelihood method.

Note that the random variable in this model, assumed to be non-negative, stands to capture both the statistical noise *and* the inefficiency of the firm, and this is the major limitation of this model; all the deviations from the frontier is taken to indicate the effect of inefficiency. Another problem is that it does not satisfy the regularity condition of maximum likelihood (ML) method that the dependent variable be distributed independent of the parameter vector.

Attempts to solve these problems of the deterministic frontier method led to the development of the stochastic frontier approach.

Stochastic frontiers

Introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) independently, the stochastic frontier approach to efficiency analysis defines the frontier property in a stochastic, rather than a deterministic, sense and seeks to decompose the random error term into two components, one for the random noise and the other for technical efficiency. This effectively helps us estimate technical efficiency directly. For detailed reviews of literature, see Forsund, Lovell and Schmidt (1980), Schmidt and Sickles (1984), Schmidt (1986), Bauer (1990), Seiford and Thrall (1990), Lovell (1993), Greene (1993), Ali and Seiford (1993) and Kumbhakar and Lovell (2000).

Since our data set contains information on three sectors (primary, secondary and tertiary) over a period of time that defines a panel data, we discuss first the features of panel data stochastic frontier and then the pooled data stochastic frontier.

Panel Data Stochastic Frontier

As earlier, we start with a frontier production function, but this time in a panel framework:

$$y_{it} = f(x_{it}; \beta),\ i = 1, 2, \ldots, n;\ t = 1, 2, \ldots, T, \qquad (4)$$

where $f(x_{it}; \beta)$ is the frontier production level of the ith firm at time t in the sample. As stated above, the random disturbance term in this model has two components, one having a strictly nonnegative distribution, representing technical efficiency, and the other representing the usual idiosyncratic error having a symmetric distribution. These two components we introduce in (4) as follows.

Note that the basic assumption of the (stochastic) frontier production function is that each firm is subject to some degree of inefficiency and hence potentially produces less than the frontier output. Thus we modify (4) as

$$y_{it} = f(x_{it}; \beta)\varepsilon_{it}, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T, \tag{5}$$

where ε_{it}, lying in the interval (0;1] represents the degree of technical efficiency of firm i at time t. Since the actual output is strictly positive, ($y_{it} > 0$), the degree of technical efficiency also is assumed to be strictly positive ($\varepsilon_{it} > 0$). When $\varepsilon_{it} = 1$, there is no inefficiency and the firm produces its optimal output, determined by the frontier function $f(x_{it}; \beta)$. On the other hand, when $\varepsilon_{it} < 1$, the firm produces less, depending upon the degree of inefficiency.

Now we modify (5) by adding the usual noise term (as the output is subject to random shocks, v_{it}),

$$y_{it} = f(x_{it}; \beta)\varepsilon_{it} \exp(v_{it}), \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T. \tag{6}$$

Taking the natural log of (6), we get

$$\ln(y_{it}) = \ln f(x_{it}; \beta) + \ln(\varepsilon_{it}) + v_{it}, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T. \tag{7}$$

If we define inefficiency term $-u_{it} = \ln(\varepsilon_{it})$, we can rewrite the above equation as

$$\ln(y_{it}) = \ln f(x_{it}; \beta) + v_{it} - u_{it}, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T. \qquad (8)$$

Note that we are subtracting u_{it} from $\ln f(x_{it}; \beta)$; hence, if we restrict $u_{it} \geq 0$, we will get

$0 < \varepsilon_{it} \leq 1$, as required above.

The above equation is estimated under different specifications of the u_{it} term. In general, there are two models: (i) time-invariant inefficiency model and (ii) time-varying decay model; the former is the simplest specification.

In the time-invariant inefficiency specification, the inefficiency term u_{it} is assumed to be a time-invariant truncated normal random variable, truncated at zero with mean μ and variance σ^2. Note that the time-invariant model implies $u_{it} = u_i$, and hence we have the following assumptions:

$$u_i \sim \text{iid } N^{+}(\mu\,;\sigma_u^2), \text{ and } v_{it} \sim \text{iid } N(0; \sigma_v^2),$$

where u_i and v_{it} are distributed independently of each other and of the covariates in the model.

In the time-varying decay model, the inefficiency term is specified as

$$u_{it} = \exp\{-\eta(t - T_i)\}\, u_i, \qquad (9)$$

where

η = the decay parameter,

T_i = the last period in the ith panel, and

$u_i \sim$ iid $N^+(\mu ;\sigma_u^2)$, and $v_{it} \sim$ iid $N(0; \sigma_v^2)$, both distributed independently of each other and of the covariates in the model ($\sim$ iid = independently and identically distributed as; N^+ = truncated (at zero) normal distribution; and N = normal distribution).

With the above specification (9), the time-varying decay model functions as follows:

when $\eta > 0$, the degree of inefficiency decreases over time;

when $\eta < 0$, the degree of inefficiency increases over time.

Note that since $t = T_i$ in the last period, the last period for firm i is assumed to contain the base level of its inefficiency, and hence, when $\eta > 0$, the degree of inefficiency decays toward the base level and when $\eta < 0$, it increases to the base level.

Also note that when $\eta = 0$, the time-varying decay model reduces to the time-invariant model.

5.4 Panel Data Stochastic Frontier: Regression Results

For estimating the panel data stochastic frontier of the power sector in Kerala, we consider three sectors as above (Primary, Secondary and Tertiary) for the period from 1970-71 to 2016-17. Because of the data unavailability for estimating a usual production function in terms of factors of production, we propose the following relationship:

Sectoral energy consumption = f(Sectoral number of consumers; Sectoral GSDP at constant 2011-12 prices); all variables in log.

Note that unlike the usual frontier function with factors of production, we have a frontier function with activity factors.

Below we give the regression results for the time-invariant inefficiency model:

Table 5.1:

Panel Data Stochastic Frontier Results

for Time-invariant Inefficiency Model

```
Time-invariant inefficiency model               Number of obs      =       141
Group variable: sect                            Number of groups   =         3

                                                Obs per group:
                                                            min =           47
                                                            avg =           47
                                                            max =           47

                                                Wald chi2(2)       =    567.43
Log likelihood  = -50.598226                    Prob > chi2        =    0.0000
```

e	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y	.360787	.0533456	6.76	0.000	.2562314	.4653425
n	.441173	.054168	8.14	0.000	.3350056	.5473404
_cons	-2.118838	.481568	-4.40	0.000	-3.062694	-1.174982
/mu	.2731814	4.993982	0.05	0.956	-9.514844	10.06121
/lnsigma2	1.466197	2.134616	0.69	0.492	-2.717574	5.649968
/lgtgamma	3.696187	2.191414	1.69	0.092	-.5989048	7.99128
sigma2	4.332726	9.248708			.0660347	284.2824
gamma	.975783	.0517842			.3545943	.9996617
sigma_u2	4.227801	9.248752			-13.89942	22.35502
sigma_v2	.1049254	.0126262			.0801786	.1296723

Remember that we have used all the variables in log in the model specification; hence, the estimated coefficients are to be taken as elasticity measures. The estimates are highly significant; and energy consumption appears highly inelastic with respect to real

GSDP and number of consumers, which signify positive implication for energy efficiency in general!

In the third (bottom) panel of the results, we have the variance estimates of the error components. Thus, sigma_v2 is the estimate of the variance of the usual idiosyncratic error component, σ_v^2, and sigma_u2 is that of the inefficiency component, σ_u^2. The first estimate reported, sigma2, is the estimate of the total error variance in terms of the sum of the above two, $\sigma_S^2 = \sigma_v^2 + \sigma_u^2$. The second one, gamma, gives the estimate of the ratio of the variance of the inefficiency component to the total error variance estimate, $\gamma = \sigma_u^2 / \sigma_S^2$.

The estimates given in the intermediate panel are;

/mu is the estimate of μ, the mean of the inefficiency term ($u_i \sim$ iid $N^+(\mu ; \sigma_u^2)$).

/lgtgamma is the estimate of the logit of γ; logit of γ is used to parameterize the optimization, as γ must be between 0 and 1.

/lnsigma2 is the estimate of $\ln(\sigma_S^2)$; $\ln(\sigma_S^2)$ is used to parameterize the optimization, as σ_S^2 must be positive.

Below we report some summary indicators of the panel time-invariant technical efficiency measures:

```
summarize tecefpnl
```

Variable	Obs	Mean	Std. Dev.	Min	Max
tecefpnl	141	.3657113	.3863919	.0389499	.9062921

Table 5.2 below reports the results for the time-varying decay inefficiency model:

Table 5.2:

Panel Data Stochastic Frontier Results

for Time-varying Decay Inefficiency Model

```
Time-varying decay inefficiency model           Number of obs      =       141
Group variable: sect                            Number of groups   =         3

Time variable: year                             Obs per group:
                                                             min =        47
                                                             avg =        47
                                                             max =        47

                                                Wald chi2(2)       =    286.71
Log likelihood  = -50.588669                    Prob > chi2        =    0.0000
```

e	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y	.3592522	.0542185	6.63	0.000	.2529858	.4655186
n	.447967	.0730351	6.13	0.000	.3048209	.5911132
_cons	-2.169179	.6060753	-3.58	0.000	-3.357065	-.9812934
/mu	.334731	4.869846	0.07	0.945	-9.209993	9.879455
/eta	-.0002099	.0015121	-0.14	0.890	-.0031736	.0027538
/lnsigma2	1.46332	2.104342	0.70	0.487	-2.661115	5.587755
/lgtgamma	3.693502	2.160548	1.71	0.087	-.5410951	7.928098
sigma2	4.320278	9.091343			.0698703	267.1352
gamma	.9757195	.0511855			.3679329	.9996397
sigma_u2	4.215379	9.091384			-13.60341	22.03417
sigma_v2	.1048985	.012623			.0801579	.1296391

We know that if $\eta = 0$, the time-varying decay model reduces to the time-invariant model. In the above result, we find that the estimate of η is insignificant (zero); and the other estimates are not much different from the estimates of the time-invariant model. That means the time-varying decay model reduces to the time-invariant model. Its implication that the sector-wise technical efficiency estimates of the Kerala power sector are independent of time, that they remain constant over time, is highly significant in that it may refer to a technically stagnant situation in energy efficiency.

Below we report some summary indicators of the panel time-varying decay technical efficiency measures:

```
summarize tecefpnltv
```

Variable	Obs	Mean	Std. Dev.	Min	Max
tecefpnltv	141	.3632659	.3859875	.0379863	.9039742

Next we turn to the pooled data stochastic frontier model, just for comparative purpose.

5.5 Pooled Data Stochastic Frontier: Regression Results

We start with our earlier model

$$\ln(y_{it}) = \ln f(x_{it}; \beta) + v_{it} - u_{it}, \; i = 1, 2, \ldots, n; \; t = 1, 2, \ldots, T. \qquad (8)$$

where v_{it} is the idiosyncratic error and u_{it} is a time-varying panel-level effect. If the panel-level effect is insignificant, we get the pooled data model. There are three different models depending upon the distributional specification of the inefficiency term; in all these models, the idiosyncratic noise term is assumed to be independently distributed as normal, N(0; σ_v^2). The three models are:

(i) Exponential model, in which the inefficiency component is independently exponentially distributed with variance σ_u^2;

(ii) Half-normal model, with the inefficiency component independently and half-normally distributed, $N^+(0; \sigma_u^2)$;

(iii) Truncated-normal model, with the inefficiency component independently and truncated-normally distributed with truncation point at 0, $N^+(\mu; \sigma_u^2)$.

Table 5.3 presents the pooled data stochastic frontier model estimation results for the Kerala power sector with three sectors (Primary, Secondary and Tertiary) for the period from 1970-71 to 2016-17, for the same relationship as above:

Sectoral energy consumption = *f*(Sectoral GDP at constant 2011-12 prices; Sectoral number of consumers); all variables in log.

Table 5.3:

Pooled Data Stochastic Frontier Results for Half-Normal Model

```
Stoc. frontier normal/half-normal model          Number of obs   =       141
                                                 Wald chi2(2)    =  4.77e+09
Log likelihood = -187.47731                      Prob > chi2     =    0.0000
```

e	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y	.4933377	.0000116	4.2e+04	0.000	.4933149	.4933605
n	.0416695	6.33e-06	6583.47	0.000	.0416571	.0416819
_cons	.5266126	.000133	3959.43	0.000	.5263519	.5268732
/lnsig2v	-32.74632	206.774	-0.16	0.874	-438.0159	372.5233
/lnsig2u	1.20767	.1190983	10.14	0.000	.9742415	1.441098
sigma_v	7.75e-08	8.01e-06			7.69e-96	7.81e+80
sigma_u	1.82912	.1089225			1.627623	2.055562
sigma2	3.34568	.3984646			2.564703	4.126656
lambda	2.36e+07	.1089225			2.36e+07	2.36e+07

```
LR test of sigma_u=0: chibar2(01) = 91.27              Prob >= chibar2 = 0.000
```

As in the earlier model (Table 5.1), the estimates are highly significant; and energy consumption appears highly inelastic with respect to real GSDP and number of consumers, which signify positive implication for energy efficiency in general!

In the bottom panel, sigma_v and sigma_u, represent the estimates of the standard deviations of the two error components, v and u, respectively. The next term, sigma2, is the estimate of the total error variance, $\sigma_S^2 = \sigma_v^2 + \sigma_u^2$, and lambda represents the estimate of the ratio of the standard deviation of the inefficiency term to that of the idiosyncratic term, $\lambda = \sigma_u / \sigma_v$.

In the intermediate panel, we have

/lnsig2v and /lnsig2u, to represent the estimates of $\ln \sigma_v^2$ and $\ln \sigma_u^2$ respectively.

Note that at the bottom of the output (last line), the result of a test that there is no technical inefficiency term in the model is given, with the null hypothesis H_0: $\sigma_u^2 = 0$, against the alternative hypotheses H_1: $\sigma_u^2 > 0$. If we fail to reject the null hypothesis, the stochastic frontier model reduces to an OLS model with normal errors. For our half-normal model, we have the results that the likelihood ratio statistic (LR) = 91.27 with a p-value of 0.000. Thus we reject the null hypothesis; the stochastic frontier model is valid.

Below we report some summary indicators of the pooled data half-normal model technical efficiency measures:

```
summarize tecef
```

Variable	Obs	Mean	Std. Dev.	Min	Max
tecef	141	.5052589	.3596574	.0117641	.9999996

Next we turn to the exponential model results (Table 5.4).

Table 5.4:

Pooled Data Stochastic Frontier Results for Exponential Model

```
Stoc. frontier normal/exponential model          Number of obs    =       141
                                                 Wald chi2(2)     =     32.88
Log likelihood = -233.06765                      Prob > chi2      =    0.0000
```

e	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y	.1535739	.1451959	1.06	0.290	-.1310049	.4381527
n	.2886048	.073699	3.92	0.000	.1441574	.4330522
_cons	1.475255	1.787001	0.83	0.409	-2.027202	4.977713
/lnsig2v	.4010961	.2491265	1.61	0.107	-.0871828	.8893749
/lnsig2u	-2.24892	3.260228	-0.69	0.490	-8.638849	4.141009
sigma_v	1.222072	.1522253			.957345	1.560003
sigma_u	.3248279	.5295064			.0133075	7.928823
sigma2	1.598974	.1919779			1.222704	1.975244
lambda	.2658009	.6648633			-1.037307	1.568909

```
LR test of sigma_u=0: chibar2(01) = 0.09                 Prob >= chibar2 = 0.380
```

Note that for our exponential model, the results of the likelihood ratio test shows that the statistic (LR) = 0.09 with a p-value of 0.380. Thus we fail to reject the null hypothesis; the stochastic frontier model reduces to an OLS model with normal errors.

Though we have tried to estimate the truncated normal model, the estimation process has failed to converge.

Table 5.5: Technical Efficiency Estimates: Primary Sector

Year	Pooled Half-Normal	Panel Time-Invariant	Panel Time-Varying	Year	Pooled Half-Normal	Panel Time-Invariant	Panel Time-Varying
1970-71	0.0118	0.0389	0.0392	1994-95	0.0722	0.0389	0.0386
1971-72	0.0216	0.0389	0.0392	1995-96	0.0871	0.0389	0.0385
1972-73	0.0241	0.0389	0.0391	1996-97	0.0925	0.0389	0.0385
1973-74	0.0299	0.0389	0.0391	1997-98	0.0996	0.0389	0.0385
1974-75	0.0321	0.0389	0.0391	1998-99	0.1046	0.0389	0.0385
1975-76	0.0363	0.0389	0.0391	1999-00	0.1258	0.0389	0.0384
1976-77	0.0337	0.0389	0.0390	2000-01	0.1217	0.0389	0.0384
1977-78	0.0279	0.0389	0.0390	2001-02	0.0963	0.0389	0.0384
1978-79	0.0307	0.0389	0.0390	2002-03	0.0355	0.0389	0.0384
1979-80	0.0295	0.0389	0.0390	2003-04	0.0411	0.0389	0.0383
1980-81	0.0322	0.0389	0.0389	2004-05	0.0340	0.0389	0.0383
1981-82	0.0382	0.0389	0.0389	2005-06	0.0331	0.0389	0.0383
1982-83	0.0377	0.0389	0.0389	2006-07	0.0401	0.0389	0.0382
1983-84	0.0389	0.0389	0.0389	2007-08	0.0421	0.0389	0.0382
1984-85	0.0336	0.0389	0.0388	2008-09	0.0398	0.0389	0.0382
1985-86	0.0374	0.0389	0.0388	2009-10	0.0461	0.0389	0.0382
1986-87	0.0552	0.0389	0.0388	2010-11	0.0433	0.0389	0.0381
1987-88	0.0644	0.0389	0.0387	2011-12	0.0526	0.0389	0.0381
1988-89	0.0715	0.0389	0.0387	2012-13	0.0574	0.0389	0.0381
1989-90	0.0740	0.0389	0.0387	2013-14	0.0585	0.0389	0.0381
1990-91	0.0637	0.0389	0.0387	2014-15	0.0549	0.0389	0.0380
1991-92	0.0669	0.0389	0.0386	2015-16	0.0555	0.0389	0.0380
1992-93	0.0723	0.0389	0.0386	2016-17	0.0628	0.0389	0.0380
1993-94	0.0755	0.0389	0.0386				

Tables 5.5, 5.6, and 5.7 provide the technical efficiency estimates for the three sectors, primary, secondary and tertiary respectively, for the study period from 1970-71 to 2016-17 derived from the three models estimated, viz., (i) panel data stochastic frontier time invariant model, (ii) panel data stochastic frontier time-varying model, and (iii) pooled data half-normal model.

Table 5.6: Technical Efficiency Estimates: Secondary Sector

Year	Pooled Half-Normal	Panel Time-Invariant	Panel Time-Varying	Year	Pooled Half-Normal	Panel Time-Invariant	Panel Time-Varying
1970-71	0.7334	0.9063	0.9040	1994-95	0.9391	0.9063	0.9035
1971-72	0.6943	0.9063	0.9040	1995-96	0.9462	0.9063	0.9035
1972-73	0.7237	0.9063	0.9039	1996-97	0.6492	0.9063	0.9035
1973-74	0.7467	0.9063	0.9039	1997-98	0.7201	0.9063	0.9035
1974-75	0.7536	0.9063	0.9039	1998-99	0.9011	0.9063	0.9034
1975-76	0.7800	0.9063	0.9039	1999-00	0.9133	0.9063	0.9034
1976-77	0.8075	0.9063	0.9039	2000-01	1.0000	0.9063	0.9034
1977-78	0.8838	0.9063	0.9038	2001-02	0.8583	0.9063	0.9034
1978-79	0.8736	0.9063	0.9038	2002-03	0.7899	0.9063	0.9034
1979-80	0.7851	0.9063	0.9038	2003-04	0.7070	0.9063	0.9033
1980-81	0.8547	0.9063	0.9038	2004-05	0.7507	0.9063	0.9033
1981-82	0.8092	0.9063	0.9038	2005-06	0.7578	0.9063	0.9033
1982-83	0.8925	0.9063	0.9037	2006-07	0.7834	0.9063	0.9033
1983-84	0.7083	0.9063	0.9037	2007-08	0.7740	0.9063	0.9033
1984-85	0.8753	0.9063	0.9037	2008-09	0.7512	0.9063	0.9033
1985-86	0.9279	0.9063	0.9037	2009-10	0.8166	0.9063	0.9032
1986-87	0.8376	0.9063	0.9037	2010-11	0.7843	0.9063	0.9032
1987-88	0.7339	0.9063	0.9037	2011-12	0.6835	0.9063	0.9032
1988-89	0.8514	0.9063	0.9036	2012-13	0.6863	0.9063	0.9032
1989-90	0.9658	0.9063	0.9036	2013-14	0.6908	0.9063	0.9032
1990-91	0.9596	0.9063	0.9036	2014-15	0.6976	0.9063	0.9031
1991-92	0.9862	0.9063	0.9036	2015-16	0.6665	0.9063	0.9031
1992-93	0.8758	0.9063	0.9036	2016-17	0.6608	0.9063	0.9031
1993-94	0.8772	0.9063	0.9035				

Table 5.7: Technical Efficiency Estimates: Tertiary Sector

Year	Pooled Half-Normal	Panel Time-Invariant	Panel Time-Varying	Year	Pooled Half-Normal	Panel Time-Invariant	Panel Time-Varying
1970-71	0.2662	0.1519	0.1490	1994-95	0.6574	0.1519	0.1476
1971-72	0.2515	0.1519	0.1490	1995-96	0.6718	0.1519	0.1476
1972-73	0.1278	0.1519	0.1489	1996-97	0.7510	0.1519	0.1475
1973-74	0.2647	0.1519	0.1489	1997-98	0.7907	0.1519	0.1474
1974-75	0.1448	0.1519	0.1488	1998-99	0.8629	0.1519	0.1474
1975-76	0.1626	0.1519	0.1487	1999-00	0.8052	0.1519	0.1473
1976-77	0.3927	0.1519	0.1487	2000-01	0.8129	0.1519	0.1473
1977-78	0.8080	0.1519	0.1486	2001-02	0.6496	0.1519	0.1472
1978-79	1.0000	0.1519	0.1486	2002-03	0.7036	0.1519	0.1471
1979-80	0.9315	0.1519	0.1485	2003-04	0.7010	0.1519	0.1471
1980-81	0.8203	0.1519	0.1484	2004-05	0.6351	0.1519	0.1470
1981-82	0.8963	0.1519	0.1484	2005-06	0.7382	0.1519	0.1470
1982-83	0.5175	0.1519	0.1483	2006-07	0.8131	0.1519	0.1469
1983-84	0.3876	0.1519	0.1483	2007-08	0.8557	0.1519	0.1468
1984-85	0.3681	0.1519	0.1482	2008-09	0.7869	0.1519	0.1468
1985-86	0.4218	0.1519	0.1481	2009-10	0.7970	0.1519	0.1467
1986-87	0.4542	0.1519	0.1481	2010-11	0.8171	0.1519	0.1467
1987-88	0.4651	0.1519	0.1480	2011-12	0.8874	0.1519	0.1466
1988-89	0.5399	0.1519	0.1480	2012-13	0.8903	0.1519	0.1465
1989-90	0.4859	0.1519	0.1479	2013-14	1.0000	0.1519	0.1465
1990-91	0.6204	0.1519	0.1478	2014-15	0.9615	0.1519	0.1464
1991-92	0.6533	0.1519	0.1478	2015-16	0.9757	0.1519	0.1464
1992-93	0.7161	0.1519	0.1477	2016-17	0.9822	0.1519	0.1463
1993-94	0.5990	0.1519	0.1477				

Fig. 5.1 provides a visual representation of these tables and brings out the patterns and the trends of the efficiency estimates. As the theory has already suggested, the panel data stochastic frontier time invariant model yields a constant estimate for each of the three sectors, and the panel data stochastic frontier time-varying decay model presents

smoothly falling estimates over the time; note that the latter model is statistically not different from the former one such that their mean values are very close to each other (as Table 5.8 shows). The mean technical efficiency estimates for the three sectors derived from these two models are: primary sector = 0.039; secondary sector = 0.906; and tertiary sector = 0.152. While the secondary sector performance goes well with the general expectation, the tertiary sector presents poor results, contrary to the expectation, and the primary sector remains as always the worst performer.

To be more precise, we have already seen that the time-varying decay model reduces to the time-invariant model of the Kerala power sector. Its implication that the sector-wise technical efficiency estimates of the Kerala power sector are independent of time, that they remain constant over time, is highly significant in that it may refer to a technically stagnant situation in energy efficiency. It goes without saying that this has immense policy implications. If we take the time-varying decay model into confidence, there is, though insignificant, a falling trend in the technical efficiency of all the three sectors (Fig. 5.1, third column).

The pooled data stochastic frontier half-normal model, which we use only for a comparative purpose, on the other hand, shows fluctuations in the estimates of all the three sectors. Both the primary and the tertiary sector estimates trend upwards over time through oscillations, whereas the secondary sector estimates show very high fluctuations, without any particular trend. It should be noted that a sharp fall in 2002-03 marks the primary sector estimates and a steep rise in 1977-78, followed by a fall around 1982-83, marks the tertiary sector estimates.

Fig. 5.2: Technical Efficiency Estimates (Sector- and Model-wise)

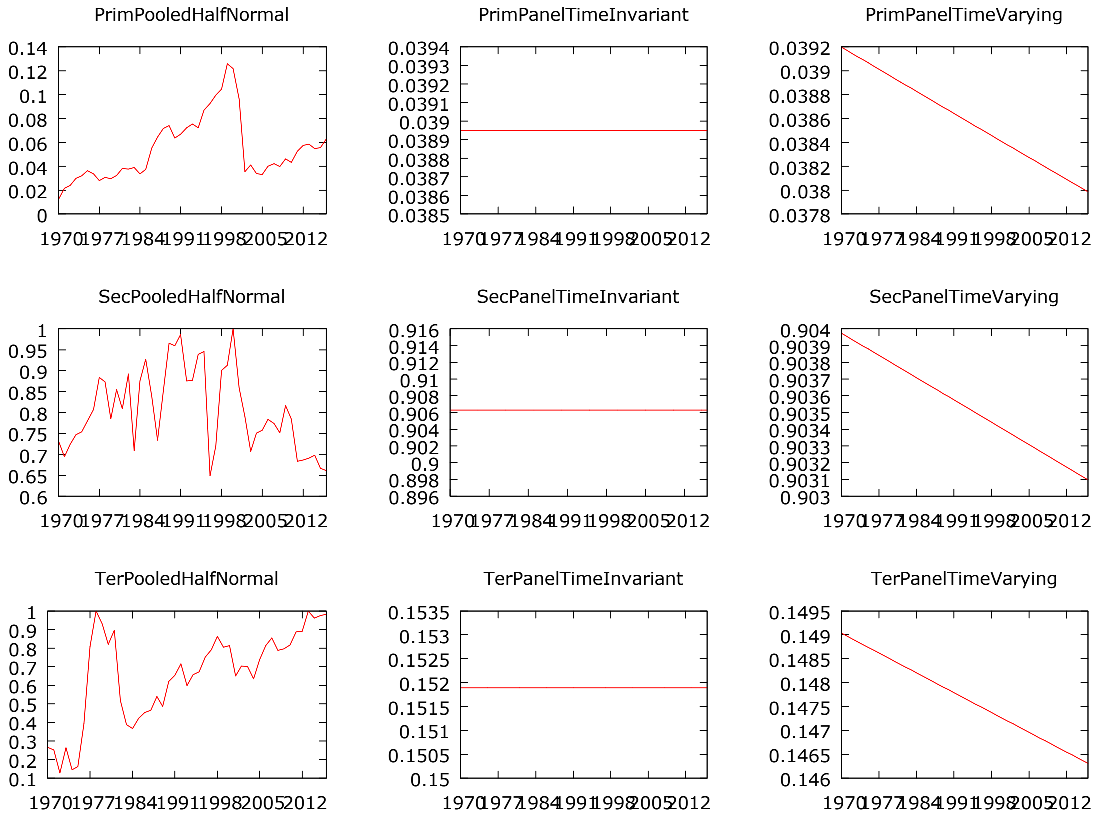


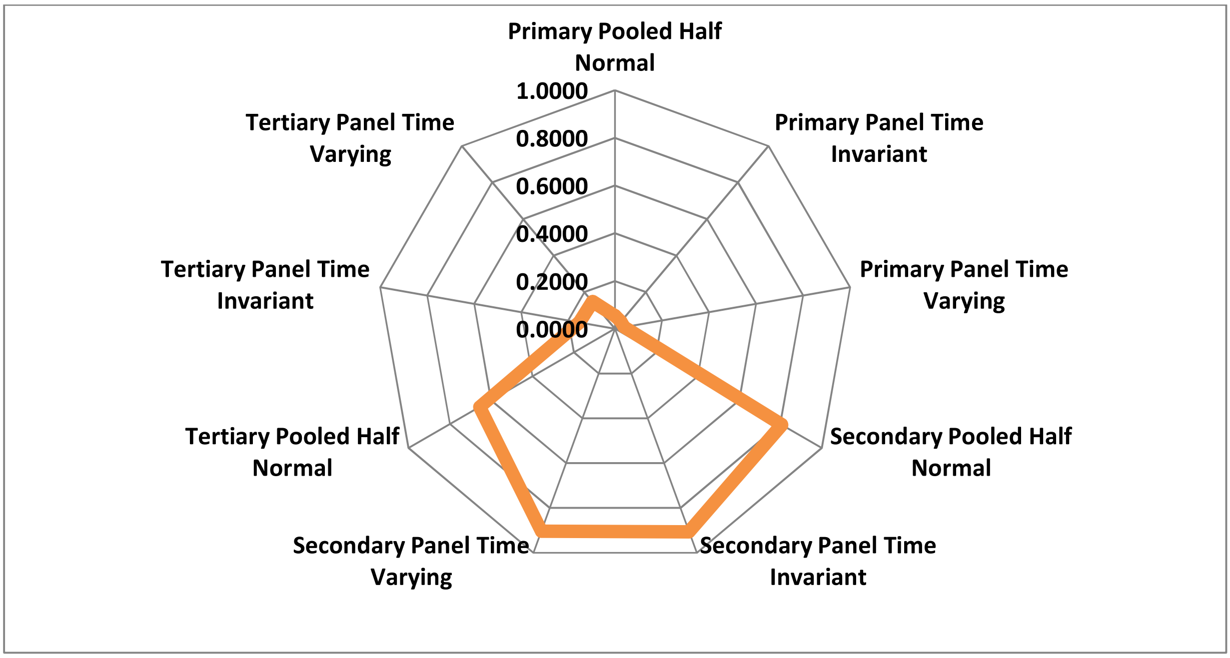
Table 5.8: Technical Efficiency Estimates: Summary Statistics

Sector	Model	Mean	Median	Minimum	Maximum	Std. Dev.	C.V.
Primary	Pooled Half Normal	0.0539	0.0433	0.0118	0.1258	0.0265	0.4919
	Panel Time Invariant	0.0390	0.0390	0.0390	0.0390	0	0
	Panel Time Varying	0.0386	0.0386	0.0380	0.0392	0.0004	0.0094
Secondary	Pooled Half Normal	0.8056	0.7852	0.6492	1	0.0964	0.1196
	Panel Time Invariant	0.9063	0.9063	0.9063	0.9063	0	0
	Panel Time Varying	0.9035	0.9035	0.9031	0.9040	0.0003	0.0003
Tertiary	Pooled Half Normal	0.6562	0.7036	0.1278	1	0.2452	0.3737
	Panel Time Invariant	0.1519	0.1519	0.1519	0.1519	0	0
	Panel Time Varying	0.1477	0.1477	0.1463	0.1490	0.0008	0.0055

Sector	Model	Skewness	Excess kurtosis	5% Percentile	95% Percentile	Inter-quartile range
Primary	Pooled Half Normal	0.9764	0.3304	0.0226	0.1149	0.0379
	Panel Time Invariant	undefined	undefined	0.03895	0.03895	0
	Panel Time Varying	0.0077	-1.2010	0.0380	0.0392	0.0006
Secondary	Pooled Half Normal	0.2721	-1.0031	0.6631	0.9781	0.1535
	Panel Time Invariant	undefined	undefined	0.90629	0.90629	0
	Panel Time Varying	-0.0030	-1.2011	0.9031	0.9040	0.0005
Tertiary	Pooled Half Normal	-0.5967	-0.6341	0.1519	0.9929	0.3552
	Panel Time Invariant	undefined	undefined	0.15189	0.15189	0
	Panel Time Varying	0.0031	-1.2011	0.1464	0.1490	0.0014

Table 5.8 reports the sector-wise summary statistics of the technical efficiency estimates for the three models under consideration. The pooled data stochastic frontier half-normal model stands apart from the other two models with much higher variation of the estimates, coming out of lower minimum and higher maximum values (the maximum being unity for secondary (in 2000-01) and tertiary sectors (1978-79 and 2013-14). Fig. 5.2 visualizes the sector-wise and model-wise mean values of these estimates. Further information is given in the appendix to this chapter.

Fig. 5.2: Mean Technical Efficiency Estimates (Sector- and Model-wise)



5.6 Conclusion

The present chapter has continued with our empirical exercise for the Kerala power sector in terms of the second approach, viz., multi-factor productivity analysis, with the stochastic frontier production function method. We have started with a general theoretical framework of frontier production function in general; and then introduced both the deterministic and stochastic frontiers. In our empirical exercise for the Kerala power sector, we have utilized the panel data stochastic frontier model, and for a comparative purpose only, we have also estimated a pooled data stochastic frontier model.

The panel data stochastic frontier model comes in two variants – (i) time-invariant inefficiency model and (ii) time-varying decay model; the former being the simplest specification. The empirical results for the two models show that the differentiating characteristic of the second model is insignificant and it reduces to the time-invariant model, yielding constant efficiency estimates over time. The sector-wise difference among these estimates is very high; while the secondary sector performance goes well with the general expectation (with an efficiency of 0.906), the tertiary sector presents poor results (0.152), contrary to the expectation, and the primary sector remains as always the worst performer (0.039). That the sector-wise technical efficiency estimates of the Kerala power sector are independent of time can significantly refer to a technically stagnant situation in energy efficiency. The implication of the time-varying decay model, even though statistically insignificant, of a falling trend in the technical efficiency of all the three sectors also is a hot matter of serious concerns. It goes without saying that this has immense policy implications, and we need to go a long way.

Appendix to Chapter 5

Fig. 5.A1: Technical Efficiency Estimates: Primary Sector (Time-variant Model)

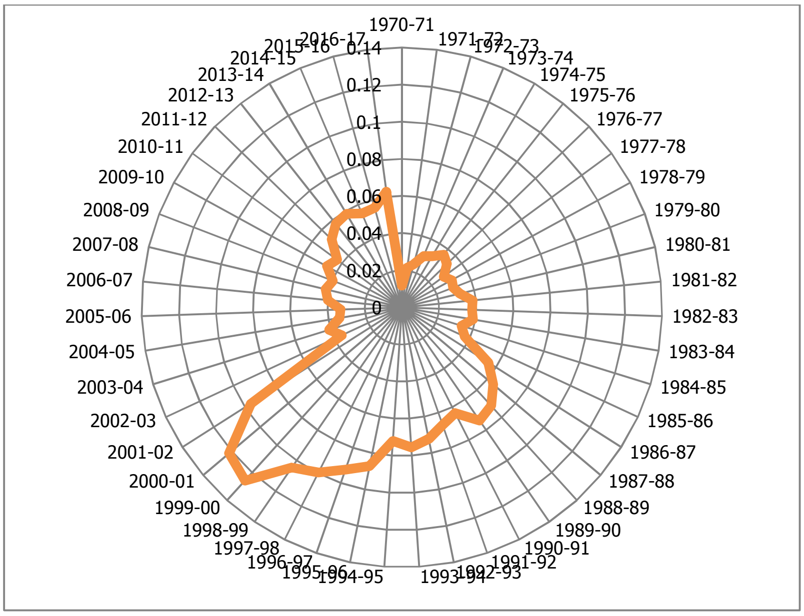


Table 5.A1: Technical Efficiency Estimates: (Time-variant Model)

```
Frequency distribution for Primary, obs 1-47
number of bins = 7, mean = 0.0539442, sd = 0.0265331
```

interval	midpt	frequency	rel.	cum.
< 0.021266	0.011764	1	2.13%	2.13%
0.021266 - 0.040271	0.030769	20	42.55%	44.68%
0.040271 - 0.059275	0.049773	10	21.28%	65.96%
0.059275 - 0.078280	0.068778	9	19.15%	85.11%
0.078280 - 0.097285	0.087782	3	6.38%	91.49%
0.097285 - 0.11629	0.10679	2	4.26%	95.74%
>= 0.11629	0.12579	2	4.26%	100.00%

Fig. 5.A2: Technical Efficiency Estimates: Secondary Sector (Time-variant Model)

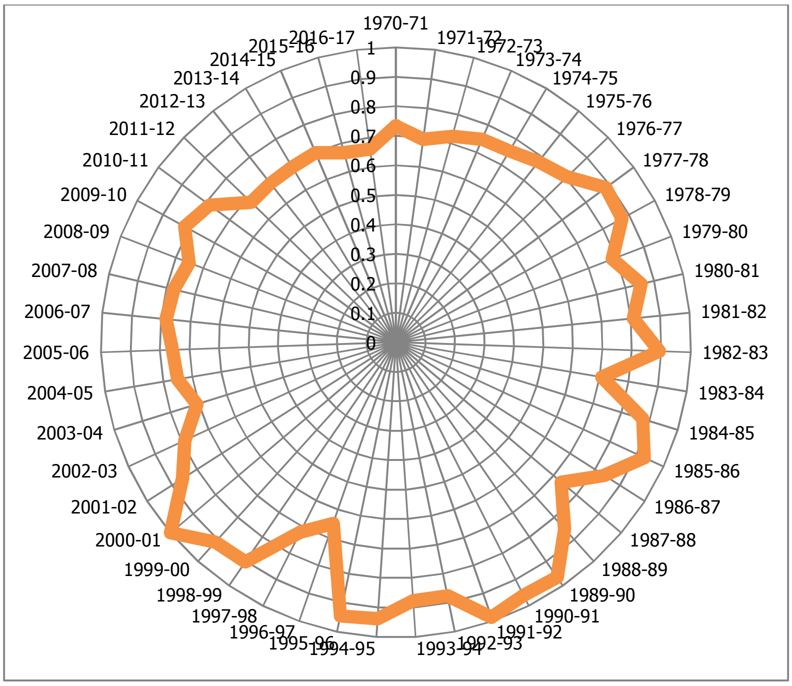


Table 5.A2: Technical Efficiency Estimates: (Time-variant Model)

```
Frequency distribution for Secondary, obs 1-47
number of bins = 7, mean = 0.805637, sd = 0.0963621

       interval          midpt    frequency    rel.      cum.

           < 0.67842    0.64918        3      6.38%     6.38%
   0.67842 - 0.73689    0.70765       11     23.40%    29.79%
   0.73689 - 0.79536    0.76612       11     23.40%    53.19%
   0.79536 - 0.85383    0.82459        5     10.64%    63.83%
   0.85383 - 0.91230    0.88306        9     19.15%    82.98%
   0.91230 - 0.97076    0.94153        6     12.77%    95.74%
          >= 0.97076    1.0000         2      4.26%   100.00%
```

Fig. 5.A3: Technical Efficiency Estimates: Tertiary Sector (Time-variant Model)

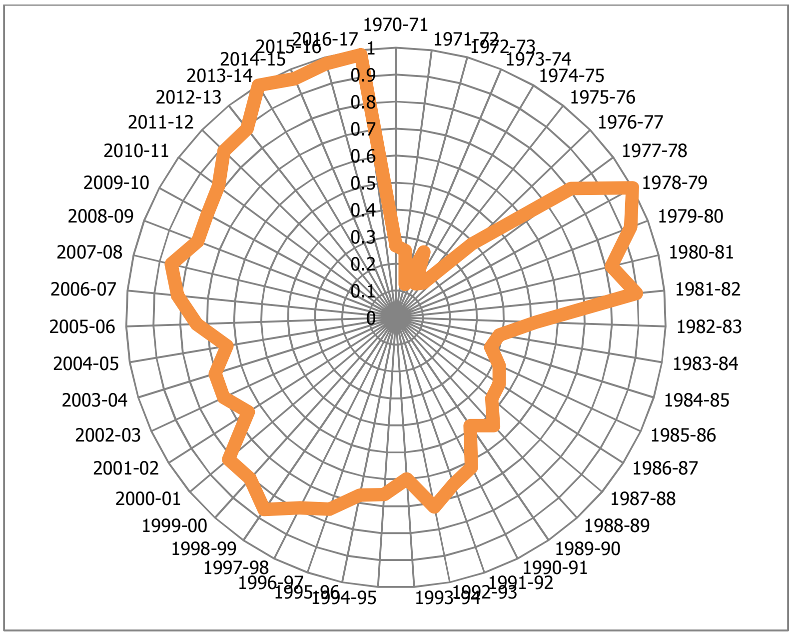


Table 5.A3: Technical Efficiency Estimates: (Time-variant Model)

```
Frequency distribution for Tertiary, obs 1-47
number of bins = 7, mean = 0.656195, sd = 0.245186

       interval          midpt   frequency    rel.     cum.

           < 0.20047   0.12779         3     6.38%    6.38%
   0.20047 - 0.34584   0.27316         3     6.38%   12.77%
   0.34584 - 0.49121   0.41852         7    14.89%   27.66%
   0.49121 - 0.63658   0.56389         5    10.64%   38.30%
   0.63658 - 0.78195   0.70926         9    19.15%   57.45%
   0.78195 - 0.92732   0.85463        14    29.79%   87.23%
          >= 0.92732   1.0000          6    12.77%  100.00%
```

Appendix B

Table 5.B1: Panel Data Regression results

```
Fixed-effects (within) regression               Number of obs      =       141
Group variable: sect                            Number of groups   =         3

R-sq:                                           Obs per group:
     within  = 0.8051                                         min =         47
     between = 0.0548                                         avg =       47.0
     overall = 0.1978                                         max =         47

                                                F(2,136)           =    280.82
corr(u_i, Xb)  = -0.3210                        Prob > F           =    0.0000

------------------------------------------------------------------------------
           e |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           y |   .3573911   .0537269     6.65   0.000     .2511429    .4636393
           n |   .4462498   .0545185     8.19   0.000     .3384361    .5540634
       _cons |  -3.877152   .4773492    -8.12   0.000    -4.821139   -2.933165
-------------+----------------------------------------------------------------
     sigma_u |  1.5828703
     sigma_e |  .32640377
         rho |  .95921183   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(2, 136) = 989.39                    Prob > F = 0.0000


Random-effects GLS regression                   Number of obs      =       141
Group variable: sect                            Number of groups   =         3

R-sq:                                           Obs per group:
     within  = 0.8005                                         min =         47
     between = 0.0689                                         avg =       47.0
     overall = 0.1993                                         max =         47

                                                Wald chi2(2)       =     34.36
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000

------------------------------------------------------------------------------
           e |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           y |   .1451635    .142425     1.02   0.308    -.1339843    .4243112
           n |   .2949346   .0689581     4.28   0.000     .1597792      .43009
       _cons |   1.194298   1.790664     0.67   0.505    -2.315339    4.703936
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |  .32640377
         rho |          0   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. hausman fe

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       fe           .          Difference          S.E.
-------------+----------------------------------------------------------------
           y |    .3573911     .1451635        .2122276               .
           n |    .4462498     .2949346        .1513152               .
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =   -30.63    chi2<0 ==> model fitted on these
                                        data fails to meet the asymptotic
                                        assumptions of the Hausman test;

Breusch and Pagan Lagrangian multiplier test for random effects

        e[sect,t] = Xb + u[sect] + e[sect,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                       e |   2.010001       1.417745
                       e |   .1065394       .3264038
                       u |          0              0

        Test:   Var(u) = 0
                             chibar2(01) =     0.00
                          Prob > chibar2 =   1.0000
```

Chapter 6

Measuring Energy Efficiency in Kerala: Data Envelopment Analysis

6.1 Introduction

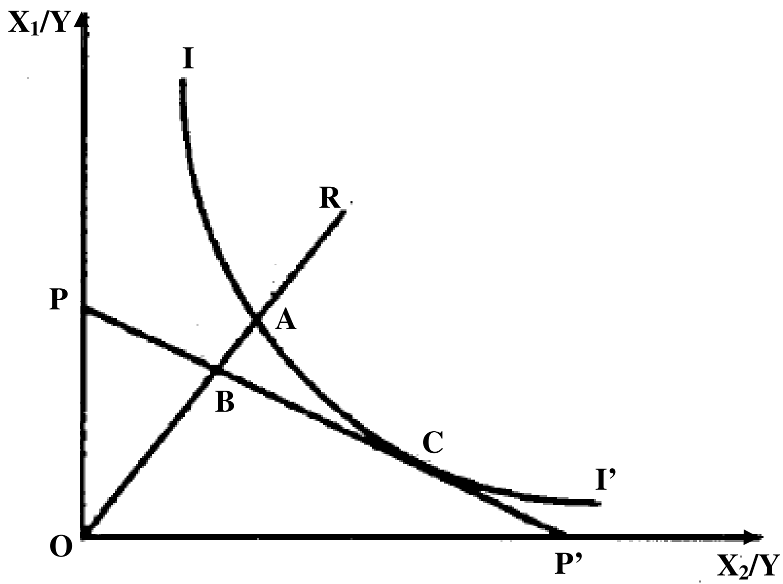
In this chapter we turn to the second approach in multi-factor productivity analysis, that is, the non-parametric mathematical programming method of data envelopment analysis. The chapter is structured in four parts. The next section presents the theoretical framework of data envelopment analysis (DEA) as a prelude to our empirical exercise for the Kerala power sector. Part three discusses the DEA results from the empirical study. The last section concludes the chapter.

6.2 Data Envelopment Analysis (DEA)

As already stated in the last chapter, it was Farrell (1957) who stimulated econometric modeling of production functions as frontiers. He decomposed the concept of economic efficiency (which he called overall efficiency) of a production unit into two components, viz., technical efficiency and allocative efficiency (which he called price efficiency); the former refers to the capability of the unit to produce maximum output from a given bundle of inputs, and the latter to the capability of the unit to utilize the inputs in an optimum proportion subject to the given input prices. He illustrated the concept using isoquant and price line (now called isocost line; these are the basic tools used in economic textbooks) implyng a production function of two inputs (X_1 and X_2) for a single output (Y), under the assumption of constant returns to scale. "'Returns to scale' describes the output response to a proportionate increase of all inputs. If output increases by the same proportion, returns to scale are constant for the range of input combinations under consideration. They are increasing if output increases by a greater proportion and decreasing if it increases by a smaller proportion." (Henderson and Quandt 1971: 79).

An isoquant is "the locus of all combinations of X_1 and X_2 which yield a specified output level", that is, Y^0, which is a parameter. (Henderson and Quandt 1971: 58). An isocost line is "the locus of input combinations that may be purchased for a specified total cost: $C^0 = r_1 X_1 + r_2 X_2 + b$" (Henderson and Quandt 1971: 63), where r_1 and the r_2 are the respective prices of the two inputs and b is the cost of the fixed inputs. The production unit is said to be in equilibrium at C, where the isoquant, II', is tangential to the price line (PP'). Thus the point C represents an efficient point.

Fig. 6.1: Farrel's Representation of Technical and Allocative Efficiencies



Note that Farrel used isoquant in a two-input space as an output frontier (maximum output) and hence all the points on the isoquant II' are technically efficient. Thus the points A and C are both technically efficient, but R is not. If a production unit is producing at point R, its technical inefficiency is given by the distance AR, which implies that the unit could proportionally reduce all inputs by this amount without reducing its output. This distance can also be represented in percentage terms by the ratio AR/OR. This allows us to measure the technical efficiency of the unit by one minus AR/OR, which is equal to the ratio OA/OR. Since this ratio lies between zero and one, it functions as a measure of the degree of technical efficiency of the production unit; a value of one means the unit is technically efficient, and a value close to zero means it is technically inefficient.

We have seen that the points A and C are both technically efficient; but there is some difference between them; this is in terms of allocative efficiency. Note that Farrel used price line in a two-input space as a cost frontier (minimum cost) and hence all the points on the price line PP' are allocatively efficient. Thus points B and C are both allocatively efficient. But C is also on the isoquant and hence is also technically efficient; Thus point C is both technically and allocatively efficient. But point A is only technically efficient, not allocatively.

If the unit is producing at point R, its allocative efficiency is given by the ratio OB/OA, because the distance BA can be taken as the fall in production costs corresponding to the production at the technically and allocatively efficient point C, rather than at the technically efficient, but allocatively inefficient, point A. The overall (economic) efficiency is then defined by the ratio OB/OR, the distance BR being taken as representing a cost reduction. This economic efficiency measure also is bounded by zero and unity. Also note that the overall (economic) efficiency at point R is obtained from the product of technical and allocative efficiency: (OA/OR)(OB/OA) = OB/OR.

As already noted, the efficiency of a production unit is measured in relation to an efficient isoquant (representing an efficient firm), which is in fact unknown and must be estimated using the sample data. For estimation, Farrell suggested (i) a non-parametric piecewise-linear convex isoquant, estimated from the data in such a way that no actual data point should lie to the left or below it, or (ii) a parametric frontier function, such as the Cobb-Douglas production function, estimated from the data in such a way that no actual data point should lie to the right or above it. The second of these we have employed in the last chapter, and the first one we are estimating in this chapter.

Very few researchers were enthused with Farrell's (1957) proposal of the piecewise-linear convex isoquant. Suggestions came up after a while from Boles (1966) and Afriat (1972) to employ mathematical programming methods that also failed in appeal. However, a new model, proposed by Charnes, Cooper and Rhodes (1978) by the name of 'data envelopment analysis (DEA)', immediately caught the fancy of the world and a large number of papers have followed it in applications and extensions. Charnes, Cooper and Rhodes (1978) assumed constant returns to scale (CRS), whereas Banker, Charnes and Cooper (1984) proposed a variable returns to scale (VRS) model. For detailed discussions, see Coelli, Rao, O'Donnell and Battese (2005) and Cooper, Seiford and Tone (2006).

"Data Envelopment Analysis (DEA) was accorded this name because of the way it "envelops" observations in order to identify a "frontier" that is used to evaluate observations representing the performances of all of the entities that are to be evaluated." (Cooper, Seiford and Tone 2006: xix). DEA is a linear programming technique that seeks to optimize an objective function subject to certain inequality constraints. Here the objective function relates to the frontier function of the production unit, called in the DEA literature as decision making unit (DMU). The model seeks to estimate for each DMU an efficiency measure in terms of weighted output-input ratio, which can be written in matrix notation as a'Yi/b'Xi, where the numerator is a weighted average of all the outputs of the ith DMU and the denominator is its weighted inputs, with a and b being column vectors of output and input weights respectively. Then the linear programming (LP) problem is to choose the optimal weights such as to maximize the efficiency measure (the weighted output-input ratio) subject to the constraints that this measure (ratio) is less than or equal to unity and the weights are non-negative:

$$\mathrm{Max}_{a,b}\,(a'Y_i / b'X_i),$$

$$\text{s t } a'Y_i / b'X_i \leq 1, \quad i = 1, 2, \ldots, N,$$

$$a, b \geq 0.$$

However, this formulation has a problem that it would yield an infinite number of solutions. This problem can be averted by adding another constraint that $\beta'X_i = 1$. Thus the above LP problem can be reformulated as

$$\mathrm{Max}_{\alpha,\beta}\,(\alpha'Y_i / \beta'X_i),$$

$$\text{s t } \beta'X_i = 1$$

$$\alpha'Y_i - \beta'X_i \leq 0, \quad i = 1, 2, \ldots, N,$$

$$\alpha, \beta \geq 0.$$

Note that the notations change from a and b to α and β to reflect the transformation, which is known as the multiplier form of the LP problem.

We can use the duality in LP to derive an equivalent envelopment form of the multiplier form problem:

$$\min_{\theta,\lambda} \theta,$$

$$\text{st} \quad -Y_i + y\lambda \geq 0,$$

$$\theta X_i - x\lambda \geq 0,$$

$$\lambda \geq 0,$$

where θ is a scalar representing the efficiency score for the ith DMU that satisfies $\theta \leq 1$, and λ is a column (Nx1) vector of constants. The advantage of this envelopment form is that it has fewer constraints than the multiplier form, and hence its appeal. A value of $\theta = 1$ means a point on the frontier representing a technically efficient DMU, according to the Farrell (1957) definition.

6.3 Data Envelopment Analysis: Empirical Results

For estimating the DEA frontier of the power sector in Kerala, we consider three sectors as above (Primary, Secondary and Tertiary) for the period from 1970-71 to 2016-17. As already indicated in the previous chapter, because of the data unavailability for estimating the usual output-input relationship, we propose the following relationship as in the last chapter:

> Sectoral energy consumption = *f*(Sectoral number of consumers; Sectoral GSDP at constant 2011-12 prices); all variables in log.

Note that unlike the usual frontier function with factors of production, we have a frontier isoquant with two activity factors and one output.

For estimating DEA, we have made use of a Stata module for DEA, provided by Yong-bae Ji and Choonjoo Lee, (2010).

Tables 6.1 – 6.3 report the DEA estimates of efficiency measures for the three sectors under the two scale assumptions of constant returns to scale (CRS) and variable returns to scale (VRS); the latter includes both increasing (IRS) and decreasing returns to scale (DRS). Thus we examine whether the observed performance of the sectors in each year is along the frontier corresponding to a particular returns to scale. Scale efficiency measures are also given; scale efficiency denotes whether a firm is operating at its optimal size or not, implying degrees of capacity utilization. If the firm is in underutlization, then using information on increasing or decreasing returns to scale, we can find out whether the firm is too large or too small.

Table 6.1: DEA Efficiency Estimates – Primary Sector

Year	CRS	VRS	NIRS	Scale	RTS	Year	CRS	VRS	NIRS	Scale	RTS
1970-71	0.519	0.519	1.000	0.999	IRS	1994-95	0.691	0.696	0.696	0.992	IRS
1971-72	0.595	0.596	0.970	0.998	IRS	1995-96	0.712	0.717	0.717	0.994	IRS
1972-73	0.601	0.603	0.851	0.997	IRS	1996-97	0.720	0.725	0.725	0.993	IRS
1973-74	0.622	0.624	0.798	0.996	IRS	1997-98	0.728	0.731	0.731	0.996	IRS
1974-75	0.625	0.628	0.741	0.995	IRS	1998-99	0.734	0.737	0.737	0.996	IRS
1975-76	0.635	0.638	0.701	0.994	IRS	1999-00	0.754	0.757	0.757	0.996	IRS
1976-77	0.609	0.613	0.613	0.993	IRS	2000-01	0.750	0.753	0.753	0.996	IRS
1977-78	0.581	0.585	0.585	0.993	IRS	2001-02	0.723	0.726	0.726	0.996	IRS
1978-79	0.588	0.593	0.593	0.993	IRS	2002-03	0.607	0.610	0.610	0.996	IRS
1979-80	0.578	0.583	0.583	0.992	IRS	2003-04	0.624	0.626	0.626	0.996	IRS
1980-81	0.588	0.592	0.592	0.993	IRS	2004-05	0.606	0.609	0.609	0.994	IRS
1981-82	0.604	0.607	0.607	0.995	IRS	2005-06	0.603	0.607	0.607	0.993	IRS
1982-83	0.602	0.604	0.604	0.997	IRS	2006-07	0.624	0.626	0.626	0.996	IRS
1983-84	0.604	0.604	0.604	0.999	IRS	2007-08	0.629	0.632	0.632	0.996	IRS
1984-85	0.588	0.589	0.589	0.999	IRS	2008-09	0.624	0.628	0.628	0.994	IRS
1985-86	0.603	0.603	0.603	0.999	IRS	2009-10	0.640	0.643	0.643	0.995	IRS
1986-87	0.648	0.649	0.649	0.999	IRS	2010-11	0.632	0.634	0.634	0.996	IRS
1987-88	0.668	0.668	0.668	0.999	IRS	2011-12	0.655	0.658	0.658	0.996	IRS
1988-89	0.683	0.684	0.684	0.998	IRS	2012-13	0.664	0.667	0.667	0.996	IRS
1989-90	0.686	0.688	0.688	0.998	IRS	2013-14	0.666	0.669	0.669	0.996	IRS
1990-91	0.671	0.673	0.673	0.997	IRS	2014-15	0.660	0.662	0.662	0.996	IRS
1991-92	0.678	0.679	0.679	0.997	IRS	2015-16	0.658	0.661	0.661	0.996	IRS
1992-93	0.687	0.689	0.689	0.997	IRS	2016-17	0.673	0.676	0.676	0.996	IRS
1993-94	0.694	0.698	0.698	0.995	IRS						

Note: CRS = Constant returns to scale; VRS = Variable returns to scale; NIRS = Non-increasing returns to scale; RTS = Returns to scale; Scale = Scale efficiency.

Table 6.1 shows that energy efficiency in the primary sector is much lower than in the other two sectors; the scale efficiency is below, but close to, optimum. Surprisingly, the sector during the entire period is found to be in IRS stage.

Table 6.2: DEA Efficiency Estimates – Secondary Sector

Year	CRS	VRS	NIRS	Scale	RTS	Year	CRS	VRS	NIRS	Scale	RTS
1970-71	1.000	1.000	1.000	1.000	CRS	1994-95	0.995	0.998	0.998	0.997	DRS
1971-72	0.988	0.988	0.988	1.000	IRS	1995-96	0.997	1.000	1.000	0.997	DRS
1972-73	0.993	0.994	0.994	0.999	DRS	1996-97	0.948	0.950	0.950	0.997	IRS
1973-74	0.991	0.991	0.991	1.000	IRS	1997-98	0.960	0.962	0.962	0.998	IRS
1974-75	0.987	0.987	0.987	1.000	CRS	1998-99	0.987	0.990	0.990	0.997	DRS
1975-76	0.989	0.989	0.989	1.000	CRS	1999-00	0.988	0.991	0.991	0.997	DRS
1976-77	0.986	0.988	0.986	0.999	IRS	2000-01	0.999	1.000	1.000	0.999	DRS
1977-78	1.000	1.000	1.000	1.000	CRS	2001-02	0.981	0.985	0.985	0.996	DRS
1978-79	0.998	0.998	0.998	1.000	IRS	2002-03	0.973	0.979	0.979	0.994	DRS
1979-80	0.983	0.983	0.983	1.000	IRS	2003-04	0.961	0.968	0.968	0.992	DRS
1980-81	0.995	0.997	0.997	0.997	DRS	2004-05	0.971	0.981	0.981	0.990	DRS
1981-82	0.985	0.986	0.986	0.999	IRS	2005-06	0.973	0.984	0.984	0.989	DRS
1982-83	0.992	0.993	0.992	0.999	IRS	2006-07	0.978	0.990	0.990	0.987	DRS
1983-84	0.968	0.969	0.969	0.998	IRS	2007-08	0.979	0.992	0.992	0.987	DRS
1984-85	0.994	0.995	0.995	0.999	DRS	2008-09	0.976	0.988	0.988	0.988	DRS
1985-86	1.000	1.000	1.000	1.000	DRS	2009-10	0.988	1.000	1.000	0.988	DRS
1986-87	0.981	0.986	0.981	0.995	IRS	2010-11	0.987	0.999	0.999	0.987	DRS
1987-88	0.963	0.968	0.963	0.996	IRS	2011-12	0.985	0.998	0.998	0.987	DRS
1988-89	0.982	0.985	0.982	0.997	IRS	2012-13	0.987	1.000	1.000	0.987	DRS
1989-90	1.000	1.000	1.000	1.000	CRS	2013-14	0.986	0.999	0.999	0.987	DRS
1990-91	0.997	0.997	0.997	1.000	IRS	2014-15	0.987	1.000	1.000	0.987	DRS
1991-92	1.000	1.000	1.000	1.000	CRS	2015-16	0.988	1.000	1.000	0.988	DRS
1992-93	0.986	0.986	0.986	0.999	IRS	2016-17	0.986	1.000	1.000	0.986	DRS
1993-94	0.986	0.988	0.988	0.998	DRS						

Note: CRS = Constant returns to scale; VRS = Variable returns to scale; NIRS = Non-increasing returns to scale; DRS = decreasing returns to scale; RTS = Returns to scale; Scale = Scale efficiency.

However, the story is different for the other two sectors. Table 6.2 shows that energy efficiency in the secondary sector is the highest for all the years, its performance in a number of years being on or very close to the frontier; so is the scale efficiency also. However, the returns to scale registers a variable pattern: in the initial years, the sector mostly experienced IRS or CRS, whereas from the late 1990s the sector fell in the stage of DRS.

Table 6.3: DEA Efficiency Estimates – Tertiary Sector

Year	CRS	VRS	NIRS	Scale	RTS	Year	CRS	VRS	NIRS	Scale	RTS
1970-71	0.830	0.832	0.830	0.998	IRS	1994-95	0.946	0.953	0.966	0.993	DRS
1971-72	0.823	0.824	0.823	0.999	IRS	1995-96	0.948	0.956	0.969	0.992	DRS
1972-73	0.737	0.737	0.737	0.999	IRS	1996-97	0.961	0.969	0.982	0.992	DRS
1973-74	0.830	0.831	0.830	0.999	IRS	1997-98	0.967	0.975	0.989	0.992	DRS
1974-75	0.753	0.754	0.753	0.999	IRS	1998-99	0.976	0.985	1.000	0.991	DRS
1975-76	0.769	0.769	0.775	1.000	CRS	1999-00	0.968	0.977	0.986	0.991	DRS
1976-77	0.881	0.882	0.881	1.000	IRS	2000-01	0.969	0.978	0.989	0.991	DRS
1977-78	0.973	0.973	0.973	1.000	IRS	2001-02	0.944	0.953	0.963	0.991	DRS
1978-79	1.000	1.000	1.000	1.000	CRS	2002-03	0.953	0.962	0.972	0.990	DRS
1979-80	0.991	0.991	0.995	1.000	IRS	2003-04	0.952	0.962	0.976	0.990	DRS
1980-81	0.975	0.976	0.982	0.999	IRS	2004-05	0.941	0.951	0.960	0.990	DRS
1981-82	0.986	0.988	1.000	0.999	DRS	2005-06	0.958	0.968	0.977	0.990	DRS
1982-83	0.918	0.920	0.933	0.998	IRS	2006-07	0.968	0.978	0.986	0.989	DRS
1983-84	0.882	0.884	0.901	0.998	IRS	2007-08	0.973	0.984	0.988	0.989	DRS
1984-85	0.876	0.878	0.893	0.998	IRS	2008-09	0.964	0.975	0.978	0.989	DRS
1985-86	0.893	0.895	0.919	0.998	IRS	2009-10	0.965	0.976	0.978	0.989	DRS
1986-87	0.903	0.905	0.934	0.998	IRS	2010-11	0.968	0.979	0.981	0.989	DRS
1987-88	0.906	0.908	0.938	0.997	IRS	2011-12	0.976	0.988	0.990	0.989	DRS
1988-89	0.924	0.927	0.961	0.997	IRS	2012-13	0.977	0.988	0.988	0.989	DRS
1989-90	0.912	0.915	0.947	0.997	IRS	2013-14	0.988	1.000	1.000	0.988	DRS
1990-91	0.941	0.945	0.980	0.996	IRS	2014-15	0.984	0.996	0.996	0.988	DRS
1991-92	0.948	0.952	1.000	0.996	IRS	2015-16	0.986	0.999	0.999	0.987	DRS
1992-93	0.959	0.963	1.000	0.996	DRS	2016-17	0.986	1.000	1.000	0.986	DRS
1993-94	0.935	0.942	0.954	0.993	DRS						

Note: CRS = Constant returns to scale; VRS = Variable returns to scale; NIRS = Non-increasing returns to scale; DRS = decreasing returns to scale; RTS = Returns to scale; Scale = Scale efficiency.

The tertiary sector comes second to the secondary sector in terms of efficiency performance, being close to the frontier for a few years (Table 6.3). In scale efficiency, the same pattern as in the secondary sector holds here, the fall into DRS, however, starting from the early 1990s.

Fig. 6.2: DEA Efficiency Estimates – Primary Sector- Model-wise

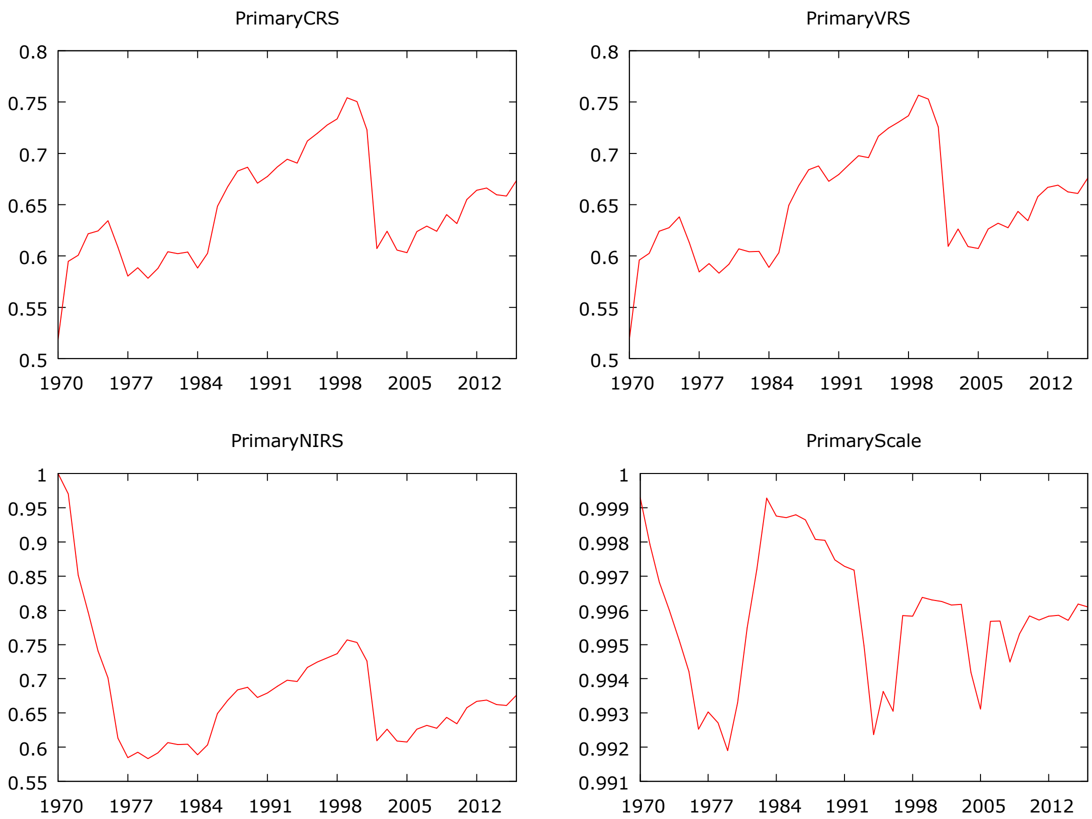


Fig. 6.3: DEA Efficiency Estimates – Secondary Sector- Model-wise

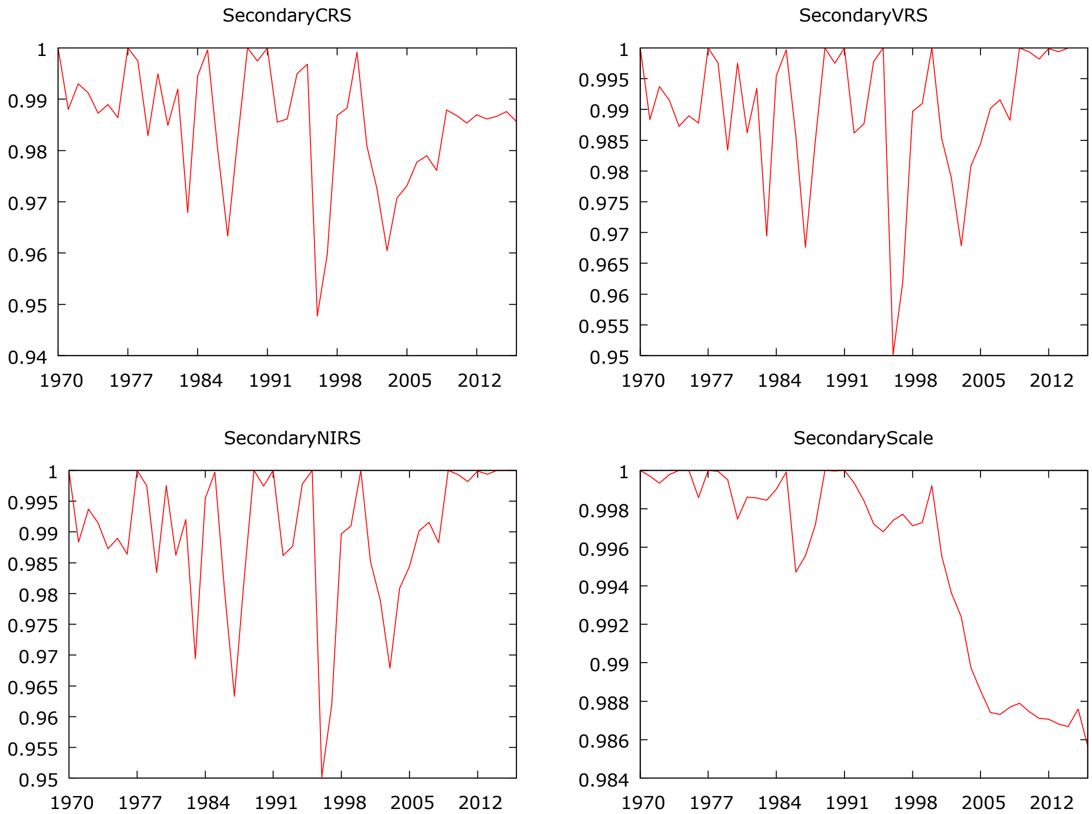


Fig. 6.4: DEA Efficiency Estimates – Tertiary Sector- Model-wise

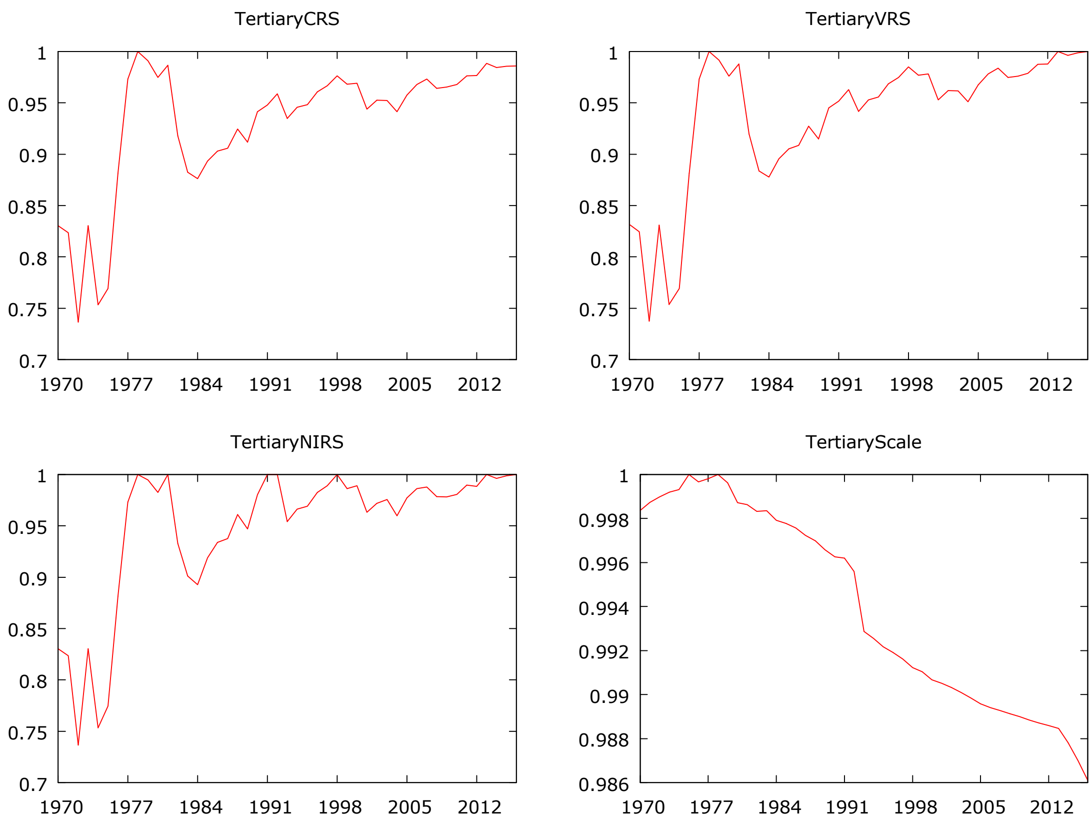
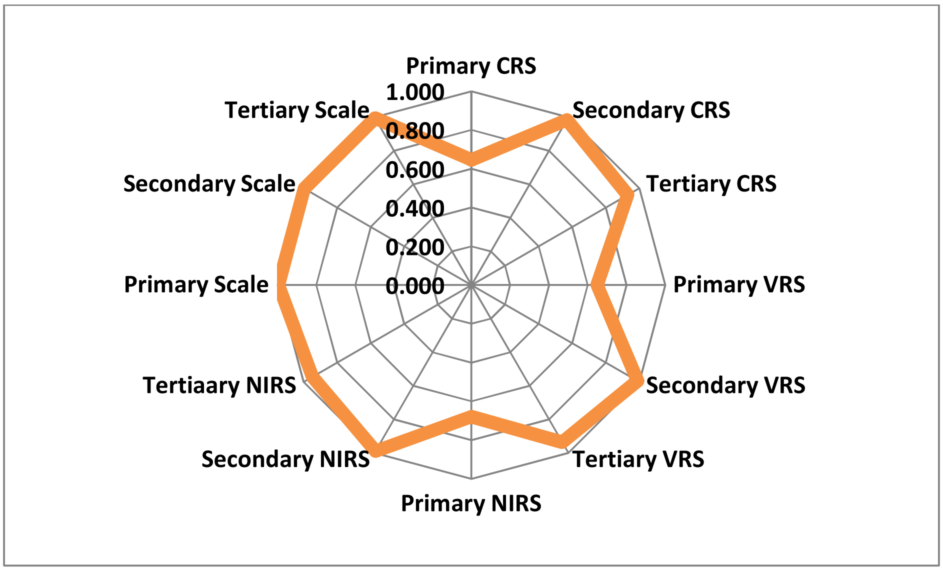


Table 6.4: DEA Efficiency Estimates – Summary Statistics

Variable	Mean	Median	Minimum	Maximum	Std. Dev.	C.V.	Skewness	Ex. kurtosis	5% Perc.	95% Perc.	IQ range
Primary CRS	0.645	0.635	0.519	0.754	0.052	0.080	0.221	-0.368	0.579	0.744	0.079
Primary VRS	0.648	0.638	0.519	0.757	0.052	0.080	0.218	-0.329	0.584	0.746	0.077
Primary NIRS	0.679	0.667	0.583	1	0.088	0.130	1.881	4.171	0.586	0.923	0.107
Primary Scale	0.996	0.996	0.992	0.999	0.002	0.002	-0.153	-0.638	0.992	0.999	0.003
Secondary CRS	0.985	0.987	0.948	1	0.012	0.012	-1.065	1.076	0.960	1	0.014
Secondary VRS	0.990	0.991	0.950	1	0.011	0.011	-1.521	2.289	0.964	1	0.014
Secondary NIRS	0.990	0.991	0.950	1	0.012	0.012	-1.449	1.927	0.962	1	0.014
Secondary Scale	0.995	0.997	0.986	1	0.005	0.005	-0.740	-1.151	0.987	1	0.011
Tertiary CRS	0.931	0.953	0.737	1	0.064	0.069	-1.584	1.824	0.760	0.990	0.067
Tertiary VRS	0.937	0.962	0.737	1	0.067	0.071	-1.538	1.624	0.760	1	0.070
Tertiary NIRS	0.948	0.977	0.737	1	0.068	0.072	-1.772	2.186	0.762	1	0.055
Tertiary Scale	0.994	0.993	0.986	1	0.004	0.005	-0.060	-1.590	0.987	0.9999	0.009

Fig. 6.5: Mean DEA Efficiency Estimates – Sector- and Model-wise



6.4 Conclusion

In this chapter we have taken up the non-parametric mathematical programming method of data envelopment analysis, the second approach in multi-factor productivity analysis. We have started with the theoretical framework of data envelopment analysis (DEA) as a prelude to our empirical exercise for the Kerala power sector. This approach originated with Farrell who decomposed the concept of economic efficiency (overall efficiency) of a production unit into two components, viz., technical efficiency and allocative efficiency (price efficiency); for illustrating this approach, he used the usual economic concepts of isoquant and price line (isocost line) involving a production function of two inputs and one output under the assumption of constant returns to scale.

In this context, for measuring the unknown efficiency of a production unit in relation to an efficient isoquant (representing an efficient firm) using the sample data, Farrell suggested (i) a non-parametric piecewise-linear convex isoquant, or (ii) a parametric frontier function, such as the Cobb-Douglas production function. The second of these we have employed in the last chapter, and the first one in this chapter.

The non-parametric linear programming data envelopment analysis (DEA) was proposed by Charnes, Cooper and Rhodes (1978), which paved the way for a large number of papers in applications and extensions. DEA model has two variants, one under the assumption of constant returns to scale (CRS), and the other under variable returns to scale (VRS) assumption. One advantage of this approach is that it can be used for multiple output-multiple input cases, unlike in the parametric production function analysis.

Following the theoretical framework, we have turned to estimating the DEA frontier of the power sector in Kerala, considering three sectors as in the earlier chapters (Primary, Secondary and Tertiary) for the period from 1970-71 to 2016-17. As in the previous chapter, we have used the sectoral energy consumption as a function of sectoral number of consumers and sectoral GSDP at constant 2011-12 prices (all variables taken in log), unlike the usual frontier function with factors of production, to represent frontier isoquant with two activity factors and one output. For estimating our DEA, we have made use of a Stata module for DEA, provided by Chonjoo Lee and Ji Yong-Bae (2009).

We have estimated the efficiency measures for the three sectors under the two scale assumptions of constant returns to scale (CRS) and variable returns to scale (VRS); t he latter includes both increasing (IRS) and decreasing returns to scale (DRS). Scale efficiency measures are also given to find out whether a firm is operating at its optimal size or not, implying degrees of capacity utilization.

The results have shown that energy efficiency in the primary sector is much lower than in the other two sectors; the scale efficiency is below, but close to, optimum. Surprisingly, the primary sector during the entire period is found to be in IRS stage. The secondary sector is found to have the highest energy efficiency scores for all the years, its performance in a number of years being on or very close to the frontier; the scale efficiency also faring similarly. Coming to the returns to scale, the sector mostly experienced IRS or CRS in the initial years, whereas from the late 1990s the sector fell in the stage of DRS. The tertiary sector follows the secondary sector in terms of efficiency performance, being close to the frontier for a few years. After the initial years of mostly IRS, the sector fell into DRS, starting from the early 1990s.

Chapter 7
The Way Forward

7.1 Introduction

An ambitious project, this study is first of its kind in India in that

(i) it contains a comprehensive documentation of conceptualization of energy productivity,

(ii) as well as a comprehensive documentation of analytical methods of measuring energy productivity;

(iii) it utilizes all the three important methods of measuring energy productivity: logarithmic mean Divisia index decomposition method under single factor productivity approach; and both parametric (stochastic production frontier) and non-parametric (data envelopment analysis) under multi-factor productivity approach; and

(iv) it utilizes logarithmic mean Divisia index decomposition method for energy efficiency simulation purposes.

However, we have soon experienced a lot of difficulties in respect of the very fundamental requirement for the successful completion of the project in terms of the required and suitable data and other information, which we will discuss in detail below, after the section on a summary.

7.2 Summary

We have started out attempt at a comprehensive documentation of the techno-economic conceptualization of energy productivity with a discussion of the energy efficiency indicators in terms of its conceptual definition. Defining energy efficiency in the Patterson's sense of useful output per unit of input leads us to define energy efficiency also as an increase in net benefits per unit of energy. This helps us differentiate between energy efficiency and energy conservation, which is an important complement to the former. Energy conservation is defined in terms of reduction in total energy use, which can happen in two ways: one representing efficiency-improving energy conservation, where energy savings go along with an increase in net benefits per unit of energy use; and the other representing efficiency-reducing energy conservation, where energy savings results in a decrease in net benefits per unit of energy use.

In this background, we have then turned to a brief discussion of the laws of conservation of mass and thermodynamics and of some of the important earlier studies on energy-economic growth relationship. Following this, light is thrown onto energy efficiency indicators at different aggregation levels, presented in a pyramidal structure, and onto the determinants of energy efficiency indicators. It is generally believed that energy consumption is essentially determined by three effects, viz., activity, structure and intensity. A detailed illustration of this for the bottom micro-level sectors also is provided thereafter. For example, the residential or domestic sector consists of a number of subsectors such as space heating/cooling, water heating, cooking, lighting, appliances, etc. Activity in each subsector is measured in terms of the corresponding population or number of households; structure in the case of space heating/cooling and lighting is defined in terms of floor area per capita and intensity in terms of energy per square feet floor area. We have then introduced a conceptual framework to be utilized in our empirical exercise in the later chapters.

After the documentation of the conceptualization of energy productivity, we have then attempted at a comprehensive documentation of the analytical methods of its measurement. We have started with an introduction to a comprehensive list of the estimation methods of energy productivity indicators. In general these methods can be grouped under three heads: traditional single factor productivity analysis, decomposition analysis and multi-factor productivity analysis. This second document contains the first two approaches only, the theoretical framework of the multi-factor productivity analysis being left for the later chapters.

The traditional indicators as identified by Patterson to monitor changes in energy efficiency are in terms of thermodynamic, physical-thermodynamic, economic-thermodynamic and economic indicators. The last one, in which output is measured in terms of economic value (Rs) and energy input in thermodynamic terms, is the commonly used indicator. When we analyze the indicator in terms of energy intensity changes, the corresponding index falls under two major decomposition methods, namely, structural decomposition analysis and index decomposition analysis. We have discussed in detail the structural decomposition analysis in terms of its two approaches, viz., input-output method and neo-classical production function method; the problems and limitations of these approaches are also considered. We have then turned to the index decomposition analysis in terms of Laspeyres' and Divisia indices. The discussion is finally zeroed in on the Logarithmic Mean Divisia index (LMDI), the recently developed method that has captured wider popularity in applied studies.

In the first core chapter of the Report, we have applied the index decomposition analysis to measure energy productivity in Kerala in terms of the Logarithmic Mean Divisia Index (LMDI) method. This method helps us to decompose the changes in energy consumption over time into three different effects of activity, structure and intensity. As already indicated, non-availability of suitable time-series data for Kerala has forced us to limit our ambition down to an empirical decomposition exercise for Kerala in terms of only two sectors, power and petroleum, that too, for a limited period (from 2007-08 to 2016-17); first we have analysed the two sectors of power and petroleum separately, and then the combined sector has been analysed for decomposition.

Note that energy conservation means the energy consumption change be less than unity; this in turn requires the combined effect of activity, structure and intensity be less than unity. The activity effect is expected to be greater than unity; since unity minus activity effect represents the growth rate of the economic activity (here the real GSDP), and higher the growth rate, greater the social benefit. Hence, we have to take the activity effect as given. This in turn requires that given the activity effect, the combined effect of structure and intensity must more than compensate the activity effect in order for an effective energy conservation. That is, the combined effect of structure and intensity must be sufficiently smaller. The empirical exercise for Kerala power sector shows that this was possible only for two years during the study period (from 2007-08 to 2016-17). Energy consumption reduced by about 9% in 2008-09 over 2007-08 and nearly 5% in 2013-14 over the previous year.

It is significant to note that energy intensity in the power sector reduced in all but one year: 2013-14 over 2012-13, thanks to energy efficiency improvements; and this lies behind the energy use reduction in the two years of 2008-09 and 2013-14; no energy efficiency improvement means that consumption would have increased. Thus in these two years, social benefit increased along with positive energy conservation. That this occurred only for two years is explained by the performance of the other component, structure effect, that was greater than unity in all but one year (2008-09 over 2007-08).

In short, despite energy intensity reduction thanks to energy efficiency improvement in the power sector of Kerala for a number of recent years, energy conservation along with increased social benefit (real GSDP) could not be achieved because of the anomaly in the real GSDP structure (composition of sectoral shares). If the current state of nature dictates this activity structure as given, then the only recourse for energy conservation is through higher levels of energy efficiency improvement for greater reduction in intensity.

The results for the petroleum sector (with only two sectors, secondary and tertiary), however, show that no year witnessed energy conservation effort in this sector. This is despite energy intensity reduction (thanks to energy efficiency improvement) in all but two years. The structure effect was less than unity only for three years. Their combined effect was incapable of containing the activity effects of the secondary and tertiary sectors for occasioning any energy conservation. Such performance of the petroleum sector has overshadowed that of the power sector, and the combined sector of energy in Kerala has shown almost similar results as the petroleum sector, with the net result that the energy consumption increased in all the years under consideration.

Following this, we have then turned to a simulation analysis for energy consumption in Kerala under different scenarios that offer energy savings. This exercise shows some strange results, emanating from the peculiar characteristics of the petroleum sector in Kerala. As already remarked earlier, the petroleum consumption data relating only to the secondary and tertiary sub-sectors, the less-efficient petroleum sector overweighs the combined energy sector of Kerala to such an extent that the energy-efficiency potential of these two sub-sectors gets clouded. In this situation, the simulation with an assumption of a small reduction in the real GSDP shares of secondary and tertiary sectors yields greater energy conservation. A sufficiently high degree of energy efficiency in the petroleum sector can indeed reverse this anomaly.

After the index decomposition analysis, we have turned to the second approach, viz., multi-factor productivity analysis, with the stochastic frontier production function method. We have started with a general theoretical framework of frontier production function in general; and then introduced both the deterministic and stochastic frontiers. In our empirical exercise for the Kerala power sector, we have utilized the panel data stochastic frontier model, and for a comparative purpose only, we have also estimated a pooled data stochastic frontier model.

The panel data stochastic frontier model comes in two variants – (i) time-invariant inefficiency model and (ii) time-varying decay model; the former being the simplest specification. The empirical results for the two models show that the differentiating characteristic of the second model is insignificant and it reduces to the time-invariant model, yielding constant efficiency estimates over time. The sector-wise difference among these estimates is very high; while the secondary sector performance goes well with the general expectation (with an efficiency of 0.906), the tertiary sector presents poor results (0.152), contrary to the expectation, and the primary sector remains as always the worst performer (0.039). That the sector-wise technical efficiency estimates of the Kerala power sector are independent of time can significantly refer to a technically stagnant situation in energy efficiency. The implication of the time-varying decay model, even though statistically insignificant, of a falling trend in the technical efficiency of all the three sectors also is a hot matter of serious concerns. It goes without saying that this has immense policy implications, and we need to go a long way.

After the parametric approach comes up the non-parametric mathematical programming method of data envelopment analysis, the second approach in multi-factor productivity analysis. We have started with the theoretical framework of data envelopment analysis (DEA) as a prelude to our empirical exercise for the Kerala power sector. This approach originated with Farrell who decomposed the concept of economic efficiency (overall efficiency) of a production unit into two components, viz., technical efficiency and allocative efficiency (price efficiency); for illustrating this approach, he used the usual economic concepts of isoquant and price line (isocost line) involving a production function of two inputs and one output under the assumption of constant returns to scale.

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7.3 Limitations, Scope for Further Research and Data Required

As already indicated, the major problem that we experienced during the execution of this project was availability and suitability of the required data for Kerala. But for this, we could have successfully carried out our ambitious study in its fulsome. This has indeed precluded us from meeting some of the ancillary objectives such as (i) to estimate the State's potential to meet the power demand, factoring in energy efficiency enhancement and renewable energy based electricity generation; (ii) to assess the positive effects of energy efficiency on investment; (iii) to draw up an action plan and road map of supply side and sector-wise demand side management strategies for enhancing energy productivity; (iv) to propose an impact analysis of structural and regulatory reforms in energy sector; and (v) tp plan to conduct some case studies to establish relationship between energy efficiency improvement and productivity in domestic, commercial, industrial, agricultural, and buildings sectors. Let us repeat we could have successfully carried out such an ambitious project in its fulsome, but for the data problem.

In a positive sense, however, this experience has opened our eyes to the dire requirement for developing a system for processing and storing varieties of data and other informative materials in the energy sector at different aggregation levels not only for Kerala but also for the entire country itself. We are providing an illustration below for the suitable kind of data required for such a study of the bottom micro-level sectors.

As already discussed in chapter two (in Table 2.1), we can think of a number of subsectors for the residential or domestic sector such as space heating/cooling, water heating, cooking, lighting, appliances, etc. Activity in each subsector is measured in terms of the corresponding population, number of households, and floor area (sq. ft.); structure in the case of space heating/cooling and lighting is defined in terms of floor area per capita, in the case of water heating and cooking, in terms of number of persons per household, and in the case of appliances, in terms of number of ownership per capita; and intensity in terms of energy per square feet floor area. Thus for analyzing energy efficiency in the residential or domestic sector, the data required are on population, number of households, number of appliances per capita, floor area per capita, energy consumption per square feet floor area, etc.

In transport sector, passenger and freight transport are the two subsectors, with passenger-km and ton-km as respective activities. The other two factors are similarly defined. Thus the data required here are on passenger-km and ton-km. Both in services and manufacturing, value-added measures the activity with corresponding shares and intensity factors, and the required data are on subsector-wise value added and energy consumption.

If these data were available, one could easily proceed with a comprehensive energy efficiency study; and this is our recommendation for further research.

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Appendix

LMDI Program for Stata module by Kerry Du

Kerry Du, 2017. "**LMDI: Stata module to compute Logarithmic Mean Divisia Index (LMDI) Decomposition**," Statistical Software Components S458435, Boston College Department of Economics, revised 01 Jan 2018.

```
*! version 3.2.3, 2017-12-31
* By Kerry Du
capture program drop lmdi
program define lmdi, rclass
	version 12.0
	* syntax
	*	lmdi decom_var = varlist, t(varname) over(varlist) [ADD ///
	*				zero(real 1e-20) tol(real 0.01) sav(string) replace]
	*			lmdi decom_var = (factor_1_varlist).. factor_k_varname ... 
factor_n_varname, ///
	*				t(varname) over(varlist) [ADD zero(real 1e-20) tol(real 
0.01) sav(string) replace]
	*			lmdi decom_var = factor_1_varname ... 
factor_k_varname...(factor_n_varlist), ///
	*				t(varname) over(varlist) [ADD zero(real 1e-20) tol(real 
0.01) sav(string) replace]
	*
	* example
	*	lmdi E= (Es1 Es2 Es3) I Y, t(year) over(region sector)


	//disp "`0'"
```

```
gettoken cmla 0: 0, p(",")

syntax, t(varname numeric) over(varlist) [ADD zero(real 1e-20) TOLerance(real
0.01) SAVing(string) REPLACE]



preserve
gettoken yvar cmla: cmla, p("= ( ),")

if ("`yvar'"=="=" | "`yvar'"=="," | "`yvar'"=="(" | "`yvar'"==")"){
        disp as red "The decomposed variable must be specified!"
        exit 198
}
gettoken word cmla: cmla, p("= ( ),")

if !strmatch("`word'","=") {
        disp as red `"Only one variable before "=" is allowed!"'
        exit 198

}

local k=0
gettoken word cmla:cmla,p("= ( ),")
local idflag `over'
//local pjlist
while !("`word'"==","| "`word'"=="") {
//disp "`word'"
        local k=`k'+1
        if ("`word'"=="(" ){
                local pj=0
                gettoken word cmla: cmla,p("= ( ),")
                while !("`word'"==")" | "`word'"==""){
                        //tempvar _eff`k'_`t'
                        //qui gen _eff`k'_`t'=`word'
```

```
					//disp "`word'"
					local pj=`pj'+1
					rename `word' _eff`k'_`pj'
					local eff`k' `eff`k'' `word'
					gettoken word cmla: cmla,p("= ( ),")
				}

				local pjlist `pjlist' `pj'
				local reshvar `reshvar' _eff`k'_
				gettoken word cmla: cmla,p("= ( ),")
				//tempvar _eff`k'
				//tempvar id`k'
				//qui reshape long _eff`k'_, i(`t' `idflag') j(`id`k'')
				//local idflag `idflag' `id`k''
				//disp "`idflag'"
			}
			else {
				//disp "`word'"
				//tempvar  _eff`k'
				//qui gen `_eff`k''=`word'
				rename `word' _eff`k'_
				local eff`k'  `word'
				gettoken word cmla: cmla,p("= ( ),")
			}
			//disp "eff`k'=`eff`k''"

		}

		gettoken pj1 pjlist: pjlist
		while !("`pjlist'"==""){
			//disp "`pj1'"
			gettoken pj2 pjlist: pjlist
			//disp "`pj2'"
			if !strmatch("`pj1'","`pj2'"){
				disp as red "ERROR: the # of vars in different parenthese ( ) 
should be equal."
				restore
```

```
			exit 198
		}
		local pj1 `pj2'
}

if !("`pj1'"=="") {
		tempvar _newid
		qui reshape long `reshvar', i(`t' `idflag') j(`_newid')
		local idflag `idflag' `_newid'
}
//disp "`0'"

//local 0 ", `0'"
//syntax, t(varname) over(varlist) [ADD zero(real 1e-20) crtv(real 0.01)]

//syntax varlist, t(varname) over(varlist) [ADD zero(real 1e-20) crtv(real 0.01)]

/*
qui egen _chsum0=rowtotal(`sum')
qui egen _chsum1=total(_chsum0), by(`t')

cap assert abs(_chsum/`yvar'-1)<=`crtv'
if _rc!=0 {
		disp as red "ERROR:The varlist can not form an identity"
		restore
		exit
}
*/

//disp "k=" `k'


tempvar chprod chsum2 lfun dfun Dtot2

qui gen `chprod'=1
forvalues i=1/`k' {
		qui replace _eff`i'_=`zero' if missing(_eff`i'_)| _eff`i'_==0
```

```
		qui replace `chprod'=`chprod'*_eff`i'_

	}

	qui egen `chsum2'=total(`chprod'), by(`t')

	cap assert abs(`chsum2'/`yvar'-1)<=`tolerance'

	if _rc!=0 {
		disp as red "ERROR:The specified variables can not form an identity"
		restore
		exit
	}


	qui gen `lfun'=0

	qui bys `idflag' (`t'): replace `lfun'= ///
		(`chprod'-`chprod'[_n-1])/ln(`chprod'/`chprod'[_n-1])			if
`chprod'!=`chprod'[_n-1]


	tempvar _Dtot
	if !("`add'"==""){
		qui bys `idflag' (`t'): gen `_Dtot'=`yvar'-`yvar'[_n-1]
		qui gen `Dtot2'=0
		qui gen `dfun'=1
	}
	else {
		qui bys `idflag' (`t'): gen `_Dtot'=`yvar'/`yvar'[_n-1]
		qui gen `dfun'=0
		qui gen `Dtot2'=1
		qui bys `idflag' (`t'): replace `dfun'= ///
		  (`yvar'-`yvar'[_n-1])/ln(`yvar'/`yvar'[_n-1]) if `yvar'!=`yvar'[_n-1]

	}
```

```
	//disp "k="`k'

	qui su `t'
	local mint=r(min)


	forvalues i=1/`k' {
		tempvar tempEFF`i' _EFF`i'
		qui bys `idflag' (`t'): gen `tempEFF`i''=`lfun'/`dfun'*ln(_eff`i'_/_eff`i'_[_n-1])
		//qui bys `idflag' (`t'): gen `tempEFF`i''=`lfun'/`dfun'*ln(`_eff`i''/`_eff`i''[_n-1])
		qui egen `_EFF`i''=total(`tempEFF`i''), by(`t')
		//label var _EFF`i' `"Effecf of change in (`eff`i'')"'
		qui replace `_EFF`i''=. if `t'==`mint'
		if !("`add'"==""){
			qui replace `Dtot2'=`Dtot2'+`_EFF`i''

		}
		else {
			qui replace `_EFF`i''=exp(`_EFF`i'')
			qui replace `Dtot2'=`Dtot2'*`_EFF`i''

		}

		local resmat `resmat' `_EFF`i''
		local matcnames `matcnames' "Eff_`i'"
		//local matcnames `matcnames' _EFF`i'
	}


		cap assert abs(`_Dtot'/`Dtot2'-1)/`_Dtot'<`tolerance' if ~missing(`_Dtot')
		if _rc!=0 {
			disp as red "Warning: The difference between the real change and the decomposed effects in total is large than `=`crtv'*100'%."
			disp as red "	Please check your data preparation!"
```

```
}

qui tab `t', nofreq
local nt=r(r)
sort `idflag' `t'
tempvar From To
qui bys `idflag' (`t'): gen `From'=`t'[_n-1] if _n>1
qui bys `idflag' (`t'): gen `To'  =`t'       if _n>1
sort `idflag' `t'

//tempvar t0
//qui bys `idflag' (`t'): gen `t0'=`t'[_n-1] if _n>1
//qui cap mkmat `t0' `t' `_Dtot' `resmat' in 2/`nt', mat(mat4prt)
qui cap mkmat `From' `To' `_Dtot' `resmat' in 2/`nt', mat(mat4prt)
if _rc!=0 {

        disp _n as red "Warning: Matsize too small to create a `=`nt'-
1'x`=`k'+3', results are not displayed."
        disp    as red "          You should improve the matsize, or save
the results in filename.dta."
}
else {
        //matrix    colnames    mat4prt    =    "From"    "To"    "_Dtot"
`matcnames'
        matrix colnames mat4prt = "From" "To" "Dtot" `matcnames'
        //disp _n
        matlist   mat4prt,   name(c)   bor   title("LMDI   decomposition
results:")
        //disp "    The decomposition results are presented as follows."
        //list  _Period _Dtot _EFF* in 2/`nt', c sep(0) t
        disp "Note:"
        disp as yellow "     Dtot  : Change in  `yvar' over times"
        forvalues i=1/`k'{
                disp as yellow "     Eff_`i' : Effect of change
in ( `eff`i'' )"
        }
```

```
}

if !("`saving'"==""){
            //qui putmata period=`_Period' in 1/`nt', replace
            //qui putmata result=(`_Dtot' `resmat') in 1/`nt', replace
            sort `idflag' `t'
            qui drop if _n>`nt'
            //list `_Dtot'
            mata: effmat=st_data(.,"`_Dtot' `resmat'")
            qui keep `t'
            sort `t'
            //qui   getmata   _Period=period   (   _Dtot   `matcnames')=result,
force
            qui gen From=`t'[_n-1] if _n>1
            qui gen To=`t' if _n>1
            qui gen Dtot=.
   mata: st_view(X2=.,.,"Dtot")
   mata: X2[1::rows(effmat)]=effmat[.,1]
            label var Dtot "change of `yvar'"
            forvalues i=1/`k'{
                        qui gen Eff_`i'=.
                        mata: st_view(X3=.,.,"Eff_`i'")
               mata: X3[1::rows(effmat)]=effmat[.,`=`i'+1']
                        label var Eff_`i' "Effect of change in ( `eff`i'' )"

            }
            //list From To Dtot Eff_* if _n>2,  t sep(0)
            save `saving', `replace'
            disp _n
            disp as yellow "The results are also saved in `saving'.dta."
}

restore

end
```