KADIR HAS UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES

INPUT SUBSTITUTABILITY, ENERGY INTENSITY AND EFFICIENCY IN US AGRICULTURE

DISSERTATION

TUĞÇE UYGURTÜRK GAZEL

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INPUT SUBSTITUTABILITY, ENERGY INTENSITY AND EFFICIENCY IN US AGRICULTURE

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“I, Tuğçe Uygurtürk Gazel, confirm that the work presented in this dissertation is my own. Where information has been derived from other sources, I confirm that this has been indicated in the dissertation.”

TUĞÇE UYGURTÜRK GAZEL

ABSTRACT

INPUT SUBSTITUTABILITY, ENERGY INTENSITY AND EFFICIENCY IN US AGRICULTURE

Tuğçe Uygurtürk Gazel

Doctor of Philiosophy in Economics

Advisor: Prof. Osman Zaim

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Non-renewable resources, particularly energy, have significantly determining effects on production process. The petrol crises which have been experienced since 1970s have stimulated the awareness of using limited non-renewable resources and then performance indicators regarding the use of resources have been intensively studied. In this thesis, the answers of three crucial questions are sought by employing the panel data set of US agriculture for the years 1960-2004. First, the question to what extent the inputs can be substituted for each other is studied with the help of flexible functional forms and then energy intensity and energy productivity are recalculated with the new method which is developed for overcoming the shortcomings of the existing methods in the literature. Finally, technical efficiency scores of the agricultural sector are calculated by using parametric, semi-parametric and non-parametric methods. The derived results not only represent a detailed framework regarding the elasticity of substitution but also reveal substantial differences between the performance indicators (energy intensity, energy productivity) derived by existing method and the new method.

Keywords: Elasticity of Substitution, Energy Intensity, Partial Factor Productivity, Technical Efficiency, US Agriculture Sector

ÖZET

AMERİKAN TARIMINDA GİRDİ İKAMESİ, ENERJİ YOĞUNLUĞU VE ETKİNLİĞİ

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Yenilenemeyen kaynakların, özellikle enerjinin, üretim aşamasında önemli ölçüde belirleyici etkisi bulunmaktadır. 1970 lerden itibaren yaşanan petrol krizleri, sınırlı enerji kaynaklarının kullanımı konusundaki bilinci daha da pekiştirmiş, bu alandaki performans ölçüm yöntemleri yoğun bir şekilde çalışımaya başlanmıştır. Bu tezde Amerikan tarım sektörünün 1960-2004 yılları arasındaki panel veri seti kullanlarak üç önemli soruya yanıt aranmıştır. İlk olarak, girdilerin birbirlerinin yerine ne ölçüde ikame edilebileceği sorusu esnek fonksiyonel formların yardımıyla çalışılmış daha sonra enerji yoğunluğu ve enerji üretkenliği kavramları literatürde var olan ölçüm tekniklerinin kabul edilen eksikliklerini gidermek amacıyla yeni geliştirilen ölçüm tekniğiyle hesaplanmıştır. Son olarak da tarım sektörünün etkinliği parametrik, yarı parametrik ve parametrik olmayan teknikler kullanılarak hesaplanmıştır. Elde edilen bulgular, Amerikan tarımında girdi ikamesi bağlamında kapsamlı bir veri çerçevesi sunarken, yeni yöntemle elde edilen performans belirleyicileri (enerji yoğunluğu, enerji verimliliği) var olan yöntemlerle elde edilen bulgulara göre bariz farklar ortaya koymaktadır.

Anahtar Kelimeler: İkame Esnekliği, Enerji Yoğunluğu, Kısmi Faktör Verimliliği, Teknik Etkinlik, Amerikan Tarım Sektörü

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Chapter 1

Introduction

Environmental problems have been attracting a lot of attention for a long time. Increasing use of non-renewable resources, the bulk of the content constituted by fossil fuels, has led to compounding these problems. Greenhouse gases, particularly CO_2, released by fossil fuels have become hazardous for the atmosphere. Greenhouse gases are seen as dangerous not only as they lead to air pollution but also they greatly contribute to global warming. Despite both scarcity and negative impacts on the environment, today's world consumption behaviour strongly tends to use non-renewable resources. This behaviour can be explained by non-renewable resources' ease of use and renewable resources' complex infrastructure requirement when employed directly in the production process. All resources need to be more efficiently used and non-renewable resources should be more effectively utilized in order to cope with these issues.

All producers in the modern economy aim to produce as much as possible using as little inputs (resources) as possible. The production economics literature is mainly devoted to understanding the key elements of producer performance. To do this, researchers study efficient use of inputs to maximize outputs. The performance analysis of production is not only based on the better utilization of production factors but is also based on changes in exogenous variables resulting from changing world conditions. In today's world the utilization of some inputs requires great attention due to their scarcity and the monopolistic behaviour of those who determine prices without any restrictions.

Both scarcity and monopolies unavoidably lead to fluctuation in prices of inputs making continuous, steady and reliable use of inputs difficult for producers. Where there is great fluctuation in input prices and availability, the ability to substitute one input for another becomes very important. Technological advances have increased the possibilities of substituting inputs and increasing productivity. A technological development which has been growing at a rapid pace generally results in more mechanization and hence some major transformations in production. One of the examples of this is the substitution between labour and capital. Thanks to technological developments, new types of input substitutions are increasingly possible to reduce cost and increasing productivity. Another tool for understanding the production performance is the performance indicators (efficiency, productivity, intensity). Although there have been numerous studies to develop these indicators which also constitute a new literature, some main problems remain unsolved. These issues are major concerns for most sectors.

In this thesis, our focus is to look at substitution possibilities, efficiency and productivity of production factors in the agricultural sector of US. Since the US agricultural sector has undergone marked changes and interesting transformations since the beginning of the 1900s, it is informative to study the impacts of these changes using reliable data going back to 1960.

For the years 1960-2004 covering the data set dramatic changes occured in US agriculture which are well worth studying. One striking transformation is in the labour intensive structure of agricultural sector which now largely favours mechanization over labour. Although almost half of the US workforce was employed in agriculture in the beginning of the 1900s, this ratio declined markedly to about 2% of the labour workforce in 2000.

Another important change experienced in US agriculture is productivity growth. Actually productivity growth was seen from the beginning of the 20th century, however, the growth rate seen from the 1960s onwards has been considerably steeper than the years between 1900 and 1960. When we look at the changing structure of US agriculture, it is realized that the changes seen in the second half of the century were more pronounced than the first half. This can be explained by the technological advances whose implementation in the production process takes time and by large exogenous events such as oil crises and wars which forced agriculture to transform. To better understand the impact of technological advances, it is important to analyse input substitution possibilities and performance indicators.

Energy intensity in US agriculture also reveal significant changes. Approximately three-fold difference between the increase of output quantity and the decrease of energy quantity needed supports this change from the mid 1970s to the mid 2000s. Increasing energy efficiency accompanying decreasing energy intensity trend is also one of the strongest indicator revealing the decline in energy use in US agriculture in this period.

In this thesis, input substitution possibilities and performance indicators are studied using panel data covering 48 US states from 1960 to 2004 to better understand the microeconomic side of producer performance. The main interest is on the improvement of performance indicator measurement. While developing new methodologies, comprehensive studies are also conducted using existing methodologies with some adaptations and more detailed data.

This thesis consists of three essays which employ econometric methods, linear programming methods and parametric, semi–parametric and non–parametric methods to analyse input utilization in the production process. We focus on substitution possibilities, efficiency, partial and total factor productivity variations with different production factors. Substitution possibilities, efficiency and productivity can not be considered individually as they are interdependent and closely connected.

In Chapter 2, the substitution possibilities for different production factors in US agriculture are studied. Economically, the most important factor determining the use of resources is the change of relative prices. Changes in prices may result in substitution of inputs. The substitution possibilities are investigated with Allen, Morishima and Cross elasticities. To do this, two questions are addressed to better understand substitution possibilities: 1) What is the most appropriate functional form to represent production, 2) What estimation technique should be adopted to determine the coefficients of functional forms. Since there is lack of consensus in the literature on the best answers to these questions, Chapter 2 provides a comprehensive comparison and a useful study of current practice. Chapter 2 also provides an overview of types of elasticity of substitution and flexible functional forms which makes the imposition of constraints on production easier.

The best known flexible functional forms (Translog Production, Translog Cost and Generalized Leontief Cost functions) are applied to enable us to compute elasticity of substitution showing whether production factors are substitutes or complements. While Translog Production function is estimated using a single equation, both Translog Cost and Generalized Leontief Cost functions are estimated utilizing a system of equations. Since the correlation between the error term and the explanatory variables in the single equation lead to simultaneity bias in the single equation, the system of equations (SURE (Seemingly Unrelated Regression Method)) which guarantee all the error terms in the system of equations are uncorrelated and Translog Cost function is generally preferred. Chapter 2 ends with a comparison of all types of elasticity of substitution derived by flexible functional forms.

In Chapter 3, fundamental indicators are investigated to attempt to overcome their shortcomings. Energy intensity which is one of the most commonly used of these indicators exhaustively studied in the energy and environmental literature for about last 30 years is analysed. Energy intensity is used to track the changes in energy efficiency. Energy intensity and energy efficiency can be used interchangeably. The other indicators which are also widely used in the literature are partial factor productivity measures which are inverses of intensities. Although energy intensity indicator is commonly used for policy making with a number of aims including determining environmental and energy policies this indicator has shortcomings that all of scholars note. The most obvious shortcoming is the inability in production process to keep input quantities fixed while energy use is varied. Comparing energy intensities using methods with such shortcomings fails to produce the most accurate results. In this chapter, we propose a new method which not only better calculates energy intensity but also provides a correct measurement of all partial factor productivities (PFP).

PFP measurements are still commonly used despite its inability to factor in inputs other than the input whose productivity is calculated. The best known attempt to overcome this shortcoming is the development of total factor productivity. In total factor productivity measurements all inputs and outputs are taken into account through aggregation techniques. The measurement of total factor productivity, however, is still far from answering the question of how an increase or decrease in the quantity of a particular input affects the quantity of an output while considering the effects of all other inputs.

Our methodology for measuring PFP while also factoring in all inputs is based on the construction of a new index methodology which is explained in Chapter 3. Our methodology is based on the comparison of two inefficient observations under Constant Returns to Scale Technology. A very nice feature of the new methodology proposed in Chapter 3 is that it simultaneously allows the calculation traditional partial factor productivity while considering only aggregate output and the particular input without taking into account the effects of the other inputs. Another important advantage of the new methodology is the ability to calculate total factor productivity. In this methodology while expanding outputs all the inputs are held fixed and similarly while contracting inputs all the outputs are held fixed.

Another advantage of the new methodology is that it allows the tracking of the growth of performance indicators over time. We are able to derive all the efficiency scores of all production units over time. A considerable difference obtained in the efficiency scores between the new and the traditional methodologies reveals that the commonly used traditional method may lead to misleading results.

In Chapter 4, efficiency measurement is studied using a number of methods. In the literature, efficiency is measured using two methods. One of the efficiency measurement methods is based on output orientation which analyses the success of decision making units in producing maximum outputs for a given set of inputs. The other efficiency measurement method is based on input orientation which determines the minimum amount of inputs for a given level of output. Both methods are built around the relation between inputs and outputs and do not take into account the effects of exogenous variables in the production process. The exogenous variables are things like type of industry, weather conditions, education level and technological level.

A production function basically shows the maximum possible outputs for a given set of inputs. Since it reveals the maximum output, the production function can be seen as a boundary (frontier) for the production process. The production units (firms, countries, states, regions) on the frontier therefore are taken to be fully efficient. In the literature, there are two types of efficiency incorporating technical and allocative efficiency. While technical efficiency shows the ability of production units to produce maximum output for a given set of inputs, allocative efficiency is used to determine how equal the marginal rate of substitution between any pair of inputs is with their price ratios. Both types of measurements are widely applied to compare performances of production units. Our focus, in Chapter 4, is on technical efficiency.

Differences between production units in terms of technical efficiency may lead to development of policies for production units. The convergence (divergence) rate between production units may also give some insights about the reasons that lie behind the differences or similarities. A number of techniques have been developed in order to measure efficiency. While one type of methods called parametric methods specify a functional form, non–parametric methods do not employ any functional forms. In the literature, parametric methods are analysed using either Deterministic or Stochastic Frontier Analysis. Interest in these methods is relatively recent and there are few studies in the literature which compare these two types of analysis using comprehensive methods. In Chapter 4, we compare these two types of analyses using 8 methods and uniquely utilize panel data in doing this.

Chapter 2

Elasticity of Substitution in US Agriculture

2.1 Introduction

The agricultural sector in the US has undergone major changes since the early 1900s. These changes have been mainly due to factors including both technological development and the variations of quantities and relative prices of inputs over time. The technological development side of the change has mostly led to a significant decrease [1] in the number of work animals in favour of the utilization of more mechanized tools. On the other hand the variation in input quantities and price altered the agricultural structure of the US in terms of the share of inputs utilized.

Although most of the inputs have experienced substantial changes in terms of quantity demanded and price, labour and energy use show more remarkable changes. While the agricultural sector was more labour intensive employing 41% of the labour force in the beginning of the 20 th century, this figure decreased dramatically to 1.9% in 2000 indicating a sharp decline in the utilization of labour in production. Another striking change was observed in the use of energy due

[1]The number of tractors increased from 2.4 million to 4.7 million by almost 50%; however the number of horses and mules decreased from 11.6 million to 3 million by nearly 75% from 1945 to 1960., "The 20th Century Transformation of US Agriculture and Farm Policy", USDA, ERS, Economic Information Bulletin Number 3, 2005.

to energy crisis in 1973, 1979, 1990 and 2000s. Since energy consumption makes up a considerable share of the total US agriculture expenses, markedly increased energy prices inevitably caused a decline in energy use. The downward trend in energy use over time can be seen as evidence of the efforts to mitigate the energy dependence.

All these changes mostly due to the reasons above inevitably resulted in the transformation of US agriculture. Increasing migration from rural to urban areas is one of the most crucial consequences of this transformation. The shift of workforce from rural to urban areas with the intention of finding new opportunities has also led to a change in the overall US economic structure. The changes which have been mentioned up to now are purely related to the production process. Although they are considerably important, it could be misleading to ignore the role of the structural changes to account for the changes in US agriculture. There have been a number of studies investigating the structural transformation of US agriculture considering the impacts of factors such as education level, farm size, research and development spending (Oehmke and Schimmelpfennig, 2004; Huffman and Evenson, 2001; Gebremedhin and Christy, 1996; Drabenstott, 2000). Our focus in this study is, however, to investigate the changing structure of inputs utilized.

The changing trends of agricultural inputs' utilization bring to mind the issue of input substitutability where the measure of elasticity of substitution has gained importance since it was first introduced by Hicks (1932). The elasticity of substitution between two goods is basically defined as the response of the ratio of relative quantities demanded to any change in their relative prices. Following Hicks, the subsequent attempts have aimed to improve the use of the measure of the elasticity of substitution for more than two inputs and Allen elasticity (Uzawa, 1962) and Morishima elasticity of substitution (Morishima, 1967; Blackorby and Russell, 1981; 1989) were proposed. It should be underlined that, the interpretations of both cross price and Allen elasticities are the same but the latter one differs from the former by its formulation which scale the cross price elasticity with the cost share.

While the Allen elasticity between the inputs i and j is based on the question of how the ith demand for input quantity changes in response of the jth price, the Morishima elasticity is based on how the ratio demanded for input i to j when the price of the jth input increases. Compared to the Morishima elasticity, both cross price and Allen elasticity are uninformative. Moreover, it should be noted that the Allen elasticities are symmetric while the Morishima elasticities are non-symmetric and the results generated by both implementations generally yield different results. With the consideration of these points taken into account, the literature offers contradictory findings on the elasticity of substitution for US agriculture inputs. Since the time period and analytical approach vary over studies, another objective of this study is to do a robustness check of input substitution possibilities by using different functional forms and estimation processes. Therefore a main issue boils down to which functional form to use and which estimation technique to adopt.

Microeconomic theory provides a wide range of choices for both. Functional forms vary from the most restricted to the least restricted translog function. In a similar vein, estimation techniques vary from single equation estimation techniques to systems of equations techniques which capture the parameters of the production or cost function through simultaneous estimation of input demand functions. The single equations estimations, however, suffer from the simultaneity bias due to simultaneity arising from the correlation between the error term and one or more of the independent variables. This is not surprising since the estimation of single equations which do not consider the inter-temporal relation between the error terms lead the estimations to be biased. In econometrics this is corrected by the Seemingly Unrelated Regression Method (SURE), (Zellner, 1962) which is a system of equations in which error terms are uncorrelated. The reasons why SURE (also known as system of equations) is preferred are explained by Henningsen and Hamann (2007) with two reasons: First, the method considers the covariance between the residuals when estimating the all equations simultaneously and secondly it allows imposing the constraints regarding cross equations.

Currently, flexible functional forms have become more available for econometric estimations. This type of function has a number of attractive features: First, it provides the imposition of constraints on production such as homogeneity and monotonicity and secondly it creates the opportunity to obtain supply and demand functions by only taking the derivative with the help of Sheppard's Lemma, Hotellings Lemma and Roy's Identity (Thompson, 1988). As Green states, the choice of functional form of production (cost) is based on the type of isoquant and thereby the values of factor substitution. It should be noted that although functional forms provide significant convenience in econometric estimation, this comes at a cost: multicollinearity due to use of many parameters in the flexible function.

In general, translog cost function is widely used in empirical studies in order to derive the system of equations representing cost shares. The derivation of these equations is based on Sheppard's Lemma which states that first partial derivatives of cost function with respect to factor prices produces cost share equations of each production factor. Another purpose of this chapter is to review various forms of production and cost functions including the translog cost function to analyse input substitution possibilities. This analysis also provides a robust check for the elasticity of substitution by comparing the estimated results yielded by different functional forms.

We need to explain why the most prominent production function the Cobb Douglas function fails to help in determining the elasticity of substitution. The Cobb Douglas function is the most referenced one because it renders the computation easier and enables the linearity in parameters. However, there are limits to how far the functional form of Cobb Douglas can be utilized. The main limitation is associated with the inefficiency of this function in econometric estimation. The evidence of inefficiency can clearly be seen in the case of elasticity of substitution. The Cobb Douglas production function stating unitary elasticity of substitution[2] for any two inputs is considered to be restrictive and this limitation requires the application of flexible functional forms.

This study also contributes to the literature by employing comprehensive data. Although, there have been attempts to estimate the elasticity of substitution for inputs in US agriculture, these studies either relied on cross section or time series data. When comparing the results produced by these data sets, it becomes increasingly difficult to ignore the inconsistent results produced by time series and cross section data. At this point, the importance of panel data should be reemphasized. The use of panel data brings substantial advantages which provide credible and reliable estimation results. Firstly, the organization of panel data provides analysis of dynamic effects by observing the changes in each units over time. Secondly, more observations provided by panel data compared to time series and cross section data makes it easier to capture the characteristics of individual units (Wooldridge, 2004), thus increasing degrees of freedom and reducing the multicollinearity which enables more efficient results (Hsiao, 2003). Another issue that should be touched upon is the superiority of panel data over time series data. This superiority brings more accurate results which are derived from the analysis of one unit's behaviour when considered simultaneously with others.

[2]Unitary elasticity of substitution means that the elasticity of substitution between any two inputs is 1.

However, it could be expected that the estimation would be more complicated, since panel data requires more observations than cross section and time series data. Contrary to this expectation, the use of panel data makes estimation and inference easier by providing solutions for problems such as measurement error, analysis of non stationary time series and dynamic tobit models (Hsiao, 2007).

The elasticity of substitution, which provides a measure of how easy an input can be substituted for another in production has been widely used by policymakers since it was first demonstrated by Hicks (1932). Subsequently, there has been an increasing interest in the term because of its ease of interpretation and economic implications and much more information has become available on methods of estimating elasticity of substitution. In this chapter, we review of production and cost function approaches for econometric estimation of the elasticity of substitution. In particular, we first analyse the production function which enables us to estimate the elasticity of substitution between inputs by using a single equation. Then the related literature (regarding translog production function) will be reviewed. Thirdly, translog cost and generalized cost function approaches with their theoretical and empirical facts are examined and the econometric implications of system estimation is investigated. In this way, we establish a link between production and cost function by taking into account superiorities and weaknesses of flexible functional forms. Finally, panel data including from 48 contiguous states in the US from 1960 to 2004 is analysed using flexible functional forms and conclusions are drawn.

2.2 Literature Review

The US agricultural sector has undergone numerous changes over the years. While some inputs utilized in the production process do not exhibit substantial changes, some of them experience considerable changes. At this point, it is crucial to ask how input combinations for production can adapt to these changes and can keep on producing. In order to answer this question, the elasticity of substitution which determines the response of agricultural sector to the changes in both input quantities and prices may be a useful guideline. In the literature, there are many studies pertaining to the elasticity of substitution in the agricultural sector covering all these issues. There are few recent studies concerning the elasticity of substitution in US agriculture. The purpose of the literature review is to provide an overview of the studies which have been conducted up to now. In addition, the literature review does not only consider one type of functional form for elasticity of substitution estimation, it concerns all prominent flexible functional forms (Translog cost, Translog production, Generalized Leontief cost) to give a comparative insight for the elasticity of substitution results yielded by each functional form.

As mentioned before, the number of studies concerning the elasticity of substitution in the US agriculture has not increased considerably over time. The best known studies go back to almost forty years ago. The study conducted by Binswanger (1974) is one of the most cited of these studies. The aim of this study is to estimate own and cross price elasticities for every five year period from 1949 to 1964 by employing the translog cost function. In addition to the inputs of capital, land, labour, fertilizer and the aggregate output, geographical dummy variables and the effects of four time periods (1949, 1954, 1959, 1964) are added to his model as well. The results emerging from his estimation suggest that fertilizer is a complement to labour and machinery while it is a substitute for land. All other inputs are found to be substitutes for each other. Moreover, the own price elasticities for each input are found to be negative as expected.

Following the early work of Binswanger (1974), Ray (1982) also applies the translog cost function with an extended time period from 1939 to 1977. His study differs from the former one in the utilization of fewer inputs and two different outputs including crops and livestock. In this way, two cost share equations are derived from the translog cost function. This study also diverges from the Binswanger's study by using no dummy variables and excluding some of the inputs so that there are fewer inputs. Hired labour, farm capital, farm real estate, machinery and miscellaneous inputs are utilized with the two outputs of crops and livestock to estimate the translog cost function. The results derived from the estimation reveal the decreasing trend in substitutability of labour for capital in contrast to the increasing trend in substitutability of labour for fertilizer. The elasticity of substitution between the inputs in this study are different to the Binswanger's findings. Some of the input pairs are found to be complement in Ray's study, while Binswanger finds some of these input pairs are to be substitutes. The important similarity between the studies is the agreement on the low degree of elasticity of substitution between inputs.

In order to underline the fact that elasticity of substitution estimations may vary depending on the estimation method, Schumway and Lim (1993) conduct a study offering a comprehensive comparison of the most referenced functional forms. The Translog, Generalized Leontief and Normalized Quadratic functions are employed using US agriculture time series data from 1948 to 1979. The findings of this study are essential when discussing the different elasticity of substitution estimations. It is also worth noting that, the elasticity of substitution estimations derived by both Generalized Leontief and Normalized Quadratic functions tend to be fairly similar, on the other hand the estimations produced by the Translog function are very different. This difference arises from very high estimation results yielded by translog production function. Similarly, O'Donnell et al. (1999) contribute to the literature by examining the elasticity of substitution for inputs used in US agriculture. The pooled data including the inputs of labour, capital, materials from 48 contiguous states from 1960 to 1993 is employed. In order to consider the regional impacts, the maximum likelihood method is applied. According to the results, the own price elasticity for labour and materials are found to be negative as expected, but interestingly it is found to be positive for capital.

It is certainly true that, the length of the time period for agricultural studies is a key issue. The importance of this issue arises from the fact that the completion of agricultural activities may take several years and any time in that period may affect the following years. Motivated by this fact, Moss et al. (2003) apply translog cost function analysis to the US agricultural sector in order to determine whether short run or long run effects are more significant for the estimated coefficients of the translog cost function. State level data from 1948 to 1999 including two outputs of crops and livestock and the inputs of purchased input, capital and labour are employed by Moss et al. (2003). The results of their Maximum Likelihood estimation show that short term effects are more significant than the long term effects. In order to investigate energy alternatives in US agricultural production, Webb and Duncan (1979) conduct a study determining the elasticity of substitution for each pair of inputs. To do this, translog production function, a second order approximation to production function, is employed. The data is obtained from the 1974 Annual survey including the inputs of hired labour, land, chemical and mechanical energy and the crops output. The results of elasticity of substitution derived by using the estimated coefficients of translog production function are analysed for both regional and for the whole US. The results indicate that, the elasticity of substitution between pairs of inputs are similar for 10 regions and for the US with one exception. The only complementarity that is found is between land and hired labour in the Corn Belt and Northern Plains. It should also be noted that, the strongest substitution is exhibited between hired labour and mechanical energy while the substitution between hired labour and chemical energy is recorded as the lowest one. There is one more point that should be taken into account when deriving elasticity of substitution which is that elasticity of substitution needs to be derived for data collected over a long period. This issue is studied by Fernandez-Cornejo (1992) in order to investigate the multicollinearity within series and no allowance given for the impacts of shocks happening at any time in that period. To do this, he investigates both short-run and long-run substitution possibilities for the agricultural inputs of Illionis. Both short and long run Hicksian, Marshallian and Allen Uzawa elasticites are calculated and he concludes that the conceptual framework is in favor of the utilization of Morishima elasticity.

Having reviewed the relevant studies on US agriculture, it seems that there is no consensus on the most appropriate flexible functional form to be used for the elasticity of substitution. The literature review unfortunately fails to suggest the best practical method for determining elasticty of substitution. To alleviate this lack of consensus, several studies have been conducted with the intention of comparing the existing methods in terms of their strenghts and weaknesses. The variety of the results generated by these methods stimulate our interest and lead us to deeper examination of these methods while considering their theoretical grounds. In line with this intention, the next section of the second chapter introduces the data and then the methodology.

2.3 Data

The panel data used for the estimation using the methods (Translog production, Translog cost and Generalized Leontief cost functions) includes state level observations of agricultural outputs and inputs from 1960 to 2004. The output considered in this study is the aggregate output and the inputs consist of capital, labour, land, energy, materials, fertilizer and pesticides. All quantity data are real values and expressed in terms of 1996 Alabama prices and price data is expressed in 1996 Alabama prices. Since the change of data over time is likely to serve as a guideline to track major changes in US agrultural structure, we now present the summary statistics, average annual change of price and quantity, cost shares of inputs and the changes in aggregate output.

2.3.1 Summary Statistics

Table 2.1 shows the summary statistics for the price and quantity data for each region. The variables $q_q, q_k, q_l, q_e, q_m, q_n, q_p, q_f$ and $p_q, p_k, p_l, p_e, p_m, p_n, p_p, p_f$ respectively refer to the quantity and the price of aggregate output, capital, labour, energy, materials, land, pesticides and fertilizer.

Table 2.1: Summary Statistics (Price and Quantity)

Var.	Obs.	Appalachia			
		Mean	Std. Dev.	Min	Max
q_q	225	2.837.123	1.860.938	347.358	8.584.621
q_k	225	546.863	228.409	115.198	995.556
q_l	225	1.953.228	1.243.101	322.812	6.841.834
q_e	225	118.784	70.009	15.801	279.378
q_m	225	904.858	554.924	162.275	3.293.072
q_n	225	395.688	148.490	122.008	630.097
q_p	225	54.688	45.953	4.149	210.765
q_f	225	178.132	100.895	12.172	464.480
p_q	225	0,7366	0,2499	0,3192	1,1821
p_k	225	0,6336	0,3631	0,1528	1,1735
p_l	225	0,3980	0,2795	0,0588	1,2952
p_e	225	0,7529	0,3850	0,1766	1,4619
p_m	225	0,8851	0,3351	0,3388	1,4323
p_n	225	0,6732	0,5757	0,0108	2,2597
p_p	225	0,7599	0,2752	0,2225	1,3007
p_f	225	0,6163	0,2851	0,1254	1,1981

Var.	Obs.	Corn Belt			
		Mean	Std. Dev.	Min	Max
q_q	225	7.548.615	3.345.561	3.918.654	17.600.000
q_k	225	1.596.875	611.011	822.925	3.330.621
q_l	225	3.705.175	1.489.343	1.465.795	8.382.092
q_e	225	300.673	102.577	169.197	597.835
q_m	225	2.551.796	1.248.669	1.286.414	6.017.331
q_n	225	948.265	225.563	609.129	1.296.106
q_p	225	221.155	169.571	10.192	660.271
q_f	225	551.519	271.351	193.829	1.637.918
p_q	225	0,7430	0,2316	0,3282	1,0670
p_k	225	0,6346	0,3659	0,1426	1,1597
p_l	225	0,4804	0,3468	0,0845	2,0043
p_e	225	0,7641	0,3892	0,2408	1,4424
p_m	225	0,9304	0,3839	0,3301	1,7187
p_n	225	0,7976	0,6045	0,0203	2,0760
p_p	225	0,7753	0,2602	0,2564	1,2960
p_f	225	0,6437	0,2444	0,1687	1,1865

Var.	Obs.	Delta			
		Mean	Std. Dev.	Min	Max
q_q	135	3.101.171	1.461.817	1.069.474	6.923.788
q_k	135	482.300	122.439	287.255	796.635
q_l	135	1.566.235	816.062	643.233	4.411.981
q_e	135	148.151	46.515	64.337	277.919
q_m	135	1.123.881	523.117	459.915	2.492.516
q_n	135	438.839	123.394	239.564	648.484
q_p	135	141.405	82.285	8.860	301.024
q_f	135	147.755	61.321	65.870	371.760
p_q	135	0,7337	0,2282	0,3400	1,0851
p_k	135	0,6297	0,3598	0,1547	1,1376
p_l	135	0,3937	0,2979	0,0486	1,2464
p_e	135	0,7683	0,3973	0,2336	1,4248
p_m	135	0,7704	0,3217	0,2927	1,4912
p_n	135	0,6113	0,4681	0,0175	1,9474
p_p	135	0,7589	0,2735	0,2300	1,1669
p_f	135	0,7189	0,2895	0,2627	1,2212

Var.	Obs.	Lake States			
		Mean	Std. Dev.	Min	Max
q_q	135	6.545.118	2.412.984	2.819.310	12.100.000
q_k	135	1.435.529	410.006	697.691	2.372.843
q_l	135	4.208.506	1.707.058	1.488.043	8.251.606
q_e	135	268.749	96.991	142.765	464.721
q_m	135	2.450.395	894.329	1.034.559	4.358.329
q_n	135	735.621	215.622	457.634	1.107.758
q_p	135	159.025	105.899	9.798	417.894
q_f	135	357.603	189.645	130.600	1.053.131
p_q	135	0,7085	0,2381	0,2798	1,0672
p_k	135	0,6422	0,3726	0,1495	1,1998
p_l	135	0,5206	0,4831	0,0620	1,9452
p_e	135	0,7765	0,3892	0,2543	1,4524
p_m	135	0,8509	0,3507	0,3152	1,4370
p_n	135	0,5292	0,4147	0,0137	1,3448
p_p	135	0,7056	0,2848	0,2318	1,3130
p_f	135	0,6082	0,2484	0,1643	1,0406

Table 2.1 (continued)

Var.	Obs.	Mountain Mean	Std. Dev.	Min	Max
q_q	360	1.728.879	1.165.519	177.263	5.152.063
q_k	360	269.280	171.132	41.190	637.289
q_l	360	782.062	447.587	83.025	1.962.453
q_e	360	88.251	56.980	9.933	267.470
q_m	360	686.614	481.206	71.393	2.182.874
q_n	360	823.754	451.575	108.759	1.730.191
q_p	360	30.862	31.650	915	146.204
q_f	360	53.186	49.582	1.834	267.983
p_q	360	0,8068	0,3008	0,2926	1,4103
p_k	360	0,6410	0,3782	0,1300	1,2376
p_l	360	0,4341	0,3020	0,0747	1,4830
p_e	360	0,7458	0,3801	0,2340	1,4559
p_m	360	0,9583	0,4269	0,2974	1,7780
p_n	360	0,3128	0,2870	0,0061	1,2002
p_p	360	0,7162	0,2997	0,1633	1,4559
p_f	360	0,7737	0,3791	0,1866	1,8652

Var.	Obs.	North East Mean	Std. Dev.	Min	Max
q_q	495	1.150.744	1.368.028	42.856	5.395.627
q_k	495	237.160	296.953	7.351	1.090.522
q_l	495	820.165	1.052.438	18.189	5.055.331
q_e	495	41.767	50.975	1.497	212.396
q_m	495	406.816	483.756	9.234	1.799.652
q_n	495	127.174	148.917	4.015	626.763
q_p	495	17.804	23.174	194	97.879
q_f	495	50.268	57.453	1.301	289.282
p_q	495	0,7725	0,2782	0,3028	1,3840
p_k	495	0,6449	0,3799	0,1440	1,2313
p_l	495	0,4517	0,3614	0,0791	2,1105
p_e	495	0,9083	0,4755	0,2594	1,8421
p_m	495	1,0365	0,4229	0,3591	2,1646
p_n	495	0,8156	0,7569	0,0086	3,6316
p_p	495	0,8461	0,4248	0,1621	2,5340
p_f	495	0,6692	0,3505	0,0690	1,4595

Var.	Obs.	Northern Plains Mean	Std. Dev.	Min	Max
q_q	180	5.739.617	2.632.108	1.642.394	12.200.000
q_k	180	1.001.529	244.322	604.543	1.560.267
q_l	180	2.353.260	842.095	1.044.930	4.516.406
q_e	180	277.258	88.039	158.027	500.562
q_m	180	2.301.656	1.126.122	825.480	4.830.989
q_n	180	1.415.579	138.771	1.219.174	1.646.485
q_p	180	137.930	108.333	7.787	415.722
q_f	180	319.374	199.225	15.306	1.126.829
p_q	180	0,7672	0,2508	0,3304	1,1473
p_k	180	0,6313	0,3622	0,1464	1,1711
p_l	180	0,4757	0,3635	0,0683	1,5687
p_e	180	0,7174	0,3705	0,2087	1,4355
p_m	180	0,8742	0,3928	0,2316	1,7247
p_n	180	0,3282	0,2484	0,0102	1,0211
p_p	180	0,6703	0,2213	0,2510	1,0117
p_f	180	0,5564	0,2340	0,1354	1,0235

Var.	Obs.	Pacific Mean	Std. Dev.	Min	Max
q_q	135	8.653.085	8.650.357	1.423.835	31.600.000
q_k	135	764.329	382.123	372.157	1.617.403
q_l	135	3.458.452	2.476.843	1.147.496	9.090.775
q_e	135	307.703	233.565	91.694	815.765
q_m	135	2.054.237	1.882.251	498.421	7.006.473
q_n	135	954.959	697.506	383.826	2.263.359
q_p	135	235.176	226.129	16.916	964.614
q_f	135	306.705	298.917	57.904	1.558.389
p_q	135	0,7283	0,2629	0,3114	1,1593
p_k	135	0,6431	0,3752	0,1525	1,2227
p_l	135	0,4389	0,2877	0,0861	1,1359
p_e	135	0,7640	0,4390	0,2175	1,8657
p_m	135	0,9800	0,4508	0,3156	1,7428
p_n	135	0,7026	0,5515	0,0167	1,7479
p_p	135	0,7639	0,4676	0,1137	2,0313
p_f	135	0,7674	0,3548	0,2234	1,4642

Var.	Obs.	South East Mean	Std. Dev.	Min	Max
q_q	180	3.482.926	1.730.989	1.209.718	7.449.302
q_k	180	393.501	112.051	209.683	705.906
q_l	180	1.516.890	619.217	395.649	3.111.916
q_e	180	119.754	37.771	55.489	205.892
q_m	180	1.000.950	434.320	306.701	2.022.647
q_n	180	429.233	163.312	173.975	772.341
q_p	180	99.051	77.601	13.871	355.120
q_f	180	212.936	95.233	70.684	525.742
p_q	180	0,7359	0,2598	0,3123	1,1763
p_k	180	0,6313	0,3645	0,1474	1,1676
p_l	180	0,3838	0,2716	0,0610	1,0401
p_e	180	0,7761	0,3943	0,2405	1,5197
p_m	180	0,8701	0,3471	0,2999	1,5544
p_n	180	0,6711	0,5399	0,0130	1,8630
p_p	180	0,8185	0,3261	0,2850	1,3422
p_f	180	0,6937	0,2789	0,1915	1,2356

Var.	Obs.	Southern Plains Mean	Std. Dev.	Min	Max
q_q	90	7.196.055	4.142.914	2.451.708	15.300.000
q_k	90	1.334.987	696.633	584.656	2.548.731
q_l	90	3.949.132	1.952.156	1.475.317	9.476.398
q_e	90	421.619	262.469	132.968	860.383
q_m	90	2.792.879	1.497.144	854.390	5.353.199
q_n	90	2.913.536	1.818.102	1.039.669	5.155.293
q_p	90	160.754	134.692	15.617	479.661
q_f	90	397.052	245.284	70.560	1.110.973
p_q	90	0,8355	0,2987	0,3468	1,3155
p_k	90	0,6474	0,3751	0,1567	1,1868
p_l	90	0,3834	0,2417	0,0708	1,0596
p_e	90	0,7281	0,3933	0,2040	1,5131
p_m	90	0,9730	0,4122	0,3590	1,5912
p_n	90	0,3816	0,2762	0,0168	1,0186
p_p	90	0,6026	0,2233	0,1784	0,9402
p_f	90	0,5503	0,2239	0,1435	0,8785

The figures in Table 2.1 provide a closer look at the quantity and input data and helps to create a framework for the amounts of both inputs and aggregate output for each region. It is clear that the highest mean aggregate output is recorded in the Pacific, while the lowest is seen in the Northeast. It should also be highlighted that the maximum mean aggregate output recorded in the Pacific is higher by about eight times than the minimum mean aggregate output recorded in the Northeast. Materials and labour are the largest inputs which are most widely used in US agricultural production. When considering the input prices, the most marked difference between min and max prices is seen in land prices in all regions. Due to specific events occuring in the period, we now intend to analyse changes in inputs and outputs by dividing the periods into three sub-periods: 1960-1970, 1971-1990 and 1991-2004. The reason for this division of time periods is the energy crisis of the mid 1970s and the changing structure caused by accelerating mechanization and the simultaneous dramatic decrease in labour input. The inputs quantity and price changes occuring in these periods are presented in Table 2.2.

Table 2.2: Average Annual Change for Price and Quantity

	CAPITAL						LABOR					
Average of Changes	1960 - 1970		1971 - 1990		1991 - 2004		1960 - 1970		1971 - 1990		1991 - 2004	
	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P
Northeast	-0,3%	4,4%	-0,7%	7,4%	-2,5%	2,4%	-5,1%	6,5%	-1,2%	6,4%	-2,8%	19,6%
Appalachia	1,6%	4,2%	-0,7%	7,2%	0,0%	1,2%	-4,9%	11,2%	-2,5%	5,5%	-1,2%	5,9%
Southeast	1,7%	4,2%	-0,4%	7,3%	0,4%	1,3%	-3,1%	5,9%	-2,1%	7,2%	-0,4%	5,4%
Corn Belt	2,0%	4,6%	-0,6%	7,4%	-1,9%	1,2%	-4,5%	9,0%	-1,4%	5,4%	-2,8%	6,8%
Lake States	0,5%	4,5%	-0,4%	7,3%	-1,4%	1,3%	-4,1%	9,2%	-1,0%	7,9%	-4,2%	6,6%
Delta	2,9%	4,2%	0,0%	7,1%	-0,7%	1,3%	-5,4%	10,9%	-2,8%	8,7%	-1,0%	5,4%
Northern Plains	1,3%	4,7%	-0,5%	7,5%	-1,0%	1,0%	-4,1%	9,2%	-0,2%	6,0%	-1,9%	6,5%
Southern Plains	1,3%	4,4%	-0,1%	7,5%	-0,1%	1,0%	-3,4%	9,1%	-1,3%	6,9%	0,4%	4,7%
Mouintain	1,4%	4,9%	-0,2%	7,7%	-0,4%	1,1%	-2,7%	5,8%	-0,1%	5,5%	-1,5%	4,4%
Pacific	0,1%	4,4%	-0,6%	7,4%	0,4%	1,3%	-2,7%	8,3%	-0,3%	6,0%	0,4%	4,5%

	LAND						ENERGY					
Average of Changes	1960 - 1970		1971 - 1990		1991 - 2004		1960 - 1970		1971 - 1990		1991 - 2004	
	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P
Northeast	-3,2%	21,0%	-1,0%	17,4%	0,2%	-0,8%	-1,4%	1,4%	0,2%	7,9%	4,4%	-1,1%
Appalachia	-1,8%	18,2%	-0,9%	15,4%	0,0%	3,4%	2,2%	0,8%	-0,8%	7,9%	2,1%	2,2%
Southeast	-2,1%	20,1%	-1,6%	15,5%	-0,2%	1,8%	2,7%	0,7%	0,1%	8,1%	1,2%	1,9%
Corn Belt	-0,3%	17,7%	-0,4%	14,0%	-0,1%	2,8%	1,3%	0,9%	-0,1%	7,8%	-0,6%	2,2%
Lake States	-1,3%	18,7%	-0,5%	14,7%	0,0%	4,2%	0,2%	0,7%	1,2%	7,5%	1,2%	2,1%
Delta	-0,8%	19,4%	-1,0%	13,8%	0,0%	1,9%	2,1%	1,4%	-0,6%	8,2%	2,0%	2,1%
Northern Plains	-0,1%	18,0%	-0,2%	13,7%	0,1%	0,7%	0,8%	0,6%	0,9%	8,1%	1,0%	2,4%
Southern Plains	-0,3%	18,8%	-0,5%	13,5%	0,1%	0,3%	1,8%	0,8%	-0,1%	8,5%	1,1%	3,0%
Mouintain	-0,9%	16,3%	-0,2%	15,2%	-1,0%	2,4%	1,2%	0,3%	1,6%	7,5%	1,4%	2,2%
Pacific	-1,0%	15,6%	-0,7%	15,4%	-0,5%	1,8%	0,4%	0,7%	1,7%	7,7%	0,1%	3,0%

	MATERIALS						PESTICIDE					
Average of Changes	1960 - 1970		1971 - 1990		1991 - 2004		1960 - 1970		1971 - 1990		1991 - 2004	
	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P
Northeast	0,1%	2,2%	0,7%	5,1%	2,8%	0,1%	0,9%	2,1%	4,2%	4,6%	-3,5%	-6,1%
Appalachia	1,4%	2,4%	1,2%	4,8%	3,9%	0,8%	6,3%	3,3%	5,7%	3,7%	3,7%	0,7%
Southeast	3,0%	2,6%	1,4%	5,2%	1,6%	1,2%	10,0%	3,5%	3,9%	4,4%	1,3%	1,1%
Corn Belt	0,5%	2,5%	-0,5%	5,8%	0,1%	1,5%	15,0%	5,5%	7,5%	2,9%	2,1%	0,9%
Lake States	0,4%	2,3%	0,8%	6,1%	0,5%	1,7%	7,7%	4,1%	7,6%	3,4%	1,6%	1,6%
Delta	3,7%	2,2%	2,1%	5,1%	0,6%	1,7%	16,8%	3,1%	6,0%	3,6%	2,4%	0,5%
Northern Plains	3,1%	2,2%	1,5%	6,2%	0,6%	1,4%	11,7%	3,9%	8,5%	3,6%	5,5%	0,5%
Southern Plains	3,5%	2,7%	1,7%	5,7%	1,8%	1,3%	11,9%	3,8%	5,4%	3,5%	2,4%	1,2%
Mouintain	4,1%	1,6%	0,1%	6,2%	1,1%	1,4%	6,3%	2,7%	5,4%	3,6%	2,4%	2,1%
Pacific	1,4%	2,1%	1,3%	6,4%	2,3%	1,6%	8,3%	2,3%	5,8%	4,3%	0,9%	3,8%

Table 2.2 (continued)

Average of Changes	FERTILIZER 1960 - 1970		1971 - 1990		1991 - 2004	
	Δ in Q	Δ in P	Δ in Q	Δ in P	Δ in Q	Δ in P
Northeast	-4,3%	9,0%	0,3%	7,1%	-7,1%	-4,3%
Appalachia	2,2%	2,0%	-0,6%	7,0%	2,7%	1,4%
Southeast	2,8%	0,4%	-0,5%	6,4%	3,0%	-0,4%
Corn Belt	4,7%	4,2%	2,3%	6,0%	5,0%	-1,6%
Lake States	2,3%	6,1%	3,4%	6,4%	5,2%	-1,3%
Delta	3,0%	2,0%	2,9%	7,2%	4,6%	-1,0%
Northern Plains	10,5%	3,1%	3,0%	7,0%	7,0%	-0,9%
Southern Plains	8,8%	5,8%	2,1%	6,8%	4,1%	0,9%
Mouintain	6,8%	3,5%	1,8%	7,4%	5,6%	-0,7%
Pacific	1,8%	4,2%	2,7%	7,2%	5,4%	-1,1%

There are some key points that should be emphasized in Table 2.2. One of these is the percentage change in land prices which are dramatically high compared to the percentage change in land quantities. These increases are particularly notable for the first two periods. Similar to the land prices, labour prices exhibit positive percentage changes but the increase is nearly half compared to the increase in land prices. There is a generally positive percentage change in the quantity and price of materials but the increase is not so high. One interesting issue regarding capital is that it exhibits similar positive percentage price changes within each subperiod for each region while there is a decrease in the quantity percentage of capital for the last two periods. If we now turn to analysis of percentage change of pesticides, we see that the first period including the years from 1960 to 1970 exhibits the highest increase in terms of quantity percentage change except for the Northeast region.

There is one more important issue emerging from Table 2.2. This is the decrease both in quantity and price percentage change occuring between the years 1991 and 2004 which is only seen in the Northeast region. Similar to percentage changes in pesticide use over the period 1991-2004, percentage change of both quantity and price of fertilizer use decreased with two considerable exceptions. First there is a decrease of quantity percentage change seen in the Northeast and second there is a decrease of price percentage changes seen in all regions except the Appalachia in the last period.

Table 2.3: Average Cost Shares per Region

Average of Cost Shares	CAPITAL 1960 - 1970	CAPITAL 1971 - 1990	CAPITAL 1991 - 2004	LABOR 1960 - 1970	LABOR 1971 - 1990	LABOR 1991 - 2004
Appalachia	11,1%	16,3%	13,4%	43,1%	26,1%	25,0%
Corn Belt	10,9%	16,7%	14,2%	33,2%	21,3%	23,9%
Delta	10,3%	15,2%	11,7%	32,7%	19,0%	19,4%
Lake States	14,0%	17,4%	14,2%	33,5%	25,1%	32,5%
Mouintain	10,0%	11,6%	10,6%	28,6%	18,5%	21,1%
Northeast	11,0%	15,6%	12,8%	38,1%	26,9%	30,5%
Northern Plains	12,3%	13,6%	11,8%	27,5%	18,6%	21,2%
Pacific	9,2%	10,3%	7,4%	33,3%	25,1%	27,3%
Southeast	8,9%	11,7%	10,0%	32,0%	20,5%	22,0%
Southern Plains	11,5%	13,2%	11,5%	31,4%	17,4%	22,1%

Average of Cost Shares	LAND 1960 - 1970	LAND 1971 - 1990	LAND 1991 - 2004	ENERGY 1960 - 1970	ENERGY 1971 - 1990	ENERGY 1991 - 2004
Appalachia	3,0%	9,9%	12,4%	3,6%	4,3%	3,5%
Corn Belt	3,1%	11,3%	13,5%	3,1%	3,9%	3,3%
Delta	4,0%	11,4%	9,9%	5,2%	5,4%	4,5%
Lake States	1,8%	6,6%	6,8%	3,3%	4,1%	3,6%
Mouintain	4,8%	13,9%	14,2%	4,2%	4,4%	4,4%
Northeast	1,6%	6,6%	8,4%	2,8%	3,7%	3,7%
Northern Plains	3,7%	10,1%	9,3%	4,2%	4,4%	4,0%
Pacific	5,4%	12,3%	11,4%	4,8%	5,1%	4,9%
Southeast	3,7%	11,3%	12,2%	4,1%	4,4%	3,8%
Southern Plains	6,5%	16,1%	14,8%	4,7%	4,5%	4,2%

Average of Cost Shares	MATERIALS 1960 - 1970	MATERIALS 1971 - 1990	MATERIALS 1991 - 2004	PESTICIDE 1960 - 1970	PESTICIDE 1971 - 1990	PESTICIDE 1991 - 2004
Appalachia	32,9%	36,1%	39,4%	1,0%	1,9%	2,4%
Corn Belt	44,7%	38,4%	34,4%	0,8%	2,4%	4,6%
Delta	40,4%	39,4%	44,0%	2,4%	4,4%	6,1%
Lake States	43,7%	40,6%	35,9%	0,8%	1,8%	3,1%
Mouintain	49,2%	47,2%	44,9%	0,9%	1,3%	1,9%
Northeast	42,4%	42,4%	40,4%	0,8%	1,3%	1,7%
Northern Plains	49,1%	47,7%	46,2%	0,6%	1,5%	3,2%
Pacific	41,4%	39,5%	40,9%	2,1%	3,2%	4,3%
Southeast	40,0%	41,2%	42,3%	2,2%	3,6%	4,6%
Southern Plains	41,5%	43,6%	42,0%	1,1%	1,5%	2,0%

Average of Cost Shares	FERTILIZER 1960 - 1970	FERTILIZER 1971 - 1990	FERTILIZER 1991 - 2004
Appalachia	5,2%	5,5%	3,9%
Corn Belt	4,3%	6,1%	6,1%
Delta	5,0%	5,2%	4,4%
Lake States	2,9%	4,5%	3,9%
Mouintain	2,2%	3,0%	3,0%
Northeast	3,3%	3,4%	2,5%
Northern Plains	2,6%	4,0%	4,3%
Pacific	3,8%	4,5%	3,9%
Southeast	9,2%	7,3%	5,1%
Southern Plains	3,2%	3,6%	3,4%

Table 2.3 above illustrates each production factor's cost shares as a percentage change of the total cost for each region. This table is quite revealing in several

ways: Firstly, it shows the significant share of materials input for each region, secondly it shows the decrease of labour input use as an evidence of the transformation in labour intensive agriculture and finally shows that for all regions energy, pesticides and fertilizer have similar cost shares to each other which are all below 10%. An important point from Table 2.3 is that, for all regions there is no significant change in the average cost share of capital. On the other hand, labour cost share is seen to decrease by nearly 50 % in both the second and the last period. A similar dramatic change is seen in the cost shares of land input. The percentage change in the cost share of land in the second period is roughly as three times as high as the percentage change in the first period. After this dramatic rise in the second period, there are no significantly substantial changes seen in the last period.

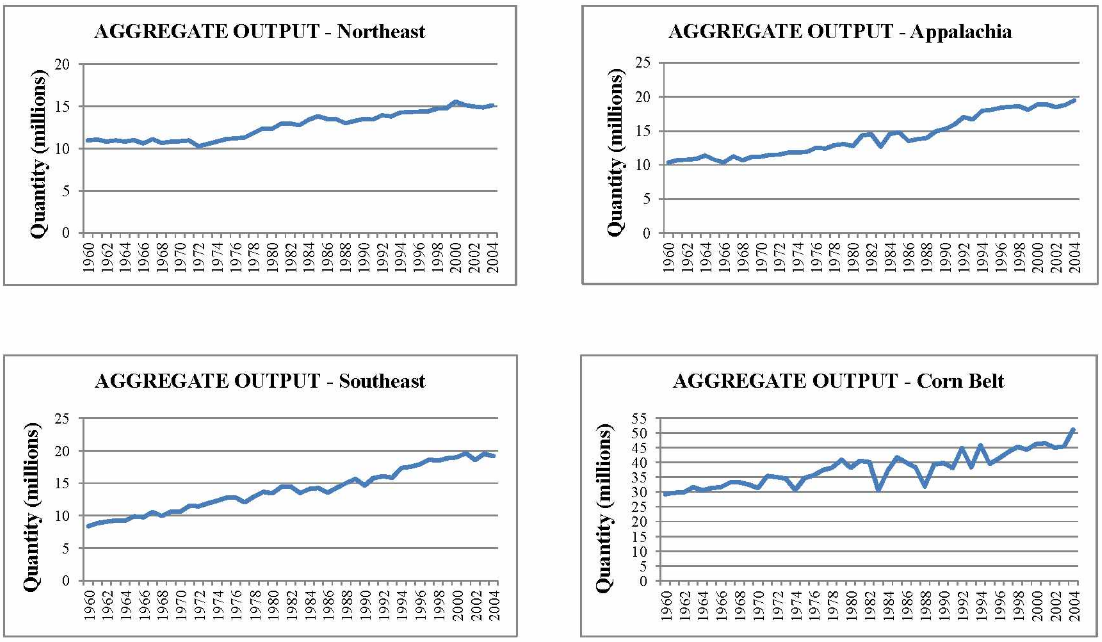

Figure 2.1: Aggregate Output Change

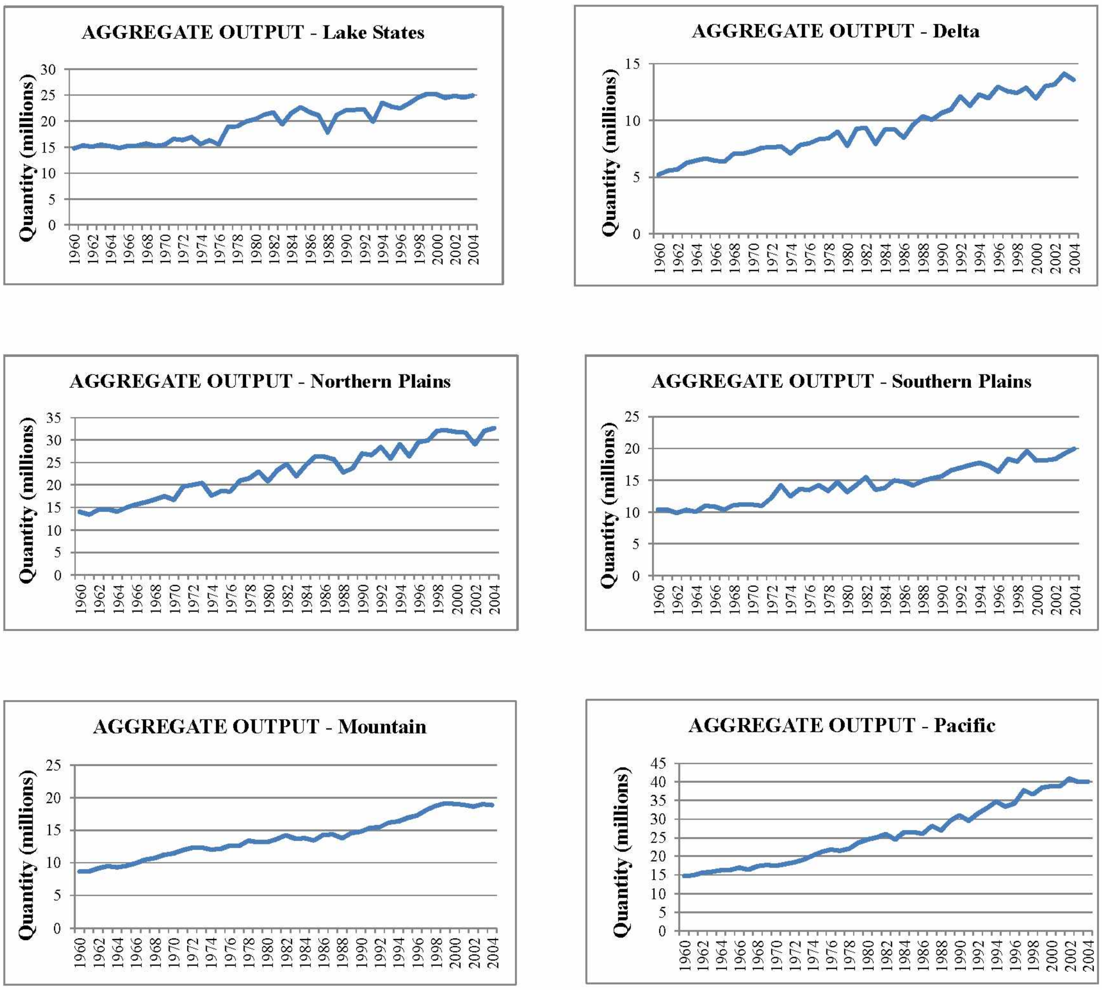

Figure 2.1 (continued)

Figure 2.1 presents the aggregate output trends for all regions over the whole period. As one of the expected results of increasing agricultural productivity, the aggregate output shows an increasing trend. While this increase is considerably sharp at about 200% in the Pacific and Delta regions, the other regions see an increase of almost 100%. If we compare the figures recorded in the last years of this period, it is clear that the Corn Belt reached by far the highest figure in terms of aggregate output quantity. Moreover, both the growth rate and the quantity of aggregate output recorded in the last years are considerably similar in the Appalachia, Southeast, Southern Plains and Mountain regions. It is noteworthy that, the lowest growth of aggregate output quantity is seen in the Northeast at just under 50%.

2.4 Methodology

In the dissertation, US agricultural structure is analysed with reference to production and cost using the translog production, translog cost and generalized leontief cost functions. First, the transcendental logarithmic production function and its properties are discussed and substitution elasticities for each pair of inputs are calculated at a mean value for all data. Then the same process is employed using the generalized leontief cost and the translog cost function on the grounds that it makes possible a comparison of estimation of elasticity of substitutions obtained using each model. Data management and estimation is performed using STATA (2011).

2.4.1 The Translog Production Function

The translog production function in a panel data context, assuming that a time trend representation of technical change may be *non neutral* and *scale augmenting*, has the following form:

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_{jk} \ln x_{jit} + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} \beta_{jk} \ln x_{jit} \ln x_{kit} + \gamma t \tag{2.1}$$

where $i = 1, ..., N$ are the cross-section units; $t = 1, ..., T$ are time periods; $j, k = 1, ..., J$ are the numbers of inputs and lnx_{it}, lny_{it} are the logarithm of ith unit's input and output in period t, respectively. A number of restrictions are required for estimation of Eq.(2.1). First *symmetry* constraint which requires $\beta_{jk} = \beta_{kj}$ proposed by *Young's Thm.*[3]is imposed. The translog production func-

[3]**Young's Theorem:** Let $f : \mathbb{R} \to \mathbb{R}$ is a twice continously differentiable function on its domain of definition, $\mathbb{X} \subset \mathbb{R}$. Then on the interior of its domain, the $n \times n$ matrix of second order partial derivatives is *symmetric* and satisfies the following condition:

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$$

tion is homothetic and technology exhibits constant returns to scale implying linear homogeneity. In a homothetic and linear homogenous production function[4], for the marginal rate of technical substitution to be homogeneous of degree zero in inputs and translog production function to be homogenous of degree one requires that the following restrictions[5] to be held:

$$\sum_{k}^{J} \beta_{jk} = 0 \quad and \quad \sum_{k}^{J} \beta_{k} = 1 \tag{2.2}$$

$$\beta_k + \beta_l + \beta_e + \beta_m + \beta_n + \beta_p + \beta_f = 1 \tag{2.3}$$

$$\beta_{kk} + \beta_{kl} + \beta_{ke} + \beta_{km} + \beta_{kn} + \beta_{kp} + \beta_{kf} = 0 \tag{2.4}$$

$$\beta_{kl} + \beta_{ll} + \beta_{le} + \beta_{lm} + \beta_{ln} + \beta_{lp} + \beta_{lf} = 0 \tag{2.5}$$

$$\beta_{ke} + \beta_{le} + \beta_{ee} + \beta_{em} + \beta_{en} + \beta_{ep} + \beta_{ef} = 0 \tag{2.6}$$

$$\beta_{km} + \beta_{lm} + \beta_{em} + \beta_{mm} + \beta_{mn} + \beta_{mp} + \beta_{mf} = 0 \tag{2.7}$$

$$\beta_{kn} + \beta_{ln} + \beta_{en} + \beta_{nm} + \beta_{nn} + \beta_{np} + \beta_{nf} = 0 \tag{2.8}$$

$$\beta_{kp} + \beta_{lp} + \beta_{ep} + \beta_{mp} + \beta_{np} + \beta_{pp} + \beta_{pf} = 0 \tag{2.9}$$

$$\beta_{kf} + \beta_{lf} + \beta_{ef} + \beta_{mf} + \beta_{nf} + \beta_{pf} + \beta_{ff} = 0 \tag{2.10}$$

Rearranging the above constraints and then imposing them to the production function Eq.(2.1) yields:

[4]Homothetic function is a monotonic transformation of a function which is homogenous of degree one.

[5]Here the subscripts are used in terms of the notations capital, labour, energy, material, land pesticides and fertilizers, respectively.

$$
\begin{aligned}
\ln q = {} & \beta_0 + (1 - \beta_l - \beta_e - \beta_m - \beta_n - \beta_f - \beta_p)\ln k + \beta_l \ln l + \beta_e \ln e \\
& + \beta_m \ln m + \beta_n \ln n + \beta_f \ln f + \beta_p \ln p \\
& + \frac{1}{2}\ln k^2(-\beta_{kl} - \beta_{ke} - \beta_{km} - \beta_{kn} - \beta_{kf} - \beta_{kp}) + \beta_{kl} \ln k \ln l \\
& + \beta_{ke} \ln k \ln e + \beta_{km} \ln k \ln m + \beta_{kn} \ln k \ln n + \beta_{kf} \ln k \ln f + \beta_{kp} \ln k \ln p \\
& + \frac{1}{2}\ln l^2(-\beta_{kl} - \beta_{le} - \beta_{lm} - \beta_{ln} - \beta_{lf} - \beta_{lp}) + \beta_{le} \ln l \ln e \\
& + \beta_{lm} \ln l \ln m + \beta_{ln} \ln l \ln n + \beta_{lf} \ln l \ln f + \beta_{lp} \ln l \ln p \\
& + \frac{1}{2}\ln e^2(-\beta_{ke} - \beta_{le} - \beta_{em} - \beta_{en} - \beta_{ep} - \beta_{ef}) + \beta_{em} \ln e \ln m \\
& + \beta_{en} \ln e \ln n + \beta_{ep} \ln e \ln p + \beta_{ef} \ln e \ln f \\
& + \frac{1}{2}\ln m^2(-\beta_{km} - \beta_{lm} - \beta_{em} - \beta_{mn} - \beta_{mf} - \beta_{mp}) + \beta_{mn} \ln m \ln n \\
& + \beta_{mf} \ln m \ln f + \beta_{mp} \ln m \ln p \\
& + \frac{1}{2}\ln n^2(-\beta_{kn} - \beta_{ln} - \beta_{en} - \beta_{mn} - \beta_{nf} - \beta_{np}) + \beta_{nf} \ln n \ln f + \beta_{np} \ln n \ln p \\
& + \frac{1}{2}\ln f^2(-\beta_{kf} - \beta_{lf} - \beta_{ef} - \beta_{mf} - \beta_{nf} - \beta_{pf}) + \beta_{pf} \ln f \ln p \\
& + \frac{1}{2}\ln p^2(-\beta_{kp} - \beta_{lp} - \beta_{ep} - \beta_{mp} - \beta_{np} - \beta_{pf})
\end{aligned}
\tag{2.11}
$$

$$
\begin{aligned}
(\ln q - \ln k) = {} & \beta_0 + \beta_l(\ln l - \ln k) + \beta_e(\ln e - \ln k) + \beta_m(\ln m - \ln k) + \beta_n(\ln n - \ln k) \\
& + \beta_f(\ln f - \ln k) + \beta_p(\ln p - \ln k) + \beta_{kl}(\ln k \ln l - 0.5\ln k^2 - 0.5\ln l^2) \\
& + \beta_{ke}(\ln k \ln e - 0.5\ln k^2 - 0.5\ln e^2) + \beta_{km}(\ln k \ln m - 0.5\ln k^2 - 0.5\ln m^2) \\
& + \beta_{kn}(\ln k \ln n - 0.5\ln k^2 - 0.5\ln n^2) + \beta_{kf}(\ln k \ln f - 0.5\ln k^2 - 0.5\ln f^2) \\
& + \beta_{kp}(\ln k \ln p - 0.5\ln k^2 - 0.5\ln p^2) + \beta_{le}(\ln l \ln e - 0.5\ln l^2 - 0.5\ln e^2) \\
& + \beta_{lm}(\ln l \ln m - 0.5\ln l^2 - 0.5\ln m^2) + \beta_{ln}(\ln l \ln n - 0.5\ln l^2 - 0.5\ln n^2) \\
& + \beta_{lf}(\ln l \ln f - 0.5\ln l^2 - 0.5\ln f^2) + \beta_{lp}(\ln l \ln p - 0.5\ln l^2 - 0.5\ln p^2) \\
& + \beta_{em}(\ln e \ln m - 0.5\ln e^2 - 0.5\ln m^2) + \beta_{en}(\ln e \ln n - 0.5\ln e^2 - 0.5\ln n^2) \\
& + \beta_{ep}(\ln e \ln p - 0.5\ln e^2 - 0.5\ln p^2) + \beta_{ef}(\ln e \ln f - 0.5\ln e^2 - 0.5\ln f^2) \\
& + \beta_{mn}(\ln m \ln n - 0.5\ln m^2 - 0.5\ln n^2) + \beta_{mf}(\ln m \ln f - 0.5\ln m^2 - 0.5\ln f^2) \\
& + \beta_{mp}(\ln m \ln p - 0.5\ln m^2 - 0.5\ln p^2) + \beta_{nf}(\ln n \ln f - 0.5\ln n^2 - 0.5\ln f^2) \\
& + \beta_{np}(\ln n \ln p - 0.5\ln n^2 - 0.5\ln p^2) \\
& + \beta_{pf}(\ln p \ln f - 0.5\ln p^2 - 0.5\ln f^2)
\end{aligned}
\tag{2.12}
$$

where k: capital, l: labour, e: energy, m: materials, n: land, p: pesticides, f: fertilizers.

In order to make the estimation of this equation easier, we use the y^* and z notations whose explicit forms are given as follows:

$$y^* = \ln q - \ln k \tag{2.13}$$

$$z_n = \ln x_n - \ln k \tag{2.14}$$

$$z_{nm} = \ln x_n \ln x_m - 0.5(\ln x_m)^2 - 0.5(\ln x_n)^2 \tag{2.15}$$

where x_n in Eq.(2.14) refers to the quantity of each input except capital while x_n and x_m in Eq.(2.15) represent the quantities of the seven inputs including capital. Having replaced these notations, Eq.(2.12) transforms into Eq.(2.16) named *restricted equation* by Coelli (2005) as follows:

$$\begin{aligned} y^* = {} & \beta_0 + \beta_l z_l + \beta_e z_e + \beta_m z_m + \beta_n z_n + \beta_p z_p + \beta_f z_f \\ & + \beta_{kl} z_{kl} + \beta_{ke} z_{ke} + \beta_{km} z_{km} + \beta_{kn} z_{kn} + \beta_{kp} z_{kp} \\ & + \beta_{kf} z_{kf} + \beta_{le} z_{le} + \beta_{lm} z_{lm} + \beta_{ln} z_{ln} + \beta_{lp} z_{lp} + \beta_{lf} z_{lf} \\ & + \beta_{em} z_{em} + \beta_{en} z_{en} + \beta_{ep} z_{ep} + \beta_{ef} z_{ef} + \beta_{mn} z_{mn} + \beta_{mp} z_{mp} \\ & + \beta_{mf} z_{mf} + \beta_{mp} z_{mp} + \beta_{nf} z_{nf} + \beta_{np} z_{np} + \beta_{pf} z_{pf} \end{aligned} \tag{2.16}$$

While applied econometrics proposes a number of methods to estimate coefficients of single equations like the equation above, the choice of method depends on the type of data (time series, cross section or panel data) employed in the model. Since the data used in this equation is panel data, we first give panel data estimation techniques and then the criteria to determine the most appropriate for estimation. A variety of methods with advantages and drawbacks are used to assess the panel data:

1. **Pooled Model**

2. **Fixed Effect Model**

3. **Random Effect Model**

1. Pooled Model The fixed parameter α, explanatory variables β_{it} do not change with respect to cross-section and time trend. For all i, t $\beta_{it} = \beta$ and $\alpha_{it} = \alpha$ which converts the panel equation:

$$y_{it} = \alpha_{it} + \beta_{it}x_{it} + \epsilon_{it}$$

to the equation below:

$$y_{it} = \alpha + \beta x_{it} + \epsilon_{it}$$

where y_{it} and x_{it} are one direction vector notations of all units for each period.

2. Fixed Effect Model Fixed and Random Effects models differ in the assumptions about how the heterogeneity is captured (Arellano, 2003). The fixed Effect Model assumes that individual heterogeneity is captured by the intercept term. This means each unit gets its own intercept α_i while the slope coefficients are the same for all units. This also means that heterogeneity is associated with the regressors on the right hand side (Baltagi, 2005).

3. Random Effect Model Random Effects Model assumes that individual effects are captured by the intercept and a random component μ_i. This random component is not associated with the regressors on the right hand side and is not a part of the error term. The intercept becomes $\alpha + \mu_i$. The regression equation for random effect model takes the following form:

$$y_{it} = \alpha_i + \beta x_{it} + \epsilon_{it} \qquad where \qquad \epsilon_{it} = \mu_i + v_{it} \qquad and \qquad E(\mu_i) = 0.$$

Panel Estimation Criteria

Hausman Test: Hausman Test is a test which is used to decide whether to employ fixed or random effects model (Hausman, 1978). This is a test of the null hypothesis which states that random effects would be consistent and efficient as opposed to the alternative hypothesis where random effects would be inconsistent. The question is whether there is significant correlation between the unobserved unit specific random effects and the regressors. If there is no correlation, then the random effects model may be more powerful. The test statistic is calculated using the formula below:

$$\frac{\beta_{FE} - \beta_{RE}}{{S_{\beta FE}}^2 - {S_{\beta RE}}^2}$$

where β_{FE} are the fixed effect model coefficients β_{RE} are the random effects model coefficients, ${S_{\beta FE}}^2$, ${S_{\beta RE}}^2$ are the variances of the fixed and random effect model coefficients and the statistic has chi square distribution. An insignificant p value (greater than 0.05) means it is safe to use random effects. If the p value is significant, however, fixed effects model should be used (Menard, 2007). One question that needs to be addressed is whether correlation among individuals or heteroskedasticity arise in panel estimations. We employ tests[6]to find the answer to this question. As a consequence of employing panel data, the individual heterogeneity can be captured in the model (Biørn and Skjerpen, 2002). On this basis, we test fixed and random effects using Hausman test (Chi-square statistic=171.40 with p-value <0.00001). Since test statistic rejects random effect, we use fixed effects while adding time effects. The results for estimated translog production function are presented in Table 2.4 below:

[6]Friedman, Frees and Paseran tests were applied for correlation and the results: Friedman's test of cross sectional independence = 533.886, Pr = 0.0000, Frees' test of cross sectional independence = 4.355, Pr = 0.0000 and Pesaran's test of cross sectional independence = 55.725, Pr = 0.0000 rejecting null hypethosis of no correlation were derived respectively. Wald test revealed the existence of heteroskedasticity. Cluster(id) command was used in STATA to correct heteroskedasticity and correlation. While t statistics change, parameter estimations would be the same.

Table 2.4: **Translog Production Function Parameter Estimates**

Ystar	Coef.	Std. Err.	t	P > |t|	[95% Conf. Interval]	
β_l	-0,09620	0,07529	-1,28	0,20	-0,24385	0,05145
β_e	0,39143	0,09906	3,95	0,00	0,19715	0,58571
β_m	0,25847	0,07562	3,42	0,00	0,11017	0,40678
β_n	0,05124	0,04397	1,17	0,24	-0,03499	0,13747
β_f	0,04340	0,04280	1,01	0,31	-0,04054	0,12734
β_p	0,35709	0,03313	10,78	0,00	0,29213	0,42206
β_{kl}	-0,06506	0,02722	-2,39	0,02	-0,11844	-0,01168
β_{ke}	-0,10791	0,03864	-2,79	0,01	-0,18370	-0,03213
β_{km}	0,11519	0,02895	3,98	0,00	0,05842	0,17196
β_{kn}	0,02495	0,01733	1,44	0,15	-0,00904	0,05894
β_{kf}	-0,00919	0,01786	-0,51	0,61	-0,04421	0,02583
β_{kp}	-0,01059	0,01340	-0,79	0,43	-0,03686	0,01569
β_{le}	-0,00268	0,02727	-0,10	0,92	-0,05616	0,05081
β_{lm}	-0,04460	0,02370	-1,88	0,06	-0,09108	0,00187
β_{ln}	0,04188	0,01511	2,77	0,01	0,01226	0,07151
β_{lf}	0,02629	0,01442	1,82	0,07	-0,00198	0,05457
β_{lp}	-0,03816	0,01204	-3,17	0,00	-0,06178	-0,01454
β_{em}	0,00931	0,03552	0,26	0,79	-0,06034	0,07897
β_{en}	-0,00832	0,02322	-0,36	0,72	-0,05386	0,03721
β_{ep}	0,10000	0,01971	5,07	0,00	0,06136	0,13865
β_{ef}	-0,00510	0,02273	-0,22	0,82	-0,04966	0,03947
β_{mn}	-0,05124	0,01573	-3,26	0,00	-0,08208	-0,02039

Table 2.4 (continued)

β_{mp}	-0,07916	0,01314	-6,02	0,00	-0,10493	-0,05339
β_{mf}	-0,00556	0,01763	-0,32	0,75	-0,04014	0,02901
β_{np}	-0,01595	0,00785	-2,03	0,04	-0,03135	-0,00055
β_{nf}	-0,01664	0,00981	-1,70	0,09	-0,03589	0,00260
β_{pf}	0,03352	0,00925	3,62	0,00	0,01538	0,05166
γ_{1961}	0,01424	0,01392	1,02	0,31	-0,01305	0,04154
γ_{1962}	0,03161	0,01414	2,24	0,03	0,00388	0,05935
γ_{1963}	0,06502	0,01440	4,52	0,00	0,03678	0,09326
γ_{1964}	0,06879	0,01478	4,65	0,00	0,03980	0,09778
γ_{1965}	0,09802	0,01508	6,50	0,00	0,06844	0,12761
γ_{1966}	0,09122	0,01598	5,71	0,00	0,05989	0,12255
γ_{1967}	0,10212	0,01694	6,03	0,00	0,06890	0,13534
γ_{1968}	0,11054	0,01706	6,48	0,00	0,07709	0,14399
γ_{1969}	0,12894	0,01757	7,34	0,00	0,09449	0,16340
γ_{1970}	0,12714	0,01798	7,07	0,00	0,09187	0,16241
γ_{1971}	0,18405	0,01842	9,99	0,00	0,14792	0,22017
γ_{1972}	0,17804	0,01891	9,41	0,00	0,14094	0,21513
γ_{1973}	0,17275	0,01912	9,04	0,00	0,13526	0,21024
γ_{1974}	0,16903	0,01951	8,66	0,00	0,13076	0,20729
γ_{1975}	0,22990	0,01977	11,63	0,00	0,19114	0,26866
γ_{1976}	0,17389	0,02077	8,37	0,00	0,13316	0,21462
γ_{1977}	0,19454	0,02057	9,46	0,00	0,15421	0,23487
γ_{1978}	0,14460	0,02138	6,76	0,00	0,10268	0,18653
γ_{1979}	0,16060	0,02177	7,38	0,00	0,11790	0,20329
γ_{1980}	0,13148	0,02168	6,07	0,00	0,08898	0,17399
γ_{1981}	0,23513	0,02147	10,95	0,00	0,19303	0,27723

Table 2.4 (continued)

γ_{1982}	0,29420	0,02118	13,89	0,00	0,25267	0,33573
γ_{1983}	0,22113	0,02105	10,50	0,00	0,17984	0,26242
γ_{1984}	0,30781	0,02143	14,37	0,00	0,26579	0,34983
γ_{1985}	0,37510	0,02126	17,65	0,00	0,33342	0,41679
γ_{1986}	0,34650	0,02168	15,98	0,00	0,30397	0,38902
γ_{1987}	0,34987	0,02192	15,96	0,00	0,30689	0,39285
γ_{1988}	0,33241	0,02170	15,32	0,00	0,28985	0,37497
γ_{1989}	0,38889	0,02207	17,62	0,00	0,34561	0,43217
γ_{1990}	0,40337	0,02218	18,19	0,00	0,35987	0,44686
γ_{1991}	0,41327	0,02258	18,30	0,00	0,36898	0,45756
γ_{1992}	0,47524	0,02245	21,17	0,00	0,43122	0,51927
γ_{1993}	0,43366	0,02299	18,86	0,00	0,38857	0,47875
γ_{1994}	0,48015	0,02338	20,54	0,00	0,43429	0,52600
γ_{1995}	0,42426	0,02391	17,74	0,00	0,37737	0,47114
γ_{1996}	0,47561	0,02392	19,89	0,00	0,42871	0,52252
γ_{1997}	0,45945	0,02468	18,62	0,00	0,41105	0,50785
γ_{1998}	0,45118	0,02506	18,00	0,00	0,40203	0,50033
γ_{1999}	0,46445	0,02485	18,69	0,00	0,41572	0,51317
γ_{2000}	0,48746	0,02505	19,46	0,00	0,43834	0,53658
γ_{2001}	0,50853	0,02474	20,56	0,00	0,46002	0,55704
γ_{2002}	0,45213	0,02551	17,73	0,00	0,40211	0,50215
γ_{2003}	0,52815	0,02470	21,38	0,00	0,47970	0,57659
γ_{2004}	0,54669	0,02492	21,94	0,00	0,49782	0,59556
β_0	2,02879	0,10910	18,59	0,00	1,81483	2,24276

From Table 2.4 above we can see that, the effects of time variables (years) are substantially significant with a high t statistic. This underlines the importance of the use of time variables in the estimation.

Of these parameters, β_{kl}, β_{ke}, β_{ln} and β_{np} are found to be statistically significant at the 0.05 level of confidence. On the other hand, β_{km}, β_{lp}, β_{ep}, β_{mn}, β_{mp} and β_{pf} are found to be statistically significant at the 0.01 level of confidence. In a similar vein, all the time variable estimations ($\gamma_t' s$) except for two years 1961 and 1962 are found to be statistically significant at the 0.01 level of confidence. If we now turn to the estimation process again, we employ Hessian bordered matrix for AES (Allen Elasticity Substitution) formulation after the estimating the parameters in the translog production function.

Hessian bordered matrix of production function with inputs is defined as:

$$H = \begin{bmatrix} 0 & f_k & f_l & f_e & f_m & f_n & f_p & f_f \\ f_k & f_{kk} & f_{kl} & f_{ke} & f_{km} & f_{kn} & f_{kp} & f_{kf} \\ f_l & f_{lk} & f_{ll} & f_{le} & f_{lm} & f_{ln} & f_{lp} & f_{lf} \\ f_e & f_{ek} & f_{el} & f_{ee} & f_{em} & f_{en} & f_{ep} & f_{ef} \\ f_m & f_{mk} & f_{ml} & f_{me} & f_{mm} & f_{mn} & f_{mp} & f_{mf} \\ f_n & f_{nk} & f_{nl} & f_{ne} & f_{nm} & f_{nn} & f_{np} & f_{nf} \\ f_p & f_{pk} & f_{pl} & f_{pe} & f_{pm} & f_{pn} & f_{pp} & f_{pf} \\ f_f & f_{fk} & f_{fl} & f_{fe} & f_{fm} & f_{fn} & f_{fp} & f_{ff} \end{bmatrix}$$

Since the form of minor cofactors for each input are similar, we only show minor cofactors of capital for the Hessian bordered matrix:

$$M_{KL} = \begin{bmatrix} 0 & f_k & f_e & f_m & f_n & f_p & f_f \\ f_l & f_{lk} & f_{le} & f_{lm} & f_{ln} & f_{lp} & f_{lf} \\ f_e & f_{ek} & f_{ee} & f_{em} & f_{en} & f_{ep} & f_{ef} \\ f_m & f_{mk} & f_{me} & f_{mm} & f_{mn} & f_{mp} & f_{mf} \\ f_n & f_{nk} & f_{ne} & f_{nm} & f_{nn} & f_{np} & f_{nf} \\ f_p & f_{pk} & f_{pe} & f_{pm} & f_{pn} & f_{pp} & f_{pf} \\ f_f & f_{fk} & f_{fe} & f_{fm} & f_{fn} & f_{fp} & f_{ff} \end{bmatrix} M_{KM} = \begin{bmatrix} 0 & f_k & f_l & f_e & f_n & f_p & f_f \\ f_l & f_{lk} & f_{ll} & f_{le} & f_{ln} & f_{lp} & f_{lf} \\ f_e & f_{ek} & f_{el} & f_{em} & f_{en} & f_{ep} & f_{ef} \\ f_m & f_{mk} & f_{ml} & f_{mm} & f_{mn} & f_{mp} & f_{mf} \\ f_n & f_{nk} & f_{nl} & f_{nm} & f_{nn} & f_{np} & f_{nf} \\ f_p & f_{pk} & f_{pl} & f_{pm} & f_{pn} & f_{pp} & f_{pf} \\ f_f & f_{fk} & f_{fl} & f_{fm} & f_{fn} & f_{fp} & f_{ff} \end{bmatrix}$$

$$M_{KN} = \begin{bmatrix} 0 & f_k & f_l & f_e & f_m & f_p & f_f \\ f_l & f_{lk} & f_{ll} & f_{le} & f_{lm} & f_{lp} & f_{lf} \\ f_e & f_{ek} & f_{el} & f_{ee} & f_{em} & f_{ep} & f_{ef} \\ f_m & f_{mk} & f_{ml} & f_{me} & f_{mm} & f_{mp} & f_{mf} \\ f_n & f_{nk} & f_{nl} & f_{ne} & f_{nm} & f_{np} & f_{nf} \\ f_p & f_{pk} & f_{pl} & f_{pe} & f_{pm} & f_{pp} & f_{pf} \\ f_f & f_{fk} & f_{fl} & f_{fe} & f_{fm} & f_{fp} & f_{ff} \end{bmatrix} M_{KP} = \begin{bmatrix} 0 & f_k & f_l & f_e & f_m & f_n & f_f \\ f_l & f_{lk} & f_{ll} & f_{le} & f_{lm} & f_{ln} & f_{lf} \\ f_e & f_{ek} & f_{el} & f_{ee} & f_{em} & f_{en} & f_{ef} \\ f_m & f_{mk} & f_{ml} & f_{me} & f_{mm} & f_{mn} & f_{mf} \\ f_n & f_{nk} & f_{nl} & f_{ne} & f_{nm} & f_{nn} & f_{nf} \\ f_p & f_{pk} & f_{pl} & f_{pe} & f_{pm} & f_{pn} & f_{pf} \\ f_f & f_{fk} & f_{fl} & f_{fe} & f_{fm} & f_{fn} & f_{ff} \end{bmatrix}$$

$$M_{KF} = \begin{bmatrix} 0 & f_k & f_l & f_e & f_m & f_n & f_p \\ f_l & f_{lk} & f_{ll} & f_{le} & f_{lm} & f_{ln} & f_{lp} \\ f_e & f_{ek} & f_{el} & f_{ee} & f_{em} & f_{en} & f_{ep} \\ f_m & f_{mk} & f_{ml} & f_{me} & f_{mm} & f_{mn} & f_{mp} \\ f_n & f_{nk} & f_{nl} & f_{ne} & f_{nm} & f_{nn} & f_{np} \\ f_p & f_{pk} & f_{pl} & f_{pe} & f_{pm} & f_{pn} & f_{pp} \\ f_f & f_{fk} & f_{fl} & f_{fe} & f_{fm} & f_{fn} & f_{fp} \end{bmatrix} M_{KE} = \begin{bmatrix} 0 & f_k & f_l & f_m & f_n & f_p & f_f \\ f_l & f_{lk} & f_{ll} & f_{lm} & f_{ln} & f_{lp} & f_{lf} \\ f_e & f_{ek} & f_{el} & f_{em} & f_{en} & f_{ep} & f_{ef} \\ f_m & f_{mk} & f_{ml} & f_{mm} & f_{mn} & f_{mp} & f_{mf} \\ f_n & f_{nk} & f_{nl} & f_{nm} & f_{nn} & f_{np} & f_{nf} \\ f_p & f_{pk} & f_{pl} & f_{pm} & f_{pn} & f_{pp} & f_{pf} \\ f_f & f_{fk} & f_{fl} & f_{fm} & f_{fn} & f_{fp} & f_{ff} \end{bmatrix}$$

All the minor cofactors of each input pair, like the capital represented above, are computed, then Allen elasticity substitution among for all input pairs is derived using the estimated coefficient from the formula:

$$\Theta_{ij} = \frac{\sum_{i=1}^{7} X_i f_i}{X_i X_j} \frac{F_{ij}}{F} \qquad where \qquad i,j = 1,...,7 \tag{2.17}$$

where X's are input quantities, f_i is the first derivative with respect to each input and F is the Hessian bordered matrix which is denoted by H. Logarithmic marginal product f_i for input i is defined as:

$$f_i = \frac{\partial \ln y}{\partial \ln x_i} \frac{y}{x_i} = (\beta_i + \sum_{j=1}^{n} \beta_{ij} \ln x_j) \frac{y}{x_i} \qquad where \qquad i,j = 1,...,7 \tag{2.18}$$

The first term in the formula represents the production elasticity ϵ_i :

$$f_i = \epsilon_i \frac{y}{x_i} \qquad where \qquad \epsilon_i = \beta_i + \sum_{j=1}^{n} \beta_{ij} \ln x_j \qquad and \qquad i,j = 1,...,7 \tag{2.19}$$

$$\begin{aligned}\epsilon_k =& \beta_k + \beta_{kk} \ln k + \beta_{kl} \ln l + \beta_{ke} \ln e + \beta_{km} \ln m + \beta_{kn} \ln n + \beta_{kp} \ln p \\ &+ \beta_{kf} \ln f \end{aligned} \tag{2.20}$$

$$\begin{aligned}\epsilon_l =& \beta_l + \beta_{lk} \ln k + \beta_{ll} \ln l + \beta_{le} \ln e + \beta_{lm} \ln m + \beta_{ln} \ln n + \beta_{lp} \ln p \\ &+ \beta_{lf} \ln f \end{aligned} \tag{2.21}$$

$$\begin{aligned}\epsilon_e =& \beta_e + \beta_{ke} \ln k + \beta_{le} \ln l + \beta_{ee} \ln e + \beta_{em} \ln m + \beta_{en} \ln n + \beta_{ep} \ln p \\ &+ \beta_{ef} \ln f \end{aligned} \tag{2.22}$$

$$\begin{aligned}\epsilon_m =& \beta_m + \beta_{km} \ln k + \beta_{lm} \ln l + \beta_{em} \ln e + \beta_{mm} \ln m + \beta_{mn} \ln n + \beta_{mp} \ln p \\ &+ \beta_{mf} \ln f \end{aligned} \tag{2.23}$$

$$\begin{aligned}\epsilon_n =& \beta_n + \beta_{kn} \ln k + \beta_{ln} \ln l + \beta_{ne} \ln e + \beta_{mn} \ln m + \beta_{nn} \ln n + \beta_{np} \ln p \\ &+ \beta_{nf} \ln f \end{aligned} \tag{2.24}$$

$$\begin{aligned}\epsilon_p =& \beta_p + \beta_{kp} \ln k + \beta_{lp} \ln l + \beta_{ep} \ln e + \beta_{mp} \ln m + \beta_{np} \ln n + \beta_{pp} \ln p \\ &+ \beta_{pf} \ln f \end{aligned} \tag{2.25}$$

$$\begin{aligned}\epsilon_f =& \beta_f + \beta_{kf} \ln k + \beta_{lf} \ln l + \beta_{ef} \ln e + \beta_{mf} \ln m + \beta_{nf} \ln n + \beta_{pf} \ln p \\ &+ \beta_{ff} \ln f \end{aligned} \tag{2.26}$$

It is common to use mean (arithmetic mean), geometric mean and median at sample mean to calculate the elements of Hessian matrix and so Allen elasticity of substitution in translog production function with panel data studies (Goldar, 2012; Skjerpen and Biorn, 2002). In line with this view, we employ the mean data for the calculation of elasticity of substitution of each input pair. The results of Allen elasticity of substitution for each input pair are presented in. It is noticeable that own elasticticities for each input are negative indicating as expected that an increase in the prices lead to a decrease in the quantity demanded. Additionaly, the own elasticity of substitution for all inputs except fertilizer is inelastic. 10% increase in capital, labour, energy, materials, land, pesticides and fertilizer prices decreases the demand by 3.9, 1.2, 9.1, 8.0, 7.7, 7.7 and 15.9%, respectively. Except the cross price effect between capital and materials, all cross price effects between capital and the rest of the inputs are negative suggesting that each pair of inputs are complements. Similarly, the cross price effects between labour and the other inputs are negative except for land. The sign of the price effect between the energy and pesticides and between the energy and fertilizer are positive indicating strong substitutability with the values of 7.64 and 4.64, respectively.

On the other hand, energy is a complement for both materials and land due to a negative signed cross price effect. While the materials is substitute for both land and pesticide, it is found to be a complement for fertilizer. Furthermore, the fertilizer is substitute for land and pesticides as well. While the strongest complementarity is shown in cross price effects between labour and pesticides, the lowest is recorded between materials and fertilizer. Likewise, the strongest substitutability is exhibited between energy and pesticides, while the lowest substitutability is seen between materials and pesticides.

Table 2.5: AES of Inputs

Allen Elasticity Substitution (AES) of Inputs						
θ_{kl}	θ_{ke}	θ_{km}	θ_{kn}	θ_{kp}	θ_{kf}	θ_{le}
-6,22	-0,98	3,40	-1,59	-3,58	-3,99	-1,84
θ_{lm}	θ_{ln}	θ_{lp}	θ_{lf}	θ_{em}	θ_{en}	θ_{ep}
-1,05	7,09	-10,87	-1,23	-0,58	-1,48	7,64
θ_{ef}	θ_{mn}	θ_{mp}	θ_{mf}	θ_{np}	θ_{nf}	θ_{pf}
4,64	2,16	1,02	-0,24	-6,61	1,97	1,20
Own Price Elasticity of Inputs						
ϵ_{kk}	ϵ_{ll}	ϵ_{ee}	ϵ_{mm}	ϵ_{nn}	ϵ_{pp}	ϵ_{ff}
-0,39	-0,12	-0,91	-0,80	-0,77	-0,77	-1,59

2.4.2 The Generalized Leontief Cost Function

Let P_i be prices of inputs, the input quantitites be X_i, total costs be C, and output be Y where $i = 1, ..., n$. Assume that P_i and Y are exogenous but the X_i and C are endogenous. With constant returns to scale imposed, the Generalized Leontief (GL) cost function can be written as:

$$C = Y \times [\sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}(P_i P_j)^{1/2}] \qquad i = 1, ..., n \tag{2.27}$$

where $d_{ij} = d_{ji}$. To obtain equations that are amenable to estimation, it is convenient to employ Sheppard's Lemma, which states that the optimal cost minimizing demand for input i can simply be derived by differentiating the cost function with respect to P_i . In the GL context, therefore, optimal factor demands are obtained by differentiating the cost function with respect to P_i yielding:

$$\frac{\partial C}{\partial P_i} = X_i = Y \times [\sum_{j=1}^{n} d_{ij}(\frac{P_j}{P_i})^{1/2}] \qquad i = 1, ..., n \tag{2.28}$$

A more convenient equation for estimation purposes can be obtained by dividing X_i by Y, yielding optimal input-output demand equations denoted by a_i:

$$a_i = \frac{X_i}{Y} \qquad i = 1, ..., n \tag{2.29}$$

$$a_k = \underbrace{d_{kk}}_{a_{11}} + \underbrace{d_{kl}}_{a_{12}} \underbrace{(P_L/P_K)^{1/2}}_{b} + \underbrace{d_{ke}}_{a_{13}} \underbrace{(P_E/P_K)^{1/2}}_{c} + \underbrace{d_{km}}_{a_{14}} \underbrace{(P_M/P_K)^{1/2}}_{d} + \underbrace{d_{kn}}_{a_{15}} \underbrace{(P_N/P_K)^{1/2}}_{e}$$

$$+ \underbrace{d_{kp}}_{a_{16}} \underbrace{(P_P/P_K)^{1/2}}_{f} + \underbrace{d_{kf}}_{a_{17}} \underbrace{(P_F/P_K)^{1/2}}_{g} \tag{2.30}$$

$$a_l = \underbrace{d_{ll}}_{a_{21}} + \underbrace{d_{kl}}_{a_{12}} \underbrace{(P_K/P_L)^{1/2}}_{\frac{1}{b}} + \underbrace{d_{le}}_{a_{22}} \underbrace{(P_E/P_L)^{1/2}}_{h} + \underbrace{d_{lm}}_{a_{23}} \underbrace{(P_M/P_L)^{1/2}}_{i} + \underbrace{d_{ln}}_{a_{24}} \underbrace{(P_N/P_L)^{1/2}}_{j}$$

$$+ \underbrace{d_{lp}}_{a_{25}} \underbrace{(P_P/P_L)^{1/2}}_{k} + \underbrace{d_{lf}}_{a_{26}} \underbrace{(P_F/P_L)^{1/2}}_{l} \tag{2.31}$$

$$a_e = \underbrace{d_{ee}}_{a_{31}} + \underbrace{d_{ke}}_{a_{13}} \underbrace{(P_K/P_E)^{1/2}}_{\frac{1}{c}} + \underbrace{d_{le}}_{a_{22}} \underbrace{(P_L/P_E)^{1/2}}_{\frac{1}{h}} + \underbrace{d_{em}}_{a_{32}} \underbrace{(P_M/P_E)^{1/2}}_{m} + \underbrace{d_{en}}_{a_{33}} \underbrace{(P_N/P_E)^{1/2}}_{n}$$

$$+ \underbrace{d_{ep}}_{a_{34}} \underbrace{(P_P/P_E)^{1/2}}_{p} + \underbrace{d_{ef}}_{a_{35}} \underbrace{(P_F/P_E)^{1/2}}_{r} \tag{2.32}$$

$$a_m = \underbrace{d_{mm}}_{a_{41}} + \underbrace{d_{km}}_{a_{14}} \underbrace{(P_K/P_M)^{1/2}}_{\frac{1}{d}} + \underbrace{d_{lm}}_{a_{23}} \underbrace{(P_L/P_M)^{1/2}}_{\frac{1}{i}} + \underbrace{d_{em}}_{a_{32}} \underbrace{(P_E/P_M)^{1/2}}_{\frac{1}{m}} + \underbrace{d_{mn}}_{a_{42}} \underbrace{(P_N/P_M)^{1/2}}_{s}$$

$$+ \underbrace{d_{mp}}_{a_{43}} \underbrace{(P_P/P_M)^{1/2}}_{t} + \underbrace{d_{mf}}_{a_{44}} \underbrace{(P_F/P_M)^{1/2}}_{u} \tag{2.33}$$

$$a_n = \underbrace{d_{nn}}_{a_{51}} + \underbrace{d_{kn}}_{a_{15}} \underbrace{(P_K/P_N)^{1/2}}_{\frac{1}{e}} + \underbrace{d_{ln}}_{a_{24}} \underbrace{(P_L/P_N)^{1/2}}_{\frac{1}{j}} + \underbrace{d_{en}}_{a_{33}} \underbrace{(P_E/P_N)^{1/2}}_{\frac{1}{n}} + \underbrace{d_{mn}}_{a_{42}} \underbrace{(P_M/P_N)^{1/2}}_{\frac{1}{s}}$$

$$+ \underbrace{d_{np}}_{a_{52}} \underbrace{(P_P/P_N)^{1/2}}_{v} + \underbrace{d_{nf}}_{a_{53}} \underbrace{(P_F/P_N)^{1/2}}_{y} \tag{2.34}$$

$$a_p = \underbrace{d_{pp}}_{a_{61}} + \underbrace{d_{kp}}_{a_{16}} \underbrace{(P_K/P_P)^{1/2}}_{\frac{1}{f}} + \underbrace{d_{lp}}_{a_{25}} \underbrace{(P_L/P_P)^{1/2}}_{\frac{1}{k}} + \underbrace{d_{ep}}_{a_{34}} \underbrace{(P_E/P_P)^{1/2}}_{\frac{1}{p}} + \underbrace{d_{mp}}_{a_{43}} \underbrace{(P_M/P_P)^{1/2}}_{\frac{1}{t}}$$

$$+ \underbrace{d_{np}}_{a_{52}} \underbrace{(P_N/P_P)^{1/2}}_{\frac{1}{v}} + \underbrace{d_{pf}}_{a_{62}} \underbrace{(P_F/P_P)^{1/2}}_{z} \tag{2.35}$$

$$a_f = \underbrace{d_{ff}}_{a_{71}} + \underbrace{d_{kf}}_{a_{17}} \underbrace{(P_K/P_F)^{1/2}}_{\frac{1}{g}} + \underbrace{d_{lf}}_{a_{26}} \underbrace{(P_L/P_F)^{1/2}}_{\frac{1}{l}} + \underbrace{d_{ef}}_{a_{35}} \underbrace{(P_E/P_F)^{1/2}}_{\frac{1}{r}} + \underbrace{d_{mf}}_{a_{44}} \underbrace{(P_M/P_F)^{1/2}}_{\frac{1}{u}}$$

$$+ \underbrace{d_{nf}}_{a_{53}} \underbrace{(P_N/P_F)^{1/2}}_{\frac{1}{y}} + \underbrace{d_{pf}}_{a_{62}} \underbrace{(P_P/P_F)^{1/2}}_{\frac{1}{z}} \tag{2.36}$$

The equations above can be written with the notations of intensity coefficients as follows:

$$a_k = a_{11} + a_{12}b + a_{13}c + a_{14}d + a_{15}e + a_{16}f + a_{17}g \tag{2.37}$$

$$a_l = a_{21} + a_{12}\frac{1}{b} + a_{22}h + a_{23}i + a_{24}j + a_{25}k + a_{26}l \tag{2.38}$$

$$a_e = a_{31} + a_{13}\frac{1}{c} + a_{22}\frac{1}{h} + a_{32}m + a_{33}n + a_{34}p + a_{35}r \tag{2.39}$$

$$a_m = a_{41} + a_{14}\frac{1}{d} + a_{23}\frac{1}{i} + a_{32}\frac{1}{m} + a_{42}s + a_{43}t + a_{44}u \tag{2.40}$$

$$a_n = a_{51} + a_{15}\frac{1}{e} + a_{24}\frac{1}{j} + a_{33}\frac{1}{n} + a_{42}\frac{1}{s} + a_{52}v + a_{53}y \tag{2.41}$$

$$a_p = a_{61} + a_{16}\frac{1}{f} + a_{25}\frac{1}{k} + a_{34}\frac{1}{p} + a_{43}\frac{1}{t} + a_{52}\frac{1}{v} + a_{62}z \tag{2.42}$$

$$a_f = a_{71} + a_{17}\frac{1}{g} + a_{26}\frac{1}{l} + a_{35}\frac{1}{r} + a_{44}\frac{1}{u} + a_{53}\frac{1}{y} + a_{62}\frac{1}{z} \tag{2.43}$$

$$\underbrace{\begin{bmatrix} (a_k) \\ (a_l) \\ (a_e) \\ (a_m) \\ (a_n) \\ (a_p) \\ (a_f) \end{bmatrix}}_{\substack{\textit{Demand} \\ \textit{Matrix}}} = \underbrace{\begin{bmatrix} (a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17}) \\ (a_{21} & a_{12} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26}) \\ (a_{31} & a_{13} & a_{22} & a_{32} & a_{33} & a_{34} & a_{35}) \\ (a_{41} & a_{14} & a_{23} & a_{32} & a_{42} & a_{43} & a_{44}) \\ (a_{51} & a_{15} & a_{24} & a_{33} & a_{42} & a_{52} & a_{53}) \\ (a_{61} & a_{16} & a_{25} & a_{34} & a_{43} & a_{52} & a_{62}) \\ (a_{71} & a_{17} & a_{26} & a_{35} & a_{44} & a_{53} & a_{62}) \end{bmatrix}}_{\textit{Coefficient Matrix}} \underbrace{\begin{bmatrix} (1 & b & c & d & e & f & g)^T \\ (1 & \frac{1}{b} & h & i & j & k & l)^T \\ (1 & \frac{1}{c} & \frac{1}{h} & m & n & p & r)^T \\ (1 & \frac{1}{d} & \frac{1}{i} & \frac{1}{m} & s & t & u)^T \\ (1 & \frac{1}{e} & \frac{1}{j} & \frac{1}{n} & \frac{1}{s} & v & y)^T \\ (1 & \frac{1}{f} & \frac{1}{k} & \frac{1}{p} & \frac{1}{t} & \frac{1}{v} & z)^T \\ (1 & \frac{1}{g} & \frac{1}{l} & \frac{1}{r} & \frac{1}{u} & \frac{1}{y} & \frac{1}{z})^T \end{bmatrix}}_{\textit{Price Ratio Matrix}}$$

$$\underbrace{I}_{\textit{intensity}} = \underbrace{C}_{\textit{coefficients}} \times \underbrace{R}_{\textit{price ratio}}$$

Once the symmetry restrictions of the coefficient matrix are imposed, SURE method is applied to the system of demand matrix, coefficient matrix and price ratio matrix. Thereafter, fixed effect is employed with the dummy variables which represent the effect of each state. This method is similar to that used in the study of Paul et al. (2001). There is another study by Addison et al. (2005) which also applied Generalized Leontief with panel data for analysing the labour demand in Germany between the years 1993-2002. Table 2.6 shows the estimated paremeters which are derived from factor - demand equation system.

Table 2.6: GL Cost Function Parameter Estimates

Parameter	Coef	Std Err	z	P> $\|z\|$	[95% Conf.	Interval]
a12	-0,08369	0,00500	-16,72	0,00	-0,09350	-0,07389
a13	-0,00476	0,00421	-1,13	0,26	-0,01302	0,00350
a14	0,08733	0,00647	13,49	0,00	0,07464	0,10002
a15	0,05835	0,00410	14,22	0,00	0,05031	0,06640
a16	0,00630	0,00405	1,56	0,12	-0,00163	0,01423
a17	0,02146	0,00372	5,77	0,00	0,01417	0,02875
a11	0,03291	0,01247	2,64	0,01	0,00848	0,05735
a12	-0,08369	0,00500	-16,72	0,00	-0,09350	-0,07389
a22	0,11228	0,00312	36,02	0,00	0,10617	0,11839
a23	0,22925	0,00737	31,09	0,00	0,21480	0,24371
a24	-0,24196	0,00623	-38,81	0,00	-0,25418	-0,22974
a25	0,16401	0,00389	42,22	0,00	0,15639	0,17162
a26	0,02808	0,00342	8,21	0,00	0,02137	0,03478
a21	0,02892	0,03156	0,92	0,36	-0,03293	0,09076
a13	-0,00476	0,00421	-1,13	0,26	-0,01302	0,00350
a22	0,11228	0,00312	36,02	0,00	0,10617	0,11839
a32	-0,04301	0,00400	-10,74	0,00	-0,05085	-0,03516
a33	0,05426	0,00187	29,01	0,00	0,05059	0,05793
a34	-0,02220	0,00225	-9,88	0,00	-0,02661	-0,01780
a35	-0,00553	0,00216	-2,56	0,01	-0,00977	-0,00130
a31	0,00493	0,00714	0,69	0,49	-0,00907	0,01894
a14	0,08733	0,00647	13,49	0,00	0,07464	0,10002
a23	0,22925	0,00737	31,09	0,00	0,21480	0,24371
a32	-0,04301	0,00400	-10,74	0,00	-0,05085	-0,03516

Table 2.6 (continued)

Parameter	Coef	Std Err	z	P> $\|z\|$	[95% Conf.	Interval]
a42	0,01084	0,00393	2,76	0,01	0,00314	0,01855
a43	-0,02024	0,00477	-4,25	0,00	-0,02958	-0,01089
a44	0,07572	0,00462	16,39	0,00	0,06667	0,08478
a41	0,18744	0,01580	11,86	0,00	0,15647	0,21842
a15	0,05835	0,00410	14,22	0,00	0,05031	0,06640
a24	-0,24196	0,00623	-38,81	0,00	-0,25418	-0,22974
a33	0,05426	0,00187	29,01	0,00	0,05059	0,05793
a42	0,01084	0,00393	2,76	0,01	0,00314	0,01855
a52	0,07040	0,00217	32,50	0,00	0,06616	0,07465
a53	0,02683	0,00206	13,03	0,00	0,02280	0,03087
a51	0,03225	0,01391	2,32	0,02	0,00498	0,05951
a16	0,00630	0,00405	1,56	0,12	-0,00163	0,01423
a25	0,16401	0,00389	42,22	0,00	0,15639	0,17162
a34	-0,02220	0,00225	-9,88	0,00	-0,02661	-0,01780
a43	-0,02024	0,00477	-4,25	0,00	-0,02958	-0,01089
a52	0,07040	0,00217	32,50	0,00	0,06616	0,07465
a62	-0,02803	0,00250	-11,19	0,00	-0,03294	-0,02312
a61	-0,01805	0,00257	-7,01	0,00	-0,02310	-0,01301
a17	0,02146	0,00372	5,77	0,00	0,01417	0,02875
a26	0,02808	0,00342	8,21	0,00	0,02137	0,03478
a36	-0,00553	0,00216	-2,56	0,01	-0,00977	-0,00130
a44	0,07572	0,00462	16,39	0,00	0,06667	0,08478
a53	0,02683	0,00206	13,03	0,00	0,02280	0,03087
a62	-0,02803	0,00250	-11,19	0,00	-0,03294	-0,02312
a71	-0,04611	0,00582	-7,92	0,00	-0,05752	-0,03470
a32	-0,04301	0,00400	-10,74	0,00	-0,05085	-0,03516
a33	0,05426	0,00187	29,01	0,00	0,05059	0,05793

Table 2.6 (continued)

Parameter	Coef	Std Err	z	P> $\|z\|$	[95% Conf.	Interval]
a34	-0,02220	0,00225	-9,88	0,00	-0,02661	-0,01780
a35	-0,00553	0,00216	-2,56	0,01	-0,00977	-0,00130
a31	0,00493	0,00714	0,69	0,49	-0,00907	0,01894
a14	0,08733	0,00647	13,49	0,00	0,07464	0,10002
a23	0,22925	0,00737	31,09	0,00	0,21480	0,24371
a32	-0,04301	0,00400	-10,74	0,00	-0,05085	-0,03516
a42	0,01084	0,00393	2,76	0,01	0,00314	0,01855
a43	-0,02024	0,00477	-4,25	0,00	-0,02958	-0,01089
a44	0,07572	0,00462	16,39	0,00	0,06667	0,08478
a41	0,18744	0,01580	11,86	0,00	0,15647	0,21842
a15	0,05835	0,00410	14,22	0,00	0,05031	0,06640
a24	-0,24196	0,00623	-38,81	0,00	-0,25418	-0,22974
a33	0,05426	0,00187	29,01	0,00	0,05059	0,05793
a42	0,01084	0,00393	2,76	0,01	0,00314	0,01855
a52	0,07040	0,00217	32,50	0,00	0,06616	0,07465
a53	0,02683	0,00206	13,03	0,00	0,02280	0,03087
a51	0,03225	0,01391	2,32	0,02	0,00498	0,05951
a16	0,00630	0,00405	1,56	0,12	-0,00163	0,01423
a25	0,16401	0,00389	42,22	0,00	0,15639	0,17162
a34	-0,02220	0,00225	-9,88	0,00	-0,02661	-0,01780
a43	-0,02024	0,00477	-4,25	0,00	-0,02958	-0,01089
a52	0,07040	0,00217	32,50	0,00	0,06616	0,07465
a62	-0,02803	0,00250	-11,19	0,00	-0,03294	-0,02312
a61	-0,01805	0,00257	-7,01	0,00	-0,02310	-0,01301
a17	0,02146	0,00372	5,77	0,00	0,01417	0,02875
a26	0,02808	0,00342	8,21	0,00	0,02137	0,03478

Table 2.6 (continued)

Parameter	Coef	Std Err	z	P> $\|z\|$	[95% Conf.	Interval]
a36	-0,00553	0,00216	-2,56	0,01	-0,00977	-0,00130
a44	0,07572	0,00462	16,39	0,00	0,06667	0,08478
a53	0,02683	0,00206	13,03	0,00	0,02280	0,03087
a62	-0,02803	0,00250	-11,19	0,00	-0,03294	-0,02312
a71	-0,04611	0,00582	-7,92	0,00	-0,05752	-0,03470

Table 2.7: Cross and Own Price Elasticities of Input Demand for Year 1960-2004 (at the mean value)

Cross and Own Price Elasticities									
ϵ_{kl}	-0,1291	ϵ_{lm}	0,435	ϵ_{ef}	-0,058	ϵ_{nk}	0,355	ϵ_{pn}	0,390
ϵ_{ke}	-0,0150	ϵ_{ln}	-0,100	ϵ_{ee}	0,169	ϵ_{nl}	-0,904	ϵ_{pf}	-0,565
ϵ_{km}	0,3312	ϵ_{lp}	0,277	ϵ_{mk}	0,0809	ϵ_{ne}	0,415	ϵ_{pp}	-0,639
ϵ_{kn}	0,0484	ϵ_{lf}	0,042	ϵ_{ml}	0,1303	ϵ_{nm}	0,100	ϵ_{fk}	0,1733
ϵ_{kp}	0,0212	ϵ_{le}	0,178	ϵ_{me}	-0,0501	ϵ_{np}	0,575	ϵ_{fm}	0,9229
ϵ_{kf}	0,0647	ϵ_{ek}	-0,042	ϵ_{mn}	0,0033	ϵ_{nf}	0,196	ϵ_{fe}	-0,056
ϵ_{kk}	-0,321	ϵ_{el}	0,605	ϵ_{mp}	-0,0251	ϵ_{pk}	0,106	ϵ_{fp}	-0,304
ϵ_{ll}	-0,726	ϵ_{em}	-0,570	ϵ_{mf}	0,0841	ϵ_{pl}	1,691	ϵ_{ff}	-0,947
ϵ_{lk}	-0,105	ϵ_{en}	0,157	ϵ_{mm}	-0,223	ϵ_{pe}	-0,469	ϵ_{fl}	0,139
ϵ_{le}	0,178	ϵ_{ep}	-0,261	ϵ_{nn}	-0,738	ϵ_{pm}	-0,513	ϵ_{fn}	0,072

Table 2.8: Allen Elasticity of Substitution for Years 1960-2004 (at the mean values)

Allen Elasticities					
θ_{kl}	-0,485	θ_{ln}	-1,08	θ_{kk}	-2,448
θ_{ke}	-0,376	θ_{lp}	9,282	θ_{ee}	4,232
θ_{km}	0,816	θ_{lf}	1,032	θ_{ff}	-23,097
θ_{kn}	0,521	θ_{me}	-1,253	θ_{mm}	-0,550
θ_{kp}	1,012	θ_{mn}	0,036	θ_{ll}	-2,729
θ_{kf}	1,577	θ_{mp}	-1,192	θ_{nn}	-7,933
θ_{le}	4,439	θ_{mf}	2,051	θ_{pp}	-30,444
θ_{lm}	1,416	θ_{pf}	-13,777		

Table 2.9: Calculated Morishima Elasticities of Substituiton for Year 1960-2004 (at the mean value)

Morishima Elasticities											
μ_{kl}	0,216	μ_{le}	1,330	μ_{em}	-0,219	μ_{mn}	0,323	μ_{np}	1,128	μ_{pf}	0,336
μ_{ke}	0,278	μ_{lm}	0,856	μ_{en}	0,246	μ_{mp}	-0,290	μ_{nf}	0,809	μ_{fk}	1,012
μ_{km}	0,402	μ_{ln}	-0,178	μ_{ep}	-0,639	μ_{mf}	1,146	μ_{pk}	0,661	μ_{fl}	0,989
μ_{kn}	0,677	μ_{lp}	2,417	μ_{ef}	-0,226	μ_{nk}	0,786	μ_{pl}	0,916	μ_{fe}	0,889
μ_{kp}	0,427	μ_{lf}	0,865	μ_{mk}	0,555	μ_{nl}	0,637	μ_{pe}	0,378	μ_{fm}	1,031
μ_{kf}	0,495	μ_{ek}	-0,184	μ_{ml}	0,658	μ_{ne}	0,895	μ_{pm}	0,614	μ_{fn}	1,143
μ_{lk}	0,597	μ_{el}	0,008	μ_{me}	-0,346	μ_{nm}	0,741	μ_{pn}	1,214	μ_{fp}	0,382

The estimations of the cross price, the Allen and the Morishima elasticities of substitutions are presented in Table 2.7, 2.8 and 2.9, respectively. It is noteworthy that, the figures in Table 2.8 indicating Allen elasticity of substitutions are considerably higher compared to the figures in Table 2.7 and Table 2.9 in terms of absolute values. One interesting issue that emerged from the estimated elasticities of substitution is the positive sign of own price elasticity of energy, failing to support the inverse relation between price and quantity, shown in both the cross price and Allen elasticities. The own elasticity figures in Table 2.8 are substantially higher in terms of absolute values compared to the figures in Table 2.7. The highest own elasticty in Table 2.8 is recorded for pesticides followed by fertilizer with -30.44 and -23.097, respectively.

Since the Allen elasticities are symmetric, it may be misleading to analyse each input's price effect on elasticities. Because of this, Morishima elasticities for all inputs are calculated and shown in Table 2.9. The highest elastic Morishima substitution is found to be between labour and pesticides followed by that between labour and energy. It simply indicates that, a 1% increase in pesticides prices will increase the ratio of labour to pesticides by 2.4%. Similarly, the ratio of labour to energy increase by 1.3% if energy prices increase by 1%. For the inputs which are Morishima complements, the highest complementarity level is revealed between energy and pesticides, while the lowest is seen between energy and capital. The findings demonstrate that the ratio of energy to pesticides will decrease by 0.63% if pesticide prices increase by 1%. Likewise, if the price of capital increases by 1%, the ratio of energy to capital decreases by 0.18%. Table 2.9 also reveals that only six figures out of forty two figures are Morishima complements. A 1% increase in the price of capital, materials, pesticides and fertilizer will decrease the ratios of energy to these inputs by 0.18, 0.21, 0.63 and 0.22%, respectively.

2.4.3 Translog Cost Function

The following investigation of production relationships for all inputs is facilitated by estimating state level transcendental logarithmic cost function. The results of this procedure allow one to draw inferences regarding the presence of economies of scale in the agriculture sector. In addition to providing information on economies of scale, the translog cost function allows the calculation of input direct and cross price elasticities to show the responsiveness of input demand in reaction to price changes. An implicit function of production technology in the agriculture sector is represented by:

$$\tau(q, K, L, E, M, N, P, F) = 0 \tag{2.44}$$

where q is real output K is capital, L is labour, E is energy, M is materials, N is land, P is pesticides and F is fertilizer. If the transformation function in implicit form has a strictly convex input structure there exists a unique cost function as follows:

$$TC = f(q, P_K, P_L, P_E, P_M, P_N, P_P, P_F) \tag{2.45}$$

where P_K, P_L, P_E, P_M, P_N, P_P, P_F are price of capital, labour, energy, materials, land, pesticides and fertilizer respectively. To obtain cost minimizing input demands Shephard's Lemma is generally applied. Shephard's Lemma produces cost minimizing input demands as follows:

$$X_i{}^* = \frac{\partial C(q,p)}{\partial p_i} \tag{2.46}$$

In line with Greene (2000), the translog cost function is:

$$\begin{aligned}\ln C_{it} = \beta_0 + \sum_{j=1}^{J} \beta_{jit} \ln p_{jit} + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} \beta_{jkit} \ln p_{jit} \ln p_{kit} + \gamma_1 t + \frac{1}{2}\gamma_2 t^2 \\ + \beta_q \ln q_i + \sum_{i=1}^{J} \beta_{it} \ln q_i \ln t + \epsilon_{it}\end{aligned} \tag{2.47}$$

For a well behaving cost function the following restrictions must be held:

$$\sum_{i=1}^{J} \beta_{jit} = 1, \sum_{j=1}^{J}\sum_{k=1}^{J} \beta_{jkit} = \sum_{j=1}^{J}\sum_{k=1}^{J} \beta_{kjit} = \sum_{i=1}^{J} \beta_{it} = 0 \tag{2.48}$$

The function is homothetic if $\beta_{it} = 0$ for all i as well. In addition to these constraints, $\beta_q = 1$ is imposed to make the production constant return to scale. Using Sheppard Lemma the cost share equations are derived as below:

$$s_k = \beta_k + \beta_{kk}\ln(pk/pf) + \beta_{kl}\ln(pl/pf) + \beta_{ke}\ln(pe/pf) + \beta_{km}\ln(pm/pf)$$
$$+ \beta_{kn}\ln(pn/pf) + \beta_{kp}\ln(pp/pf) \tag{2.49}$$

$$s_l = \beta_l + \beta_{kl}\ln(pk/pf) + \beta_{ll}\ln(pl/pf) + \beta_{le}\ln(pe/pf) + \beta_{lm}\ln(pm/pf)$$
$$+ \beta_{ln}\ln(pn/pf) + \beta_{lp}\ln(pp/pf) \tag{2.50}$$

$$s_e = \beta_e + \beta_{ke}\ln(pk/pf) + \beta_{le}\ln(pl/pf) + \beta_{ee}\ln(pe/pf) + \beta_{me}\ln(pm/pf)$$
$$+ \beta_{ne}\ln(pn/pf) + \beta_{pe}\ln(pp/pf) \tag{2.51}$$

$$s_m = \beta_m + \beta_{km}\ln(pk/pf) + \beta_{lm}\ln(pl/pf) + \beta_{em}\ln(pe/pf) + \beta_{mm}\ln(pm/pf)$$
$$+ \beta_{nm}\ln(pn/pf) + \beta_{pm}\ln(pp/pf) \tag{2.52}$$

$$s_n = \beta_n + \beta_{kn}\ln(pk/pf) + \beta_{ln}\ln(pl/pf) + \beta_{en}\ln(pe/pf) + \beta_{mn}\ln(pm/pf)$$
$$+ \beta_{nn}\ln(pn/pf) + \beta_{pn}\ln(pp/pf) \tag{2.53}$$

$$s_p = \beta_p + \beta_{kp}\ln(pk/pf) + \beta_{lp}\ln(pl/pf) + \beta_{ep}\ln(pe/pf) + \beta_{mp}\ln(pm/pf)$$
$$+ \beta_{np}\ln(pn/pf) + \beta_{pp}\ln(pp/pf) \tag{2.54}$$

In translog cost function models with cross section and time series data the intercept terms for each cost share equation are assumed to be identical. However, panel data reveals the effect of each cross section unit in the equation. These constants capture the unobservable heterogeneity triggered by time invariant factors that exist for each individual unit (Arnberg and Bjørner, 2007).

The cost share system is a reduced system due to a singularity problem[7] which arises if the error variance-covariance matrix is non-diagonal and singular. Since cost share equations must sum to one, the error terms for each equation in the system are zero at each observation which gives rise to this singularity problem (Paterson, 2012). Price homogeneity restriction and constant returns to scale are imposed on the cost share equations to get a reduced system. By leaving the coefficient β_{kf} alone in the constraint equation, we get six cost share equations for seven inputs. System of the equations above is known as Zellner's (1962) seemingly unrelated regression (SUR) model. Each equation of the system seems unrelated, however the errors may be correlated. This correlation is the reason for using seemingly unrelated regression (Wooldridge, 2004).

Having solved the cost shares S_k, S_l, S_e, S_m, S_n, S_p within this system, the estimated parameters of cost share equation system are derived and presented in Table 2.10:

Table 2.10: Translog Cost Function Parameter Estimates

	Coef	**Std Err**	**z**	**P> $\|z\|$**	**[95% Conf.**	**Interval]**
β_{kk}	0,05714	0,00275	20,81	0,00	0,05176	0,06252
β_{kl}	-0,05774	0,00122	-47,46	0,00	-0,06012	-0,05535
β_{ke}	-0,00859	0,00112	-7,67	0,00	-0,01078	-0,00640
β_{km}	-0,01426	0,00251	-5,68	0,00	-0,01918	-0,00934
β_{kn}	0,01259	0,00081	15,49	0,00	0,01100	0,01418
β_{kp}	0,00284	0,00152	1,87	0,06	-0,00014	0,00583
β_{k}	0,09461	0,00265	35,67	0,00	0,08941	0,09980

[7] 'Econometric Analysis of Cross Section and Panel Data", J. Wooldridge, p.167

Table 2.10 (continued)

	Coef	Std Err	z	P> $\lvert z \rvert$	[95% Conf.	Interval]
β_{kl}	-0,05774	0,00122	-47,46	0,00	-0,06012	-0,05535
β_{ll}	0,10716	0,00242	44,30	0,00	0,10242	0,11191
β_{le}	-0,00598	0,00050	-11,88	0,00	-0,00697	-0,00499
β_{lm}	-0,00048	0,00228	-0,21	0,83	-0,00495	0,00399
β_{ln}	-0,04803	0,00085	-56,71	0,00	-0,04969	-0,04637
β_{lp}	0,00677	0,00061	11,20	0,00	0,00559	0,00796
β_{l}	0,23905	0,00600	39,83	0,00	0,22729	0,25082
β_{ke}	-0,00859	0,00112	-7,67	0,00	-0,01078	-0,00640
β_{le}	-0,00598	0,00050	-11,88	0,00	-0,00697	-0,00499
β_{ee}	0,02805	0,00093	30,30	0,00	0,02623	0,02986
β_{me}	-0,01390	0,00113	-12,35	0,00	-0,01610	-0,01169
β_{ne}	0,00099	0,00032	3,06	0,00	0,00035	0,00162
β_{pe}	-0,00126	0,00062	-2,03	0,04	-0,00249	-0,00004
β_{e}	0,03408	0,00108	31,66	0,00	0,03197	0,03618
β_{km}	-0,01426	0,00251	-5,68	0,00	-0,01918	-0,00934
β_{lm}	-0,00048	0,00228	-0,21	0,83	-0,00495	0,00399
β_{em}	-0,01390	0,00113	-12,35	0,00	-0,01610	-0,01169
β_{mm}	0,04542	0,00431	10,55	0,00	0,03698	0,05386
β_{mn}	-0,01758	0,00114	-15,43	0,00	-0,01981	-0,01534
β_{mp}	-0,00393	0,00127	-3,10	0,00	-0,00641	-0,00145
β_{m}	0,46879	0,00677	69,26	0,00	0,45553	0,48206
β_{kn}	0,01259	0,00081	15,49	0,00	0,01100	0,01418
β_{ln}	-0,04803	0,00085	-56,71	0,00	-0,04969	-0,04637
β_{en}	0,00099	0,00032	3,06	0,00	0,00035	0,00162
β_{mn}	-0,01758	0,00114	-15,43	0,00	-0,01981	-0,01534

Table 2.10 (continued)

	Coef	Std Err	z	P> $\lvert z \rvert$	[95% Conf.	Interval]
β_{nn}	0,05416	0,00058	94,12	0,00	0,05303	0,05528
β_{pn}	0,00239	0,00037	6,50	0,00	0,00167	0,00312
β_{n}	0,08139	0,00339	24,02	0,00	0,07475	0,08803
β_{kp}	0,00745	0,00116	6,42	0,00	0,00518	0,00973
β_{lp}	0,00677	0,00061	11,20	0,00	0,00559	0,00796
β_{ep}	-0,00126	0,00062	-2,03	0,04	-0,00249	-0,00004
β_{mp}	-0,00393	0,00127	-3,10	0,00	-0,00641	-0,00145
β_{np}	0,00239	0,00037	6,50	0,00	0,00167	0,00312
β_{pp}	-0,00180	0,00089	-2,03	0,04	-0,00354	-0,00006
β_{p}	0,03110	0,00133	23,36	0,00	0,02849	0,03371

The assumption that composite error must not correlate with explanatory variables must be true for all cost share equation systems.[8] Failing of this assumption results in inconsistent parameter estimations. The differences between results yielded by different panel data estimation methods (pooled, fixed effect, random effect) show this inconsistency in parameter estimations. We employ state dummies to each cost share equation system and calculated Allen Elasticity of Substitution as:

$$\sigma_{ij} = \frac{\beta_{ij} + s_i s_j}{s_i s_j} \begin{cases} > 0 & \textit{substitute} \\ < 0 & \textit{complement} \end{cases} \qquad i,j = K,L,E,M,N,P,F \tag{2.55}$$

$$\sigma_{ii} = \frac{\beta_{ii} + {s_i}^2 - s_i}{{s_i}^2} \qquad i,j = K,L,E,M,N,P,F \tag{2.56}$$

[8] "Econometric Analysis of Cross Section and Panel Data", J. Wooldridge p.254

Table 2.11: Allen Elasticity of Substitution for Years 1960-2004 (at the mean values)

Allen Elasticities					
θ_{kl}	-0,651	θ_{np}	0,004	θ_{mn}	0,537
θ_{ke}	-0,616	θ_{ll}	-1,244	θ_{mp}	0,541
θ_{km}	0,733	θ_{mm}	-1,186	θ_{ml}	0,996
θ_{kn}	2,026	θ_{pp}	-50,465	θ_{lp}	2,206
θ_{kp}	2,027	θ_{em}	0,155	θ_{kk}	-3,302
θ_{le}	0,445	θ_{en}	1,261	θ_{ee}	-6,589
θ_{ln}	-0,930	θ_{ep}	0,000	θ_{nn}	-3,499

Table 2.11 demonstrates the Allen elasticity of substitution results derived by the estimation of Translog cost function. It is noticeable that, the signs of the all own Allen elasticities are negative supporting that an increase in the price will decrease the quantity demanded. Pesticides is found to the most elastic input implying that the farmer first gives up using pesticides among the other inputs as a response to an 1% increase in the price. Although the Allen cross elasticity between energy and pesticides is negative, which indicates complementarity the magnitude is almost 0. Additionally capital and both labour and energy and labour and land are found to be complements. Other input pairs are found to be substitutes supporting that a 1% increase in one of the inputs will increase the quantity demanded of the other. The cross and own price elasticities are presented in Table 2.12 and 2.13, respectively. The all own elasticities have negative sign as expected and further pesticides is again found to be the most elastic input . It is noteworthy that, cross price elasticities shown in Table 2.12 are all inelastic and considerably low. While the highest decrease is shown in the quantity demand of land if the price of labour increases by 1%, the highest increase is

seen in the quantity demand of pesticedes if the price of labour increases by 1%. Moreover, Table 2.14 shows Morishima elasticities of substitution which indicates that all inputs are substitutes except the elasticity between labour and land. A 1% increase in land price will decrease the ratio of labour to land by 5.9%. The Morishima elasticites are found to be elastic for the input pairs including pesticide and capital, pesticide and labour, pesticide and energy, pesticide and materials and pesticide and land. The ratios of pesticides to capital, labour, energy, materials and land will increase by 1.1, 1.1, 1.0, 1.0 and 1.0% if the price of capital, labour, energy, materials and land increase by 1%, respectively.

Table 2.12: Price Elasticities of Input Demand (Cross Price Elasticities)

Cross Price Elasticities									
ϵ_{kl}	-0,173	ϵ_{le}	0,018	ϵ_{ep}	0,000	ϵ_{ne}	0,040	ϵ_{pm}	0,220
ϵ_{ke}	-0,025	ϵ_{lm}	0,405	ϵ_{ek}	-0,081	ϵ_{nm}	0,218	ϵ_{pn}	0,000
ϵ_{km}	0,298	ϵ_{ln}	-0,087	ϵ_{mn}	0,011	ϵ_{np}	0,021	ϵ_{mk}	0,096
ϵ_{kn}	0,189	ϵ_{lp}	0,047	ϵ_{mp}	0,011	ϵ_{pk}	0,266	ϵ_{ml}	0,265
ϵ_{kp}	0,043	ϵ_{em}	0,063	ϵ_{nk}	0,266	ϵ_{pl}	0,588	ϵ_{me}	0,006
ϵ_{lk}	-0,085	ϵ_{en}	0,118	ϵ_{nl}	-0,930	ϵ_{pe}	0,000	ϵ_{el}	0,018

Table 2.13: Own Price Elasticities for Years 1960 - 2004 (at the mean values)

Own Price Elasticities					
ϵ_{kk}	-0,434	ϵ_{ee}	-0,267	ϵ_{nn}	-0,327
ϵ_{ll}	-0,331	ϵ_{mm}	-0,482	ϵ_{pp}	-1,064

The price elasticities of input demand are calculated at the mean of the fitted cost shares and shown in Table 2.12 and Table 2.13. All own price elasticities are negative as should be expected.

Although Allen Elasticity of substitution is more common in empirical work, it fails to provide information about cross price elasticities and factor shares. At this point, Morishima elasticity of substitution is of very significance. Since the formulation of Morishima elasticity of substitution:

$$\mu_{ji} = \epsilon_{ij} - \epsilon_{jj} \tag{2.57}$$

$$\mu_{ij} = \epsilon_{ji} - \epsilon_{ii} \tag{2.58}$$

include cross price elasticity (ϵ_{ij}) and own price elasticity (ϵ_{ii}) it makes possible to analyse the effect of input j price on thse quantities of input i and input j. All Morishima elasticities except land and labour obtained from translog cost function indicate that the production factors are all substitute as presented in Table 2.14.

Table 2.14: Morishima Elasticities of Substitution for Years 1960 -2004 (at the mean values)

Morishima Elasticities					
μ_{kl}	0,349	μ_{ek}	0,242	μ_{nk}	0,516
μ_{ke}	0,353	μ_{el}	0,285	μ_{nl}	0,240
μ_{km}	0,530	μ_{em}	0,273	μ_{ne}	0,445
μ_{kn}	0,593	μ_{en}	0,307	μ_{nm}	0,338
μ_{kp}	0,700	μ_{ep}	0,780	μ_{np}	0,327
μ_{lk}	0,158	μ_{mk}	0,780	μ_{pk}	1,107
μ_{le}	0,349	μ_{ml}	0,747	μ_{pl}	1,111
μ_{lm}	0,596	μ_{me}	0,545	μ_{pe}	1,064
μ_{ln}	-0,599	μ_{mn}	0,700	μ_{pm}	1,076
μ_{lp}	0,919	μ_{mp}	0,702	μ_{pn}	1,085

2.5 Discussion

The organization of this section is based on the comparison between the elasticity of substitution estimates revealed in the Results section and the other studies in the literature regarding input substitution possibilities in US agriculture.

First, the Generalized Leontief cost function and the comparison between Allen and cross price elasticities produced by this function support the findings of the previous work of Blackorby and Russell (1981) in the sense that Allen elasticities overestimate cross price elasticities in both substitutability and complementarity cases. Another of our findings also consistent with Blackorby and Russell (1981), Stiroh (1999), Shankar et al. (2003) is that the input pairs exhibiting Allen substitutes are also for the most part Morishima substitutes revealing the substitution bias of Allen formula when treating elasticity of substitution between inputs.

When we compare magnitudes of elasticity of substitution results yielded by cross price, Allen and Morishima, it is clear that cross price elasticities are remarkably low. This does not mean cross price elasticity formula is not appropriate for elasticity of substitution as Frondel (2011) underlines. In Frondel's study, cross price elasticities are thought to be the most relevant measures in the economic context as they measure the relative change of only one factor due to price changes of another input. The determined elasticity of substitution results of Generalized Leontief cost function also prove the complementarity bias of Morishima substitutes which state that the input pairs appearing to be complements in Morishima elasticity results are also complements for Allen elasticity results. This finding is consistent with the finding of Frondel (2004).

Of all these results, the positive sign of Allen own energy elasticity is noticeably interesting. Since the own elasticity measure shows the change of quantity demanded in response to an increase of an input's price, a negative sign is expected in line with the demand theory in microeconomics. This positive energy own elasticity reveals that energy demand does not exhibit any decrease when an increase in energy prices occurs. It should be kept in mind that, this figure is calculated at the mean value of the data and therefore it may be misleading for an analysis of some periods, in particular for the 1970s when the oil crises occurred. In order to more accurately analyse the quantity demanded in response to huge increases in prices, the calculations should only be based on the data from years in which we are interested. Another interesting result emerging from the Allen own elasticities is a considerably high figure for pesticides input which indicates that it is the most sensitive input to price changes. This sensitivity arises from the growing substantial role of pesticides utilization in the US agriculture which support our findings suggesting that over long period pesticides are a substitute for energy.

For Translog cost function, Allen own elasticity for pesticides is again found to be the most sensitive input similar to the results for Generalized Leontief cost function. It proves the robustness of the results obtained from both flexible cost functions. Although Assa et al. (2013) treat Allen elasticities are uninformative in the study which they analyse ease of substitutability of Irish farms through Translog cost function, we calculate three types of substitution including Allen substitution.

When calculating Allen elasticity of substitution particularly for the Translog cost function, the fitted cost shares are very important. This importance is related to the formulation of the Allen elasticity which scales cross price elasticity formula by cost shares. Actually differences appearing between Allen and cross price elasticity figures are strongly associated with this. Another issue that deserves further exploration is the results yielded by the Translog cost function also support the complementarity bias of Morishima and substituibility bias of Allen elasticity similar to the results for Generalized Leontief cost function.

When considering the results yielded by Translog production function, the Allen own elasticities are smaller, on the other hand, the cross price elasticities are relatively higher compared to the results generated by Translog and Generalized Leontief cost functions. These differences can be explained by a structural form of each flexible functions (Banda and Hassan, 2011). Comparison of the derived cross price elasticities from all flexible functional forms does not provide significant differences between the figures. Although Koetse et al. (2008) state that the functional forms which do include instrumental variables contrast to the ones that do not, yield higher cross price elasticities, the translog and generalized leontief cost functions using instrumental variables while estimating do not produce such higher cross price elasticities.

While all definitions of elasticity of substitution formulas used in this study have a close relationship which make them confusing in the application, each has distinctive characteristics. As underlined by Mundlak (1968), there is no one way of calculating substitution elasticities. The choice of which formula is the most appropriate is based on the question that you are interested in. These questions actually correspond to the characteristics of the formulas mentioned above.

2.6 Conclusion

The structure of US agriculture in terms of inputs used has changed in a remarkable way. In order to investigate the changes and to determine the drivers behind these changes, several studies have been conducted. Most of these studies fail to come to a consensus for particularly two issues. The first disagreement is choice of flexible functional form for estimation of elasticity of substitution and the second disagreement is about whether input pairs are substitutes or complements. To make our study comprehensive and inclusive of the most recent trends, we apply translog cost, translog production and generalized leontief cost function with the panel data of 48 contiguous states of the US from 1960 to 2004. For this panel data set capital, labour, energy, materials, pesticides and fertilizer are treated as distinctive inputs but the output is considered as aggregate.

The contribution of this study to the literature is twofold. One of them is that it allows for comparison of the best known flexible functional forms while calculating all substitution possibilities. The other contribution comes from the type of the data utilized. Since panel data has superiorities over time series and cross section data, the application of panel data, particularly for the agriculture sector is of significance.

It is highly interesting that, elasticity of substitution results yielded by the all flexible functions are of the same order. While the cross price elasticities are the lowest, the Allen elasticities are the highest with considerable difference between them. The results derived from this study have important agricultural policy implications. The most striking implication is related to the utilization of pesticide use. The highest own elasticities for pesticides derived by both Translog cost and Generalized Leontief cost function indicate that this input is more highly sensitive to price changes than other inputs. This basically means that, more attention should be paid to substitution possibilities for input pairs including pesticides.

Another important policy implication raised by the results is about the importance of the choice of elasticity of substitution formula. Although several formulae are applied to calculate elasticity of substitution, they are distinguished from each other with minor differences. Therefore it is crucial to identify what you are really interested in. If relative change of inputs with respect to change of one factors price is the scope of the study, it will be convenient to apply Morishima elasticity of substitution formula, on the other hand , if the interest is only on the demand change of one factor in response its own price change, Cross price or Allen elasticity should be preferred.

The results also have implications for two major inputs: energy and labour. Both of the inputs have undergone significant changes in terms of quantity and price and the elasticity of substitution results show that they have been used interchangeably to a varying extent. In other words, they are found to be substitutes according to the all formulas for each functional form. That energy and labour are substitutes answers the question posed in the introduction about how labour and energy utilization are affected by critical changes in agricultural production.

Agricultural policy should be managed specifically in order to meet the demand in situations of resource scarcity and elasticity of substitution answers the question of how production factors are utilized in the production process. While the literature regarding the attempts to calculate elasticity of substitution grew considerably from the mid 1970s to the late 1980s, later studies fail to further investigate this. To the best of our knowledge, our study is one of the few recent studies to compare the various types of flexible functional forms in terms of the elasticity of substitution results derived from these. We are able to use the data up to 2004 as later data is not available. In future, using more recent data as well as further production factors may help to increase our understanding of recent trends.

Chapter 3

Energy Intensity Revisited

3.1 Introduction

It is becoming increasingly difficult to ignore the role of energy use in the development process. The term energy receives significant attention for exploring development due to the bilateral causality between them. In a broad sense the linkage can be associated with the driving force of energy on development. It is generally seen as a decisive factor for development, the consumption level of energy is an indicator of whether the country is agricultural, industrial or developing (Recalde and Ramos-Martin, 2012).

More energy provision and use can be seen as an evidence of enhanced economic development. To draw a framework for the relationship between energy and development, the energy ladder has been used (Barnes and Floor, 1996; Bianca et al., 2013; Burke, 2011; Masera et al., 2000). These studies show that the linkages between energy and economic activity do not remain the same at all stages of development. There are some substantial differences which can be recognized as we approach to the top rung of the ladder. On this basis following examples supporting the relationship of development and energy are given by Toman and Jemelkova (2003) as : time flexibility through the day; increase in afforadability in transportation and enhanced communication services.

Having addressed the relation between energy and sustainable development, it is now necessary to explain how sustainable development is measured. To measure sustainable development some indicators are developed by international organizations such as UN (United Nations), IEA (International Energy Agency) and IAEA (International Atomic Energy Agency). These indicators are comprised of a variety of components which are population, gdp per capita, energy intensity of manufacturing, residential, transportation and agriculture, end use energy prices, income inequality, quantities of air pollutant emissions[9]. A number of indicators have an implication for human well being which is a part of sustainable development's social dimension and they are the most likely guidelines of policy recommendations[10]. The main focus of this chapter is to analyse energy intensity, one of the most important indicators, with the main drivers of energy efficiency, partial factor productivity and total factor productivity.

While many studies examine energy consumption in order to link between development and energy, this may not be sufficient when comparing performances at different development levels. It is mostly aggreed that if the amount of energy to produce the same level of output is used, the comparison would be more reliable. The most crucial point of this chapter is to build a new measurement method which eliminates the shortcomings leading to mismeasurement of efficiency, intensity and productivity of energy in the previous studies. In the applied economic texts, they are usually used exchangably and unavoidably causes a confusion. The following part of this thesis attempts to clearly distinquish these terms thereby reach a more reliable measurement method. To surpass this problem, they are

[9]These are the some of the sustainable development indicators listed in the report of IAEA and IEA whose full text consists of 40 items.

[10]The recommendations are improved by some organizations: IEAE, IEA and UNITED NATIONS.

included with definitions and applications in the following phase of the thesis.

It may be misleading to analyse energy inidicators without an analysis of the production process. On the one hand, as a part of the process, one should consider substititution between energy and other inputs, technological change, shifts in the composition of energy input and output as they are the factors affecting the contribution of energy input. On the other hand, environment side should be scrutinized since the utilization of energy input has significant negative implications for environment. However, the analysis of these issues is beyond the scope of this chapter since they are, except the environment dimension, are examined in a detailed manner in Chapter 2.

In literature, energy intensity generally measured as a ratio of energy use to GDP is the most common indicator when comparing countries. This ratio is also a common unit of the most known organizations whose aim is to develop energy policy. Furthermore, it is also accepted a key indicator of economic development (Burcea et al., 2012). One of the objectives of this chapter is to determine whether the traditional method is the most appropriate one to measure energy intensity. Although the traditional energy intensity measurement is simple and easy for calculation, it suffers from several major drawbacks which arise from several reasons: Firstly, the diversity of GDP structure among countries, means that it may not be useful to compare gdp values of countries dominated by high energy intensive sectors with those having low energy intensive sectors. Secondly, the difficulty of aggregation of different sectors in a country results in biased results. Lastly utilization of gdp data does not take into account the contribution of the non monetarized sector (Ang, 2006). There is another view that supports inadequancy of traditional energy intensity measurement. The claim is if climate, composition of output and the outsourcing of goods produced by energy intensive sectors are neglected, energy intensity would not be a reliable indicator

(Dayringer, 2011). There are also other aspects which regard energy intensity doubtful; one of these is the fact that it does not underline the structure of sector which uses energy as an input and also it fails to draw a logical framework for justifying the heterogenous nature of output (US Department of Energy). Although the indicator has such shortcomings, many studies still use this ratio since it enables the ease of computation. Within this scope, this chapter seeks to address the following questions: Why the current energy intensity measurement method is not the most sensitive one and how can we improve the new method which is able to overcome its shortcomings. To begin with, we first examine the terms of energy efficiency, intensity and productivity and review the related literature. Secondly, we propose a new method which is able to overcome the shortcomings of the previous studies and provides a better understanding of this simple ratio. Finally, the comparison of new and traditional input intensity methods is discussed and total factor productivity figures are gathered and compared to all partial factor productivities for each region.

3.2 Literature Review

There seems to be a general agreement on the substantial contribution of energy intensity indicators to explain the differences in sustainable development and CO_2 emission levels across countries, firms and states (Mendiluce et al., 2010; Alcantara and Duarte 2004; Ang, 2000; Ang et al., 2004; Shahiduzzaman and Alam, 2013). Since sustainable development and CO_2 emission levels are both determining drivers of country specific policies, energy intensity has gained importance in the literature as a tool to understand these. There is a large volume of published studies describing the role of energy intensity, however this literature review focuses on three main issues. First, we focus on the underlying factors of energy use variation using the decomposition analysis, second we look at the close reciprocal relationship among energy intensity, efficiency and productivity. Finally, we examine the attempts to improve the traditional energy intensity measurement methods and suggest a new more reliable method.

Energy indicators have experienced substantial changes since the 1970s. Oil crises which occured in this decade stimulated the improvement of energy indicators and accelerated the need of deeper analysis of indicators to provide a better understanding for the energy policy makers. Within this motivation, researchers have shown an increased interest in factors that lie behind the change of energy use. Decompositon method is the most well known method as it accounts for this variation while also considering energy intensity, activity and structural effects. Numerous studies have attempted to conduct decomposition analysis, in particular for the large energy using countries, industries and firms. For instance, Ang (1987) is one of the most important studies contributing to the formation of the decomposition analysis literature. Motivated by the aggressive growth of China economy accompanied by utilization of a large amount of energy, he conducted many studies which constitute a big part of the existing literature.

Index decomposition analysis which has been one of the most well known methods for the analysis of energy intensity is widely investigated by Ang (2006). In the study, the classical energy indicators are reviewed and improvements in the index decomposition analysis are underlined. Furthermore, Ang and Liu (2003) make a considerable contribution by reviewing several decompositon methods which are commonly used in the analysis of energy intensity. Decomposition method is also undertaken by Duro and Padilla (2011) to account for differences in energy intensity across countries. 116 countries are chosen from different regions including OECD Europa, North America, OECD Pacific, Non OECD Europa, Africa, Latin America, Middle East, China and Asia. Their findings suggest that energy inequality across countries has started to converge. Similarly, Mendiluce et al. (2010) apply this method to indicate Spain's energy intensity path's difference from the other 15 EU countries. The difference can be associated with the fact that Spain's energy intensity has increased for almost two decades, however, other EU 15 have experienced downward trend in energy intensity. The findings have implications that rise in construction activities and the rapid growth of transport sector lead to a considerable distinction in Spain's energy intensity tendency.

Since China's economy has been growing at a rapid pace accompanied by increasing energy demand, Zhao et al. (2010) employ index decomposition analysis to understand China's changing energy intensity which experienced decrease from 1980s to 1990s and then started increase by 1998. According to the results of the analysis, energy intensive sectors' expansion and thereby incraese in energy demand of sectors can be seen as a main contributor of the increase in energy intensity.

Similarly, Nie and Kemp (2013) investigate the variaton of China's energy intensity from 2000 to 2009. The underlying factors of this variation are split into sectoral and subsectoral change and technological variation. They propose index decomposition analysis to bring an explanation for these factors. Technological change is found to be the most effective factor that can be attributed to the fluctuations of China's non–residential energy intensity. Although China's energy intensity is examined widely in the literature, there are also many studies focusing on country specific analysis of energy intensity for the rest of the world.

While Shahiduzzaman and Alam (2013) examine the driving forces of aggregate energy intensity in Australia from 1978 to 2009, Balezentis et al. (2011) investigate the issues that lie behind the difference of Lithunia's energy intensity trends from that of EU 15.

Both of the studies employ LMDI (Logatihmic Mean Divisia Index)[11]. As a result of the studies, efficiency is found to be the most effective component that results in the change of energy intensity.

Unlike the other studies now reviewed in the literature, Arens et al., (2012) employ structural decomposition analysis to examine the energy intensity of German iron and steel industry from 1991 to 2007. Their findings have valuable insights showing that a considerable amount of the change in energy intensity is attributable to structural changes. While the studies mentioned above applying decomposition analysis to explain energy intensity, there are also studies attempting to account for energy intensity via different approaches. For instance, Feng et al. (2009) build their analysis of China's energy intensity on the relationship of economic and consumptional structure. They apply Granger Causality Test[12] to determine the direction of the relationship. The findings indicate that there is a one sided effect from energy intensity on economic structure while the contrary is not true.

Alcantara and Duro (2004) analyse the converging trend of energy intensity inequality between OECD countries. They apply Theil Index [13]to account for

[11]Changes in energy consumption may be assessed by considering three factors, namely overall industrial activity (activity effect), activitymix (structure effect),and sectoral energy intensity (intensity effect). The following IDA identity describes the total energy consumption: $E = \sum_i^N E_i = \sum_i^N Q \frac{Q_i E_i}{Q Q_i} = \sum_i^N Q S_i I_i$ where E represents total energy consumption, $Q = \sum_i^N Q_i$ total activity level, S_i activity share and I_i energy intensity of sector i. For the additive decomposition, the difference is decomposed as below:
$\Delta E = E^t - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int}$ and for the multiplicative decomposition $D = \frac{E^t}{E^0} = D_{act} D_{str} D_{int}$ where E_t and E_0 represent energy consumption in the periods t and 0, respectively and $D_{act} = exp(\sum_i^N \frac{\frac{(E_i{}^T - E_i{}^0)}{(lnE_i{}^T - lnE_i{}^0)}}{\frac{(E^T - E^0)}{(lnE^T - lnE^0)}} ln(\frac{Q^T}{Q^0}))$, $D_{str} = exp(\sum_i^N \frac{\frac{(E_i{}^T - E_i{}^0)}{(lnE_i{}^T - lnE_i{}^0)}}{\frac{(E^T - E^0)}{(lnE^T - lnE^0)}} ln(\frac{S_i{}^T}{S_i{}^0}))$,
$D_{int} = exp(\sum_i^N \frac{\frac{(E_i{}^T - E_i{}^0)}{(lnE_i{}^T - lnE_i{}^0)}}{\frac{(E^T - E^0)}{(lnE^T - lnE^0)}} ln(\frac{I_i{}^T}{I_i{}^0})$

[12]Granger Causality is a limited notion of causality where past values of one series (xt) are useful for predicting future values of another series (yt), after past values of yt have been controlled for., Wooldridge J. M., Introductory Econometrics.

[13] $\frac{I_t{}^{Theil}}{I_{t-1}{}^{Theil}} = \prod_i^n (\frac{E_{it}}{E_{it-1}})^{w_i t^*}$ where $I_t{}^{Theil}$ Theil Index to period t, $w_i t = \frac{p_{it} E_{it}}{\sum_i^n p_{it} E_{it}}$ p_{it} refers to price of energy source i to period t, E_{it} is amount of energy type i and $w_i t^* = \frac{[\frac{1}{2}(w_i t + w_i t - 1) w_i t w_i t - 1)]^{1/3}}{\sum_i^n [\frac{1}{2}(w_i t + w_i t - 1) w_i t w_i t - 1)]^{1/3}}$.

the reduction in this inequality. Herrerias (2012) investigates this issue regarding the convergence behaviour of countries. He analyses 83 countries in terms of the energy intensity trends and findings suggest that the level of convergence is based on whether the countries are developed or developing.

In the second part of the the literature review, the relationship among energy patterns are studied. There is a wide range of studies investigating the reciprocal impacts of energy intensity, efficiency and productivity as well as total factor productivity. It is important to recognize that there is a considerable interaction between energy intensity and total factor productivity. For instance, a rise in the total factor productivity may lead to a decline in energy intensity. Sahu and Narayanan (2011) indicate that there is an inverse relation between energy intensity and productivity by utilizing Indian manufacturing firms. Both translog production and OLS (Ordinary Least Squares) regressions are applied. While the former is used to estimate total factor productivity, the latter is employed to understand the direction of explanatory variables' contribution on the dependent variable total factor productivity. Besides age of firm, ownership , the level of export and import intensity, embodied and disembodied technology intensity; energy intensity is regarded as one of the affecting factors for total factor productivity. The findings suggest that the firms which are more efficient tend to have higher total factor productivity. This close linkage has attracted great attention as it contributes to a better understanding of energy policy implications. Within this scope, Chang and Hu (2010) state that energy efficiency (energy productivity) fails to reflect other inputs' effects rather than energy input. The failure inevitably results in bias energy efficiency. They propose a new method called total factor energy producitivity change index. In fact, this method not only combines energy efficiency and Luenberger productivity index but also enhances the calculation of energy productivity with a multi input framework. Moreover, Syed (2011) is built the discussion around the strong relationship between partial energy producitivity, total factor productivity and interrelationships of inputs. It should be noted that calculation of partial or total factor productivity by taking the relationship into account would probably give more reliable results. The study is conducted by utilizing Australian industies' data.

Although energy intensity is commonly used indicator for energy efficiency change, energy elasticity and energy coefficienct are also applied in order to track these changes. Ang (2006) studies both the energy coefficient and energy elasticity [14] with numerical examples. It is mentioned in the study that, while energy coefficient is preferred in the literature due to its ease of computation, one important issue is neglected. The growth of both numerator and denominator have to be positive to draw a logical framework. If the growth in numerator or denominator for the consequtive years is too small then the ratio could be too large and thereby it cannot be practical. Energy elasticity is introduced as an alternative to energy coefficient which suffers from the inability for expressing small growth rates.

To account for high energy intensity, one can consider low productivity. Although it seems logical, this relation needs to be clarified for the improvement of guidepost for energy productivity. Boyd and Pang (2000) attempt to link between energy efficiency and productivity. Plant level data of both energy in-

[14] For a given period, energy coefficient is the ratio of average annual growth rate of energy consumption to average annual growth rate of GDP. The energy coefficienct is illustrated by the formula as follows:

$$EC_{0,t} = \frac{(\frac{E_t}{E_0})^{\frac{1}{t}} - 1}{(\frac{Y_t}{Y_0})^{\frac{1}{t}} - 1}$$

where E_t, E_0 and Y_t, Y_0 represent energy consumption and real GDP in the years 0 and t, respectivily.

Energy elasticity is defined as the ratio of proportionate change in energy to proportionate change in GDP as follows:

$$EE = \frac{\frac{dE}{E}}{\frac{dY}{Y}}$$

tensive sectors of flat glass and container glass industry is used in the regression to examine the impact of energy efficiency on energy intensity. Regarding the regression results, one may conclude that productivity differences between plants has a substantial effect on energy intensity. Moreover, the linkage between energy efficiency and productivity is studied by He et al., (2013) who expand the efficiency discussion with the utilization of bad outputs. As it is one of the most polluting industries in China, iron and steel industry is chosen. As a result of Farrell (1957) efficiency method, the efficiency figures with good outputs are recorded below those with good and bad outputs.

Finally, our intention now is to revise the methods which are related to enery intensity measurement. It is worthwhile to mention that energy efficiency has a key role for exploring the discussion of the measurement of energy intensity. The energy efficiency, as a reverse of energy intensity, in fact provides comparisons of the different stages of energy intensities. Efficiency is generally assumed to use less energy, however, it is the comparison of observed output (input) with the maximum attainable output (input). It measures the distance of inputs and outputs from the best production frontier which is created by the production possibilities, constraints and technological conditions. In this context, Ying and Yi (2010) apply Malmquist Productivity Index [15] to investigate the energy efficiency, together with energy intensity of Beijing from 2000 to 2006. Pursuing the same idea, Liu et al. (2013) apply this method for the productivity analysis of Taiwan energy companies. To account for one other significant aspect of efficiency measurement, He et al. (2013) examine China's iron and steel indusrty which has grown rapidly and accounts for approximately 45 percent of world steel production. Negative impacts of this increase is obviously on environment. If this

[15] Malmquist Productivity Index is developed by Fare et al. (1994) and is expressed as a geometric mean of two indices for the period t and $t+1$ relative to technology in period t: $MPI_t^{t+1} = [\frac{d^t_{CRS}(X^{t+1},Y^{t+1})}{d^t_{CRS}(X^t,Y^t)} \times \frac{d^{t+1}_{CRS}(X^{t+1},Y^{t+1})}{d^{t+1}_{CRS}(X^t,Y^t)}]^{1/2}$ where $d^t(X^t,Y^t)$ represents the distance function provides maximum contraction.

is not taken into account in the calculation process, efficiency and productivity results would lead to bias. The paper focuses on the comparison of efficiency measurement based on good output and joint production of good and bad outputs. There are also few studies (Watanebe et al., 2007; Mandal, 2010; Zhang et al., 2011; Hailou et al., 2001) related to comparison of efficiency estimation with and without bad output. Ray (2011), applies traditional energy intensity measurement, that is the ratio of energy to output, to illustrate the varieties of energy intensity degree among seven manufacturing industries in India. The findings imply that energy intensity degree varies depending on which industry is chosen. Furthermore, there is evidence supporting the fact that higher energy intensive industries tend to be higher energy intensity. Furthermore, Bernard and Cote (2002) analyse traditional energy intensity by addressing aggregation. Since there are several energy sources and outputs for the most of the production, it would be important how you express these differences when computing energy intensity for both energy use and output. It is underlined that, value of production, value added and value of shipments are the widely used measures of output aggragation, however, thermal and economic measures are utilized for energy use aggregation. With this in mind, six energy intensity indicators are developed and employed for asessing the the level of energy intensities for a few states in Canada from 1976 to 1996. They conclude that there are substantial differences among energy intensity indicators depending on which aggregation methos is employed.

Since the issues which we have touched upon up to now have strong interactions, their analysis deserve more attention. A variety of one of the issues may lead to a change in others. In the next part of the thesis, our goal is to improve a new method which has useful features in the application.

3.3 Methodology

Two commonly used productivity measures, PFP and MFP are distinguished by their handling of inputs. While the ratio of output to a single input is called partial productivity of that particular input, the ratio of output to all inputs combined is called multifactor productivity. The inverses of these measures are called single input intensity measure (i.e., energy intensity, labor intensity etc.) and multifactor input intensity measure respectively. In cases where there is more than one output, this off course requires the construction of a quantity index of outputs for both measures and a quantity index of inputs for the MFP measure. In developing PFP and MFP measures, a modeling technique developed in a series of papers by Fare et al. (2000, 2004), Zaim et al. (2001) and Zaim (2004) is adopted. While these papers made extensive use of output distance functions in constructing various quantity indices, this study promotes the use of the directional technology distance function which allows for simultaneous expansion of output(s) and contraction of input(s) as the most appropriate choice in developing measures which allow for bilateral and multilateral comparisons of partial and multifactor productivity levels. We will also show that the productivity measures that are presented here can easily be extended to measure productivity growth over time. The computation of productivity measures relies on the construction of quantity index of output(s) and quantity index of input(s). Intuitively, the quantity index of output(s) shows the relative success of an observation, say j, in expanding its output(s) and simultaneously contracting its input(s) while using the same level of input(s) as another observation, say i (or using some arbitrary level of inputs common to both i and j). One should note that, in constructing an output index compositional differences in inputs are accounted for. The quantity index of input(s) on the other hand, measures the relative success of observation, say j, in expanding its output(s) and simultaneously contracting its input(s) while producing the same level of output(s) as another observation, say i (or producing some arbitrary level of output(s) common to both i and j). Note this time that, in constructing an input quantity index compositional differences in output(s) are accounted for. To describe the theoretical underpinnings of the index used, suppose we observe a sample of K units each of which uses inputs $x = (x_1, ..., x_N) \in \mathbb{R}_+{}^N$, to produce a vector of outputs $y = (y_1, ...y_M) \in \mathbb{R}_+{}^M$. With this notation at hand, the technology can be described as all feasible vectors (x, y) i.e. $T = ((x, y)$: x can produce y). This technology satisfies standard regularity conditions like closedness and convexity. See Fare and Primont (1995) for details. Among alternative approaches, directional technology distance functions prove to be a particularly useful tool not only to represent a technology with distinctive characteristics such as closedness and convexity, but also as a perfect aggregator and a performance measure. Hence, to develop an MFP index one may employ the directional technology distance function,

$$\vec{D_T}(x, y; g_x, g_y) = \sup \beta : ((x - \beta g_x, y + \beta g_y) \in T),$$

where T is the technology defined as $T = ((x, y)$: x can produce y).

To construct the output quantity index, consider the following two directional distance functions which show the success of two states j and i respectively in expanding their outputs and simultaneously contracting an arbitrary vector of inputs common to both with respect to a constant returns to scale (CRS) technology:

$$\vec{D_{OT}}^{J}(y^j, x^0) = max\lambda_0^j$$

such that,

$$\sum_{k=1}^{K} z_k y_{km} \geq {y_m}^j + {\lambda_0}^j {y_m}^j, m = 1, ..., M$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq {x_n}^0 - {\lambda_0}^j {x_n}^0, n = 1, ..., n$$

$$z_k \geq 0, k = 1, ..., K$$

and (3.1)

$$\vec{D_{OT}}^{I}(y^i, x^0) = max\lambda_0^i$$

such that,

$$\sum_{k=1}^{K} z_k y_{km} \geq {y_m}^i + {\lambda_0}^i {y_m}^i, m = 1, ..., M$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq {x_n}^0 - \lambda_0 {x_n}^0, n = 1, ..., N$$

$$z_k \geq 0, k = 1, ..., K \tag{3.2}$$

where z_k's are intensity variables.

Now defining ${y_j}^*$ and ${y_i}^*$as the maximum attainable outputs and ${x_j}^*$ and ${x_i}^*$ as the minimum attainable inputs for the producing units j and i respectively, under CRS:

$$\frac{{y_j}^*}{{y_i}^*} = \frac{y_j(1 + \lambda_0^j)}{y_i(1 + {\lambda_0}^i)} = \frac{x_j(1 - \lambda_0^j)}{x_i(1 - {\lambda_0}^i)} = \frac{{x_j}^*}{{x_i}^*} \tag{3.3}$$

and restricting $x_j = x_i = x_0$ as required by the above linear programming problems, this yields a quantity index of outputs:

$$\frac{y_j}{y_i} = \frac{(1 + {\lambda_0}^i)(1 - {\lambda_0}^j)}{(1 + {\lambda_0}^j)(1 - {\lambda_0}^i)} \tag{3.4}$$

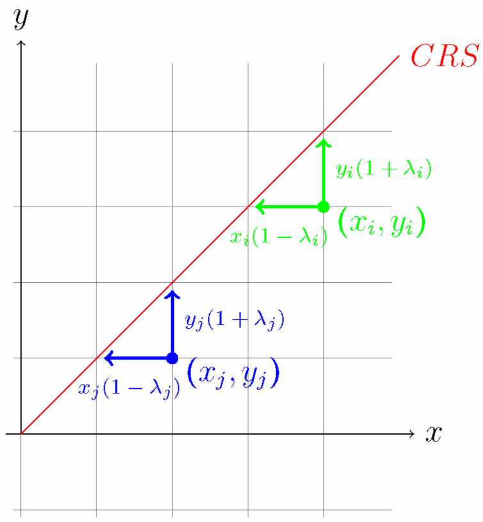

Figure 3.1: Illustration of Directional Technology Distance Function

This can be best explained by Fig. 3.1. Consider two observations (production units) (x_j, y_j) and (x_i, y_i) for which a meaningful output comparison y_j/y_i is required. The first linear programming problem expands jth producing units output (vector) y_i and simultaneously contracts an input vector common to both i.e, $x_j = x_i = x_0$ and the second program does the same thing for the ith producing unit. Simple geometry, i.e., similar triangles, allows one to write Eq. (3.3) which intuitively says that meaningful output comparisons can only be made between producing units which have the same input composition and amounts.

Now the next question is how to choose an input vector common to both. The trick is to choose a base production unit, for example production unit i in a given year, and then calculates the rate of difference between each production unit and the base production unit. By normalizing the base producing units output to one, one can do all cross section multilateral output comparisons.

If on the other hand the objective is to compute an output index for a panel of observations (i.e., panel of output index for 48 U.S states over 45 years from 1960 to 2004), one could still use the same approach by neglecting the fact that different producing units exist at different points in time. For example, input vectors for Alabama in 1970 could be chosen as a base, in which case one will construct an output index where Alabama in 1970 is equal to one. Moreover since the output quantity index satisfies all the desirable properties due to Fisher (1922) -i.e., homogeneity, time reversal, transitivity and dimensionality- and hence naturally passes the Fisher test, this allows all multilateral comparisons across space and time.

Now turning to the construction of the input quantity index, consider the following directional distance functions which show the success of two states j and i respectively in contracting their inputs while expanding an arbitrary vector of outputs which are common to both:

$$\vec{D_{IT}}^{J}(y^0, x^j) = max\lambda_i^j$$

such that,

$$\sum_{k=1}^{K} z_k y_{km} \geq {y_m}^0 + \lambda_i^j {y_m}^0, m = 1, ..., M$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq {x_n}^j - \lambda_i^j {x_n}^j, n = 1, ..., N$$

$$z_k \geq 0, k = 1, ..., K$$

and (3.5)

$$\vec{D_{IT}}^{I}(y^0, x^i) = max\lambda_i^i$$

such that,

$$\sum_{k=1}^{K} z_k y_{km} \geq {y_m}^0 + \lambda_i^i {y_m}^0, m = 1, ..., M$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq {x_n}^i - \lambda_i^i {x_n}^i, n = 1, ..., N$$

$$z_k \geq 0, k = 1, ..., K \tag{3.6}$$

Now defining x_j* and x_i* as the minimum attainable inputs for states j and i

respectively:

$$\frac{x_j{}^*}{x_i{}^*} = \frac{x_j(1-\lambda_i^j)}{x_i(1-\lambda_i{}^i)} = \frac{y_j(1+\lambda_i^j)}{y_i(1+\lambda_i{}^i)} = \frac{y_j{}^*}{y_i{}^*} \tag{3.7}$$

and restricting $y_j = y_i = y_0$ as required by the above linear programming problems, yields a quantity index of inputs:

$$\frac{x_j}{x_i} = \frac{(1+\lambda_i^j)(1-\lambda_i{}^i)}{(1+\lambda_i^i)(1-\lambda_i{}^j)} \tag{3.8}$$

As for the output index, the output vector of Alabama in 1970 could be chosen as a base, in which case one will construct an input index where Alabama in 1970 is equal to one. Finally, the MFP level index and its reciprocal multifactor input intensity index (MFII) can be defined as:

$$MFP = \frac{\frac{(1+\lambda_0^i)(1-\lambda_0^j)}{(1+\lambda_0^j)(1-\lambda_0^i)}}{\frac{(1+\lambda_i^j)(1-\lambda_i^i)}{(1+\lambda_i^i)(1-\lambda_i^j)}} MFII = \frac{\frac{(1+\lambda_i^j)(1-\lambda_i^i)}{(1+\lambda_i^i)(1-\lambda_i^j)}}{\frac{(1+\lambda_0^i)(1-\lambda_0^j)}{(1+\lambda_0^j)(1-\lambda_0^i)}} \tag{3.9}$$

Since both the output and the input quantity index satisfy all the desirable properties due to Fisher (1922) -i.e., homogeneity, time reversal, transitivity and dimensionality- both MFP and MFII indices naturally pass the Fisher test.
A very nice feature of this model is that, for a single output (Y) and single input case (i.e., ignoring all other inputs while in fact they exist), it collapses into a measure that allows for bilateral (and multilateral) comparisons of traditional partial factor productivity (energy productivity), whose reciprocal is aggregate energy intensity (AEI) :

$$PFP_E = \frac{\frac{Y_j}{E_j}}{\frac{Y_i}{E_i}} = \frac{\frac{Y_j}{Y_i}}{\frac{E_j}{E_i}} \tag{3.10}$$

$$AEI = \frac{\frac{E_j}{E_i}}{\frac{Y_j}{Y_i}} \tag{3.11}$$

This requires the computation of four linear programming problems, two of which are for the output index and the other two for the input index. The following two programming problems for example, will compare outputs of j and i provided that their energy inputs are held constant at an arbitrary level common to both.

$$\vec{D_{OT}}^{J}(Y^j, E^0) = max\gamma_0^j$$

such that,

$$\sum_{k=1}^{K} z_k Y_k \geq Y^j + {\gamma_0}^j Y^j$$

$$\sum_{k=1}^{K} z_k E_k \leq E^0 - {\gamma_0}^j E^0$$

$$z_k \geq 0, k = 1, ..., K$$

and (3.12)

$$\vec{D_{OT}}^{I}(Y^i, E^0) = max\gamma_0^i$$

such that,

$$\sum_{k=1}^{K} z_k Y_k \geq Y^i + {\gamma_0}^i Y^i$$

$$\sum_{k=1}^{K} z_k E_k \leq E^0 - {\gamma_0}^i E^0$$

$$z_k \geq 0, k = 1, ..., K \tag{3.13}$$

Similarly, the following two linear programming problems will compare energy inputs of j and i provided that their outputs are held constant at an arbitrary level common to both.

$\vec{D_{IT}}^{J}(Y^0, E^j) = max\gamma_i^j$

such that,

$\sum_{k=1}^{K} z_k Y_k \geq Y^0 + {\gamma_i}^j Y^0$

$\sum_{k=1}^{K} z_k E_k \leq E^j - {\gamma_i}^j E^j$

$z_k \geq 0, k = 1, ..., K$

and (3.14)

$\vec{D_{IT}}^{I}(Y^0, E^i) = max\gamma_i^i$

such that,

$\sum_{k=1}^{K} z_k Y_k \geq Y^0 + {\gamma_i}^i Y^0$

$\sum_{k=1}^{K} z_k E_k \leq E^i - {\gamma_i}^i E^i$

$z_k \geq 0, k = 1, ..., K$ (3.15)

The level of energy input and output that are held constant at an arbitrary level in the linear programming problems above, could easily be set to be equal to those of observation i. In this particular case observation i is considered to be the base country (for which the PFP of energy is equal to unity) with respect to which all bilateral productivity comparisons can be made. Furthermore, since this index is transitive it allows for all multilateral comparisons. Hence, our Partial Factor Productivity measure and Aggregate Energy Intensity measures are as follows:

$$PFP_E = \frac{\frac{(1+\gamma_0^i)(1-\gamma_0^j)}{(1+\gamma_0^j)(1-\gamma_0^i)}}{\frac{(1+\gamma_i^j)(1-\gamma_i^i)}{(1+\gamma_i^i)(1-\gamma_i^j)}} AEI = \frac{\frac{(1+\gamma_i^j)(1-\gamma_i^i)}{(1+\gamma_i^i)(1-\gamma_i^j)}}{\frac{(1+\gamma_0^i)(1-\gamma_0^j)}{(1+\gamma_0^j)(1-\gamma_0^i)}} \tag{3.16}$$

The most appealing feature of the general model presented is that, its special case leads to a PFP index that overcomes the shortcomings of the traditional measure.

The reciprocal of this index naturally results in the energy intensity index, which this study aims to obtain. The two following linear programming problems which will lead to the construction of an output quantity index, reveal the success of two states j and i respectively in expanding their outputs and simultaneously contracting their energy input common to both while holding all other inputs at a constant level common to both.

$$\vec{D_{OT}}^{J}(y^j, x^0, E^0) = max\beta_0^j$$

such that,

$$\sum_{k=1}^{K} z_k y_{km} \geq y_m{}^j + \beta_0{}^j y_m{}^j, m = 1, ..., M$$

$$\sum_{k=1}^{K} z_k E_k \leq E^0 - \beta_0{}^j E^0$$

$$\sum_{k=1}^{K} z_k x_{kn_{-E}} \leq x_{n_{-E}}{}^0, n = 1, ..., N$$

$$z_k \geq 0, k = 1, ..., K$$

and (3.17)

$$\vec{D_{OT}}^{I}(y^i, x^0, E^0) = max\beta_0^i$$

such that,

$$\sum_{k=1}^{K} z_k y_{km} \geq y_m{}^i + \beta_0{}^i y_m{}^i, m = 1, ..., M$$

$$\sum_{k=1}^{K} z_k E_k \leq E^0 - \beta_0{}^i E^0$$

$$\sum_{k=1}^{K} z_k x_{kn_{-E}} \leq x_{n_{-E}}{}^0, n = 1, ..., N$$

$$z_k \geq 0, k = 1, ..., K \tag{3.18}$$

Similarly, the following two programming problems compare energy inputs of j and i provided that their outputs are held constant at an arbitrary level common to both, while all other inputs except energy used by j and i are treated as fixed inputs.

$$\vec{D_{IT}}^{J}(y^0, x^j, E^j) = max\beta_i^j$$

such that,

$$\sum_{k=1}^{K} z_k y_{km} \geq {y_m}^0 + {\beta_i}^j {y_m}^0, m = 1, ..., M$$

$$\sum_{k=1}^{K} z_k E_k \leq E^j - {\beta_i}^j E^j$$

$$\sum_{k=1}^{K} z_k x_{kn_{-E}} \leq {x_{n_{-E}}}^j, n = 1, ..., N$$

$$z_k \geq 0, k = 1, ..., K$$

and (3.19)

$$\vec{D_{IT}}^{I}(y^i, x^0, E^0) = max\beta_i^i$$

such that,

$$\sum_{k=1}^{K} z_k y_{km} \geq {y_m}^0 + {\beta_i}^i {y_m}^0, m = 1, ..., M$$

$$\sum_{k=1}^{K} z_k E_k \leq E^i - {\beta_i}^i E^i$$

$$\sum_{k=1}^{K} z_k x_{kn_{-E}} \leq {x_{n_{-E}}}^i, n = 1, ..., N$$

$$z_k \geq 0, k = 1, ..., K \tag{3.20}$$

As is the usual convention, if the level of energy input, other inputs and outputs that are held constant at an arbitrary level in the linear programming problems above are set to be equal to those of observation i, observation i becomes the base economy (for which the corrected PFP of energy (CPFP) is equal to unity) with respect to which all bilateral productivity comparisons can be made. Furthermore, since this index is transitive it allows for all multilateral comparisons. The resultant indices are expressed as:

$$CPFP_E = \frac{\frac{(1+\beta_0^i)(1-\beta_0^j)}{(1+\beta_0^j)(1-\beta_0^i)}}{\frac{(1+\beta_i^j)(1-\beta_i^i)}{(1+\beta_i^i)(1-\beta_i^j)}} EI = \frac{\frac{(1+\beta_i^j)(1-\beta_i^i)}{(1+\beta_i^i)(1-\beta_i^j)}}{\frac{(1+\beta_0^i)(1-\beta_0^j)}{(1+\beta_0^j)(1-\beta_0^i)}} \tag{3.21}$$

3.4 Data

The data comprising the quantities of capital, labor, energy, land, material, fertilizer, pesticide inputs and livestock, farm related and crops outputs are compiled for forty eight states (AL, AR, AZ, CA, CO, CT, DE, FL, GA, IA, ID, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NV, NY, OH, OK OR, PA, RI, SC, SD, TN, TX, UT, VA, VT, WA, WI, WV,WY) of US from 1960 to 2004. The quantity data are expressed in terms of 1996 Alabama prices.

Capital Input is constructed by aggregating over the different capital assets using as weights the asset-specific rental prices.

Land Input To obtain a constant-quality land stock, first intertemporal price indexes of land in farms are constructed. The stock of land is then constructed implicitly as the ratio of the value of land in farms to the intertemporal price index. It is assumed that land in each county is homogeneous, hence aggregation is at the county level. Differences in the quality of land across States and regions prevent the direct comparison of observed prices. To account for these quality differences, relative prices of land from hedonic regression results are calculated.

Labor Input is constructed for each State and the aggregate farm sector using the demographically cross-classified hours and compensation data. Labor hours having higher marginal productivity (wages) are given higher weights in forming the index of labor input than are hours having lower marginal productivities.

Energy Input Data on current dollar consumption of petroleum fuels, natural gas, and electricity in agriculture are compiled for each State for period 1960-2004. Prices of individual fuels are taken from the Energy Information Administration's Monthly Energy Review. The index of energy consumption is formed implicitly as the ratio of total expenditures (less State and Federal excise tax refunds) to the corresponding price index.

Pesticides and Fertilizer Inputs Pesticides and fertilizers have undergone significant changes in input quality over the study period. Since input price and quantity series used in a study of productivity must be denominated in constant-efficiency units, price indexes for fertilizers and pesticides using hedonic methods are constructed. Under this approach, a good or service is viewed as a bundle of characteristics which contribute to the productivity (utility) derived from its use. Its price represents the valuation of the characteristics "that are bundled in it", and each characteristic is valued by its "implicit" price. However, these prices are not observed directly and must be estimated from the hedonic price function. A hedonic price function expresses the price of a good or service as a function of the quantities of the characteristics it embodies. Thus, the hedonic price function for, say pesticides, may be expressed as Wp = W(X,D), where Wp represents the price of pesticides, X is a vector of characteristics or quality variables, and D is a vector of other variables.

Materials Input consists of goods used in production during the calendar year, whether withdrawn from beginning inventories or purchased from outside (open-market purchases of feed, seed, and livestock inputs). Implicit quantity indexes are calculated for the remaining materials input, a variety of purchased services such as contract labor services, custom machine services , machine and building maintenance and repairs, and irrigation from public sellers of water.

Output The output quantity for each crop and livestock category consists of quantities of commodities sold off the farm, additions to inventory, and quantities consumed as part of final demand in farm households during the calendar year. Off-farm sales in the aggregate accounts are defined only in terms of output leaving the sector, while off-farm sales in the State accounts include sales to the farm sector in other States as well. The residual of the total output of the industry other than crop and livestock represents farm related output.

More details of data definitions are available on the website http://www.ers.usda.gov/data-products/ agricultural-productivity-in-the-us. The graphs below represent the average amount of each input and output in the all regions for three periods, including 1960-1974, 1974-1989 and 1990-2004.

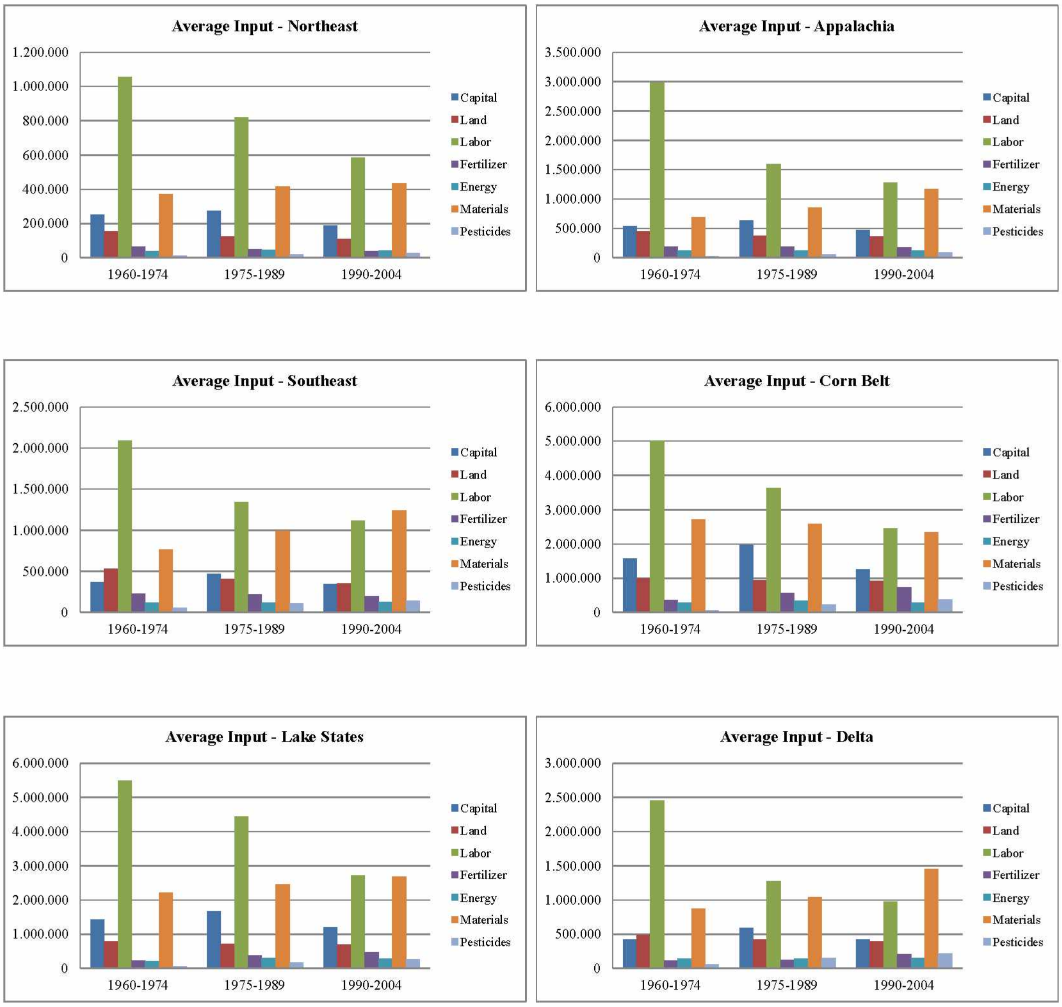

Figure 3.2: Average Quantity of Inputs

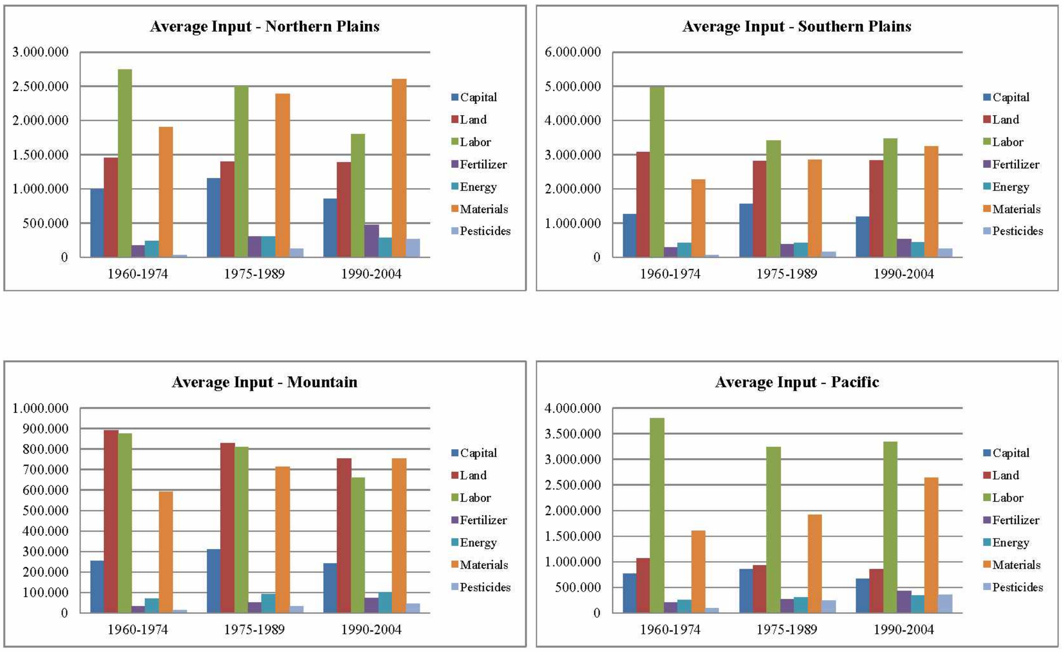

Figure 3.2 (continued)

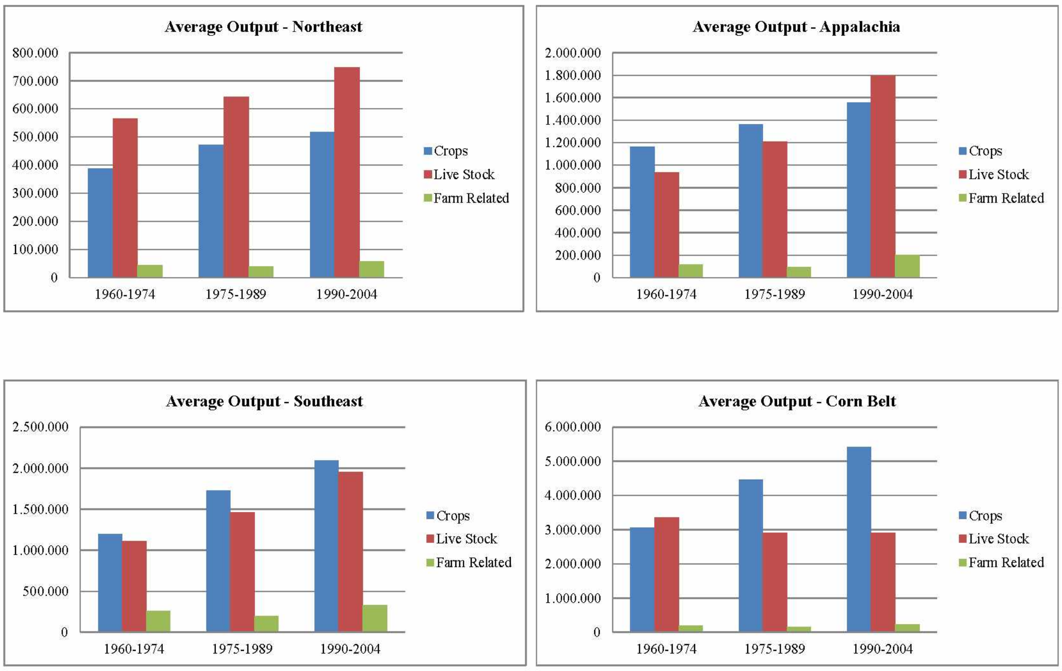

Figure 3.3: Average Quantity of Outputs

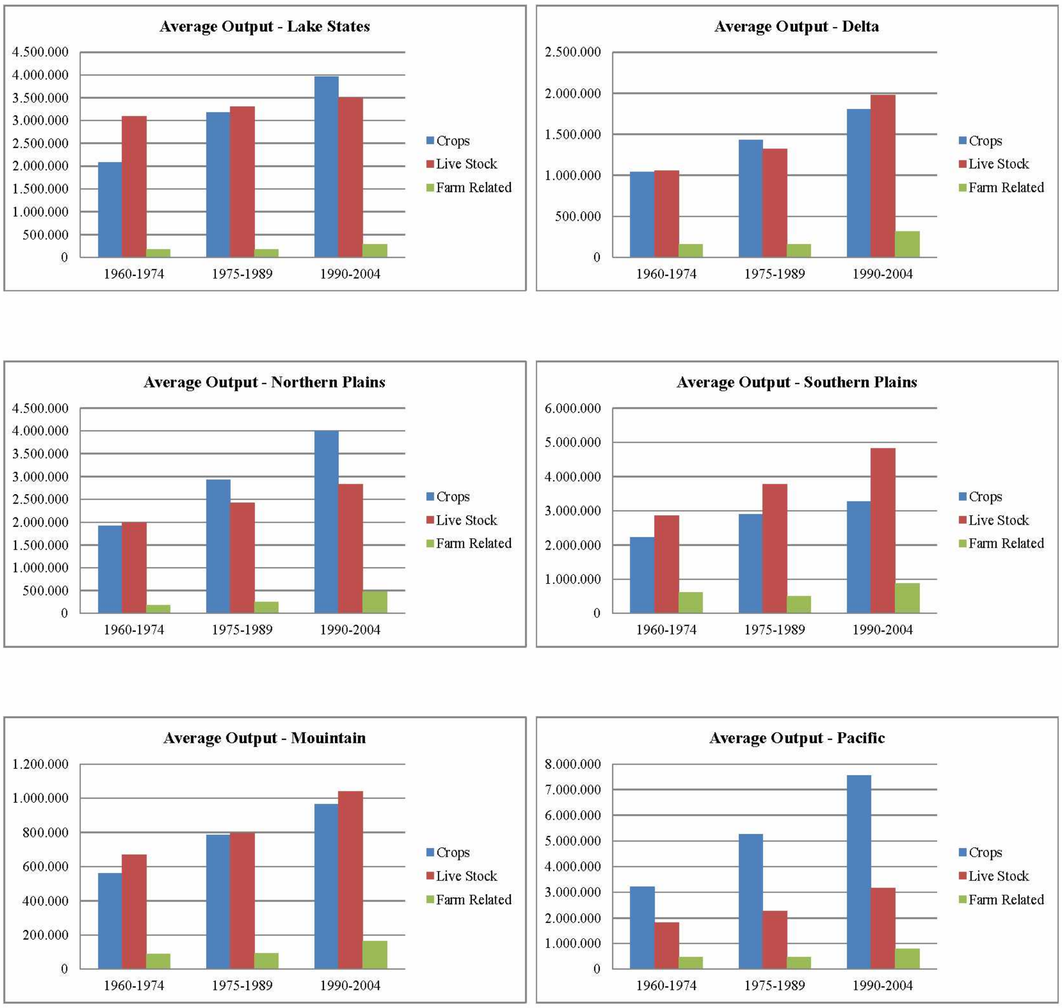

Figure 3.3 (continued)

The bar charts above compare ten regions in terms of input and output quantities for three periods including 1960-1974, 1975-1989 and 1990-2004. It is clear that labor input had by far the biggest share in agricultural production. It is also noticeable that labor had been exhibiting considerable declines in all regions for three periods. The material input which comes second after labor had a significant share in agricultural production for all periods. It should be noted that the material input differed from labor in terms of change over time. While labor saw dramatic declines over the three periods, material saw significant rises in these periods. Further, capital and land input used in each period tended to be fairly similar for any region. It is clear that, pesticide and fertilizer input saw slight rises from the first period. The utilization of energy input in Corn Belt, Lake

States and Southern Plains which is about twice that of the others tended to be fairly similar for all regions.

In the case of output production, there was a markedly increase in each type of the output. While crops and livestock saw significant increases, farm related output did not experience major changes compared to crops and livestock. The figures indicate that, Southern Plains made the greatest contribution in terms of livestock production. For the production of crops, Pacific region recorded by far the highest figures. Although there was an increase in farm related production, this rise remained very low compared to that of others.

3.5 Results

Calculation of the input intensity not only reflects the variation of the input required in the production per unit of output but also provides the implications for productivity and efficiency of that particular input. GAMS (2010) is employed for the calculation of the coefficiencts in the linear programming problems illustrated above in the methodology. Having obtained these values, we are able to derive input and output quantity index and thereby the intensity figures for each state between the years 1960 and 2004.

Fig. 3.4 compares our MFP index as expressed in Eq.(3.9) to that reported by the ERS of the USDA, where both indices are expressed relative to the level of MFP in Alabama in 1970. Although the construction of quantity indices of outputs and inputs are quite different in both methods, and the ERS relies on Fisher quantity indices of outputs and inputs (i.e., Theil–Tornqvist index) after doing a transitivity correction by a method independently proposed Elteto and Koves (1964) and Szulc (1964), both MFP measures mirror each other perfectly not only with respect to levels but with respect to trend growth rates as well (except for the Lake States). This, once again demonstrates that directional distance functions are perfect aggregators (without using information on prices).

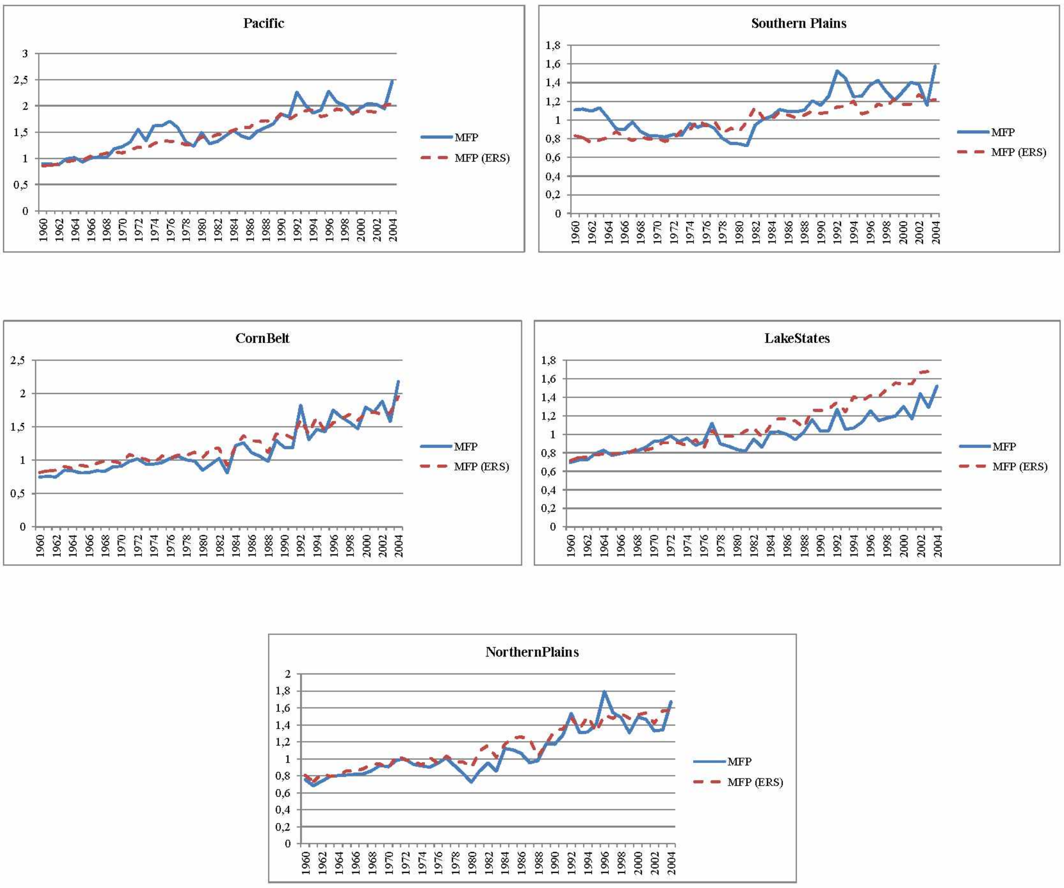

Fig.3.4: Comparison of MFP Index & Theil-Tornqvist Index of ERS

Now we turn to the comparison of AEI, EI and MFII as computed by Eq.(3.16), Eq.(3.21) and Eq. (3.9) across time and space. In computing AEI, the single output required is obtained by summing the real quantities of crop, livestock and farm related outputs and energy is considered to be the single input, ignoring the existence of all the other inputs. The figures in this section show general trends for the five regions which constitute over 75% of agricultural production in US. One should remember however that the bases for all these indices are Alabama 1970 (i.e., Alabama 1970=1). Therefore, in the figures, EI compares (geometric) average energy intensities of states in a particular region to that of Alabama in 1970 over the years, after accounting for the differences in outputs while energy use is being compared and for the differences in inputs while outputs are being compared. Hence, EI level of 1.93 in the Pacific region in 1960 indicates that energy use per unit of output in 1960 in the Pacific region was almost double that of Alabama in 1970 after accounting for the differences in output and input combinations of the Pacific region in1960 and Alabama in 1970. This, when compared with an AEI level of 1.16, implies that there emerges a substantial bias due to i) aggregation of outputs while energy use is being compared and ii) failure to hold non-energy inputs constant while output comparisons are being made. Furthermore, in the years where EI>AEI (EI<AEI) this indicates a structure of production where combinations of inputs and outputs use less (more) energy when compared to Alabama 1970.

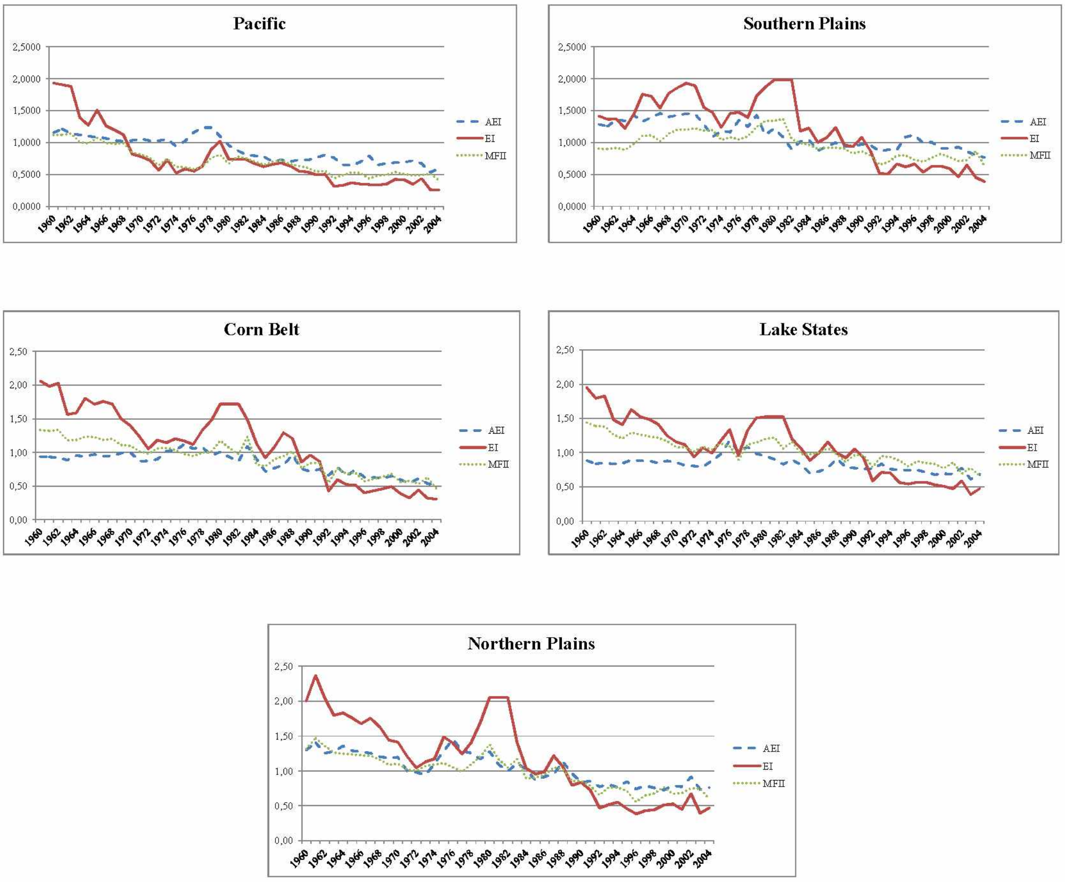

Fig.3.5: Comparison of Intensities

Comparison of figures reveals some further important results. First, there exist substantial level differences between energy intensity levels for both the AEI and EI which prior studies relying on index decomposition methods failed to show. For example, our results show while Southern Plains start off with relatively low levels of AEI (1.28) and EI (1.42) which are close to each other, the Pacific region has achieved the lowest EI level in the 1972-1976 period (0.59 in 1975). Second, improvements in energy intensity (energy productivity) will be underestimated if measured by AEI. Third, for all the five regions although EI was higher than MFII during the initial years, rapid improvements in EI indicate that particular attention was paid to increase the energy efficiency and that energy efficiency has increased at a faster rate than the average rate of increase in the efficiency of all the inputs. Fourth there has been a convergence of EI levels to somewhere between 0.26 to 0.55 (i.e., one-fourth to one-half of the levels in Alabama in 1970).

More comprehensive level and growth comparisons are provided in Table 3.1, 3.2 and 3.3. First, the results reveal that EI and AEI are not necessarily in agreement in ranking the states according to their energy intensity. For example in 1960, while the Northeast region is found to be the worst performer with respect to EI level, AEI measure ranks it as being the best performer with the lowest energy intensity. However, Florida is the only state which was consistently ranked as one of the best performers for all the selected years by both the measures. Second, is the relation between EI and MFII. While EI has been consistently higher than MFII in 1960 (except for Florida North Carolina and Oklahoma), just the reverse is true in 2004 for all the states. As for the growth rates, for all the regions EI outperforms both MFII and AEI for the 1990-2004 and for the full 1960-2014 period implying that AEI is a measure that underscores the real achievement in reducing energy intensity and that reduction in energy intensity has been larger than the average rate of decline in the intensity of all inputs. Pacific, Corn Belt and Northeastern Regions have been the most successful states in reducing energy intensity (EI) with dramatic decline rates of -4.46%, -4.25% and -3.85% per annum respectively. The new methodology employed for the calcualtion of EI is also applied to the other inputs. The results are presented in Fig. 3.6–3.11.

Table 3.1: Intensity Level Comparison

Intensity Levels (Alabama 1970 = 1)					
		1960	1975	1990	2004
Northeast	**EI**	2,102	0,899	0,736	0,373
	MFII	1,390	0,967	0,836	0,574
	AEI	0,776	0,800	0,629	0,659
Appalachia	**EI**	1,566	1,067	0,876	0,550
	MFII	1,236	1,085	0,937	0,769
	AEI	0,967	1,052	0,684	0,690
Southeast	**EI**	1,037	0,623	0,628	0,367
	MFII	0,932	0,705	0,745	0,546
	AEI	0,948	0,786	0,642	0,566
Corn Belt	**EI**	2,063	1,203	0,964	0,306
	MFII	1,335	1,036	0,838	0,460
	AEI	0,933	1,028	0,719	0,505
Lake States	**EI**	1,950	1,172	1,054	0,474
	MFII	1,437	1,132	0,967	0,658
	AEI	0,884	0,978	0,775	0,685
Delta	**EI**	1,929	1,020	0,757	0,472
	MFII	1,384	0,979	0,817	0,618
	AEI	1,468	1,194	0,773	0,731
Northern Plains	**EI**	2,001	1,488	0,836	0,465
	MFII	1,315	1,109	0,854	0,598
	AEI	1,298	1,289	0,836	0,757

Table 3.1 (continued)

Intensity Levels (Alabama 1970 = 1)					
		1960	1975	1990	2004
	EI	1,416	1,458	1,083	0,387
Southern Plains	**MFII**	0,904	1,083	0,865	0,635
	AEI	1,285	1,164	0,977	0,768
	EI	1,983	0,910	0,668	0,474
Mountain	**MFII**	1,235	0,968	0,783	0,633
	AEI	1,155	1,132	1,022	0,904
	EI	1,932	0,588	0,497	0,259
Pacific	**MFII**	1,117	0,616	0,544	0,406
	AEI	1,160	1,023	0,761	0,593

Table 3.2: Average Annual Growth Rates of Intensity Measures

Average Annual Growth Rates of Intensity Measures (%)					
		1960-1974	**1975-1989**	**1990-2004**	**1960-2004**
	EI	-7.08	-2.06	-4.73	-3.85
Northeast	**MFII**	-2.81	-1.23	-2.65	-1.99
	AEI	-0.06	-1.06	-0.03	-0.37
	EI	-4.32	-2.07	-3.27	-2.35
Appalachia	**MFII**	-1.64	-1.45	-1.40	-1.07
	AEI	0.98	-3.33	0.00	-0.76
	EI	-4.16	-0.95	-3.76	-2.33
Southeast	**MFII**	-2.09	-0.37	-2.20	-1.21

Table 3.2 (continued)

Average Annual Growth Rates of Intensity Measures (%)					
		1960-1974	**1975-1989**	**1990-2004**	**1960-2004**
	AEI	-0.90	-2.57	-0.18	-1.17
	EI	-4.11	-2.38	-7.88	-4.25
Corn Belt	**MFII**	-1.62	-2.11	-4.20	-2.39
	AEI	0.64	-2.16	-2.81	-1.39
	EI	-4.72	-1.69	-5.55	-3.16
Lake States	**MFII**	-2.26	-1.92	-2.71	-1.76
	AEI	-0.03	-0.80	-0.98	-0.58
	EI	-4.31	-3.14	-3.31	-3.15
Delta	**MFII**	-2.09	-2.05	-1.97	-1.81
	AEI	-0.93	-3.20	-0.79	-1.57
	EI	-3.74	-4.39	-4.10	-3.26
Northern Plains	**MFII**	-1.31	-1.88	-2.51	-1.77
	AEI	-1.16	-0.92	-1.74	-1.22
	EI	-0.94	-3.12	-7.08	-2.90
Southern Plains	**MFII**	1.00	-1.90	-2.18	-0.80
	AEI	-0.60	-1.69	-1.36	-1.16
	EI	-6.57	-2.56	-2.42	-3.20
Mountain	**MFII**	-2.08	-1.74	-1.50	-1.51
	AEI	-1.29	0.05	-0.50	-0.55
	EI	-8.89	-0.59	-4.54	-4.46
Pacific	**MFII**	-4.16	-0.14	-2.07	-2.28
	AEI	-1.44	-1.87	-1.44	-1.51

Table 3.5.3: Intensity Rankings (Measured with Respect to Alabama 1970=1).

		1960						1990						2004					
		AEI	Rank	EI	Rank	MFII	Rank	AEI	Rank	EI	Rank	MFII	Rank	AEI	Rank	EI	Rank	MFII	Rank
Alabama	AL	0,91	33	1,53	37	1,22	37	0,58	44	0,80	29	0,89	24	0,63	33	0,47	21	0,69	16
Arkansas	AR	1,63	4	1,50	38	1,24	34	0,72	26	1,02	14	0,90	21	0,64	32	0,49	15	0,57	29
Arizona	AZ	0,97	30	1,14	45	0,78	46	0,71	29	0,47	41	0,65	39	0,64	30	0,35	36	0,51	36
California	CA	0,87	35	1,94	25	0,79	45	0,57	46	0,66	35	0,44	48	0,41	48	0,23	45	0,39	45
Colorado	CO	1,04	22	1,74	33	1,36	19	0,77	20	0,81	25	0,80	31	0,71	19	0,54	7	0,69	15
Connecticut	CT	0,77	40	1,98	23	1,46	11	0,63	42	0,63	36	0,83	29	0,60	36	0,36	34	0,54	31
Delaware	DE	0,64	46	1,87	28	1,27	31	0,37	48	1,13	6	0,92	17	0,49	43	0,47	22	0,70	14
Florida	FL	0,60	48	0,37	48	0,51	48	0,53	47	0,31	48	0,44	47	0,41	47	0,22	47	0,35	47
Georgia	GA	1,14	14	1,40	40	1,22	36	0,68	31	0,77	31	0,85	27	0,53	42	0,35	35	0,55	30
Iowa	IA	0,68	44	1,37	42	1,20	38	0,67	33	0,91	19	0,96	12	0,46	45	0,27	42	0,48	37
Idaho	ID	1,23	9	2,12	19	1,33	22	1,16	4	0,58	38	0,76	34	1,00	4	0,57	5	0,52	35
Illinois	IL	1,00	25	2,02	21	1,25	33	0,66	34	0,82	23	0,63	41	0,48	44	0,24	44	0,32	48
Indiana	IN	1,06	20	2,49	10	1,53	6	0,76	22	1,07	9	0,85	28	0,44	46	0,28	41	0,41	42
Kansas	KS	1,21	12	2,68	5	1,31	26	0,79	18	1,05	11	0,98	11	0,81	11	0,54	8	0,73	9
Kentucky	KY	0,83	38	1,61	36	1,32	24	0,65	39	0,81	26	0,91	20	0,66	26	0,47	20	0,71	11
Louisiana	LA	1,66	2	2,84	3	1,61	2	0,89	9	0,68	34	0,82	30	0,91	7	0,50	12	0,67	22
Massachusetts	MA	0,70	43	1,79	30	1,31	27	0,72	25	0,50	40	0,69	38	0,73	16	0,23	46	0,40	43
Maryland	MD	0,87	36	2,48	11	1,49	10	0,57	45	1,19	5	1,03	6	0,58	39	0,48	18	0,69	17
Maine	ME	0,82	39	2,22	18	1,56	4	0,75	23	0,82	24	1,03	7	0,83	9	0,39	32	0,65	23
Michigan	MI	1,06	21	3,07	2	1,67	1	0,74	24	0,88	21	0,89	23	0,62	35	0,46	23	0,61	25
Minnesota	MN	0,97	29	2,02	22	1,39	18	0,82	15	1,20	4	0,98	10	0,78	13	0,48	17	0,61	27
Missouri	MO	1,03	23	2,37	14	1,32	25	0,85	13	1,50	1	1,13	2	0,57	40	0,38	33	0,62	24
Mississippi	MS	1,17	13	1,68	34	1,33	21	0,72	28	0,62	37	0,74	35	0,67	25	0,43	24	0,61	26
Montana	MT	1,66	3	2,63	7	1,49	9	1,28	2	0,36	46	0,58	42	1,13	2	0,30	39	0,46	39
North Carolina	NC	1,13	15	0,78	46	0,81	44	0,65	38	0,81	27	0,78	32	0,56	41	0,39	31	0,73	8
North Dakota	ND	1,71	1	1,91	26	1,46	12	1,00	6	0,34	47	0,51	46	0,86	8	0,43	26	0,44	40
Nebraska	NE	1,22	10	2,66	6	1,42	14	0,72	27	1,07	10	1,07	4	0,66	28	0,42	27	0,68	18
New Hampshire	NH	0,73	42	2,54	9	1,58	3	0,79	19	0,72	32	0,92	19	0,82	10	0,29	40	0,53	33
New Jersey	NJ	0,75	41	1,78	31	1,19	39	0,65	36	0,39	44	0,58	44	0,60	37	0,31	37	0,43	41
New Mexico	NM	1,11	17	1,88	27	1,09	42	0,87	10	0,92	18	0,87	26	0,68	24	0,59	4	0,72	10
Nevada	NV	1,07	18	1,94	24	1,27	30	1,39	1	0,55	39	0,76	33	1,34	1	0,43	25	0,68	20
New York	NY	0,84	37	2,07	20	1,33	20	0,64	41	0,87	22	0,95	15	0,63	34	0,56	6	0,71	12
Ohio	OH	0,95	31	2,29	16	1,40	17	0,68	32	0,70	33	0,72	36	0,59	38	0,40	29	0,54	32
Oklahoma	OK	1,02	24	0,54	47	0,62	47	0,86	11	1,24	3	1,08	3	0,81	12	0,51	11	0,77	5
Oregon	OR	1,28	8	2,70	4	1,53	5	0,92	8	0,43	42	0,65	40	0,75	14	0,19	48	0,36	46
Pennsylvania	PA	0,98	26	2,48	12	1,50	8	0,64	40	1,01	15	0,96	13	0,64	31	0,54	9	0,73	7
Rhode Island	RI	0,89	34	1,78	32	1,41	15	0,62	43	0,38	45	0,58	43	0,72	18	0,24	43	0,40	44
South Carolina	SC	1,29	7	1,45	39	1,00	43	0,80	16	0,81	28	0,94	16	0,75	15	0,50	13	0,68	21
South Dakota	SD	1,13	16	1,18	44	1,10	41	0,86	12	1,30	2	1,01	9	0,70	20	0,49	16	0,59	28
Tennessee	TN	0,95	32	1,83	29	1,40	16	0,69	30	0,89	20	0,95	14	0,69	22	0,72	1	0,83	2
Texas	TX	1,62	5	3,68	1	1,33	23	1,11	5	0,94	17	0,69	37	0,73	17	0,30	38	0,53	34
Utah	UT	1,07	19	2,26	17	1,29	28	0,98	7	0,95	16	0,92	18	0,91	6	0,49	14	0,70	13
Virginia	VA	0,97	28	1,68	35	1,27	32	0,65	35	0,79	30	0,87	25	0,65	29	0,70	2	0,80	3
Vermont	VT	0,63	47	2,34	15	1,23	35	0,65	37	1,04	12	0,89	22	0,70	21	0,42	28	0,68	19
Washington	WA	1,39	6	1,38	41	1,15	40	0,85	14	0,43	43	0,57	45	0,68	23	0,40	30	0,48	38
Wisconsin	WI	0,67	45	1,20	43	1,28	29	0,77	21	1,11	8	1,04	5	0,66	27	0,48	19	0,76	6
West Virginia	WV	0,98	27	2,45	13	1,51	7	0,79	17	1,12	7	1,23	1	0,93	5	0,53	10	0,78	4
Wyoming	WY	1,21	11	2,63	8	1,43	13	1,24	3	1,03	13	1,01	8	1,05	3	0,64	3	0,90	1

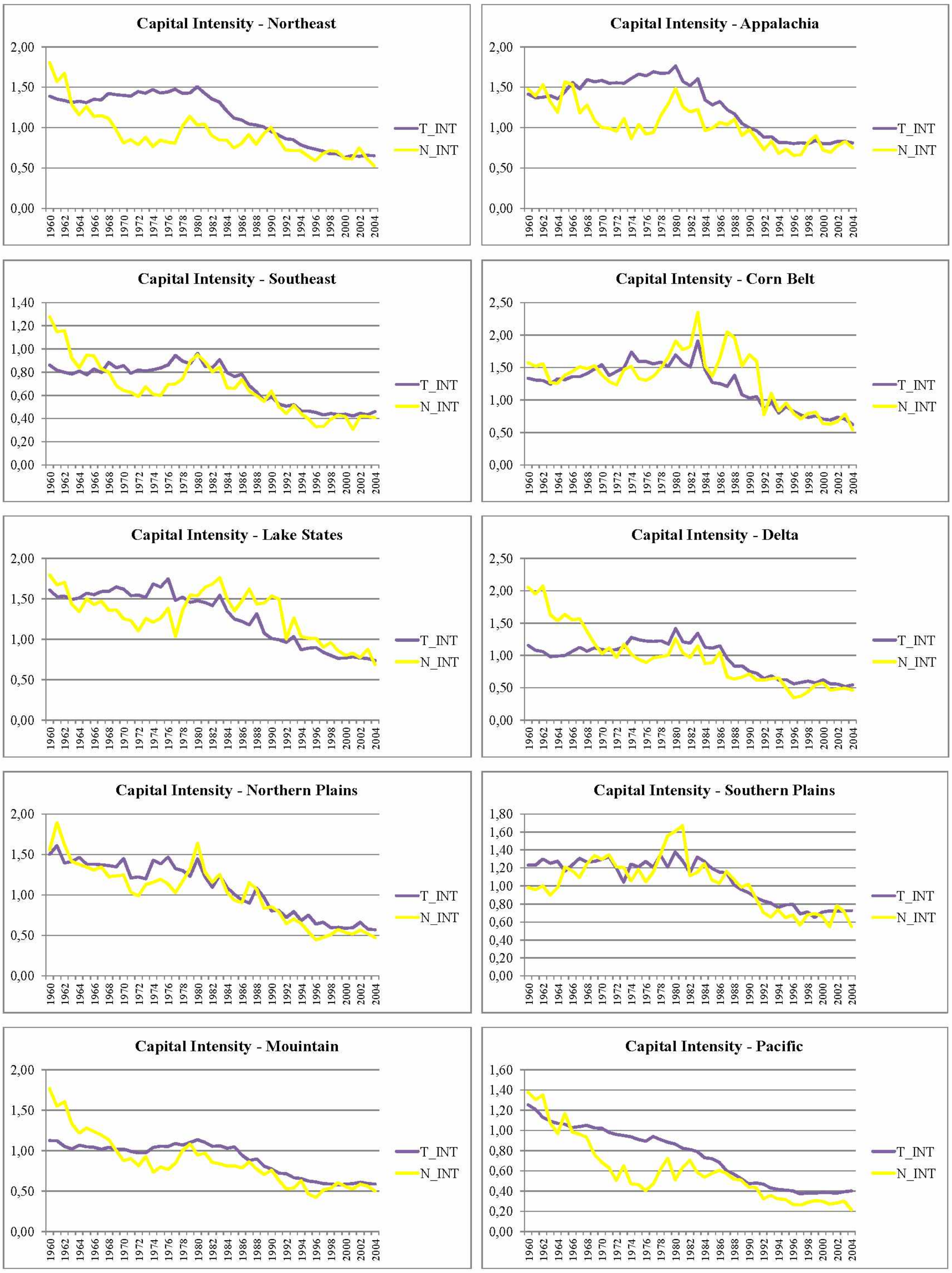

Fig.3.6: Comparison of New and Traditional Capital Intensity

Fig.3.7: Comparison of New and Traditional Land Intensity

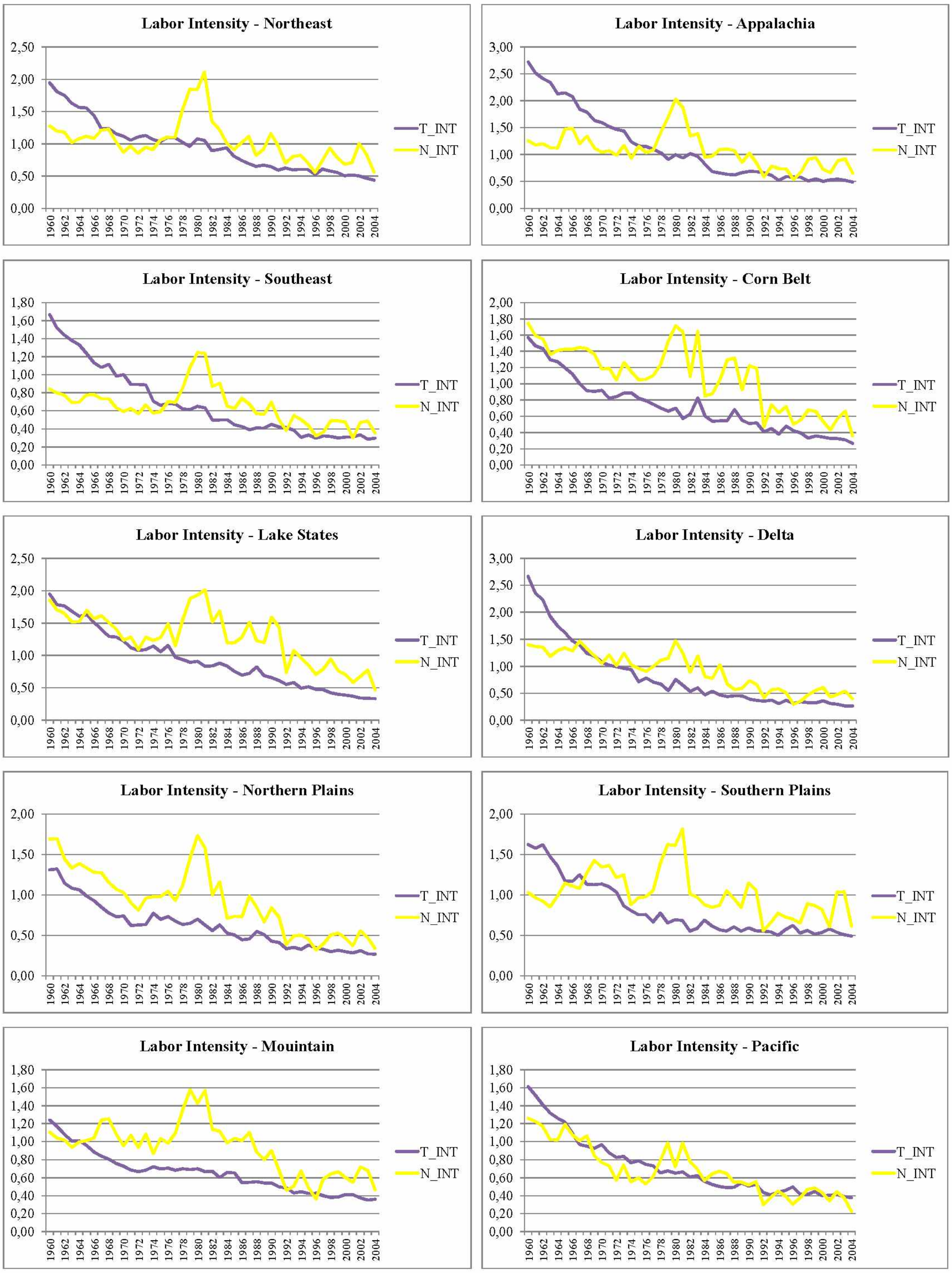

Fig.3.8: Comparison of New and Traditional Labor Intensity

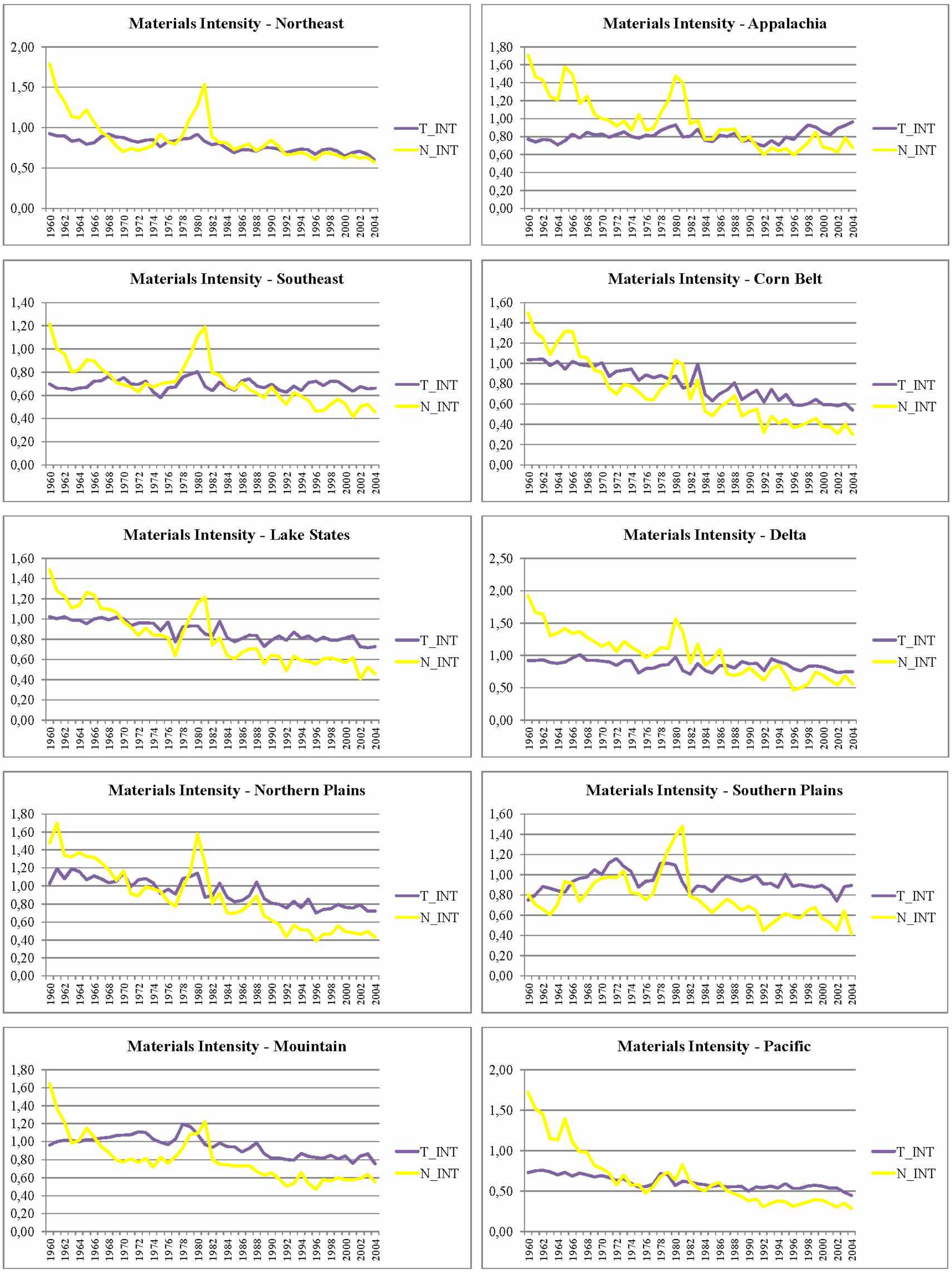

Fig.3.9: Comparison of New and Traditional Materials Intensity

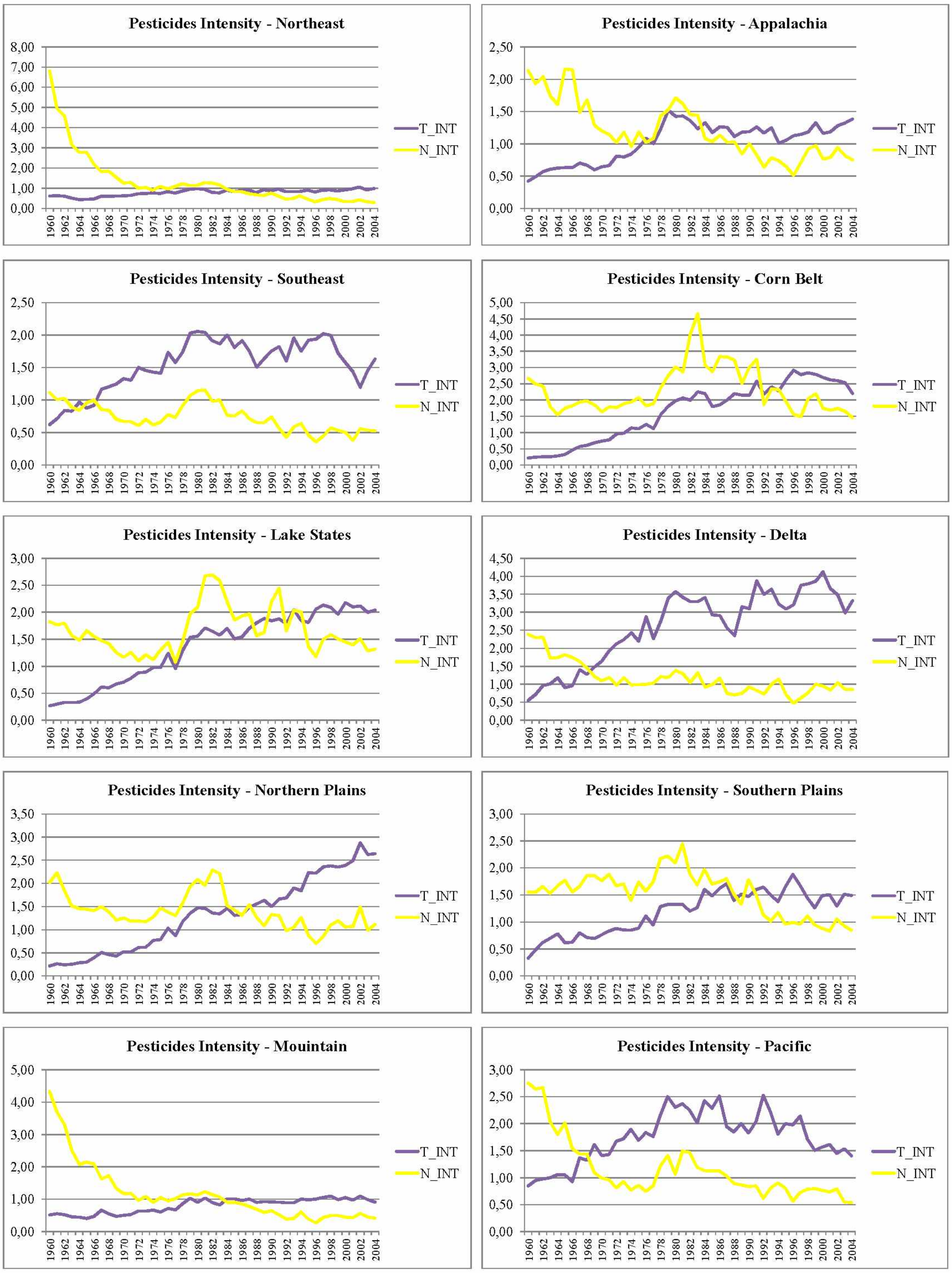

Fig.3.10: Comparison of New and Traditional Pesticides Intensity

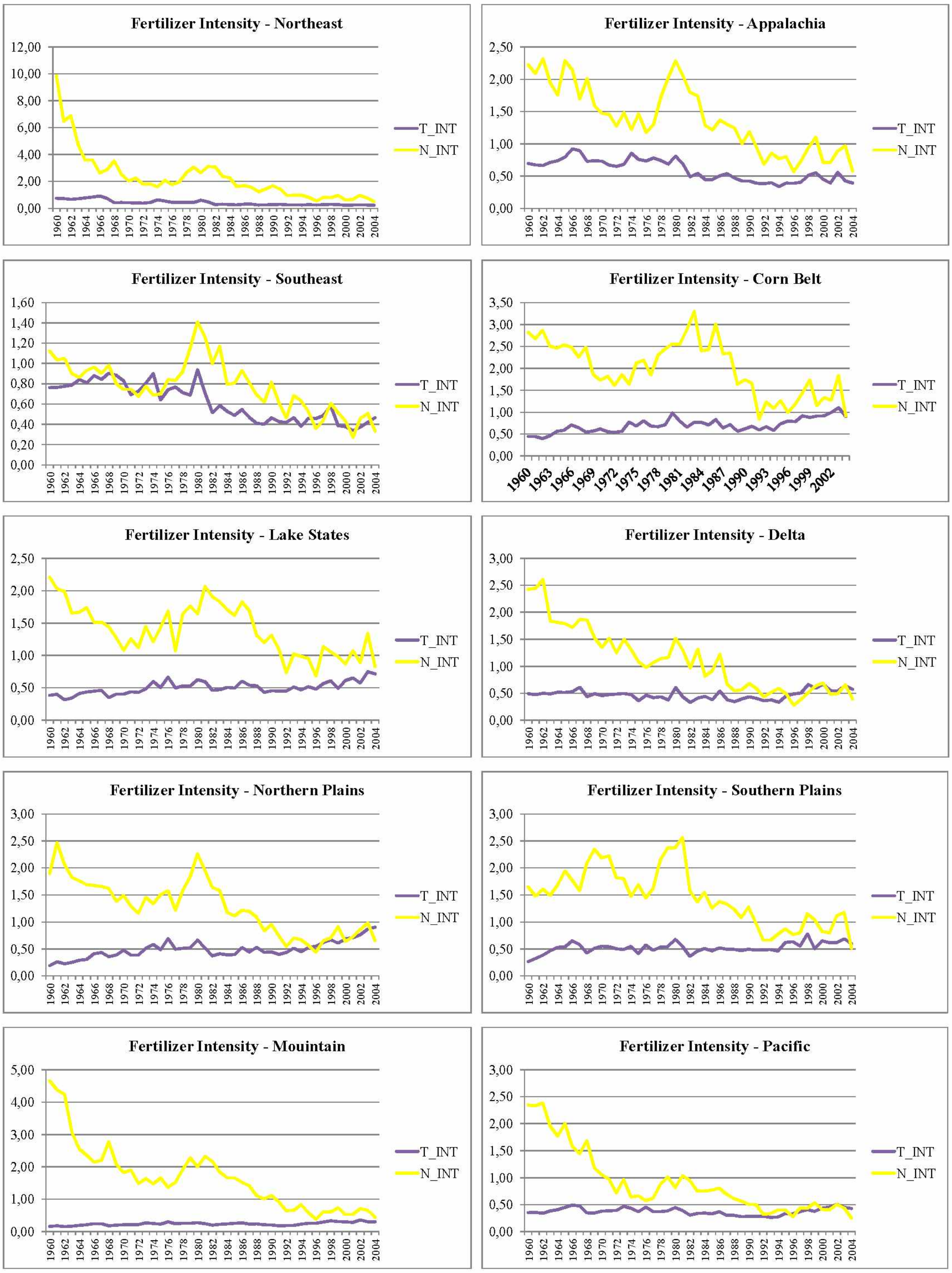

Fig.3.11: Comparison of New and Traditional Fertilizer Intensity

3.6 Discussion

As discussed in Chapter 2, US agriculture has experienced substantial changes particularly in the second half of the 20 th century. These changes can mostly be attributed to the productivity improvement. Moreover, agriculture sector in US had experienced the highest productivity growth among all the sectors. In the light of this productivity improvement, there have been numerous studies indicating the attempts for the productivity growth of US agriculture (Ball, 1985; Ball et al., 1999; 2010; Liu et al., 2011). To account for the results above and draw a conceptual framework, the discussion part is built around the productivity analysis. The figures indicating intensity and also efficiency measures in the results are expressed in terms of productivity. In fact, intensity, efficiency and productivity are identical as they only differ in definitions.

Firstly, our main focus is the analysis of energy and its productivity trend over the whole period. Since it is a major component in agriculture production, it deserves to be analysed in depth. At this point, productivity measurement and analysis have gained importance as they explore effective policies for the utilization of energy input which is a limited resource. The findings support the general productivity growth trend in US agriculture in the sense that it has exhibited a positive significant growth from 1960 to 2004. While the differences in energy intensity figures between 1960 and 2004 indicate positive energy productivity growth in all the regions, the 5 year period roughly from the mid 1970s to early 1980s saw a dramatic decline in energy productivity. Since then, it remained steady for a few years and contrary to the former period the mid 1980s saw a considerable rise. This can be associated with the impacts of oil crises. The findings are consistent with the study of Wang and McPhail, (2012) who apply Structural Var Model to identify the impacts of energy price shocks on US agricultural productivity. In the same line with our results, Cleveland (1995) attributed the dramatic rise in energy productivity which occured since 1980 due to several factors, one of which is a sharp decline in energy use per hectare and the others are decreases in the land use and a rise in average farm size.

Secondly, total factor producitivity (inverse of MFII) growth in the US agriculture is underlined. Since it is accepted as the main contributor to the growth of American agriculture (Fuglie et al., 2007), the figures presented in the results need to be analysed carefully. What the figures of MFII suggest is that total factor productivity showed an increasing trend over the entire period. Despite the general increase in total factor productivity tendency, there are some noticeable fluctuations which were apparent in the all regions. In the bulletin of Economic Research Service, the fluctuations are explained based on issues such as global energy crises, droughts and government intervention.

Thirdly, we now turn to one of the main focuses of the thesis, the difference between the traditional and new intensity figures which have significant implications that lead to some misleadings in making desicions. The comparison of the capital traditional and new intensity figures suggest that capital productivity, in fact, could be considered higher for almost three decades in the Northeast, Appalachia, Mountain and Pacific. While the gap between the figures are closer in the rest of the regions compared to these, they could probably make sense for improving capital productivity policies. When we look at the comparison of the traditional and new land intensity figures, it is clear that land productivity is generally overestimated when it was calculated by the traditional method. Another interesting issue that should be addressed is that new intensity graphs were more successful for presenting annual fluctuations compared to the traditional one. In the case of labor, it is widely accepted that labor productivity increased in US agriculture mainly due to a sharp decline of labor input utilization (Fuglie et al., 2007). With this view, productivity growth was greater from the beginning of 1960s to the 1990s than the last half decade until 2004 when traditional method was employed for the calculation. These traditional intensity figures seemed logical in the sense that a very speedy and a large amount of labor input exit (as shown in Fig.3.8) was reflected by significantly steep declines. However our findings differed from the traditional intensity figures and suggested that labor productivity did not exhibit an increase as dramatic as the traditional one implied. Although the new labor intensity figures' decline were parallel for about a decade from 1960 in the Lake States, Northern Plains and the Pacific, the genaral trend did not reflect such a considerable decline. This can be associated with the calculation method since the new method that is different from the traditional one which takes all other inputs into account. The figures of the traditional and new energy intensities indicate that, energy productivity was, in fact, greater than the one calculated by the traditional method in the all regions for nearly a decade until 2004. Prior to the this decade, the traditional intensity generally underestimated indicating higher energy productivity. The overestimation of the energy productivity by a traditional method inevitably have some shortcomings. For instance, there was a scope for improving the energy productivity considering the gap between the traditional and the new energy intensity figures as it provides the enlargement of the substitution degree between energy and others as well as the development of energy efficient policies. Moreover, special attention should be paid to the gap between the traditional and the new fertilizer intensity. New fertilizer intensity had been overestimated markedly by nearly three decades and then had been converged to the traditional one. This implies that fertilizer productivity was remarkably less than the traditional one. The lower degree of fertilizer productivity should be tackled as the utilization of fertilizer has negative impacts on the environment. Since it has a close linkage with the industrial waste, the impact on the contamination of natural water resource is regarded as a hot topic to be researcehed (US, Environmental Protection Agency). The fact that new materials intensity underestimated the traditional one coincided with the years from nearly mid 1980s to 2004. It indicates that the productivity of materials was actually higher than the traditional one. The results are consistent with the general productivity growth of US agriculture from 1980.

3.7 Conclusion

The study is set out to explore the new intensity measurement method which calculates a particular input intensity with the consideration of joint impacts' of all other inputs. Another major aim is to make a comparison of new and traditional methods by underlying drawbacks of the latter. In doing so, this chapter, in fact seeks whether traditional intensity measures, which are widely used in the application, are the best indicators for comparison, particularly in energy intensity case. Due to a dramatic rise in the productivity growth and data availability, US agriculture panel data including 48 states from 1960 to 2004 is employed to calculate intensity by applying both the traditional and the new method. The main empirical findings suggest that the differences between these two for all inputs are significant and they should be taken into consideration. As a second major aim, productivity, which is indeed nothing more than the inverse of intensity, is tackled in terms of intensity. With this in mind, a new intensity measurement both gives more reliable results and helps to draw a clear framework for US agriculture productivity which has experienced a great growth since the second half of the 20th century.

As we have discussed earlier, there have been numerous studies conducted by international organizations with the updated data and improved theoretical underpinnings. Even these studies are being developed, the calculation procedure is still based on the traditional method. Furthermore, making use of the traditional method may potentially reduce the impact of policies adopted to improve productivity and efficiency. To the best of our knowledge it is the first attempt to measure intensity of a particular input considering the other inputs' effects.

In the same line of thought, the study attracts more attention owing to the improvement of effective productivity policies. It is highlighted that, in order to generate attainable strategies with regards to the difference between the new and traditional method, there is need for more studies to allow further assessment and evidence.

Although, the traditional intensity measurement has noticeable shortcomings such as the lack of expressing joint impacts, it is still commonly used as an indicator for comparison of different units. Also utilization of a traditional method leads to biased results, there is no such an attempt in the literature to surpass this shortcoming. Accordingly, we develop a method which fills this gap and introduces the methodology enhancing the particular input intensity calculation taking all inputs into account simultaneously. This chapter also has presented substantial questions, which can be the scope of future research, in need of further investigation. One of these questions is whether the new method can be improved with adding the bad output to the calculation process. Specifically in the energy case this question has important implications worth attention since it suggests a detailed analysis with the energy input and bad output which is the integral component of the energy.

Chapter 4

Efficiency Measurement: Stochastic and Deterministic Frontier Analysis Using Parametric, Semi–parametric and Non–parametric Methods

4.1 Introduction

Performance analysis is not only based on the output quality but also on the good management of resources which are utilized in the production process. While the first issue is associated with the effectiveness of production the latter is related with efficiency. This chapter is mainly related to measurement of efficiency in US agriculture using alternative methods which have been developing at a rapid pace for almost a half century. The best known studies which can be regarded as the drivers of efficiency measurement literature date back to Debreu (1951) and Farrell (1957).

Generally, efficiency is measured as the ratio between the observed output and the maximum output under the assumption of fixed input, or alternatively, as the ratio between the observed input and the minimum input under the assumption of fixed output. The analysis of both efficiency and productivity can be seen as major fields in applied production economics. In the literature there have been numerous studies devoted to improvement of efficiency and productivity analysis.

It is widely agreed that efficiency analysis has a close relationships with frontier analysis. There are two types of frontier analysis: Deterministic Frontier Analysis (DFA) and Stochastic Frontier Analysis (SFA). The most noticeable difference between these two is based on how they treat composite error term. DFA approach attributes composite error term to only inefficiency and assumes there is no randomness in the model. If we put it in another way, Deterministic frontiers do not accommodate exogenous effects which are captured by randomness. They basically measure the distances of Decision Making Units (DMU) from the frontier and call it efficiency (inefficiency). Since this type of measurement does not include any randomness, there is no need for estimations as the efficiency can be calculated.

Unlike Deterministic Frontiers, Stochastic Frontiers decompose composite error term into two components: an efficiency (inefficiency) term and a statistical (white) noise term. The use of statistical noise term, which is an indicator of noise in data, is the most obvious difference between DFA and SFA. The statistical noise leading to the most obvious difference between these two indicates that there is some noise in data. For real world data, it is expected that data will be somewhat noisy and thus using stochastic frontiers will be more appropriate. SFA utilizes estimation of efficiencies rather than calculations.

With both DFA and SFA, there are three types of methods named parametric, semi–parametric and non–parametric in order to estimate or calculate efficiency using frontiers. These methods all have their advantages and disadvantages and the choice of which method to use depend on factors such as the data structure, whether observations are homogeneous or heterogeneous, existence of time expansion etc. The following part of the introduction explains the distinctive characteristics of these three methods based on their theoretical underpinnings.

First with the Parametric method, the most appealing feature is that it requires a specific functional form. With the help of functional forms production technology can be modelled and representative relationships between inputs and outputs can be constructed. While the parametricmethod uses specific functional forms, there is no criterion to indicate the best functional form for the method. For instance, when utilizing Cobb Douglas function the relation between parameters and error term is assumed to be linear, however, it can also be quadratic. When it is quadratic,the representative function fails to reflect the actually existing relationship. One other problem arises from using observations (production units) which have different production technologies but are represented in the parametric method by the same production technology. Another major drawback of the parametric method is related with employing assumptions for model construction. Although these assumptions have statistical and econometric grounds, they may cause errors in calculations when the number of assumptions increases.

Now we turn to the semi–parametric method which can be seen as a mix of parametric and non–parametric methods. It allows for statistical noise but does not require any functional forms. In order to estimate efficiency, it first estimates non–parametric production function and then uses the residuals which are derived from this estimation. This type of methods will be more suitable when data include observations utilizing different technologies and exogenous shocks.

Lastly the non-parametric methods unlike parametric ones, does not specify any functional form. Unlike parametric methods which indicate best production technology with a representative function, non-parametric methods construct the best production technology by enveloping data. The best known example of non-parametric method is Data Envelopment Analysis (DEA). Since this method does not require any statistical assumptions or tests to find the best fitting functional form for the production technology and it is easy to compute, DEA is widely applied in efficiency measurement.

The structure of this chapter is as follows: First, different methods regarding parametric, semi-parametric and non-parametric methods are reviewed then efficiency methodology employed is explained finally the results are presented, compared and discussed.

4.2 Literature Review

The agricultural efficiency has been a major concern for policy makers for several decades. There are main arguments that can be advanced to support this interest. One of the most crucial ones can be explained with the agricultural policy aiming at the highest possible productivity. In this line, the methods related to productivity and thereby efficiency have also gained much attention accompanying this concept. Prior to overviewing of the existing methods regarding these issues, it should be beneficial to underline the key factors that actually determine the appropriate method for the measurement of technical efficiency. Particularly in agricultural sector, these factors are likely to be associated with both the production process including numerous inputs and outputs and the impacts of exogenous variables (such as weather, farm policy programs, education of farmers, geographical properties) which should be taken into account in calculation.

As mentioned in the introduction, the efficiency measurement with the consideration of random effects (exogenous shocks) has been widely used since 1977 when the pioneering studies of both Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) were published. Following these studies, there have been many attempts to employ exogenous variables with production frontier under the name of stochastic production frontier. The following part of the literature review serves the purpose of explaining reasons that lie behind the common use of stochastic production frontier with a number of examples. Besides stochastic production frontiers, deterministic production frontiers are also underlined and comparison of these two is provided in several studies.

It is useful to underline that, the existing methods have notably distinguishing features although they seem similar. The literature review is built on the comparison of the existing methods based on their theoretical explanations. It might help us to bridge between methodology and application of efficiency measurement techniques. This part of the chapter can be divided into two parts. It begins with overviewing the applied studies concerning agricultural activities' efficiency measurement and then the studies in the context of efficiency in US agriculture are laid out.

Our first example of the applied studies concerning agricultural activities' efficiency measurement is Coelli's work (1998) which utilizes the stochastic frontier analysis with reference to the opinion that agricultural production is most likely to have exogenous shocks such as weather, drought, and flood. First, Box Cox method[16] is applied to determine the appropriate functional forms which reflect the agricultural production in China. After deriving four (translog, generalized Leontief, normalized quadratic, squared root quadratic) functional forms as a result of Box - Cox parametric test method, the estimation results suggest that as the land rights established by institutions increase, the efficiency of farmers will also increase. No explanation is made for the reciprocal proportion of this rise and it is indicated as a scope of another study which can produce numerical

[16]Box- Cox method (1964) is applied to determine the specific functional form within a particular class of functions which is optimal by reference to a maximum likelihood criterion (Boylan et al. (1982)).

results expressing their influence on the rate of increase.

Similarly, Tzouvelekas and Karagiannis (2001) employ stochastic production frontier extended by Battese and Coelli (1995) for the efficiency measurement of Greek organic and conventional olive growing farms. The data employed in this study contain the inputs of land, labour, fertilizers and pesticides and the output of olive oil production of 84 organic and 87 conventional farms from 1995 to 1996. Translog function is specified in order to examine the impacts of farm size, type of labour, soil quality, weather conditions and higher output elasticities on technical efficiency. Consistent with the other studies (Helfond and Levine, 2004; Hall and Le Veen, 1978), the findings imply that large sized farms exhibit higher efficiency scores. It should also be stressed that, the organic farms are more efficient than their conventional counterparts (relative to their best production frontier). The reasons which lead to higher efficiency scores in organic farms are described as the low profit margins that organic farms face and the restrictions on the permitted inputs result in the farmers' increased cautiousness in input use.

In the same way, Latruffe et al. (2004) analyse the technical efficiency of crop and livestock farms in Poland. The objective of this study is to measure the efficiency scores as well as to examine the drivers behind them. For this purpose, both Data Envelopment Analysis and Battase- Coelli error specification stochastic frontier model are employed. Annual survey of individual farms' data containing the capital, land, labour and variable inputs and total output of crop and livestock farms in 2000 is utilized to specify the stochastic production frontier. Furthermore, the additional variables related to the share of hired labour, the degree of market integration, soil quality index, farmers' age and education level are also included in the model as the determining factors of inefficiency. The impacts of education and market integration on technical efficiency are found to be significantly critical in the sense that low degree of education undoubtedly impedes the entrance of new technologies and unfortunately results in the impossibility of improvement in technical efficiency. Additionally, a positive relationship between the farm size and efficiency is obtained according to the results generated by both methods.

In order to extend the range of the use of exogenous variables in efficiency measurement, another example of stochastic production frontier utilization regarding the technical efficiency in post-collective Chinese agriculture, conducted by Liu and Zhuang (2000) can be given. Indeed, the motivation of this study is based on the factors that determine the efficiency of Chinese agriculture certainly deserve a deeper analysis since it serves for almost one quarter of the world population with a quite small arable land, by nearly 7%. The components such as farm size, access to credit, nutrition intake, education and farming experience constituting the stochastic part of the production frontier, known as inefficiency term, are investigated in terms of the impacts on technical efficiency. The data including capital, fertilizer, labour, land inputs and agricultural output is divided into two provincial samples. While one of these is chosen from central, the other one is selected from eastern representing more and less developed regions, respectively. In order to link these components translog function is employed and then estimated with maximum likelihood method. The findings support that the effects of stochastic term on efficiency in the less developed region are markedly higher than those in the more developed one.

A slightly different application of stochastic production frontier is applied by Bakusheva et al. (2012) to examine the technical efficiency of Russian agriculture. The panel data comprises of the 59 Russian regions from 1991 to 2008 with the inputs of capital, labour, land and variable inputs and agricultural gross output. It is worth noting that, the difference of stochastic production frontier is indeed arises from technical property regarding regional heterogeneity and endogeneity as well. This feature inserted in technical inefficiency term allows to see the impacts of panel data. Following these theoretical contributions, the methodology developed by Kumbhakar (2000) is employed to specify the heterogeneity in the inefficiency term and GMM (Generalized Method of Moments) is applied to obtain consistent estimates in the presence of endogeneity. According to the estimation results, the difference of efficiency within the region is greater than the one shown across the regions. The findings also support that both improvement of terms of trade and socio economic level have essential influences on efficiency.

Likewise, heterogeneity is examined with an elaborate study by Cechura (2010) with a focus on Czech agriculture. The panel data including the labour, land, capital and materials and output given by total sales of goods of 1004 agricultural firms over the period from 2004 to 2007 is applied. This sample, basically representing the Czech agriculture, is estimated with Random Effect Model, Truncated Battese-Coelli Model, True Fixed Effect Model, True Random Effect Model, Random Parameters Model and Fixed Management Model. These methods are employed to illustrate the framework where varying theoretical features could be compared. The results have strong implications that Random parameter model haS a considerable superiority over the other models due to a significant presence of firm heterogeneity. It should be noted that, the results generated by Truncated Battese Cooelli Model, allowing technical efficiency to change over time, produce higher efficiency scores than the other models; however, it would not be an appropriate method since it fails to generate unbiased estimates.

Another study concerning the Russian agriculture is conducted by Sotnikov (1998) with the objective of explaining the effects of price and trade liberalization on technical efficiency. The panel data including 75 regions from 1990 to 1995 with the inputs of land, labour, mineral fertilizer and total horsepower is employed to stochastic production frontier specified by a Cobb Douglas function. The indications of the results are apparently in favour of the support of considering exogenous variables related to liberalization. It is notably underlined that the improvement of efficiency by means of only contracting the inputs is not likely result in full achievement.

In a similar way, Balcombe et al. (2006) study technical efficiency of Australian dairy farms with an attempt of comparing the stochastic frontier analysis and data envelopment analysis. The translog production function with the output of total milk and inputs of number of cows, area irrigated and expenditure on fertilizer and supplementary feed as well. The findings indicate that the choice of the estimation may probably matter in terms of the estimation results.

Miljkovic et al. (2013) examine the impact of trade openness on efficiency regarding the Brazilian agriculture. The panel data comprising the capital, land, labour and agricultural output variables of 27 Brazilian states for each 5 year period from 1990 to 2005 is employed. Stochastic frontier is applied in the form of Cobb Douglas function with an inefficiency term allowing an accomadation for trade openness. Trade openness is calculated dividing agricultural imports plus agricultural exports by agricultural GDP and it is conluded that it has no significant impact on efficiency consistent with Shaik and Miljkovic (2011).

Adhikari and Bjørndal (2012) attempt stochastic deterministic frontier and data envelopment analysis with the intention of technical efficiency analysis of Nepalese agriculture. The increasing demand for food accompanied by the limited lands inevitably raises the concerns about poverty. The motivation behind this study is expressed with the aim of examining the drivers which may ease poverty alleviation.

Lassachl et al. (2004) identify the forces that drive the technical efficiency in Tunisian agro food industry by employing panel data including forty six agro food firms for over a fourteen year period. In order to identify the impacts of firm characteristics on technical efficiency, stochastic production frontier proposed by Battese and Coelli (1995) is utilized. Firstly, the specified translog production function is implemented; secondly, the inefficiency term is again regressed with respect to the explanatory variables constituting firm characteristics such as firm size, age of capital stock, share of skilled labour. The findings suggest that the size of the firm, the share of skilled labour and the age of the capital stock have considerable impact on the technical efficiency. Furthermore, it can be derived from empirical results that the age of capital stock negatively affects the technical efficiency; however, the size of the firm and share of skilled labour affect it positively.

In another example, Ahmad and Bravo Ureta (1996) utilize unbalanced panel data including ninety six Vermont dairy farmers from 1971 to 1984 for technical efficiency measurement. They employ both fixed effect and stochastic frontier models trying to find out the more efficient one of the two. To this end, the issues concerning the firm effects, functional form, type of the distribution of error term, time variant versus time invariant technical efficiency and other regressors in terms of the application of fixed effect or stochastic frontier are investigated.

The results have significant implications for the existence of firm effects as well as the correlation between efficiency and regressors allowing the use of fixed effect method. Moreover, the reason that lies behind the variation of technical efficiency is attributed to the type of one sided error term. It is stated that technical efficiency yielded by half normal one sided error term models were recorded higher than the ones which are produced by truncated normal one sided error models.

If we now turn to our main focus of efficiency in US agriculture, it is readily apparent that a considerable amount of the literature has been devoted to this issue. Since agricultural sector has been developed in the accompaniment of higher productivity scores for almost half a century, the investigation of the efficiency, namely producing maximum output with a given level of input has gained a justifiable attention. The early attempts of the literature related to US agriculture basically rely on the main concepts of agricultural production. In other words, the type of the production function, the fitness of the data to the model employed, the assumptions related to the error term are the components of the application which deserve much more interest.

Actually, this attempt dates back to Griliches (1963; 1964) who examines the efficiency, productivity and various functional forms of production of agricultural sector in the US. Particularly the specification of functional forms is investigated with the main questions providing the type of the production frontier. To do this, Cobb Douglas production function is employed with the cross sectional data including the agricultural regions in US. Different from the other studies which usually use farm related components (such as capital, land, labour, feed, seed etc.) educational level is added as an explanatory variable to the production function. The results indicate that the education level is statistically significant to account for the agricultural output.

In an attempt to measure the efficiency of the US agriculture, Timmer (1971) provides an interesting analysis. The study is actually based on the examination and the comparison of the methods supporting the assumption that there is no correlation between technical efficiency and production factors. Firstly, Cobb Douglas function is employed to the panel data including 48 states from 1960 to 1967. This is done by the assumption of no correlation between the efficiency and production factors. Secondly, AC (Analysis of Covariance)[17] method is studied in contrast with the assumption mentioned beforehand. This method enables the consideration of not only the interaction between efficiency and production components but also the addition of individual intercepts for each state; since it reflects the effect of panel data by means of consideration of the impacts of states individually. Lastly, linear programming model is applied which is based on the basic econometric model and the constraint related to the minimization of the error term. The results generated by each method imply that they have significant differences. It should also be underlined that, the efficiency scores yielded by the linear programming method are by far the highest.

Lohr and Park (2006) investigate the technical efficiency of US organic farms with the consideration of regional effects. To do this, translog production function is applied to specify the stochastic production frontier with the output of total gross organic farm income and the inputs of labour, organic acreage as well as the organic soil improvement materials. In order to account for the stochastic frontier component of production function, the dummies related to the region and the farm experience are added to the model. The findings have strong implications that farm experience has a considerable influence on the technical efficiency as the more experienced the farmers are, the higher the efficiency scores become.

Similarly, Mayen et al. (2010) adopt the stochastic production frontier for the comparison of conventional and organic dairy farms in US agriculture. The objective of the study is both to compare the efficiency and to examine the drivers of efficiency related to both operator and farm characteristics. These factors can be divided into two groups which bear these characteristics and include: education, age, experience and average weight of milking cows, region, and percent of land

[17]In most economic research, regression models contain the quantiative and qualitative variables as well. These type of regression models admixture of qualitative and quantiative variables are called analysis of covariance (ANCOVA) models., Gujarati D.,Basic Econometrics, 2004.

rented, respectively. It should also be highlighted that, what makes this method different is primarily the utilization of separate technology specifications for both conventional and organic farms. Employing the homogenous production technology to neither type of the farms definitely provides an understandable framework for efficiency estimates.

While these studies regarding the efficiency of US farms only apply stochastic production frontier, Murova and Chidmi's work (2013) employs both data envelopment analysis and stochastic production frontier to investigate the technical efficiency of US dairy farms. Data is expressed in 2005 US dollars for 17[18] states in the survey including the inputs of labour, land, feed and the output total value of milk production. To decide whether the Cobb Douglas or translog specification is appropriate for the parametric structure of the stochastic frontier, likelihood ratio test[19] is applied and Cobb Douglas is found to be the most suitable parametric functional form. Additionally, utilization of stochastic production frontier enables the reflection of not only the effects of farm technical characteristics including average age of cows, mortality percentage and the system that the number of hours that milking system was in use but also the dummy variables related to the geographical properties and the participation of federal milk programmes. The findings suggest that average technical efficiency results produced by stochastic frontier is lower than the ones yielded by data envelopment analysis. Another striking result that should be addressed is the ranking of the regions with respect to the efficiency measurement which varies based on the method used.

In order to add some aspects of the impact of trade openness to technical effi-

[18]Arizona, California, Florida, Georgia, Illinois, Indiana, Iowa, Kentucky, Michigan, Minnesota, New Mexico, Ohio, Tennessee, Texas, Vermont, Washington, Wisconsin.

[19] Likelihood ratio test is based on the difference in the log likelihood for the restricted and unrestricted models., Wooldridge J., Introductory Econometrics, 2009.

ciency measurement, the study is conducted by Miljkovic and Shaik (2010). They apply a stochastic frontier analysis to investigate whether it has a considerable effect on the efficiency of US agriculture. Hicks neutral production function employing labour, capital, farm origins, energy, chemicals and services inputs for the production of aggregate output is applied. After the estimation, the trade openness is calculated by dividing the sum of the agricultural exports and imports by agricultural GDP. The results of the estimation method imply that trade openness has no impact on efficiency when it is imposed in the form defined above. Interestingly, trade openness can affect the efficiency if it is decomposed into the two components: the ratio of the agricultural exports to the agricultural gdp and the ratio of the agricultural imports to the agricultural GDP. The relation between the latter and the efficiency is explained owing to Krugman's protectionism view which basically states that the decrease in the ratio of argricultural import to agricultural GDP imply higher efficiency.

O'Donnell (1999) investigates the technical efficieny of US agriculture with the data comprising 1632 observations obtained from 48 states for the years from 1960 to 1993 for the inputs of capital, labour, materials and the output of livestock, dairy, poultry, eggs, grains, oilseeds, cotton, tobacco, fruit, vegetables, nuts, and other miscellaneous outputs. Practically, the estimation of the efficiency scores is strongly relevant to the residuals of input demand functions derived from the the translog function. The efficiency results are presented in terms of ten regions since they are estimated with additional variables representing the effects of the regions. While the states in the Mountain experience the highest efficiency, the states in the Southeast exhibit the lowest scores according to the results.

It is also notewothy that, there are few studies employing a non–parametric method Data Envelopment Analysis for the efficiency of US agriculture, while there have been numerous studies regarding the parametric one. One of these very few studies by Schimmelpfennig et al. (2006) firstly put a considerable emphasis on the studies originated from social sciences. It is undermined that there is a common view supporting the social sciences failure to account for the factors which are difficult to quantify. In order to overcome these difficulties, several methods are developed with the ability of expressing the relation between the enviromental factors and the efficiency. Having overviewed of these methods, the outputs of livestock, crop and the inputs of capital, labour, land and materials for 48 states from 1960 to 1996 are employed for the efficiency measurement through the Data Envelopment Analysis method. Indeed, the interesting feature of this study is treating the efficiency at any time as a linear combination of the lagged variables including extension, research and developoment as well as management and marketing research. Since it takes a long time to see the effects of the each item on the efficiency, consideration of the lagged values of the items related to research and development is consistent with the idea.

Zaeske (2012) conducts the study with the primary aim of investigating the utilization of water in the US agriculture. Having employed the translog production function with cropland, labour, intermediates, total water inputs and aggregate output at the state level in a stochastic frontier also allows the estimation of technical efficiency. The Battese Coelli two stage error specification is utilized and the findings indicate that the farm characteristics including the owner type and farm size have a positive impact on technical efficiency.

The efficiency measurement with the consideration of random variables has been popular since it was firstly initiated by Aigner et al. (1977). Since there is a lack of consensus on which method produces the most robust results, there have been many attempts regarding a variety of both methodological and theoretical dimensions. The studies considered in this literature review can be seen as evidence that the methods based on distinctive methodological structures may yield different results. Although most of the literature on the efficiency measure of agricultural sector devoted to stochastic production frontier, some authors focus on deterministic frontier due to its ease of calculation and the structure enables to calculate multi input and output case as well. Within this motivation, the rest of this chapter addresses the methodology concerning the eight methods in parametric, semi–parametric and non–parametric forms.

4.3 Methodology

The structure of the methodology is based on the criterions which classify the efficiency measurement. The techniques for efficiency measurement in the literature are usually analysed depending on the criterions follows: First, what type of frontier function is used; second, whether the statistical noise is included or not in the model and lastly which type of data, that is cross sectional or panel data is utilized. In order to specify technical efficiency the following simple specification can be considered:

$$lny_i = x_i\beta - u_i \tag{4.1}$$

where $i = 1, ..., N$ represents the observations and $x_i's$ are in logarithms. In the equation u_i refers to the non negative random variable so the following equality can be inferred from the equation such that $lny_i \leq x_i\beta$.
Following this idea we can conclude that technical efficiency can be formulated by considering the ratio of actual output to optimum one as follows:

$$TE = \frac{y_i}{e^{x_i\beta}} = \frac{e^{x_i\beta - u_i}}{e^{x_i\beta}} = e^{-u_i} \tag{4.2}$$

Now it is the right time to highlight the difference between deterministic and stochastic frontier to provide an understandable explanation for technical efficiency formula.
Production frontiers can be classified as:

- Ordinary Least Squares:

$$q_i = \beta_0 + \beta_1 x_i + v_i \tag{4.3}$$

where v_i represents symmetric error term which has normal distribution. OLS (Ordinary Least Squares) method fits the production frontier through the centre of data.

- Deterministic:

$$q_i = \beta_0 + \beta_1 x_i - u_i \tag{4.4}$$

where u_i refers non negative inefficiency error term which has half normal distribution. Deterministic aproach fits the production frontier over the data.

- Stochastic:

$$q_i = \beta_0 + \beta_1 x_i + v_i - u_i \tag{4.5}$$

where v_i is noise term which is a normally distributed, u_i is a non negative inefficiency term which has a half normal distribution. Stochastic approach, however, fits production frontier somewhere between the frontiers imposed by OLS and deterministic frontier.

4.3.1 Efficiency Estimators in Parametric Model

4.3.2 Time Invariant Methods

Fixed Effect Method

Assume the relation between the inputs and outputs is given as:

$$lny_{it} = \beta_0 + \sum \beta_n lnx_{nit} + v_{it} - u_i \tag{4.6}$$

where v_{it} represents symmetric error term and u_i refers to technical efficiency. The parameters in the equation can be estimated by fixed, random and maximum likelihood methods.

In the fixed effect method each u_i can be assumed as firm specific and they can be written as a combination with the constant terms as following:

$$lny_{it} = \beta_{0i} + \sum \beta_n lnx_{nit} + v_{it} \tag{4.7}$$

Random Effect Method

The randomness can be imposed to the equation by subtracting the expected value of statistical noise from both constant term and statistical noise such that:

$$\begin{aligned} lny_{it} =& (\beta_0 - E(u_i)) + \sum \beta_n lnx_{nit} + v_{it} - (u_{it} - E(u_i)) \\ =& (\beta_0)^* + \sum \beta_n lnx_{nit} + v_{it} + (u_i)^* \end{aligned} \tag{4.8}$$

where v_{it} represents symmetric error term, u_i refers to technical efficiency and $E(u_i)$ denotes expected value of technical efficiency.

Hausman Taylor Method

Hausman Taylor is a method which is developed with the aim of the treatment of the correlation between the individual effects and explanatory variables. If we consider the model below:

$$y_{it} = \beta x_{it} + Z_i\Gamma + \alpha_i + \mu_{it} \qquad where \qquad i = 1, ..., N, t = 1, ..., T \tag{4.9}$$

where βx_{it} refers a vector of time variant variables, $Z_i\Gamma$ denotes a vector of time invariant variables, α_i is unit effect and μ_{it} represents normal distributed error term.

KSS Estimators

Following Kumbhakar (1990), Cornwell, Schmidt and Sickles (1990) and Battase and Coelli (1992); Kneip (1994) suggest an alternative method called KSS (Kneip, Sickles and Simar) which alllows heterogeneity in the model:

$$y_{it} = (x_{it})^{'}\beta + \alpha_i + \epsilon_{it} \tag{4.10}$$

As a first step the estimator estimates the parameters of β and in the second step the composite error term ϵ_{it} is decomposed to $\epsilon_{it} = \alpha_{it} + v_{it}$ where α_{it} can represented as:

$$\alpha_{it} = c_{i1}g_{1t} + c_{i2}g_{2t} + ... + c_{ik}g_{kt} \tag{4.11}$$

where c_{ik} 's are the unknown parameters and g_{kt} 's are the smooth basis functions. It should be noted that the parameterr k refers to the dimension of the model.

4.3.3 Time Variant Methods

Time Varying Effects Models (Cornwell, Schmidt and Sickles (1990))

$$lny_{it} = \beta_{0t} + \sum \beta_n lnx_{nit} + v_{it} - u_{it} = \beta_{it} + \sum \beta_n lnx_{nit} + v_{it} \tag{4.12}$$

By considering general panel estimation there are $I \times T$ constant terms. $I \times T$ terms are greater than the number of observations β_{it} is assumed to be a quadratic function of the time and is represented as follows:

$$\beta_{it} = \Omega_{i1} + \Omega_{i2}t + \Omega_{it}t^2 \tag{4.13}$$

where Ω_{ij} shows the relation between efficiency and time and $v \sim N(0, {\Theta_v}^2)$ and $u \sim N(0, {\Theta_u}^2)$. Frontier is deterministic since it is given by $e^{(x_i(\beta))}$ which is non random.

Time Varying Effects with Convergence (Battase and Coelli (1992))

Battase and Coelli (1992) explore the technical eficiency as a function of the time in the exponential form. The panel structure is modified as follows:

$$u_{it} = u_i\beta_t = \beta_t = exp[\mu(t - T)] \tag{4.14}$$

It should be noted that the variations of the firm effects depend on the parameter μ. The effects are constant, increasing or decreasing as t increases, if $\mu = 0$, $\mu > 0$ and $\mu < 0$ respectively.

4.3.4 Efficiency Estimators in Semiparametric Model

PSS Estimators

In the context of panel data, stochactic models (Cornweell, Scmidt and Sickles 1990; Schmidt and Sickles 1984) have semi–parametric generalizations whose some part is parametric while the rest is non–parametric. Park, Sickles and Simar (2003), Park and Simar (1994) and Park, Sickles and Simar (1998) devote the improvement of this methodology with the name of PSS method. Since the theory of PSS method is too technical it is not reviewed here. We only underline the general framework of semi–parametric method by imposing the following equation offered by Engle et al. (1986):

$$y_{it} = (x_{it})^{'}\beta_0 + g_0(v_{it}) + \epsilon_{it} \tag{4.15}$$

where (x_{it}) and v_{it} are vectors of exogenous variables and $g_0(v)$ is an unknown function.

4.3.5 Efficiency Estimators in Non–parametric Model

Data Envelopment Analysis

As mentioned above the technology level for production is determined by either parametric or non–parametric methods. The non–parametric representation of technology is based on the linear programming problems which impose minimal constraints on the technology and does not require any functional specification. The constraints are the piecewise linearity and convexity of the technology which are provided by weight components. If we define the input requirement set $L(y)$ as a set of input vectors which can produce output vectors, input oriented distance function representing technology through the contraction of an input can be shown as follows:

$$D(y,x) = max\Theta : (\frac{x}{\Theta}) \in L(y) \quad (4.16)$$

where $\Theta \geq 1$. In the light of this definition input based technical efficiency can be defined as follows:

$$TE(y,x) = min\Theta : \Theta x \in L(y) \quad (4.17)$$

The relation between technical efficiency and distance function can be given as: $TE(y,x) = \frac{1}{D(y,x)}$. The output oriented distance functions can be derived in a similar way with the consideration of output expanded technology. These distance functions are ususally calculated by the most known non–parametric method: Data Envelopment Analysis (DEA). The input oriented DEA linear program can be illustrated as follows:

$$\begin{aligned} D_{it}(y_{it,x_{it}}) &= min\Theta \\ subjectto &: \\ -y_{it} + Y\Lambda &\geq 0 \\ \Theta x_{it} - X\Lambda &\geq 0 \\ \Lambda &\geq 0 \end{aligned} \quad (4.18)$$

where Θ is a scalar, Λ is $NT \times 1$ constant vectors and $i = 1, ..., N$, $t = 1, ..., T$. The efficiency score of i th firm in period t is Θ where $0 \leq \Theta \leq 1$. The upper bound 1 represents the full technical efficiency. The linear programming problems above are based on the solution of $N \times T$ problems. This is done by contracting input vectors of the firm x_i to the projected point $(X\Lambda, Y\Lambda)$, on the surface of piecewise linear isoquant of technology.

4.4 Data

The data comprising the quantities of capital, labor, energy, land, material, fertilizer, pesticide inputs and livestock, farm related and crops outputs are compiled for forty eight states (AL, AR, AZ, CA, CO, CT DE, FL, GA, IA, ID, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NV, NY, OH, OK OR, PA, RI, SC, SD, TN, TX, UT, VA, VT, WA, WI, WV,WY) of US from 1960 to 2004. The quantity data are expressed in terms of 1996 Alabama prices. Both the definition of the variables and how the data changes over the years are not expressed here since they are described in detail in Chapter 3.

4.5 Results

In this section, the methods whose theoretical background is given in the methodology section are employed to the US agriculture panel data in order to gather efficiency scores. MATLAB (2007) is utilized to calculate or estimate the efficiency scores. The results are presented with respect to the type of the frontier, whether it is deterministic or stochastic; as well as the specification of functional form as follows: parametric, semi–parametric and non–parametric. The figures below illustrate the efficiency scores obtained from each method. Following the figures, the results are described and some conclusions are drawn.

4.5.1 Results of Parametric, Semi–Parametric and Non–Parametric Methods

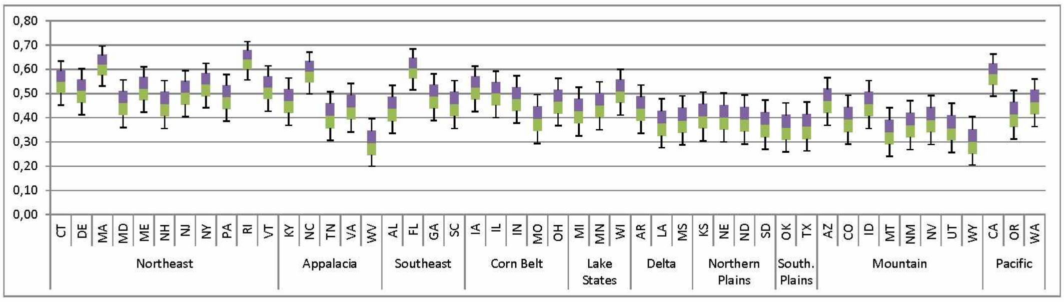

Figure 4.1: Results of BC Method

The results obtained from BC, represented in Fig 4.1,[20] illustrate that there was no state experiencing a fully efficient score for any year. Moreover, the average efficiency score was recorded nearly 0.44 units which can easily be guessed from the figure whose boxes are generally lie between the range from 0.3 units to 0.5 units. Additionally, it should be noted that the Rhode Island experincing the fully efficiency for most of the methods, failed to exhibit such a high trend in this method.

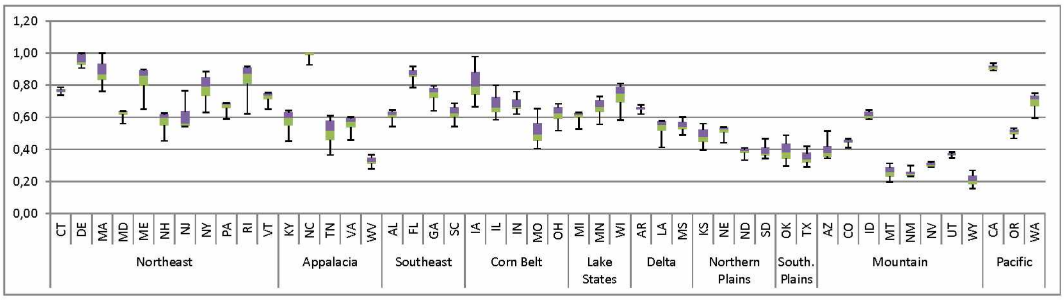

Figure 4.2: Results of CSSW Method

Turning now to the results of the CSSW method, which provides time variance efficiency scores, it should be noted that only the Delaware, Massachusetts

[20]The figures (Fig. 4.1, 4.2, 4.3 and 4.4) are derived by taking the mean of efficiency scores through 1960-2004. The box plots for each state represent the range varying from the minimum efficiency score to the maximum one.

and North Carolina exhibited a fully efficient scores for several years. It should be highlighted that, some states experienced the high efficiency scores with about above 0.85 units, however some of them did not experience such a high trend. Most notably among them is Wyoming experiencing the lowest average score with almost below 0.3 units.

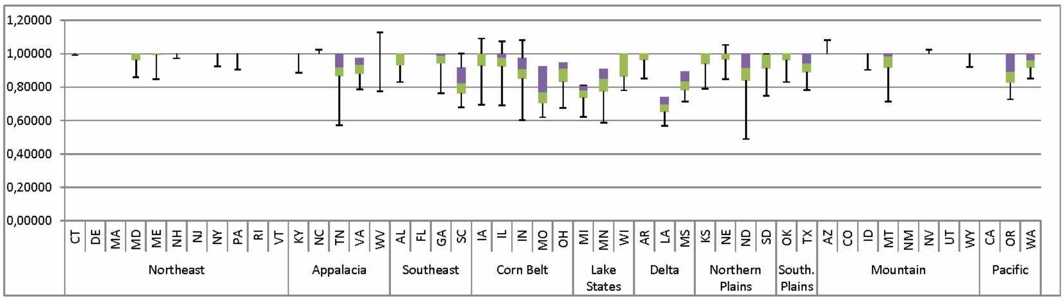

Figure 4.3: Results of DEA Method

The first thing to note about the results of DEA (Data Envelopment Analysis) method, shown in Fig. 4.3, is that almost one fourth of all states were fully efficient throughout the entire data period. While the average efficiency scores for the rest were considerably high, there were some substantial variations that should be addressed. For instance the efficiency score decreased by about 30% in Iowa between the years 1986 and 1993 and then increased again in the successive years eventually reached to the fully efficient level in 1998. The same scenario had been exhibited by Illionis in a decade from 1973 to 1983. Furthermore, a greater reduction was shown in the Indiana by nearly 40% from 1972 to 1989. It should be underlined that both Louisiana and Michigan never reached to the fully efficiency level over the entire period.

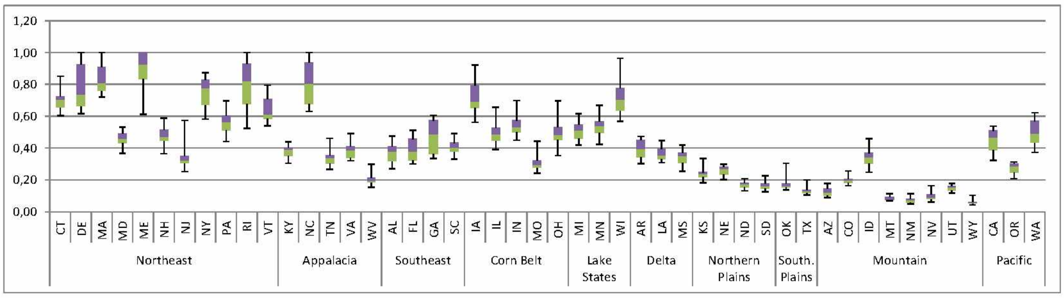

Figure 4.4: Results of KSS Method

KSS (Kneip, Sickles and Sierman) is a type of the semi–parametric method. This is the time variant model and also a mix of parametric and non–parametric methods which specify some of the variables with a functional form while the others do not. According to the results of this method, firstly it should be noted that there was no markedly increase or decrease in the successive years. The incremental difference was shown in almost all states from one year to the next. It is noticeable from the results that; except the Delaware, Massachusetts, Maine and Rhode Island, there was no other state which experienced full efficiency for several years. Moreover, the average efficiency scores of the Delaware and Massachusetts were the highest, while, the average efficiency scores of the Wyoming was the lowest with below 0.2 units. If we consider the average efficiency score of all states, it was about 0.34 units lower than the results derived by the parametric methods.

As shown in Fig.4.5,[21] time invariant method PSS (Park, Simar and Sickles) revealed that only the Rhode Island is fully efficient similar to the results of other time invariant methods. While the maximum efficiency score except the fully efficient state was experienced in the Massachusetts, the lowest one was recorded in the Mississipi. Similar to the average efficiency scores of time invariant parametric models, the average efficiency score was nearly 0.6 units in PSS method.

[21]The figures (Fig. 4.5, 4.6, 4.7 and 4.8) representing the results of time invariant methods compare the efficiency scores of the states relatively to each other.

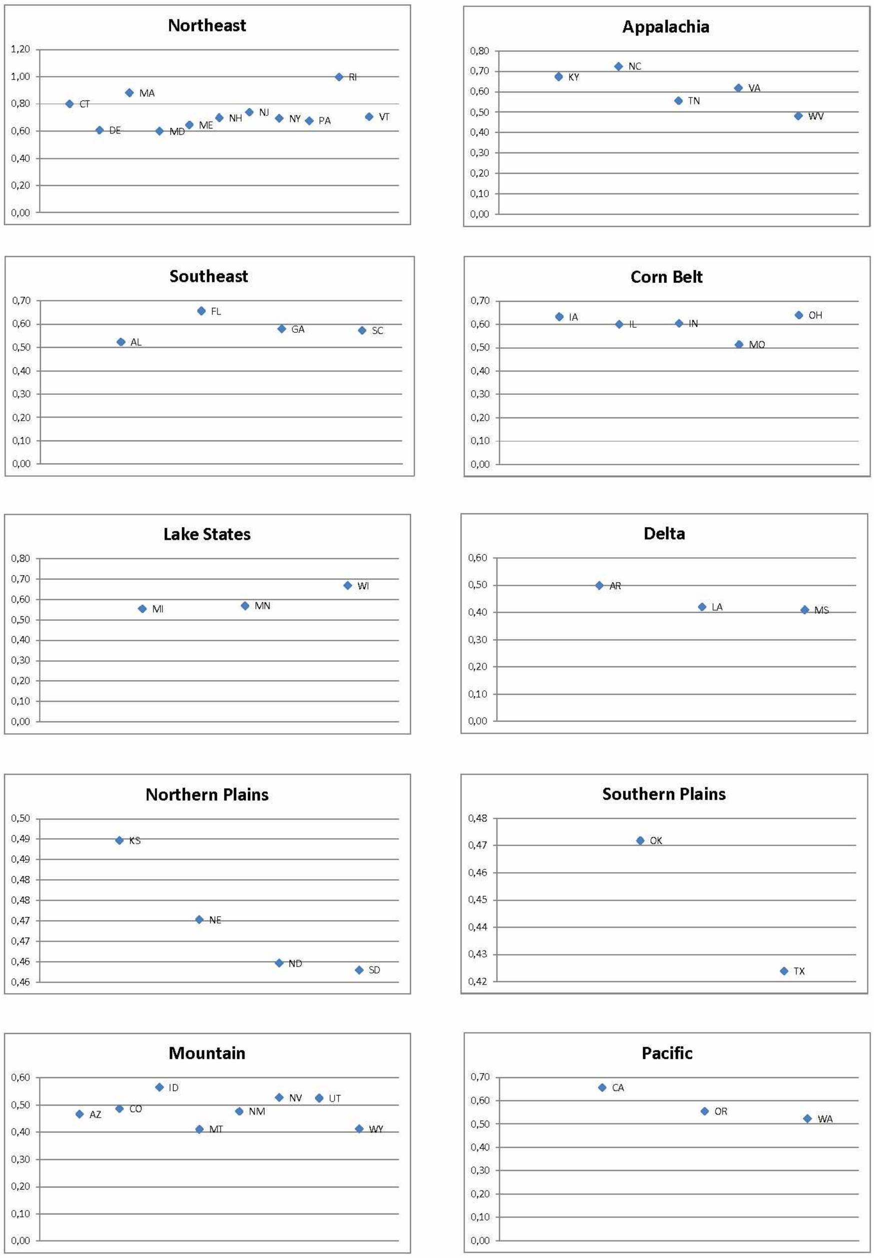

Figure 4.5: Results of PSS Method

As can be seen from the Fig 4.6, the results of fixed effect method show that the highest efficiency score except the fully efficient state was recorded with 0.88 units in the Massachusetts, however, the efficiency score of the Montana was recorded as the lowest with 0.39 units. The average efficiency scores for the rest varied in a range of approximately 0.4 to 0.8 unit. Moreover, it is noticeable that, there was no state except the Rhode Island that was fully efficient.

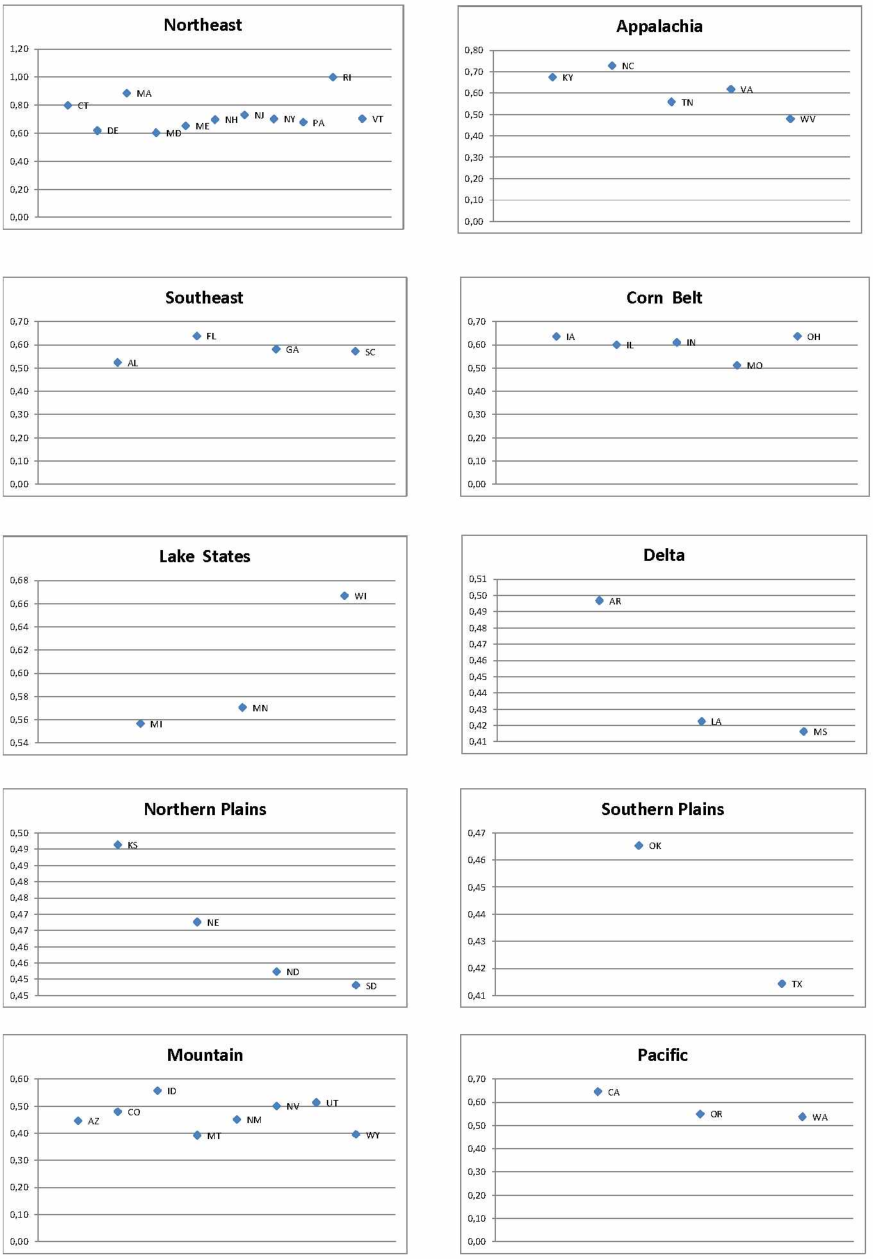

Figure 4.6: Results of Fixed Effects Method

The results of Random effects method, presented in Fig.4.7, revealed that the Rhode Island was fully efficient similar to the output of fixed effect method. Although both methods yield the same outcome for the fully efficient state, there are some differences for the efficiency scores of other states. However, this difference is not significant since it was not shown in the first digit in most of the cases. It should also be underlined that, the states which exhibited both the maximum and minimum efficiency scores are the same with the ones produced by fixed effect method.

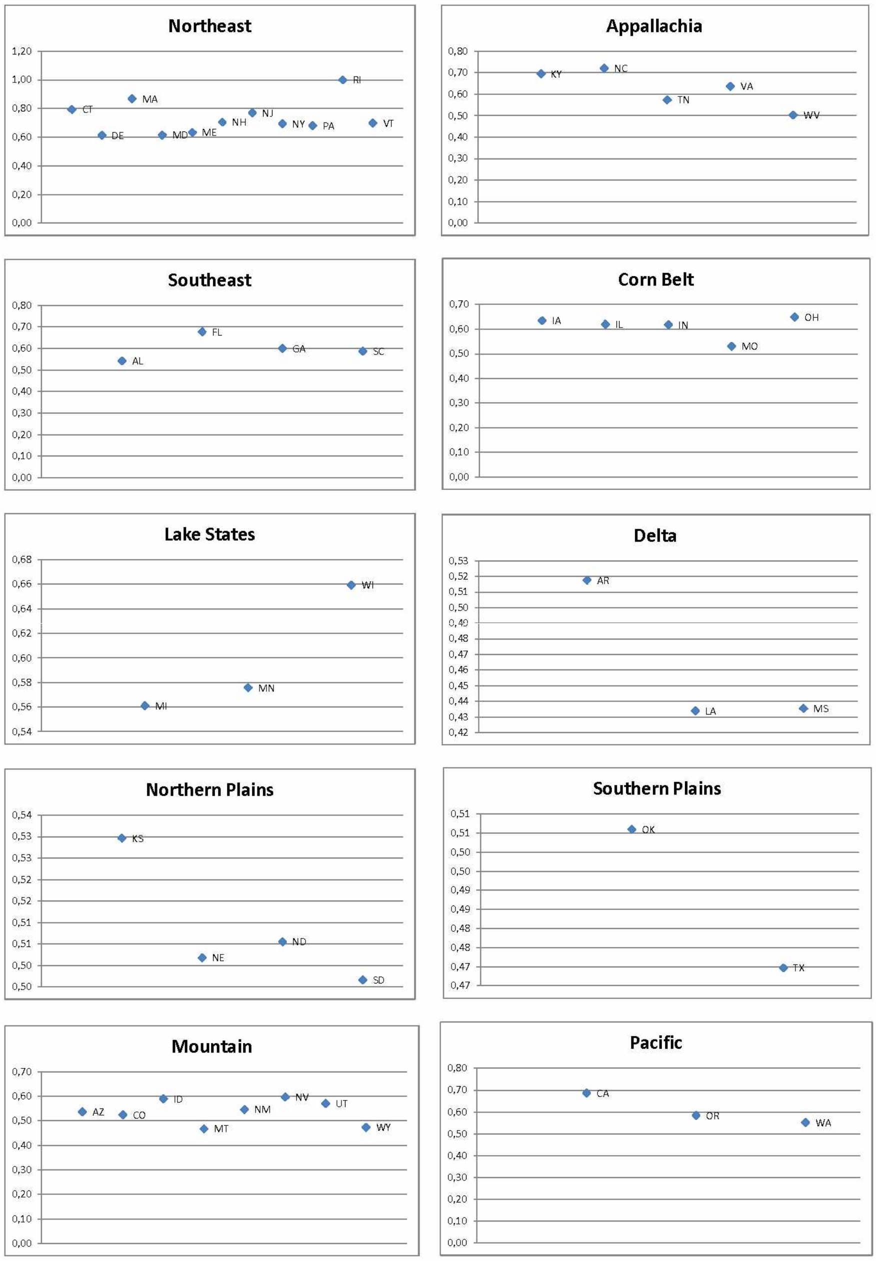

Figure 4.7: Results of Random Effects Method

Before the finishing of interpretation of time invariance methods, it should be addressed that, Hausman Taylor method yields the same results, shown in Fig4.8, for both the fully efficient state and the maximum and minimum values of efficiency scores.

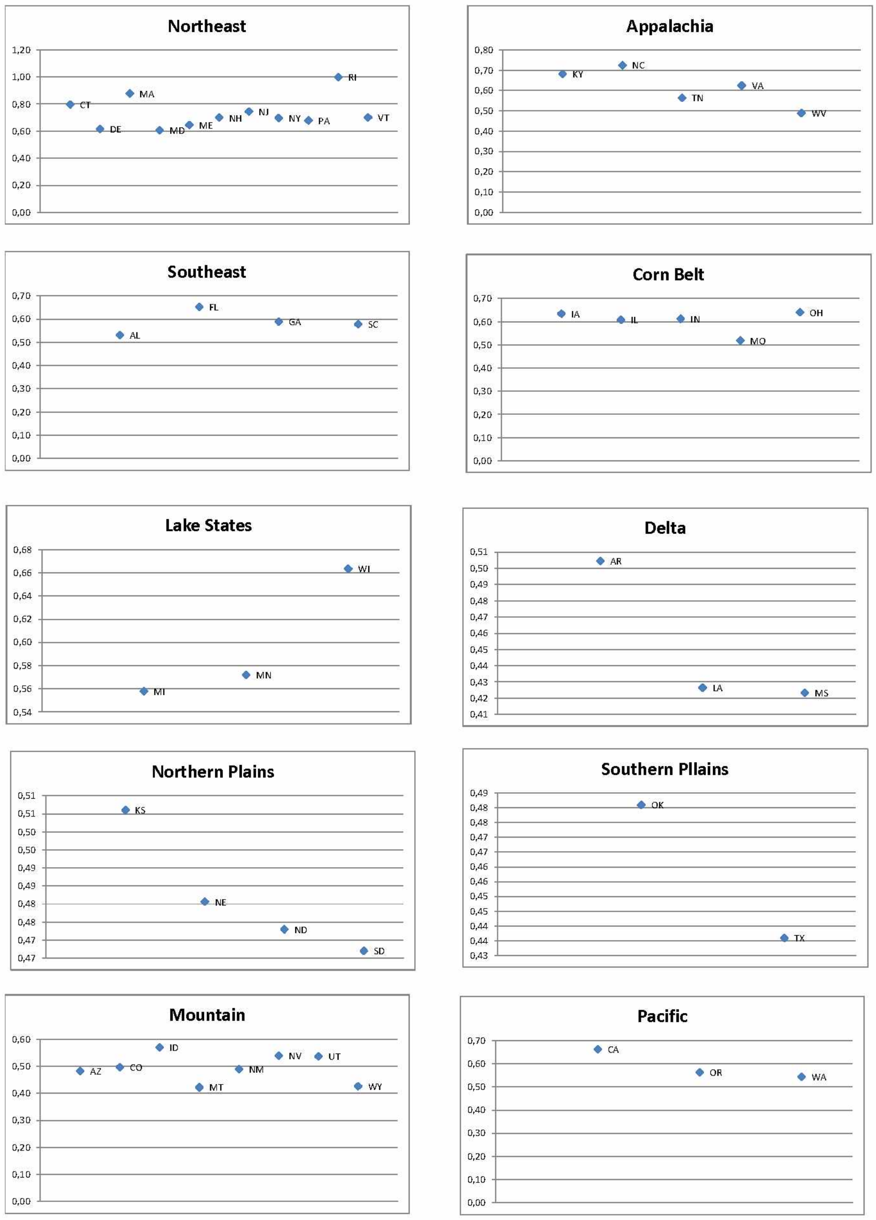

Figure 4.8: Results of Hausman Taylor Method

4.5.2 Comparison of the Methods

The most widely known methods including parametric, semi–parametric and non–parametric structure are applied to obtain efficiency scores of US agriculture over a period from 1960 to 2004. While some of these methods have no ability to calculate the time variant efficiency scores, some of them can yield different efficiency scores for each year and can take the effect of each unit into account as well. It is also noticeable that, the methods reveal several similarities but a greater number of differences in terms of the efficiency figure. The following explanations regarding both the similarites and differences are based on the classification applied in the methodology section. First, the parametric methods with time invariany and variant are compared and then the crucial points making the parametric, semi–parametric and non–parametric methods similar or different are discussed, respectively.

The efficiency scores obtained by the methods of fixed effect, random effect and Hausman Taylor, all time invariance methods, are similar in a number of ways. To begin with, the efficiency figures recorded by both fixed and random effects methods are almost generally similar. The difference among the efficiency figures is usually depicted in the second digit. Although the figures recorded by Hausman Taylor method is similar with the others, the level of similarity is not as striking as the ones experienced between the fixed and random effects method. It should also be highlighted that, Rhode Island is the state exhibiting a full efficiency over the whole period according to the results of all these methods. Apart from the methods mentioned above, another time invariance method PSS (Park, Simar and Sickles) is employed and the findings suggest that there are no considerable differences regarding the efficiency figures and should be underlined that this method also reveals Rhode Island as a fully efficient state.

If we consider the regions' performances in terms of efficiency scores the figure also provides a comparison between regions. One of the striking results illustrated in the Fig.4.6, Fig.4.7 and Fig.4.8 is that, Northeast had by far the highest average efficiency scores with about 0.7 units according to the results of Fixed Effect, Random Effect and Hausman Taylor method. While all these methods yield the same outcome for the maximum efficiency score, they fail to produce the same outcome for the minimum average efficiency score. It should be noted that, the lowest average efficiency score, nearly 0.45 units was recorded in Delta with respect to the results of Random Effect and Hausman Taylor method, however, it was recorded with 0.44 units in Southern Plains regarding the results of the Fixed Effect method.

Now turning to the time variant method of parametric models, it should be noted that, Wyoming had by far the lowest efficiency score according to the results of both BC (Battese&Coelli) and CSS (Cornwell, Schmidt and Sickles) with 0.29 and 0.20 units, respectively. Similar to the time invariant models, BC method shows that Rhode Island was a state experiencing the highest efficiency score with 0.64 units but not fully efficient. Different from all these methods mentioned above, CSS method proves that North Carolina was a state with about fully efficient score with 0.99 units over a whole period.

Additionally, Fig.4.1 and Fig.4.2 demonstrate the efficiency figures of BC and CSS, both of which are time variant parametric methods, in terms of efficiency figures with respect to the regions. It is noteworthy that, almost all regions saw less fluctuations according to the results of the BC method compared to the CSS method. Appalachia is the region experincing the highest fluctuation in a range varying from 0.20 to 0.67 units. As stated above, the results of the CSS method revealed more variations in regions than the ones of the BC method. On the contrary, Southern Plains, Northern Plains and Lake States exhibited a different pattern, in the sense that there were low variations in efficiency figures not able to create significant fluctuations.

By regarding the results of the non–parametric method DEA; it is easy to conclude that that the efficiency scores gathered by this method are by far the highest with an average efficiency of 0.82 units. As mentioned above, most of the states exhibit either a full or almost full efficiency for over all period. It basically implies that the distance of each state to the best frontier is not significantly considerable.

If we now turn to compare the results of the KSS method, it is clear that the average efficiency score was lower by 30% and 65% than the parametric methods of BC and CSS, respectively. While the minimum efficiency score was recorded in Wyoming with about 0.05 unit, the maximum average figure was recorded in Rhode Island with 1 unit similar to the fully efficient outputs of parametric time invariant methods and the states of Delaware, North Carolina, Massachusetts and Maine.

Turning to the regional comparison of KSS method's results, Fig.4.4 demonstrates that the highest fluctuation in efficiency scores was seen in the Northeast. It should also be noted that, there were some important fluctuations which were not as high as the ones of Northeast in the Corn Belt and Lake States. Contrarily, it is markedly apparent that Northern Plains, Southern Plains and Mountain did not experience considerable fluctuations compared to the other regions.

Although there have been a number of efficiency measurement methods which have recently been improved with the consideration of both statistical and theoretical dimensions, there is still a lack of agreement on the appropriate method. As it is obvious from the results, the efficiency scores obtained from each method can vary. We compare these methods in terms of both maximum and minimum efficiency scores which they yield. In addition to this, the methods are compared based on the average efficiency scores throughout the states, the years and the regions.

4.6 Conclusion

The developments on efficiency measurement have grown at a rapid pace since 1950s after the publication of Farrell's (1957) pioneering study. As a result of these improvements, there have been major advances both in parametric and non–parametric methods. These are broadly based on relaxing of assumptions belonging to parametric methods and overcoming the lack of non–parametric methods concerning the statistical properties as well. This chapter has given an account of the theoretical dimension of efficiency measurements and the improvements regarding different types of the main techniques which have been used in the literature. One of the main purposes of our chapter is to underline the critical points of the methods which may easily lead to confusion. In this sense, the theoretical dimension of this chapter provides an overview of the existing methods. By employing the US agriculture panel data; we apply parametric, semi–parametric and non–parametric approaches to obtain efficiency scores of forty eight states from 1960 to 2004.

In this research it is highlighted that these approaches' differences are mainly based on their treatment of the relation between the dependent and the independent variables in the model. While the non–parametric methods do not allow the representation of this relation in a specific functional form, the parametric methods specify the relation by imposing several functional forms. Via application of the semi–parametric methods, however, some terms are allowed to be parameterized while the others remain non–parameterized. Additionally, frontier approaches are reviewed with the implementation of deterministic and stochastic frontiers. The significance of the statistical noise depends on whether the frontier is deterministic or stochastic is also underlined. While the accommodation for statistical noise in the model refers to stochastic frontier and helps us to explain the randomness, the absence of it in the model represents a deterministic frontier. It is generally known that the stochastic frontiers can be estimated by both parametric and non–parametric approaches while the deterministic frontiers can only be calculated by non–parametric approaches.

The findings of this study make several contributions to the current literature. First, this study differs from the others with the implementation of panel data. Second, parametric, semi–parametric and non–parametric approaches are reviewed theoretically and applied in order to provide an empirical evidence. The efficiency scores that we have observed from these models therefore assist in our understanding of model constructions role and significance.

It should be noted that, the methods used for the efficiency measurement of US agriculture can be extended to the areas such as banking, education and hospitals which are mostly utilized in the context of efficiency measurement. There is no doubt that the utilization of panel data, particularly, is more likely to yield more detailed results depending on its ability concerning both time and individuals' dimension. This study will also serve as a base for future studies in the efficiency measurement context, in particular in agriculture. Since agricultural production does not develop only in the relation between inputs and outputs, the application of different approaches has gained the importance. These approaches help us to account for environmental conditions which are usually attributed to technical efficiency and may lead to over or underestimation of technical efficiency.

Chapter 5

Conclusion

Energy can be seen as the most important input for sustainable agriculture. In agriculture, non–renewable forms of energy are generally used. Due to the scarcity of non–renewable resources, energy utilization needs to be better analysed. Since there are no inputs which are full substitutes for energy, it is worth examining the inputs which may be substitutes for energy to some extent. Chapter 2 provides a unifying and comprehensive framework for input substitution possibilities. The findings of Chapter 2 derived by three flexible functional forms provide a robust check of substitution possibilities. Energy was found to be a substitute for labour to some extent which explains the transformation in US agriculture experienced over the past century.

The findings in Chapter 2 suggest that energy needs to be used more effectively. There are some commonly used indicators which are used to analyse these concerns and facilitate the tracking of changes in energy use over time. These indicators should be well understood and analysed to implement appropriate policies. Chapter 3 is devoted to the examination of existing indicators and suggest improvement to them as well. The findings of Chapter 3 have underlined the fact that energy was actually used more efficiently than thought and furthermore that more attention was paid to energy productivity than other inputs. At this point, we see that dominant energy policies are not as unsuccessful as they look.

Since the commonly used methodology disguises the real improvements in energy efficiency, it is difficult to decide which policy is more effective than others. The more accurate energy efficiency obtained in this study are likely to help enact more appropriate policies and thus contribute to energy efficiency improvements. The findings of Chapter 3 which reveal efficiency scores of all individual states through time provide deeper analysis of energy efficiency for all individual regions and states. The differences in efficiency scores between regions or states may lead to the taking into account of regional differences while implementing energy policies. Focusing on the energy policy targets of states or regions separately rather than on national targets may facilitate the reaching of energy productivity goals since some regions or states energy consumption is considerably higher than others.

Structural improvements spurred by technological developments brings to mind the question of how output level is affected by changes in inputs. Technical efficiency is generally used to answer this question. Chapter 4 examines this question through different methods. The findings strongly suggest that there is still some scope for improvement of the efficiency scores of most of the states. Future studies should focus on research which analyses the drivers of technical efficiency and whether these drivers differ from each other in different regions or states.

One direction for future research originating from this dissertation may be to extend the methodology for efficiency measurement while considering bad outputs. Calculation of energy indicators (intensity, efficiency and productivity) while taking into account the effects of bad outputs as well as good outputs will probably give insight to help understand the link between these indicators and environmental impacts.

Another direction for future studies could be the extension of the recent data. Since the data employed in this dissertation is only up to 2004, it is not able to show the trends which have been revealed in the last decade. Studies extending this dissertation could expand the time period to track recent changes in energy use.

Although recently particular attention has been paid to the adoption of renewable resources especially to mitigate energy dependence, the supply of renewable resources is still not adequate enough to meet the demand. In light of this, the use of renewable energy resources more effectively is of great importance and this study contributes to the literature by filling the gaps about effective use of indicators of non–renewable energy use.

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