Green Energy and Technology

Nabaz T. Khayyat

Energy Demand in Industry

What Factors Are Important?

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Nabaz T. Khayyat, Ph.D.
Technology Management, Economics,
and Policy Program,
College of Engineering
Seoul National University
Seoul
South Korea

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Preface

This empirical study applies the production risk approach to benchmark energy demand in the South Korean industrial sector. It is an updated and improved version of my first Ph.D. licentiate thesis, which was prepared at Swiss Management University in 2013. This improved version considers the latest data in the productivity account.

South Korea is one of our times' most successful newly industrialized economies. It serves as an important model of industrial development under the condition of lack of natural resources but human capital-driven development. Many developing countries see South Korea as a model for their development efforts. Hence, this book is an important addition to the existing literature on industrial development. In addition, it deals with energy which is one of the most important production inputs.

South Korea has enjoyed a rapid economic growth and development for the last 30 years. A rapid increase in energy use, especially petroleum, natural gas, and electricity, and particularly in the industrial sector has fueled South Korea's economic growth, but with limited fossil fuel resources of its own, South Korea became entirely dependent on energy imports.

This study investigates the effects of different inputs factors of production on the mean output and output variability. In addition, the study estimates returns from different inputs used in the production. Estimation of the returns from different inputs is achieved by determination of marginal value products and the total value products. As mentioned, South Korea is heavily dependent on energy imports, therefore, special attention is given in this study to energy use in industrial production to assess its variability and assess different factors that affect this variability in the production process. Producers are portfolio managers in the sense that they use inputs to balance expected economic return and variance of return. Understanding the determinants of technology adoption has long been a subject of interest among researchers. The existing literature has mainly concentrated on socio-economic factors with little insight into the risk nature of these technologies and inputs that impose upon their use by the producers. This book estimates the structure of the stochastic production technology in the South Korean industrial sector, allowing for a more flexible specification of the technology than previous studies.

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Finally, I beg the understanding of all those I have not mentioned in this short acknowledgment. To everyone who assisted me in this study in whatever way, I am indeed indescribably grateful.

May the Almighty God bless you all abundantly.

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Chapter 1
Overview

This book addresses the impact of different input factors of production, market, consumer, and producers' characteristics on the industrial sector's energy demand for South Korea during the period 1970–2007. The book aims at formulating an energy demand structure for the South Korean industrial sector as a tool to enable producers and policy makers to evaluate different alternatives toward reducing energy consumption, and using energy in an efficient way. Industrial policy decision makers need to understand the importance of the energy input in the industrial production structure, in order to assess and formulate necessary measures for energy conservation. Hence, it is required to acquire knowledge about the energy demand and its characteristics such as possible substitutability between energy as an input with the other input factors of production, and to develop a better relationship between various input factors of production and energy demand. Since some energy types such as electricity and natural gas cannot be stored, this will help to identify optimal investment in these input factors of production and for better optimization of energy consumption.

1.1 Introduction

The overall energy consumption worldwide is continuously increasing. According to the International Energy Outlook report published in 2011 by the US Energy Information Administration (EIA), the energy consumption will increase worldwide by 53 % in 2035. The total energy consumption in year 2008 was about 505 quadrillion Btu (British thermal unit). It is expected to reach 770 Btu by the year 2035 (EIA 2011). This steady increase of energy consumption will negatively affect the environment and the availability of depletable energy sources of fuel, or primary energy needed to produce energy output such as electricity.

The estimated world energy consumption by region for the period 2008–2035 is shown in Table 1.1 (The 2008 numbers are actual energy demand). This noticeable increase in energy consumption is due to the rapid economic development, industrialization, and population growth, especially in developing countries such as China and India with vast population size.

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Table 1.1 World estimated energy consumption 2008–2035 (in Quadrillion Btu)

Region	2008	2015	2020	2025	2030	2035	Average annual percentage change 2008–2035
OECD	**244.3**	**250.4**	**260.6**	**269.8**	**278.7**	**288.2**	**0.6**
Americas	122.9	126.1	131.0	135.9	141.6	147.7	0.7
Europe	82.2	83.6	86.9	89.7	91.8	93.8	0.5
Asia	39.2	40.7	42.7	44.2	45.4	46.7	0.6
Non-OECD	**260.5**	**323.1**	**358.9**	**401.7**	**442.8**	**481.6**	**2.3**
Europe and Eurasia	50.5	51.4	52.3	54.0	56.0	58.4	0.5
Asia	137.9	188.1	215.0	246.4	274.3	298.8	2.9
Middle East	25.6	31.0	33.9	37.3	41.3	45.3	2.1
Africa	18.8	21.5	23.6	25.9	28.5	31.4	1.9
Central and South America	27.7	31.0	34.2	38.0	42.6	47.8	2.0

Source EIA (2011)

Strong economic development leads to increase in the industrial sector's demand for energy. The industrial sector consumes at least 37 % of the total energy supply, which is relatively more energy intensive than any other major sectors including household, agriculture, and public services (Abdelaziz et al. 2011; Friedemann et al. 2010). A recent study conducted by the US Environmental Protection Agency (EPA) in 2007 revealed that 30 % of the energy consumed by the industrial and commercial premises is wasted due to inefficient way of using, and lack of risk management tools (Environmental Protection Agency EPA 2007).

Energy use efficiency is an important issue, due to limits in replacing energy as an input factor by other possible substitutable factors in the production process. Efficient use of energy may reduce the amount of fuel or primary energy needed to produce energy output such as electricity. Efficient use of energy will reduce the energy intensity, which may leads to reduction in the corresponding global emissions of air pollution and greenhouse gases (EIA 2011). A key variable of interest in a study of efficiency and productivity in the industrial sector is the energy demand. It can be considered as a significant variable in the cost structure of any industry, and an essential determinant of the level of energy demand (Allan et al. 2007; Mukherjee 2008). This book is concerned with determining the following measures:

1. The overall energy demand at the industrial sector.
2. The rate of technical change that causes shifts in the energy demand over time.
3. The variance of energy demand and its determinants.
4. The efficiency in the use of energy, given production output and industrial sector's characteristics of South Korea.

The productivity with a single factor, such as labor or capital productivity has the advantage of simplicity. However, such measure ignores the possible substitution between input factors of production, and may cause false interpretation. The total factor productivity (TFP) is a measure of overall productivity change. It is a weighted average of each single factor of productivity growth. Hence, this study uses the TFP as a measure of productivity, and decomposes the TFP growth for the South Korean industrial sector. The TFP growth is estimated parametrically and decomposed into neutral and non-neutral technical change components. The technical emphases are on the modeling and explaining the variations in the demand for energy, and the effects of different input factors of production on the level of energy use.

1.2 The Concept of Energy Use Efficiency

Any increase in the demand for energy will lead to a corresponding increase in its price. According to EIA (2011), the crude oil price will average 100 USD per barrel for the next 20 years, it will reach more than 200 USD per barrel in 2030. This increase in the energy price according to the report is due to increase in the demand for oil and the production cost. Industrial policy decision makers need to understand the importance of the energy in the industrial production structure, in order to assess and formulate necessary measures of energy conservation. Accordingly, it is important to acquire knowledge about the energy demand and its characteristics such as the possible substitutability between energy and other input factors of production (Dargay 1983; Koetse et al. 2008).

The energy input is considered as an important factor of production in many industries. It is considered as an important source of economic growth and effectiveness in production. The efficiency in energy use has continuously improved due to increase in the use of high technology in production, and in response to increase in the price of fuel (Soytas and Sari 2009; Stern 2011). The energy sector is undergoing reforms toward using more advanced technology in generation, transmission, and distribution stages (Fukao et al. 2009). The aim of such reform is to increase energy efficiency by reducing the cost of generation and waste in transmission and distribution stages of energy (Here referring mainly to electricity as a source of energy).

Unlike normal goods where supply response is used to meet increase in demand, in the case of energy, the demand response of the market is employed to reduce increase in the demand. For example, the use of smart grid technology as part of demand response program allows for the application of price variation/discrimination by type of consumer, location, season, and hours of the day, with the aim to reduce energy consumption. Smart grid technology improves the producer's and consumer's ability to optimize generation and consumption of energy. A better optimization improves energy use and efficiency, which will also reduce the amount of energy generated by peak time reserve capacity at high cost, and also reduces energy consumption during peak time at high price (Heshmati 2013).

This book aims at developing a better relationship between various input factors of production and energy demand. Since some energy types such as electricity and natural gas cannot be stored, this will help to identify optimal investment in these input factors of production and a better optimization of energy consumption.

1.3 Objectives

Energy input is considered an essential factor in the manufacturing industrial production. It is also an important factor in the production process, as it can be used directly to produce final goods. The intensity of energy use in the modern production technology is a critical issue, the modern production technology is often using energy in intensive way (Stern 2011; Zahan and Kenett 2013).

Input factors of production in economic theory are often divided into two main components. The primary component, or so-called production factors, consists of non-ICT capital input and labor input, while the secondary component is the intermediate inputs which consists of factors such as materials, ICT capital, supplied services, and energy. The Energy input as an intermediate input factor influences the productivity change. Hence, efficiency in energy use will have impact on the single and multiple or total factor productivity (Dimitropoulos 2007).

The main objectives of this book are summarized as follows:

1. To formulate an energy demand structure by examining the energy use in the production process in the industrial sector, particularly in the South Korean industrial sector. Special attention is given to the factors that increase the risk or variations of using more energy input in production. The elasticity of energy demand with respect to output and other input factors are studied. Structural changes in energy demand pattern is explored for the period 1970–2007.
2. To investigate to what extent the energy is considered as a complement or a substitute to other input factors of production such as labor, non-ICT capital, materials, value added services, and ICT capital in the production process. The pattern of substitutability or complimentarity will be useful to assess and determine the level of energy demand.

In this book three groups of models will be estimated: A production model and two groups of energy demand models. From estimating the production model, the objective is to maximize output for given inputs, where energy is one of the key input factors of production. The models for energy demand are based on a factor requirement function (Hicks 1961; Urga and Walters 2003), where the industry's objective is to minimize the use of energy to produce a given level of output. In the former model energy input is considered as one of the determinants of output, while in the latter model, the factor requirement function is employed to estimate the energy demand and to identify the determinants of the level of energy use.

Following the estimation of the production and factor requirement models, the South Korean industry-wide level of energy efficiency ratio is estimated by using panel data model and methodology. The efficiency is estimated relative to the best industry sector technology in a given year. The model includes estimation of production risk, or in other words variations in energy use.

1.4 Theoretical Justification

This book will mainly study and address four aspects of production, energy requirement, and efficiency in manufacturing as follows:

1. Establish a relationship between production (output) and energy use.
2. Investigate whether the energy demand in the South Korean industrial sector is varied (increased/decreased) through complimentarity/substitutability relations between energy and other input factors of production such as ICT capital and labor.
3. Explore whether there are possible differentiations between the input compliments/substitutes to energy.
4. Examine which factor(s) increase(s) or decrease(s) the demand for energy in the industrial sector, respectively. The information can be used in policy analysis and policy recommendations.

The significance of this subject is imperative to five groups of participants in the market, namely, environmental policy makers; and in its message to industrial sector's stakeholders: The policy makers, and the regulators; and the new entrants or the investors who might be contemplating to enter the industrial sector, and finally energy consumers:

1. The environmental policy makers will benefit from this study through the following:

   a. Identifying the factors that increase the energy demand, in which it leads to an increase in greenhouse gas emission.
   b. To include these enhancing factors into existing programs of energy conservation and efficiency enhancement toward lowering the greenhouse gas emission, and fossil fuel switching to use of renewable energy and programs for nuclear and carbon capture and storage.

2. The policy makers of the industrial sector's stakeholders will benefit from this study through the following:

   a. Directing necessary public supports to increase the energy use efficiency, and thereby reduce the energy consumption and dependency.
   b. Providing necessary justifications to increase the share of renewable energy in the energy mix, as it requires policies to stimulate changes in the energy system.

3. The regulators from the industrial sector's stakeholders may benefit from this study to introduce new or update existing regulatory frameworks regarding for example public utilities, standards for fuel economy, and provide subsidies to investors and producers of alternative fuels.
4. This study can also be an input for investment decisions by new entrants to the industrial sector business in a number of ways as follows:

   a. To provide essential data and information in order to set up business strategies.
   b. To efficiently allocate the amount of energy used in the production process.
   c. To employ appropriate and sufficient amount of ICT capital and new technology to help in producing the same amount of production with less energy use.

5. The energy consumers especially energy intensive industries may use the information provided in this book to be able to reduce their energy consumption, to make a tradeoff between the consumed amounts of energy with consuming other factors that substitute energy. This tradeoff may lead to efficiency in their energy consumption.

The results from this study may add to the bodies of knowledge for the industrial sector especially in high energy consumed countries such as China, the US, North America, and high energy consumed countries of OECD and non-OECD, with energy intensive production structure to identify alternatives to propose strategies for low carbon economy and production structure.

In order to confront possible future energy crises, the consumption of energy should be restructured and reduced. According to Finley (2012), the largest source of increase in energy consumption is China, where it is estimated to grow up to 50 % by the year 2030 in its oil consumption. This vast growing is expected to remain in the industrial sector. China is expected to implement policies to slow the growth rate of its oil consumption. Different policies and strategies are needed to achieve the stated goal. It is necessary to know how certain factors for example ICT capital can be used to affect the level of energy use, and how to quantify and assess this impact. In the aftermath of oil crisis, Europe was able to reduce its energy use and dependency through improvement of energy use efficiency and diversification of its energy sources (Favennec 2005; Terrados et al. 2007).

In the periods of economic shocks that witness extraordinary energy price change, it is difficult to apply the traditional econometric models to explain the energy demand. Advance methods such as dynamic model specification is highly desirable, as they allow for flexibility in adjustment of the input factors in the long run (Kim and Labys 1988). Although dynamic model formulation leads to increase the complexity in modeling, estimating, and interpreting the results, it has the advantage of deriving the elasticities as well as accounting for responsive heterogeneity over time and by industry's characteristics.

1.5 The Research Design

The research design adopted in this book is quantitative, correlational, and descriptive. It is based on existing literature of production risk and energy requirement, existing literature that construct a relationship between energy consumption or energy requirement with other input factors of production, and literature which analyze the risk related to energy demand in the production process (Apostolakis 1990; Dietmair and Verl 2009; Field and Grebenstein 1980; Frondel and Schmidt 2002; Imran and Siddiqui 2010; Kuemmel et al. 2008; Park et al. 2009; Pindyck 1979; Zahan and Kenett 2013).

The review of relevant literature, as well as other studies analogous to studies by the authors quoted above, literature on production function and Translog production function (Berndt and Wood 1975, 1979; Christensen et al. 1973; Griffin and Gregory 1976; Just and Pope 1978), literature on production risk and efficiency (Heshmati 2001; Just and Pope 1978, 1979; Kumbhakar 1997; Tveterås 2000; Tveterås and Heshmati 2002), and exploratory research through analysis of secondary data and longitudinal design, served as key inputs for the design of this study.

These studies provide knowledge of applying quantitative, correlational, and descriptive study, knowledge in applying different forms of production function, and knowledge in analyzing the production risk. Accordingly, this book is employing the knowledge gained from these studies, it is compiling all in one study. Through the use of quantitative, correlational, and descriptive approach (Johnson 2001) in order to establish a wide range of basic areas of knowledge for the dependent variables output and energy requirement, and basing it on the existing literature in determining the production and energy requirement, a correlational descriptive quantitative analysis is conducted to examine a panel data sample from a secondary data source of 25 main industries in South Korea for the period 1970–2007.

A secondary data analysis is a noticeable time and cost-effective tool of data collection. Researchers with limited funding can access huge datasets for small cost and expediency in comparison with the other means of data collection, such as a survey, in which it requires time and expensive process of planning to conduct in addition to data mining and documenting (Dale et al. 2008). The panel data for this study was collected from EUKLEMS Growth and Productivity Account database (For details about the databse, see: Mahony et al. 2009). The data was then transferred and the initial statistical analysis (descriptive statistics) is conducted. Finally, detailed analysis using SAS codes is conducted.

1.6 Empirical Motivations

The study addresses three research questions with respect to the production technology and the nature of the production uncertainty in the South Korean industrial sector. The research questions can be stated as follows:

1. What is the impact of energy use on the production level in the South Korean industrial sector?
2. Is there any factor substitution pattern between energy and other inputs of production in the South Korean industrial sector?
3. What factor(s) affect(s) the variability of energy demand in the South Korean industrial sector?

The empirical motivation behind research question one is that there is little knowledge about the relative importance of energy in the South Korean industrial sector when it comes to industry heterogeneity and stochastic shocks such as oil shock and financial crisis (Benjamin and Meza 2009). The research question two is motivated due to the continuous debates about the fact that whether energy and other input factors, especially non-ICT capital are substitutes or compliments; the inconsistencies in the results are still controversial and need further investigation (Koetse et al. 2008; Thompson and Taylor 1995; Welsch and Ochsen 2005). The research question three is motivated by the predictions of theoretical models as depicted by (Ramaswami 1992) in comparing between risk averse and risk neutral producers, which argues that the risk averse producers tend to use less of risk increasing input factors of production, while using more input factors that have risk decreasing effects than the risk neutral producers (Wang and Webster 2007). Therefore, if the producers in the South Korean industrial sector are risk averse, then the risk properties of input are of interest.

These research questions and their related hypotheses will be tested based on panel data estimation for 25 main industries in South Korea for the period 1970–2007. In addition, several other determinants of energy use level and efficiency will be identified and their impacts will be estimated. The differences in the responsiveness to other determinants by industry can be exploited for the purpose of policy analysis.

1.7 Assumptions and Limitations

This section outlines the following types of assumptions made to complete the book as follows: Methodological assumptions, theoretical assumptions, topic-specific assumptions, and assumptions about instruments used in the empirical estimation. The limitations of the design illustrate the boundaries of the study, and its generalizability to other factors of production, economic sectors, and countries.

1.7.1 Energy Price

The energy policy of the South Korean government aims at securing energy supply at low cost. The price of electricity, gas, and fuel are highly regulated by the government. Hence, the variable of price may fail to act as an applicable indicator for both demand and supply side of consumers and producers responses to price changes. The energy demand will be determined by supply constraint not by the ordinary low of supply and demand. Countries such as South Korea that heavily rely on import for their energy use are mostly incorporating non-market based mechanisms, rather than energy price to stabilize their local energy market (Cho et al. 2004; Kim and Labys 1988).

1.7.2 Methodological and Theoretical Assumptions

Some specific assumptions are needed in order to formulate the production and factor requirement models. The explanatory variables used to formulate the models are assumed to be independent from each other, but highly correlated with the dependent variable. In other words, the relative input factor demands are assumed to be independent of the output (production) level.

Another assumption is related to the variable materials, which is assumed to be weakly separable from the other input factors (i.e. non-ICT capital, labor, value added services, energy, and ICT capital).

Moreover, in this study it is assumed that industries are maximizing their profits through maximizing production output and minimizing the inputs used in the production, in other words, hiring the optimal input to minimize the production cost of producing a given amount of output. These assumptions permit the construction of energy requirement function.

1.8 Operational Definitions

Different terms are used throughout this book, a brief definition for each of these terms is provided as follows (definitions are listed in alphabetical order):

1. **Allocative Efficiency**: The allocative efficiency is defined by Heshmati (2003) as a firm's capability to equate the marginal cost with its marginal value of product.
2. **Btu**: An acronym for British thermal unit, it is used to measure energy consumption and defined as an amount of energy required to heat one pound of water by one degree of Fahrenheit.
3. **Coefficient of Determination**: A measure used in the regression analysis often knows as R-square (R^2), it measures the proportion of the variability in the response that is explained by the explanatory variables. It can be defines as 1-(SSE/SST) where SSE is the residual (error) sum of squares and SST is the total sum of squares that is corrected for the mean (Wooldridge 2006).

4. **Cross Price Elasticity of Demand**: It is defined as the change in energy demand with respect to change in price of substitutes (Allen et al. 2009):

$$E_{PS} = \frac{\Delta E}{\Delta PS} \cdot \frac{PS}{E} = \frac{E_t/E_{t-1}}{PS_t/PS_{t-1}} \cdot \frac{PS}{E} \tag{1.1}$$

where E_{PS} is the cross price elasticity of demand, E, E_t, and E_{t-1} are energy variable, energy variable at time t, and energy variable at time $t-1$, respectively, PS, PS_t, and PS_{t-1} are price of substitutes, price of substitutes at time t, and price of substitutes at time $t-1$, respectively. ΔE and ΔPS are changes from time $t-1$ to time t for energy and price of substitutes, respectively.
If the measure above is positive, the two goods are said to be substitutes. The demand for energy increases as the price of the other goods increase. While a negative cross price elasticity implies that goods are complements, the demand for energy decreases if the prices of other goods increase.
5. **Cross Price Elasticity of Substitution**: It is another measure used for the degree of substitutability between input factors of production. It measures a proportional change in quantity of input factor. It is a change that results from changes in the price of other input factors used in production. This measure is more appropriate for policy issues in comparison to the partial elasticity of substitution's measure (Saicheua 1987).
6. **Efficiency**: Is a measure of the firm's ability to produce output in comparison to firms with the best practice technology.
7. **Economic Efficiency**: Is a measure of overall efficiency which is decomposed into technical and allocative efficiency components. It is measured as the product of the two components (Heshmati 2003).
8. **Firm Performance**: The firm's performance is a concept depending on economic efficiency, in which it consists of two parts, technical efficiency and allocative efficiency (Heshmati 2003).
9. **F-test**: A statistical test used to evaluate a model's performance to test whether one or more explanatory variables used in the model is contributing to the model's explanation of the dependent variable. It can be also used to compare two models when one model is a special case (nested model) of the other model (Lomax 2007).
10. **Inefficiency**: Is a measure of percentage degree of inability to produce output compared with the firm that has the best practice technology.
11. **Multicollinearity**: A statistical phenomenon often used when the explanatory variables that are needed to construct a regression model is linearly related with each other. A regression model with high correlation between two or more explanatory variables is suffering from multicollinearity problem. In the presence of multicollinearity, the estimated coefficients will be sensitive to any change in the model specification or in the data; hence, the predicted estimates will not be efficient in predicting the outcome of the model (O'Mahony and

Timmer 2009; O'brien 2007; Wheeler and Tiefelsdorf 2005; Wooldridge 2006).

12. **MSE**: Mean square error, it is the variance of the error term calculated as the proportion of the residual sum of squares (SSE) to the degree of freedom defined as the difference between the number of observations and the number of parameters. MSE can be expressed as SSE/(n−k), where n is the number of observations and k is the number of parameters (Lomax 2007). The standard deviation of the dependent variable can then be calculated taking the square root of MSE and is defined as Root MSE.
13. **Output Elasticity of Energy Demand**: The output elasticity of energy demand is a measure that explains the change in energy demand as a response to change in total production (Allen et al. 2009):

$$E_Y = \frac{\Delta E}{\Delta Y} \cdot \frac{Y}{E} = \frac{E_t / E_{t-1}}{Y_t / Y_{t-1}} \cdot \frac{Y}{E} \tag{1.2}$$

where E_y is the output elasticity of energy demand, Y, Y_t, and Y_{t-1} are output variable, output at time t, and output at time $t-1$. E, E_t, and E_{t-1} are energy variable, energy variable at time t, and energy variable at time $t-1$. ΔE and ΔY are changes from time $t-1$ to time t for energy and output, respectively.
E_y is positive in general because any increase in total output implies that more input is demanded. $1/E_y$ (inverse) indicates returns to scale. An inverse value less than one indicates an increasing return to scale, while a value higher than one indicates a decreasing returns to scale (Kumbhakar et al. 1997).
14. **Outsourcing**: It measures the amount of goods and services produced previously in-house that are outsourced to outside suppliers Heshmati (2003).
15. **Productivity**: The productivity of a firm is defined as the ratio of the output produced to the input used to produce the output, i.e. Productivity = Output/Input. As emphasized by Coelli and Battese (1998), this relationship is simple to obtain when the production process involves only one output produced by a single input. For multiple inputs used to produce one or more units of outputs then the requirement to obtain a measure of productivity relation is that the inputs should be aggregated to obtain one single index of input. The most known factor productivities are labor and energy.
16. **Production Possibilities Frontier (PPF)**: The production frontier is defined as a graph that shows all possible combinations of simultaneous produced goods in a given time period assuming all other factors held constant (Kumbhakar and Lovell 2000).
17. **Partial Elasticity of Substitution**: A measure used for the degree of substitutability between input factors of production. It was first found by Allen (1938). It measures the proportionate change in the relative input factors shares that caused by the proportionate changes in the relative price of these factors (Knut and Hammond 1995; Saicheua 1987).

18. **Price Elasticity of Energy Demand**: This can be explained as a measure of how a change in price of energy will change the amount of energy used in the production. If the measure is greater than one, the demand is elastic, which means the higher the energy price, the more energy demand is reduced; less than one then the demand is inelastic, the higher the energy price, the less of energy demand will be reduced; or equal to one, which means unit elastic (Allen et al. 2009). Mathematically, the price elasticity of energy demand called often own price elasticity and can be expressed as follows:

$$E_{PE} = \frac{\Delta E}{\Delta P} \cdot \frac{P}{E} = \frac{E_t/E_{t-1}}{P_t/P_{t-1}} \cdot \frac{P}{E} \tag{1.3}$$

where E_{PE} is the price elasticity of energy demand, P, P_t, and P_{t-1} are price variable, price at time t, and price at time $t-1$. E, E_t, and E_{t-1} are energy variable, energy variable at time t, and energy variable at time $t-1$. ΔE and ΔP are changes from time $t-1$ to time t for energy and price, respectively. The sign in general is negative as the demand curve is used to have a negative slope, implying an increase in energy price reduces demand for energy. If the variable E and P are expressed in logarithms, the elasticity is directly interpretable as percentage change in demand in response to a percent increase in price of energy without the second component ratio. It can be expressed as:

$$\mathrm{E_{PE}} = \frac{\partial \mathrm{lnE}}{\partial \mathrm{lnP}} \tag{1.4}$$

19. **The Rate of Technical Scale**: It is defined by Strassmann (1959) as the productivity's rate of change resulted from changes in the production technology or technique. It measures increase in production from proportional (1 %) increase in all inputs. The measure equals to one, less than one or higher than one indicates constant, decreasing, or increasing returns to scale, respectively.
20. **toe**: An acronym for ton of oil equivalent, it is used to measure energy consumption, an amount of energy released by burning one ton of crude oil, 1 toe = 39.68320 million Btu (EIA n.d.).
21. **Total Factor Productivity (TFP)**: Is the productivity involving all the input factors to produce the output. Technical changes, scale, and technical efficiency are considered important components of TFP. In other words the TFP can be decomposed into measures of technical change, scale, and technical efficiency components (Lovell 1996).
22. **Technical Changes**: It is defined as a shift in the production function (Solow 1957), and hence, in the production frontier. If the technological change results in producing more output with the same given inputs, then the production is said to be subjected to technical progress. On the other hand, if the technological change leads to lower the production given the same amount of inputs, then it is defined as being subjected to technical regress (Lovell 1996).

The technical change can be decomposed into two components: Pure technical change which depends on only time, and non-neutral technical change, which is affected by changes in inputs over time (Kumbhakar et al. 2002).

23. **Technical Efficiency (TEF)**: According to Koopmants (1951) definition, the technical efficiency is the firm' ability to minimize the level of inputs used for producing a given amount of output. Hence a firm's production said to be technically inefficient if it fails to maximize its output with the given inputs in production (Coelli and Battese 1998; Timmer 1971).
24. **Total Factor Productivity Growth**: It is defined as annual growth rate (for example in an output variable like GDP for a country or output for a firm over time). It comes from changes in technology and in inputs utilization. Changes in technology increase productivity for a given input and positive changes in specific input increases output (Sahu and Narayanan 2011). The TFP growth can be decomposed into several components. In the case of this study, it will be decomposed into two: Technical change and scale components. Technical change is the derivative of output with respect to time or to shift in the production function over time. The technical change has two components: Neutral, which depends on only time, and non-neutral, which depends on changes in the level of inputs. When time elapses and technology changes, the intensity in the use of inputs will change as well (like energy saving, or capital using). The scale component is due to deviation from the constant returns to scale RTS (if all inputs are increased by 1 %, output increases by 1 %). If the RTS is less than unity, TFP decreases, while it will increase if RTS is bigger than unity (Heshmati 1996).
25. **Time Elasticity of Demand**: It measures how changes in some factors such as technology lead to change in energy demand (Allen et al. 2009). Mathematically, it can expressed as follows:

$$E_t = \frac{\Delta E}{\Delta T} \cdot \frac{T}{E} = \frac{E_t/E_{t-1}}{T_t/T_{t-1}} \cdot \frac{T}{E} \tag{1.5}$$

Here in the absence of a true measure of technology, time represents un-specified technology, it is interpreted as rate of technical change. If positive, changes in technology increase the demand for energy, while if negative, changes in technology decrease the demand for energy. In general, technology development progresses postulate that technology is energy saving, meaning for the same level of output less energy is expected to be used in production, or alternatively for the same level of energy input more output is produced.

1.9 Expected Outcome

The expected result from this study is to provide the industrial sector's stakeholders, and environmental and industrial policy makers with a flexible model that has the capacity to assess outcomes of various policies under certain scenarios.

Through the use of the developed models, they will be able to identify the factors that affect the level of energy use and output and their effectiveness. Better policies and regulations are expected to be derived concerning energy use, efficiency programs, and greenhouse gas emission issues.

1.10 The Structure of the Book

This book is organized into 11 chapters. It is organized as a monograph consisting of chapters that are interrelated and sequentially developed into a final product. Following this introductory chapter which provided a general overview, Chap. 2 provides details about the energy consumptions in the industry sector and their development over time, focusing on the energy consumption in the South Korean industrial sector, and sheds lights on the energy intensity and energy use efficiency programs, it further provides detail descriptions of the current status of the energy demand in the South Korean industrial sector.

Chapters 3 and 4 review the relevant literature pertaining to this study. They are divided into sections include inter-factor substitutability and complementarity, literature on energy efficiency, the theory of firm behavior under production risk, and previous literature concern the production risk estimation, as well as research paradigm assumption and theoretical ordination of the study.

Chapter 5 provides the methodology applied in this study. It discusses econometric issues in estimating panel data with production and energy requirement models. It discusses the advantages, disadvantages, and limitations of panel data sets. Industry heterogeneity and heteroskedasticity issues related to panel data are also discussed in this chapter. The methodological focus will be on the specification of heteroskedastic panel data models, and the assessment of their performance compared with homoskedastic panel data models and heteroskedastic production models that ignore firm heterogeneity. The chapter then elaborates with the issues of the econometric model specification, model estimation, testing for functional forms, and regularity conditions.

For a matter of sensitivity analysis, three groups of models are estimated and compared as follows:

1. A production model where energy is a key input factor in the production process.
2. A factor requirement function (or so called energy demand model) is estimated, where the output is considered as one of the determinants of energy use.
3. The factor requirement function is estimated by accounting for risk or variations in the demand for energy.

For each of these three models, two nested and frequently used functional forms Cobb-Douglas and Translog forms are used. Since the Translog model is flexible, it will allow for non-linearity in model specification (Berndt and Wood 1975; Christensen et al. 1973; Griffin and Gregory 1976), and allows to draw inference on substitutability and complementary relationship between input factors of production. Significant statistical tests are conducted to choose among the best functional forms. This book based on the theory of production and energy consumption utilizes a panel data approach with descriptive statistics to identify and define the specific independent variables that significantly relate to the dependent variables output and the energy requirement, respectively. The study focuses on 25 South Korean main industries. The utilized method in the case of energy requirement model provides a statistical investigation of the relationship between the independent variables of non-ICT capital, labor, materials, value added services, ICT capital, output level, and energy price, where the dependent variables is the energy requirement.

Chapter 6 describes the data used for the empirical methodology of this book. It then provides information about population and sampling strategy, research instruments, discussion of the data collection procedures, and the logistics of the different data sources. It further introduces basic analysis based on raw data. It starts with a presentation of descriptive statistics of the data, and analyzes the energy intensity based on the raw data.

Chapter 7 provides a description of the production process. It provided details about the estimation procedure of production function when the energy variable is considered as one of the input factors of production.

Chapter 8 deals with the energy demand model without risk consideration. The model is constructed and specified in two forms: Cobb-Douglas and Translog functional to allow for consistency and comparability. The Translog production function is used to measure elasticities of substitution, technical change, and total factor productivity growth.

Chapter 9 describes the risk model structure in the South Korean industrial sector. It proposes a new structure and magnitude of production risk in the South Korean industrial sector for the period 1970–2007 by means of estimation of energy demand model. Since efficiency analysis and analysis of industry behavior under risk aversion require knowledge about the conditional mean and variance of output, this chapter investigates both the mean production function and the variance production function. This has mainly been achieved through the estimation of Just and Pope model.

Chapter 10 provides conclusion for this study by summarizing the estimated models and discussion on implications of the results. In addition, policy recommendations and suggestions for further and future research related to energy demand are provided. Chapter 11 concludes this study by providing overall summary.

1.11 Summary

The overall consumption of energy worldwide is continuously increasing. The energy consumption will increase worldwide by 53 % in 2035. This increase in the energy demand will negatively affect the environment and the availability of depletable energy sources of fuel, or primary energy needed to produce energy output such as electricity.

Strong economic development leads to increase in the industrial sector's demand for energy. The industrial sector consumes at least 37 % of the total energy supply, which is relatively more energy intensive than any other major sectors including household, agriculture, and public services.

The increase in the demand for energy leads to increase in its price. This increase is attributed to increase in the demand for oil and in the production cost. Industrial policy decision makers need to understand the importance of the energy in the industrial production structure in order to assess and formulate necessary energy conservation measures. Efficient use of energy will reduce the energy intensity, which may contribute to reduction in the corresponding global emissions of air pollution and greenhouse gases.

This book addresses the econometric specification and estimation of stochastic production technologies when a panel data set is available. It will study and address mainly four aspects of production, energy requirement, and efficiency in manufacturing, First, It will establish a relationship between production (output) and energy use. Second, it will investigate whether the energy demand in the industrial sector in South Korea is varied (increased/decreased) through complimentarity/substitutability between energy and other input factors of production such as ICT capital and labor. Third, it will explore whether there are possible differentiations between the input compliments/substitutes to energy, and finally, it will examine which factor(s) increase(s) or decrease(s) the demand for energy in the industrial sectors, respectively. The information can be used in policy analysis and policy recommendations.

The expected result for this study is to provide the industrial sector's stakeholders and environmental and industrial policy makers with a flexible model that has the capacity to assess outcomes of various policies under certain scenarios.

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Chapter 2
History of Economic Development in South Korea

South Korea is a new industrialized economy that has taken advantage from its technological development, thereby serving as an economic model for emerging economies. The South Korean government has applied a sequence of industrial and technological policy initiatives across different stages of its economic development. The focus of the South Korean industrial plan strategy has been redirected from a consumer industry to a heavy and chemical industry, and then to a technology intensive industry. The government's intervention has changed from direct and sector-specific involvement to indirect sector-neutral functional support system. South Korea is completely energy import dependent, it has no crude oil production. It is placed as the fifths country with the biggest import of crude oil worldwide. As a consumer of crude oil South Korea is on place nine. The South Korean government has developed a set of five-year plan for rational utilization of energy since 1993. A basic national energy plan covers 2008–2030 was announced in an attempt to reduce the energy use intensity by the end of 2030. This Chapter provides details about the energy consumptions in the industry sector and their development over time, focusing on the energy consumption in the South Korean industrial sector, and sheds lights on the energy intensity and energy use efficiency programs, it further provides a detail description of the current status of the energy demand in the South Korean industrial sector.

2.1 Introduction

South Korea has achieved impressive economic growth in a relatively short period of time. Thus, the policies implemented by its government to support its economic growth have been extensively studied internationally, especially to derive implications from industrial and technology policies (Asafu-Adjaye 2000). South Korea is a new industrialized economy that has taken advantage from its technological development, thereby serving as an economic model for emerging economies. South Korea has enjoyed a high economic growth rate from the post-war period until 1997, in which its per capita GDP was 10,000 USD. The South Korean economy has quickly recovered from the Asian Financial Crisis of the late 1990s,

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the ICT bubble of 2001, and the credit crunch of 2003 (Borensztein and Lee 2000; Oh et al. 2012). South Korea was the first country to recover within a year from the Global Economic Crisis of 2007/08. In addition, through the conclusion of negotiations on a US–South Korea free trade agreement (FTA), and a potential Japan–South Korea FTA in the future, the liberalization of South Korean markets will continue (Fukao et al. 2009).

The primary energy composition of South Korea comes from petroleum. Due to lack of domestic energy resources, South Korea is promoting nuclear energy as a national policy (Kanagawa and Nakata 2006). In the following sections of this chapter, the stages of South Korean economics development will be covered along with the consequences of this development in terms of energy consumption and necessary driven energy policy programs aiming at energy conservation and efficiency.

2.2 The Development of Industrial and Technological Policies

South Korea has initiated a set of 5-year economic development (rolling) plan for its economic development since 1962. The first development plan was characterized by a series of trial and errors. However, South Korea commenced to establish a characteristic institutional set-up that subsequently typified its economy, which consisted of an export-orientation, focus on large conglomerates, bank domination, focus on capital-intensive assembly industries, and technology absorption and assimilation strategy. These characteristics reinforced each other based on the functional complementarity among them. For example, the large conglomerates benefited from the economies of scale and scope for capital-intensive industry, for which the capital was supplied by the debt financing from the main bank system. The export market supplemented the limited size of the domestic demand to match the supply capacity of the large firms operated by the conglomerates. The government exerted direct and indirect influence through banks for allocating capital and provided land and human resources for firms and industries. Most importantly, export performance became the ultimate litmus gauge for evaluating policy impact (Khayyat 2014; Lall 1996).

The maintained institutional arrangement that prevailed during the early stage of economic development has significant implications for technology capability upgrade. Exports were the channel through which foreign currency was acquired, and they also provided the chance for the local firms to interact with and learn from the complicated international environment and the harsh demands of foreign buyers. The bank-backed system, which supported the export-oriented conglomerates, had the patience to lend money for long-term, capital-intensive project, since it was not an equity investment but a loan indirectly guaranteed by the government (Amable 2000; Lall 1996; Park 2000).

The South Korean government has applied a sequence of industrial and technological policy initiatives across different stages of its economic development, for which it assisted in interpreting most of the economic variables estimated under this study. A brief description of the history of policy initiative is provided bellow based on literature survey conducted by Kim (1997), Oh et al. (2009), and Park (2000):

The growth of the 1960 s development stage period was an input driven growth with cheap labor, and characterized by forming the economic development plan and shift from import substitution to an export oriented strategy, or so called export oriented industrialization (EOI) for light industries such as bicycle and textile. For the technology policy, the government concentration was on the creation of the key organizations and institutional arrangements through government entities such as the Ministry of Science and Technology and science and technology promotion Act as well as technology absorption (Kim 1997).

For the period of the 1970s, the policy was shifted from input driven to investment driven growth represented by production capability. The industrial policy was concentrated on heavy and chemical industries. For the technology policy the research and educational structure represented by public research institutions and science and techno-parks. The industry policy of this period was characterized by technology absorption (Kim 1997).

From the period of the 1980s onward, the policy focused on growth in the foreign direct investment (FDI), concentrating on technology based industries as a source of economic growth. The technology policy was toward encouraging the private sector for innovativeness and R&D, also called for collaboration between the ministries' R&D activities (Park 2000).

The period of the 1990s witnessed continuously supported FDI with concentration on technology as a source of economic growth and enhancing the innovation capabilities in the private sector. Therefore, hi-tech sectors were encouraged to internationalize. This period was characterized by highly advanced technology area, ICT, Bio-technology, and R&D collaboration (Park 2000).

The globalization era in the 2000s was the last stage of the process of economic growth in South Korea, where the growth was mainly from technology and innovation, and building the national innovation system (Park 2000).

The above mentioned policies reveal the redirection of the focus of South Korean industrial plan strategy from a consumer industry to a heavy and chemical industry, and then to a technology intensive industry. The government's intervention has changed from direct and sector-specific involvement to indirect, sector-neutral functional support system (Park 2000). The mission of technology policy also has been adjusted from absorption of foreign technologies to the creation of new ones (Kim 1997). All these changes in policy initiatives were responses to the growth of the technology capability of the private sector and the changing international economic conditions, which turned out to be quite successful (Kim 1997).

2.3 Energy Consumption

South Korea has no crude oil production and therefore is completely dependent on its imports. South Korea is placed as the fifths country with the biggest import of crude oil worldwide with 2,240 thousand barrels per day. As a consumer of crude oil South Korea is on place nine worldwide with 2,301 thousand barrels per day (IEA 2011).

Oil is still the dominant source of energy in South Korea and makes out around 40 % of the Total Primary Energy Supply (TPES) (see Table 2.1), followed by coal with 28 % and natural gas with 14 %. According to the IEA 2011, the outlook for the next twenty years in the TPES will be a gradual decrease in oil down to 35–31 %, and a huge increase in nuclear energy, while natural gas will remain flat during the projection period.

The South Korean annual energy consumption growth has reached 4.9 % in year 2009. The per capita consumption of energy in South Korea is about (5.0) toe in 2009, in which it accounted for more than twice of the world's average energy consumption. There are three factors that justify the South Korea's high reliance on oil as an energy resource:

1. South Korea had started its economic and industrial development in periods where oil as a resource was plenty, which made energy intensive industries a very lucrative ones.
2. The global oil prices were low and further declined during the 1980 and 1990s, which encouraged the South Korean government to deepen its reliance on imported oil as a main form of energy. Even though South Korea is in the transitioning steps towards a knowledge-intensive industrial structure, it started out with a highly oil intensive industrial structure in steel, shipbuilding, petrochemical, and fertilizer industries, that are still an important factor in today's Korean economy (Borensztein and Lee 2000; Jung and Park 2000).
3. South Korea's oil demand also has risen rapidly due to its automotive revolution after the second oil shock in 1979–1980. Because of the economic success, the car and transport unit ownership that are highly dependent on oil have expanded drastically, in contrast to the mass-transit reliance of their Japanese neighbors (Oh et al. 2009).

Furthermore, the rapid industrial development of South Korea in the twentieth century transformed its economy to a service based economy with an annual GDP growth of 2.9 %. The electricity consumption share of total consumption of energy is rapidly growing. For example, the steel production is heavily depending on the electric arc furnaces and accounted for nearly 57 % in 2009. The chemical sector is the largest energy consumer in the South Korean industrial sector, while the largest share of fuel mix in the industrial sector is represented by liquid fuel consumption for feedstock use (IEA 2011). Figure 2.1 shows the development of energy use in the South Korean industrial sector for the period 1970–2007.

Table 2.1 South Korea key oil data

	1985	1990	1995	2000	2005	2008	2009	2010
Production (kb/d)	–	–	–	13.0	9.8	14.2	19.0	20.9
Demand (kd/d)	551.7	1048.3	2007.7	2135.3	2191.3	2142.3	2185.0	2248.6
Motor gasoline	19.0	64.9	163.9	170.5	162.9	172.0	179.8	188.9
Gas/Diesel/Oil	149.6	279.1	481.2	379.1	413.9	388.3	381.5	389.2
Residual fuel oil	212.2	333.1	558.6	487.2	433.7	331.7	313.2	306.3
Others	170.9	371.1	804.1	1098.6	1180.9	1250.3	1310.5	1364.2
Net imports (kd/d)	551.7	1048.3	2007.7	2122.3	2181.5	2128.1	2.166.0	2227.7
Import dependency	100.0 %	100.0 %	100.0 %	99.4 %	99.6 %	99.3 %	99.1 %	99.1 %
Refining capacity (kb/d)	776	887	1170	2540	2577	2577	2607	2790
Oil in TPES	48.5 %	53.4 %	63.0 %	53.3 %	44.0 %	39.5 %	40.0 %	–

Source I. E. A. IEA (2011)

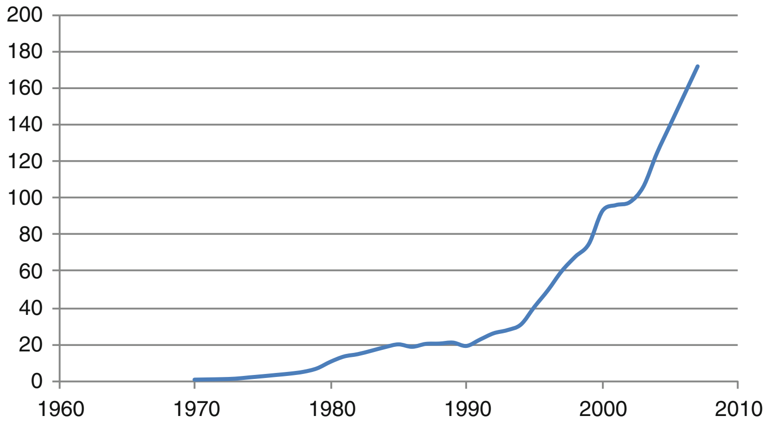

Fig. 2.1 Total industry energy consumption in South Korea (in millions of Euro), 1970–2007

2.4 Policies of Energy Conservation and Structural Changes

Although the recent noticeable increase in the use of fossil fuel caused improve in the materials well-being of many nations worldwide, it has also caused the world in facing two major challenges of climate change and peak oil (Murphy and Hall 2011). South Korea is responding to the global efforts to cope with these two challenges, and to reduce greenhouse gases. South Korea has participated in global efforts to mitigate climate change since 1992 by signing the United Nations Framework Convention on Climate Change (UNFCCC).

Different energy conservation programs have been promoted by South Korean government. For example, the energy demand management, or the so-called demand side management (DSM) is implemented targeting the energy sectors of electricity, gas, and heating. The Korea Electric Power Corporation (KEPCO) is responsible for the load management program and efficiency, and for the Variable Speed Drive (VSD) program, which aims at implementing high efficiency lighting. As part of the program, transformers are implemented and managed by the government (Lee et al. 2012). Other examples of energy conservation programs are tax breaks, loan and subsidy programs, energy conservation technologies, various pilot projects, energy exhibition, and energy service companies program.

An efficient use of energy is not only beneficial to the nation's economy but also important for conservation of natural environment. The major share of this high rate of consumption in energy comes from the electricity, as its share from the final energy consumption has doubled from 12 % to 23 % by the year 2009, compared with a decade ago. In the industrial sector, the electricity share of the annual final energy consumption growth has reached more than 5.8 % (International Energy Agency IEA 2011).

The South Korean government developed a set of five-year plan for rational utilization of energy since 1993. Hereafter, a basic national energy plan covers 2008–2030 was announced in an attempt to reduce the energy use intensity by the end of 2030 with up to (38.0) million toe that corresponds to 46 % of the actual energy consumed. Within the energy plan's framework, the South Korean industrial sector will have to reduce its energy consumption by minimum of 44 % (IEA 2009, 2011).

2.5 Energy Efficiency

Improving the energy efficiency is one of the most important objectives of energy policy and strategy in all countries. Coping with United Nations Framework Convention on Climate Change (UNFCCC) is a big challenge for many countries and their industries. Given the nature of various production processes and technologies used, some industries use more energy than others. South Korea has a high level of dependency on imported energy. The share of imported primary energy in the overall energy supply is high so that improvement in energy use efficiency is the most powerful and cost effective way of meeting the objectives of environmentally sustainable development strategy. Furthermore, it can reduce the high fossil fuels dependency by achieving a higher energy efficiency level.

Energy use efficiency is an important issue due to limit in replacing the energy factor with other substitutable factors. South Korean's dependence on energy sources from overseas is maintained at about 97 % since 2000. Energy efficiency is weighty part regarding policy formulation and evaluation, as it is evidenced and convincing that improving energy efficiency is the best way to achieve energy security and to reduce greenhouse gas emission (IEA 2011).

The main objectives of the South Korean energy policy are sustainability, high security, and competitiveness of the energy supply. Efficient use of energy can be a solution to cope with the desired reductions in emission of greenhouse gases (GHG) and effects on climate change. In order to design effective energy policies, it is necessary to have information on energy demand, its price, and consumer responses in forms of various elasticities. These can be used to monitor the progress in the energy use. A typical indicator is energy intensity to set up energy policy. This is emphasized by a report from the International Energy Agency (IEA 2009) on the Energy Efficiency Policies in the G8 (extended recently to G20). According to the report many countries have shown improved energy efficiency which is explained by the decrease in energy intensity since the 1970s. The recent civil unrest in the Middle East and subsequent increase in the oil price are two other reminders of the importance of energy security for a highly energy dependent industrialized country such as South Korea.

2.6 Summary

South Korea has adopted a series of industrial and technological policy initiatives across different stages of its economic development. Its economic development started from the 1960s, forming a set of five-year economic plan which concluded with the globalization in 2000s, in which technology innovation and building the national innovation system were the main pillars of its development. This rapid industrialization and urbanization have resulted in a noticeable increase in the demand for energy especially in the industrial sector. Although the policy of the demand side management DSM is adopted in South Korea and targeted the energy sector, the Korean annual energy consumption growth has reached 4.9 % in year 2009. The per capita consumption of energy in South Korea is about (5.0) toe in 2009 which is more than twice of the world average energy consumption.

Different energy conservation programs have been promoted by the South Korean government such as the energy demand management, or so-called the demand side management (DSM) is implemented targeting the energy sectors of electricity, gas, and heating, other examples are tax breaks, loan and subsidy programs, energy conservation technologies, various pilot projects, energy exhibition, and energy service companies program.

South Korea has a high level of dependency on imported energy. Any improvement in energy use efficiency may act as a powerful cost effective way of meeting the objectives of environmentally sustainable development strategy. It can also reduce the high fossil fuels dependency by achieving a higher energy efficiency level. Efficient use of energy can be a solution to cope with the desired reductions in emission of greenhouse gases (GHG) and effects on climate change.

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Chapter 3
Literature on Energy Demand

The substitutability and complementarity of energy input have been widely studied during the last four decades. The empirical results were mixed between energy-capital complementarity and energy-capital substitutability. From the previous literature a flexible functional form (Translog) was generally used to model production, cost, energy demand or a combination of them depending on the objective of cost minimization or output maximization. For their empirical analyses the different studies utilized data covering different countries, regions, industrial sector, and in few cases firm levels. The results in general indicated substitution between capital and energy, while complementarity between capital and energy was also frequently observed. The degree of substitutability and complementarity differ significantly by different dimensions of the data and the unit's characteristics. Energy efficiency is hard to conceptualize and there is no single commonly accepted definition. From the literature, energy intensity at the national level is calculated as the ratio of energy use to GDP. This variable is often taken as a proxy for general energy efficiency in production. However, this aggregate energy consumption to GDP ratio is too simple to explain an economy's energy use pattern, and may lead to difficulties and misunderstandings in interpreting the energy intensity indicators. The energy/GDP ratio includes a number of other structural factors that can significantly affect those indicators. Hence, it is necessary to fix the structural change effect in measuring energy intensity at the aggregated level in the industrial sector. The demand for energy is defined as a derived demand that arises for satisfying some needs which are met through the use of appliances. The response to change in the energy demand is partially characterized and explained by changes in the behavior of the decision maker. Thus, the elasticity of energy that respond to changes in the short run is incomplete, while in the long run it will be accumulated over time and fully captured. A key hypothesis required for determining demand for input factors of production is the profit maximization, which depends on the level of output and a limited combination of input factors that give a highest production output. This is called a production function, in which it explains the maximum level of production given a number of possible combinations of input factors used in the process.

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3.1 Introduction

This chapter and the next one will present the theoretical foundation of this study. The current chapter will clearly outline the background of the problem, along with presenting the relevant theories and existing research related to energy demand. The short falling of the previous empirical studies regarding the energy demand will also be discussed in this chapter.

The theoretical foundations of this study amount to more than 300 reviews of books, peer reviewed journal articles, institutional and annual reports, dissertations, and several websites. The three subtopic areas: Stochastic production functions, factor requirement, and production risk on energy demand were researched to conduct a comprehensive literature search.

3.2 Inter-Factor Substitutability and Complementarity

In this section, previous relevant literature on inter-factor substitutability is introduced. The main focus is particularly dealing with substitutability between energy and other input factors of production such as non-ICT capital and labor. The issue of energy substitutability and complementarity has been widely studied during the last four decades. The empirical results were mixed between energy-capital complementarity and energy-capital substitutability. In the following, the literature and its main findings are presented in chronological order.

Hudson and Jorgenson (1974) constructed an inter-industry production model aimed at energy policy analysis. They divided the US business sector into nine industries, namely agriculture, non-fuel mining and construction, manufacturing excluding petroleum refining, transportation, communications, trade and services, coal mining, crude petroleum and natural gas, petroleum refining, electric utilities, and finally gas utilities. Using time series data covering the period 1947–1971, they aggregated the input factors into four main commodity groups, namely capital, labor, materials, and energy. Hudson and Jorgenson (1974) thus, concluded that energy, capital, and materials are complements in the US industrial sector.

In a first attempt Berndt and Wood (1975) have empirically tested the substitutability between energy and non-energy input factors. They assumed a Translog functional form in modeling the production structure for the US manufacturing. For their analysis they consigned an empirical value on the elasticity of substitution and found that energy demand is price elastic, while energy and capital are having a complimentary relationship.

By using pooled panel data set of manufacturing for nine countries, namely Belgium, Denmark, France, Italy, Netherlands, Norway, UK, US, and West Germany, Griffin and Gregory (1976) studied the intersubstitutability between energy and capital. They applied the Translog production function to represent the production technology. In their research, the authors identified the long run substitutability between energy and capital.

The energy demand for Canadian manufacturing sector is estimated by Denny et al. (1978) during the period 1949–1970. The authors applied a non-homothetic generalized Leontief cost function. Their findings revealed that energy and capital are complement. Magnus (1979) applied a generalized Cobb-Douglas cost function using annual aggregate time series data for the Netherlands' economy covering the periods 1950–1976. According to his results, energy and labor were substitutes, whereas, energy and capital were complement. A pooled, cross sectional and time series data of manufacturing sector for the US, Canada, West Germany, Japan, the Netherlands, Norway, and Sweden covering the period 1963–1974 is used by Ozatalay et al. (1979). They estimated a Translog cost function and found that energy and capital are substituting each other.

In a ground breaking paper Pindyck (1979) has introduced an econometric model to analyze industrial demand for energy. The model was applied to ten industrial countries, namely Canada, France, Italy, Japan, Netherlands, Norway, Sweden, UK, US, and West Germany, covered the period 1963–1973. His analysis was aiming at determining the level of substitution effects among capital, labor, and energy inputs. Subsequently, comprehensive literatures have been developed based on Pindyck's original model.

By constructing a pooled dataset of ten industries in the US manufacturing sector, Field and Grebenstein (1980) disaggregated the capital stock into physical capital and working capital in their study. The disaggregation was an attempt to reveal the argument about the role of energy and its relationship's change by capital type. They found a large complementarity relationship between physical capital and energy, while substitutability was observed between working capital and energy.

The Cobb-Douglas production function is applied by Suzuki and Takenaka (1981) incorporating energy and capital investment factors as input substitutions. They found that the Japanese economy will achieve higher growth rate if actively substitutes capital for energy. In a similar study, Hazilla and Kopp (1982) by dividing the physical capital into structure and equipment, they found complementarity between energy and one component of physical capital, and substitutability between energy and other components of physical capital.

The inter-factor substitutability is investigated by Turnovsky et al. (1982) using time series data for the Australian manufacturing sector during two periods 1946–1947 and 1974–1975 focusing on energy inputs. They estimated elasticity of substitution for capital, labor, materials, and energy, and found that energy and capital have a substitutability relationship. Harper and Field (1983) estimated the elasticity of substitution for capital, labor, materials, and energy for the US manufacturing sector during the period 1971–1973, using regional cross sectional data and utilizing a Translog approximation approach. They found that capital and energy are substitutes and the degree of substitution differs by regional location.

Chichilnisky and Heal (1993) came up with a different result about the substitutability and complementarity of energy with non-energy inputs. They developed a total cross price elasticity of demand for energy and capital, in which it considers full adjustments in the long run in multi-sector economy once the energy price changes in the long run. Their finding illustrates that the capital and energy's substitutability relationship tends to change into complementarity once the energy price rises in the long run. Hunt (1984) extended the results obtained by Berndt and Wood (1979) through investigating the role of technological progress in production with the presence of factor enhancing technological progress. Hunt's study was conducted through accounting for linear trend as a determinant factor, while Iqbal (1986) applied the Translog cost function to estimate the inter-factor substitutability of labor, capital, energy, and fuel types for five manufacturing industries in Pakistan. She found that labor, capital, and energy are substitutes. Saicheua (1987) through the use of pooled cross section and time series data of manufacturing sector in Thailand for the periods 1974–1977, found the substitutability between input demand factors (capital, labor, and energy). In addition, Saicheua found that in all industries capital and energy were substitutes.

The elasticities of demand for energy and non-energy inputs are measured by Siddayao et al. (1987) for two industries in three Asian countries, namely Bangladesh for the period 1970–1978, the Philippines 1970–1980, and Thailand 1974–1977. They found labor and energy are substitutes, and the elasticity is higher than in the developed countries' industrial sector. A study conducted by Kim and Labys (1988) to investigate the long run elasticity between energy demand and price of energy and the level of inter-factor substitutability. They analyzed the production structure of Korean industrial sector using pooled time series data, covering the period 1960–1980. Their finding reveled that energy and capital have substitutability relationship in the total manufacturing and total industry level, while complementarity in some others sub-industrial sectors. The factor demands of manufacturing sectors in Japan and US is investigated by Morrison (1988) to characterize the short run and long run price elasticities of demand, she found that in both countries the energy and capital are complement, while other inputs were substitutes.

Apostolakis (1990) conducted a literature survey on energy and capital relationship. He found that studies used time series data and methodology to capture the short run effects are mainly implied complementarity between capital and energy, whereas studies that used cross sectional data captured the long run effects implied substitutability between the two factors. McNown et al. (1991) studied the substitution elasticities of capital, labor, and energy for manufacturing sector in India, Pakistan, and Bangladesh. They proved the substitutability of capital and energy using Translog cost function although the substitutability was differed in elasticity measures for the three countries.

The relationship between economic growth and elasticity of substitution is investigated by Yuhn (1991) through analyzing the inter-factor substitutability between input factors (capital, materials, labor, and energy) comparing South Korea with the US manufacturing sector. The study found substitutability between capital and energy in both countries. Watanabe (1992) through investigating the substitutability of energy and capital for Japanese manufacturing sector during the period 1970–1987 argued that the energy and capital substitution is resulted from the technological innovation and R&D investment effort that led to faster growth of Japanese industrial technology.

Atkson and Kehoe (1995) derived a model called putty-clay model and applied it to study the equilibrium dynamic of investment capital, wages, and energy. They found that energy and capital are negatively correlated and thereby are considered substitutes. Christopoulos (2000) used a Translog cost function to model a dynamic structure of production and to measure the substitutability degree between three types of energy Crude oil, electricity, and diesel, and capital and labor. He used the Greek's manufacturing sector time series data covering the period 1970–1990 and found energy and capital are substitutes.

In an attempt to study the substitution relationships in the German economy, Koschel (2000) argued that energy, materials, and capital inputs are substitutes. He applied the Translog function and used a pooled time series and cross sectional data for the period 1978–1990 to estimate price and substitutional elasticities between capital, labor, materials, and energy for fifty sectors aggregated into four sectors energy-supply, energy- intensive manufacturing, non-energy intensive manufacturing, and service sectors. The results showed variations in the degree of substitutability between capital, materials, labor, and energy for the different sectors. Kemfert and Welsch (2000) estimated the nested constant elasticity of substitution (CES) production function and the elasticity substitution using two different datasets for German economy. The datasets included aggregate time series data covering entire German industrial sector for the period 1970–1988 and a time series data which covered the same period for seven industries in Germany. The industries involved were chemical industry, stone and earth, iron, non-ferrous metal, vehicles, food and paper. They found energy and capital were substitutes, based on the aggregated time series data and the degree of substitutability were differing across the sectors under study based on the second time series dataset.

Mahmud (2000) studied the role of energy in Pakistan's manufacturing sector applying the Generalized Leontief restricted cost function on the manufacturing sector's time series data for the period 1972–1993. He found the inter-factor substitutability between energy and capital and inter-fuel substitutability between electricity and gas. Frondel and Schmidt (2002) claimed that the issue of substitutability and complementarity of energy and capital is not about the econometric methodology as discussed in previous literature such as Apostolakis (1990). Instead, they argued that the estimated Translog cost function for cost share is more appropriate for this issue. Their implication was based on the review of previous empirical works and showed that there is a correlation between cross price elasticity and the cost share of capital and energy due to technological change. In addition, they found evidence of complementarities occurring only when the cost share of both inputs are small; otherwise, the two inputs are always substitutes.

Thompson (2006) in addition to his finding about energy-capital substitutability, emphasized on the degree and direction of this substitutability. The study described the substitution of capital and energy input through the derivation of cross price elasticity, using Cobb-Douglas and the Translog production and cost functions. In contrast a high degree of complementarity between energy and capital is found in a recent study conducted by Kander and Schön (2007) on Sweden industrial and manufacturing sectors for the period 1870–2000. They used a direct measure of technical efficiency and investigated the short and long-run energy and capital relationships to identify the type of relation between capital and energy.

Arnberg and Bjorner (2007) applied Translog and linear logit approximation to estimate factor demand models for capital, labor, and energy inputs using micro panel data of Danish industrial companies for the years 1993, 1995, 1996, and 1997. The authors found labor to be substitutable with energy and capital inputs. Ma et al. (2008) applied a two-stage Translog cost function on a panel data of 31 autonomous regions in China covering the periods 1995–2004. The objective was to measure the elasticities of substitution. They found inter-factor substitutability, i.e. capital and labor are substitutes for energy. In addition, they found the inter-fuel complementarity between coal and electricity and inter-fuel substitutability between electricity and diesel. Koetse et al. (2008) through their literature survey about elasticity of substitution applied the Meta regression analysis of previous literature's results and found energy and capital are substitutes, and the degree of the substitutability differs across regions and time periods.

A different approach is taken to model the structure of Korean industries using a dynamic factor demand model by Khayyat et al. (2014), they examined the changes in the South Korean industrial productivity between 1980 and 2009. Their finding reveled that ICT and non-ICT capital are substitutes for labor and energy use.

In sum, the review of the comprehensive literature presented above suggest that a flexible functional form (Translog) is used to model production, cost, energy demand or a combination of them depending on the objectives of cost minimization or output maximization. For their empirical analysis the different studies utilized data covering different countries, regions, industrial sector and in few cases firm levels. The results in general indicate substitution between capital and energy, while complementarity between energy and capital is also frequently observed. The degree of substitutability and complementarity differ significantly by different dimensions of the data and the unit's characteristics.

3.3 Energy Efficiency

Energy efficiency is hard to conceptualize, and there is no single commonly accepted definition. A frequently occurring question concerns the level of detail necessary to carry out a cross-country or cross-industry comparison without distortions due to structural differences.

From the literature, energy intensity at the national level is calculated as the ratio of energy use to GDP, and this variable is often taken as a proxy of general energy efficiency in production (Ang 2006). A lower rate of use per unit of output indicates a higher level of efficiency. At the industry level, it is measured as the ratio of energy use to value of production for a given period of time.

However, this approach has several limitations for example the aggregate energy consumption to GDP ratio is too simple to explain an economy's energy use patterns. Furthermore, this could lead to difficulties and misunderstandings in interpreting the energy intensity indicators, because energy/GDP ratio includes a number of other structural factors that can significantly affect these indicators. Hence, it is necessary to fix the structural change effect in measuring energy intensity at the aggregated level in the industrial sector (Ang 2004; Boyd et al. 1988).

There are several studies elaborate with the structural change challenge. A look at the case of South Korea, Choi et al. (1995) proposed a method to decompose the aggregate energy demand applying the Divisia approach and using the data of the South Korean manufacturing industry. Three components are distinguished: Structural change, inter-fuel substitution, and real energy intensity. The results showed that the increase in the aggregated energy intensity since 1988 was mainly due to increase in the real energy intensity, and the contribution from the effect of structural change and fuel substitution is small. Jung and Park (2000) applied the method of real energy intensity to analyze the industrial structural change effect from energy intensity. The conventional aggregated energy intensity in South Korean manufacturing sector had improved by almost three times than the real energy intensity. It is found that the conventional energy intensity could be over-estimated, because it contains the effect of structural change.

The energy efficiency is a critical issue of many national energy policies, but little attention has been paid to define and measure the efficiency index. However, there has been continuous efforts to calculate the energy efficiency index by using the concept of Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). Below are some key literatures that evaluated both SFA and DEA:

Boyd et al. (1988) used SFA to develop an energy performance index (EPI), which is a statistical benchmarking tool of the US EPA Energy Star Program to assess industrial plant energy efficiency. Hjalmarsson et al. (1996) provided a comparison of SFA and DEA, and Heshmati (2003) provided a review of the literature on performance measurement in manufacturing and service industries.

Reinhard et al. (2000) estimated environmental efficiency measures for Dutch dairy farms. They defined environmental efficiency as the ratio of minimum feasible to observed use of environmentally detrimental inputs such as nitrogen surplus, phosphate surplus, and the total energy use, they compared two methods for calculating efficiency namely SFA and DEA. The result suggested that the environmentally detrimental input is used most inefficiently, both at individual farms and at the aggregate levels.

Hu and Wang (2006) analyzed energy efficiency of 29 administrative regions in China for the period 1995–2002. Unlike several other studies for regional productivity and efficiency in China, where energy input is neglected, this study included the energy use to find the target energy input by using DEA. The index of total factor energy efficiency (TFEE) is defined as the ratio of the target energy input to the actual energy input. The developed area (East) in China has the highest TFEE, the least developed area (West) has the second best rank, while the developing area (Central) has the worst rank, even though this area shows second highest level of GDP output in China. This "U-shaped" relationship between the area's TFEE and per capita income confirms that energy use efficiency eventually improves the economic growth.

In a recent study, Filippini and Hunt (2011) estimated aggregate energy demand frontier by using SFA for 29 countries over the period 1978–2006. Energy intensity might give a reasonable indication of energy efficiency improvements but this is not always the case. Hence, they suggested an alternative way to estimate the economy-wide level of energy efficiency, in particular through frontier estimation and energy demand modeling. Zhou et al. (2012) proposed a parametric frontier approach to estimate economy-wide energy efficiency. They used the Shephard energy distance function (Shephard 1953) to define energy efficiency index, they adopted the stochastic frontier analysis (SFA) to estimate the index by using a sample of 21 OECD countries. It is found that the proposed parametric frontier approach has a higher explanation power in energy efficiency index compared to its non-parametric DEA frontier counterpart.

The stochastic frontier function has generally been used in production theory to measure economic performance of production units (See for example: Aigner et al. 1977; Battese and Coelli 1995; Jondrow et al. 1982). The main concept of frontier approach is that the function presents maximum output or minimum level of economic input indicators. Kumbhakar and Lovell (2000) discussed the interpretation of the efficiency in an input requirement function. An input requirement function gives a minimum level of input used by an industry for production of any given level of output. Literatures on input requirement function were mainly focused on labor use efficiency because labor is an important part of input factors in production, e.g. (See for example: Battese et al. 2000; Kumbhakar et al. 2002; Masso and Heshmati 2004). However, the energy use is the main focus of this study. Therefore, energy use efficiency is estimated by means of stochastic energy requirement function.

Attempts have been also made to analyze the dynamic factor demand and its adjustment process. Pindyck and Rotemberg (1983) examined how input factors respond over time when changes in the price of energy or output level can be anticipated. This study focused on the importance of adjustment cost and the role of energy as a production factor. Urga and Walters (2003) compared dynamic flexible cost functions to analyze inter-fuel substitution in the US industrial energy demand, while Yi (2000) compared dynamic energy demand models using Swedish manufacturing industries.

The industrial demand for energy has been frequently studied but these studies solely investigated the relationships between energy and non-energy factors. A complementary relation between energy, capital, and labor were investigated based on the US manufacturing time series data. The models have different views of production technology, yet can distinguish the relationships between any two factors in forms of complementarity or substitutability.

In one example, Clifton (1995) analyzed the inter-fuel substitution of the US industrial sector for the period 1960–1992 and found that dynamic linear logit model is providing global properties that are superior to those of a comparable dynamic Translog models. Ang and Lee (1994) developed an energy consumption decomposition model, using data from Singapore and Taiwan. The authors attempted to identify the effects of structural change on energy efficiency based on energy coefficient and measures of elasticity of demand. An analysis of the relationship between energy intensity and total factor productivity is conducted recently by Sahu and Narayanan (2011). Their finding indicated that energy intensity is negatively related to the total factor productivity, and hence energy use efficiency is required by the industry to operate efficiently.

3.4 Energy Demand

The demand for energy is defined by Bhattacharyya and Timilsina (2009, p. 16) as follows:

> …a derived demand that arises for satisfying some needs which are met through use of appliances.

According to this definition, the energy demand depends on the type of energy chosen to be used in a device for a process or activity, in which it will be influenced by the price of the chosen energy type, the price of the device used by the energy type, the availability of the devise used, and other factors such as environmental conditions, decision maker's preferences, income, demand for energy substitutes, etc. Accordingly, changes in the demand for energy depend mainly on the supply of the device used. Thus, response to the change will lead to inflexible results, as changes in response to the changes in supply of the device might be influenced by factors other than energy demand. The supply of the device used depends mainly on a set of characteristics such as device cost, availability, and efficiency (Bhattacharyya and Timilsina 2009).

The response to change in the energy demand is partially characterized and explained by changes in the behavior of the decision maker. Thus, the elasticity of energy that respond to changes in the short run is incomplete, while in the long run will be accumulated over time and fully captured. The short run elasticity will depend on the output level, while in the long run other factors in addition to the level of output will determine the size of the elasticity such as taxes, prices, technical progress, changes in the industry structure, and policies toward more efficient use of energy (Schön 2000).

Factors that derive the demand for energy by industries are determined based on the production theory with a priori expected outcome. These factors are different by industries as well as over time. Energy is considered as an input in the production, and hence, the cost minimization approach is applied when the firm is maximizing the profit (Uri 1982).

The cost minimization and profit maximization goals of the producer in the industrial sector are subjected to a number of restrictions such as the production process and its capacity in producing maximum quantity of output given the level of inputs available and used, the fixed capacity of the firm during a certain time period, price and availability of different inputs used in the production process, and the price of their substitutes. The factor demand functions can be derived from the cost minimization approach, which aims at producing units of outputs up to the level that the rate of technical substitution will be equal to the price of the inputs used (Bhattacharyya and Timilsina 2009).

A key hypothesis required for determining the demand for input factors of production is the profit maximization, which depends on the level of output and a limited combination of input factors that give a highest production output. This is called a production function, in which it explains the maximum level of production given a number of possible combinations of input factors used in the process (Dougherty 2007).

In order to illustrate the discussion above in context of production of output and use of inputs, let Y_{it} be an amount of output which can be produced by an industry i at time t. Y will use different combinations of non-ICT capital K, labor L, materials M, value added service S, ICT-capital I, and energy E. In addition to that, exogenous technical changes represented by time trend T will have positive influence on the production (Heshmati 2003). In similar with the output, all these inputs are varying by industry and time. Given initial conditions described above, the production function will be specified as follows:

$$Y_{it} = F(K, L, M, S, I, E, T), \tag{3.1}$$

Here the demand for energy can be derived using the Shephard's lemma approach (Shephard 1953), and based on Diewert (1974). It is labeled as inverted factor demand (or factor requirement function) as follows:

$$E = f(Y, P, K, L, M, S, I, T), \tag{3.2}$$

The price of energy P is included due to the cost minimization requirement. This is a demand function for energy, it depends on output, the own price, other inputs, and time trend representing the state of technology. The price of alternative energy, if available, can be included to capture prevalence of substitution and complementarity in the demand for energy.

3.5 The Elasticity of Demand

The elasticity can be defined as responsiveness of the dependent variable to changes in the explanatory variables. It is a measure of changes in explanatory variables that affect the dependent variable. If the left and right-hand side variables are expressed in logarithmic form, all the variables then can be in different units of measurement, and yet the changes will express percentage changes, or elasticities. The elasticity is defined as if an explanatory variable such as materials use increases with one percent, how many percent the demand for energy will be changed, ceteris paribus (meaning everything else unchanged) (Allen et al. 2009).

3.6 Critique of Previous Literature

The data used to estimate energy demand in previous literature were mainly of two types: Cross sectional data within a country, in which it is considered inadequate due to the effects of location that exaggerate the elasticities such as price elasticity. The other data type used is the international cross sections, which also considered insufficient due to structural differences that direct the elasticities away from zero. Hence, the pooled time series cross sectional data is more desirable, as it addressed the shortcoming mentioned above by powerful econometric techniques such as flexible Translog production function (Hartman, 1979). The model also allows for capturing both dynamics and heterogeneity in production and energy demand.

An ideal model is required to combine theoretical and empirical tools of inter-factor substitution model often called (KLEMS) which refers to capital K, labor L, energy E, materials M, and value added services S. Further extensions of the inter-fuel substitution, dynamic partial adjustment, demand model for quasi-fixed factors, and econometric model that utilized Translog flexible functional form with production risk approach are incorporated. Furthermore, explicit treatment of elasticity demand is accounted for in this study in order to identify behavioral characteristics of individual industry and to derive relevant specific policy variables and recommendations.

3.7 Summary

From the study of inter-factor substitutability between energy and other factors of production, it is found that there are two directional approaches: One claims the substitutability and the other claims complementarity, and both are providing strong theoretical and empirical evidences. For their empirical analyses, these studies have utilized data of different countries, regions, industrial sector, and in a few cases, based on firm levels. The results in general indicate substitution between capital and energy, while complementarity between capital and energy is also frequently observed. The degree of substitutability and complementarity differ significantly by different dimensions of the data and the unit's characteristics.

An ideal model is required to combine theoretical and empirical tools of inter-factor substitution model often called as (KLEMS) which refers to capital, labor, energy, materials, and value added services. A derivation for energy as an input factor demand function (or factor requirement function) is offered and the factors that derive the demand for energy by industries and over time are determined based on the production theory with a priori expected outcome. The cost minimization approach is applied for firm's profit maximization, as the energy is considered an input factor of production.

Further extensions of the inter-fuel substitution, dynamic partial adjustment, demand model for quasi-fixed factors, and econometric model that utilized Translog flexible functional form with production risk approach are incorporated. Furthermore, explicit treatment of elasticity demand is accounted for in this study in order to identify behavioral characteristics of individual industry, and to derive relevant specific policy variables and recommendations.

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Chapter 4
Literature on Production Risk

A noticeable number of econometric studies on production technology and firm behavior have been conducted since 1970s, where the flexible functional form technique is introduced. These studies have mainly focused on two issues, first, in measuring the producer's responses to changes in the price of input and output, and second in measuring the productivity growth. The majority of these studies have relied on one of the two assumptions: The assumption of deterministic setting which indicates that for a given level of inputs the output level will be certainly known, or the assumption of homoskedastic production technology which implies that inputs do not affect the variability of the output. These assumptions will not be valid in the presence heteroskedasticity, in which it should be accounted for in the econometric model specification. Studies on producers' behavior under risk and uncertainty emphasized that producers often make their decisions in a risky environment that result from production. Such risky production environment and conditions may be related to different factors that are also varied according to the production type and the input factors used. From this perception, different econometric methodologies were used to analyze the production process, and different assumptions were imposed hereby in a way that they prevented the researchers to further investigate about the effects of input factors on the variability of output. As a result, many researchers attempted to propose different models to allow for analysis of the effects of production risk on the level of inputs such as the well-known Just and Pope production function model, in which it proposed a generalized stochastic production model consists of two general deterministic parts one to specify the impact of input factors on the mean of output, and the other one to specify the impact of these inputs on the variance of output. The latter is to allow for input factors to be risk increasing or decreasing. During the production process in many production cases, the decision for using the level of input and supply of output is risky. Some inputs are negatively correlated with the variance of the output.

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4.1 Introduction

This chapter provides the theoretical motivation to analyze the structure of risk in stochastic production technologies. In addition to that, it motivates the use of a primal approach in econometric productivity analyses instead of the popular dual approach. This chapter demonstrates that dual approach looses much of its attractiveness when production risk is introduced into the neo-classical production function. A primal model framework which is tractable for econometric implementation is also presented. Finally, a presentation of underlying postulates and theories of the competitive firm under production risk is provided in this chapter along with the concept of technical and allocative efficiency.

4.2 The Utility Theory and Expectation

In general, there are commonly two risk preference structure measures used in the literature: The coefficient of absolute risk aversion (ARA), and the coefficient of relative risk aversion (RRA). Let $U(W)$ denotes an utility function in a risky wealth, $\acute{U}(W)$ is the marginal utility, the ARA then will be defined as follows:

$$A(W) = -\frac{\acute{U}(W)}{U(W)}, \tag{4.1}$$

The ARA accordingly is evaluated for the final wealth W at some chosen levels. The ARA as specified above is not dimensionless measure, it is rather depends on the same unit of income measure. On the other hand, the BRA for the utility function in risky wealth is defined as follows:

$$R(W) = -\frac{\acute{U}(W)}{U(W)}W \tag{4.2}$$

This measure is dimensionless, hence, it is very convenient in measuring risk aversion by using this measure. The two measures ARA and BRA mentioned above have a linear relation and can be specified as follows:

$$R(W) = A(W)W, \tag{4.3}$$

In addition to the two measures mentioned above, a third, less used measure of risk preference structure, is the coefficient of partial relative risk aversion (PRRA), it is defined by Menezes and Hanson (1970) as follows:

$$P(W,\pi) = -\frac{\acute{U}(W)}{U(W)}\pi = A(W)\pi, \tag{4.4}$$

where π is the profit. As shown by Briys and Eeckhoudt (1985), the three coefficients, i.e. ARA, BRA, and PRRA are implicitly related as follows:

$$P(W, \pi) = R(W) - W_o A(W). \tag{4.5}$$

where W_o is the certain initial wealth. Consider a change in profit π the resulting change in the coefficient of absolute risk aversion $A(W)$, and the coefficient of relative risk aversion $R(W)$, is related to the change in the partial relative risk aversion as follows:

$$\frac{dP}{d\pi} = \frac{dR}{d\pi} - W_o \frac{dA}{d\pi'} \tag{4.6}$$

It is obvious that any effect of a change in profit π on P is explicit when A and R both having opposite signs. Any increase in R and decrease in A, the result of $dp/d\pi$ will be positive, whereas it is negative if R is decreased while A is increased. Models of producer behavior under uncertainty are mostly applying expected utility in profits instead of wealth. In such case the coefficient of relative risk aversion is identical to the coefficient of partial relative risk aversion.

4.3 The Argument of the Utility Function

For the specification of utility functions in empirical studies, two important issues are considered: First, for the argument of the utility function should final wealth or profits be used, and second, whether the argument takes both negative and positive values or not, as it affects the choice of parametric form for the utility function. Some parametric forms are not defined when the argument is negative such as the logarithmic utility function, and some parametric forms provide perverse risk preferences measures in terms of ARA or PRA in case of negative outcomes.

There have been some issues regarding the use of the end of period wealth or profit as an argument of the firm's utility function (For further reading, see: Briys and Eeckhoudt 1985; Hey 1985; Katz 1983; Pope 1988). The end of the period wealth is positive linear function of profits and can be specified as follows:

$$W = W_o + \pi \tag{4.7}$$

where W is the random wealth at the end of the period, Wo is the certain initial wealth, and π is the flow of profits in the period. The end of the period wealth W increases if realized positive profit π, and decreases if realized negative profit π.

According to Katz (1983), the relative risk aversion is defined as follows:

$$R(\pi) = -\frac{U'(\pi)}{U(\pi)}\pi, \tag{4.8}$$

This indicates that the measure of the related risk aversion has the profit π as an argument instead of terminal wealth. The relationship above deviates from the original definition of relative risk aversion provided earlier. In the literature it is generally assumed that the terminal wealth is always positive. This is, however, an assumption that is not always conforms to empirical observations. If the terminal wealth is always positive, the coefficients of absolute and relative risk aversion will always be positive and monotonously decreasing or increasing for the risk averse firm. Profits may be negative in some states of the world, and thus $R(\pi)$ may take both negative and positive values (Tveterås 1997).

Moreover, as pointed out by Tveterås (1997), two assumptions may be made when the profit is used as argument for the utility function specification: First, The special case of initial wealth equal to zero, in this case $W = \pi$, and second, The individual's risk preference structure is formulated such that initial wealth has no effect on the individual's decision. This is the case if the individual is risk neutral, or more generally if the individual's risk preference structure exhibits constant absolute risk aversion (CARA). Under risk neutrality $U'(W) = 0$, which implies that the coefficient of absolute risk aversion is $A(W) = 0$ is constant. It is worthy of mentioning that CARA implies that the risk premium required by the individual is invariant to changes in initial wealth.

The second assumption states that the individual's risk preference structure is formulated such that initial wealth has no effect on the individual's decision. This assumption is contradicting the empirical tastings that provide adequate evidence that the scale of the bet relative to initial wealth to a large extent affects the risk premium required by the individual. More clearly, If participating in a gamble is voluntary, then it determines whether an individual will participate or not. If the amount of the bet is such that the individual may lose her entire wealth in the case of an adverse outcome, and she cannot buy insurance, she will probably refrain from participating (Katz 1983).

4.4 The Theory of Firm Behavior

A noticeable number of econometric studies of production technology and firm behavior have been conducted since 1970s, where the flexible functional form technique is introduced. These studies have mainly focused on two issues: First, in measuring the producer's responses to changes in the price of input and output, and second, in measuring the productivity growth. The majority of these studies have relied on one of the two assumptions: The assumption of deterministic setting and the assumption of homoskedastic production technology. The assumption of a deterministic setting indicates that for a given level of inputs, the output level will be certainly known, while the assumption of homoskedasticity implies that inputs do not affect the variability of the output.

The two assumptions mentioned above may be appropriate in the case if the level of risk or the magnitude of heteroskedasticity is relatively small. However,

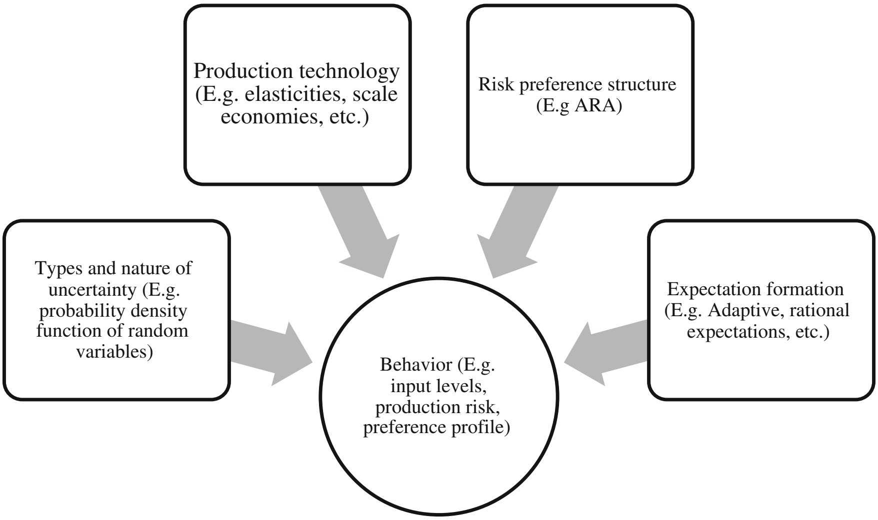

Fig. 4.1 Determinants of risk averse behavior

these assumptions lose their validity in the presence of noticeable production heteroskedasticity. Heteroskedasticity should be accounted for in the econometric model specification. According to the theory of the competitive firm under production risk, the structure of production risk, the firm's risk preference structure, and the firm's expectation formation process affect the firm's behavior (see Fig. 4.1).

In general, the competitive firm chooses different input levels, it responds differently to price changes under production heteroskedasticity or uncertainty than it would have done under production homoskedasticity or certainty. In the presence of production heteroskedasticity and risk aversion, parameter estimates from conventional dual models of the firm will be generally biased. This indicates that the use of econometric models which assume output homoskedasticity or certainty may provide regulators and policy makers with incorrect inferences with respect to the effects of policy measures which affect the input and output prices. In addition to mentioned above, homoskedastic and deterministic econometric models are not able to provide any information about the risk-reducing or risk-increasing effects of inputs (Tveterås 1999).

4.4.1 Producer's Decision in the Presence of Risk

Studies on producers' behavior under risk and uncertainty emphasized that producers often make their decisions in a risky environment that result from production (Arrow 1971; Pratt 1964; Robison and Barry 1987; Sandmo 1971; Tveteras et al. 2011).

Such risky production environment and conditions may be related to different factors that are also varied according to the production type and the input factors used in the production. For example, in the industrial sector the market and price of energy used as input factor, financial uncertainty such as interest rate, and in case of agriculture weather, disease, and pests may have significant impacts on the producer's decision and production outcome.

In general, producers are trying to minimize the risk through different institutional and managerial tools (Binswanger 1980). For example, they may change the level of different inputs used for optimal production. Empirical studies show that risk averse producers tend to optimally use inputs with less of risk during uncertainty situations than they would under certainty (Hurd 1994). These inputs might be used either to increase the level of output or to make variability in the output, hence, any possible changes in their level of utilization might have different implications regarding the variability in the output. Output risk can be presented in many different productions and industries such as agriculture, mining, medical and health, etc. However, the level of output risk may differ by production types and by industries, as well as over time (Tveteras et al. 2011).

The distributional properties for output in the case of output risk have illustrations for optimum inputs combination and output for the risk averse producers. When the level of inputs is changed as a consequence the variance of output will be changed in addition to the mean of output. For risk averse producers, the optimal level of input will be higher if an increase in the level of input leads only to a higher expected output than if the increase leads to higher mean and larger variance of output (Tveterås 2000; Tveterås and Heshmati 2002).

From this perception, different econometric methodologies were used to analyze the production process, and different assumptions were imposed in a way that they prevented the researchers from making further investigations about the effects of input factors on the variability of output (Fufa and Hassan 2003). As a consequence, many researchers attempted to propose different models that allow for analysis of the effects of production risk on the level of inputs such as the well-known Just and Pope production function model (Just and Pope 1978). Here, Just and Pope proposed a generalized stochastic production model that consists of two general deterministic parts one to specify the impact of input factors on the mean of output, and the other one specifies the impact of input factors on the output variance. The latter is to allow for input factors to be risk increasing or decreasing (Koundouri and Nauges 2005; Koundouri et al. 2006).

4.4.2 Just and Pope Postulates

There are eight important propositions offered by Just and Pope (1978) for the stochastic specification of the production function (or input-output relationship) specified as $y = f(x, \varepsilon)$. According to their argument, these propositions are important on the basis of a priori theorizing and observed behavior. The propositions are stated as follows:

Proposition 1 *The expected value of the production is always positive, i.e.* $E(y) > 0$.

Proposition 2 *The expected value of the marginal product is always positive, i.e.* $\frac{\partial E(y)}{\partial x_k} > 0$.

Proposition 3 *There is a diminishing marginal product expectation, i.e.* $\frac{\partial^2 E(y)}{\partial x_k^2} < 0$.

Proposition 4 *A change in the variance of random components in production should not necessarily imply a change in expected output when all production factors are held fixed, i.e.* $\frac{\partial E(y)}{\partial Var(\varepsilon)} = 0$ *is possible.*

Proposition 5 *Increasing, decreasing, or constant marginal risk should all be possible, i.e.* $\frac{\partial Var(y)}{\partial x_k} < = >$ *possible. Proposition 5 is considered of particular interest in this study, it states that the specification of the production function should not restrict the effects of the change in the level of an input on the variance of output a priori.*

Proposition 6 *Any change in the level of the risk should not necessarily lead to a change in factors used for risk neutral producers (profit maximizers), i.e.* $\frac{\partial x_k^*}{\partial Var(\varepsilon)} = 0$ *is possible. When x* is the optimal level of input x.*

Proposition 7 *The change in the variance of marginal product with respect to a factor change should not be constrained in sign a priori without regard to the nature of the input, i.e.* $\frac{\partial Var(\partial y/\partial x_k)}{\partial x_j} < = >$ *are all possible.*

Proposition 8 *Constant stochastic returns to scale should be possible, i.e.* $f(\alpha x) = \alpha f(x)$ *possible for scalar α.*

4.5 The Production Risk

During the production process in many production cases, the decision for using the level of input and supply of output is risky (Kumbhakar 2002b). Some inputs are negatively correlated with the variance of the output. For example, investment in the global warming reduction and improving environmental condition is negatively related to the variance of fossil fuel production. Some other inputs have positive relationship such as investing in high technology will improve the quality and the output variation of high technology products.

According to Kumbhakar and Tsionas (2010), the concept of risk in the production theory is studied mainly from two aspects: First, uncertainty arises from changes in the price of output and second, uncertainty arises from the volume of output. The latter is often referred to as the production risk, in which it can be explained by the inputs used in the production. The quantity of inputs that determine the output volume also influences the degree of output inconsistency or variability. For example, in the financial sector the interest rates and in the agriculture sector the use of fertilizer and pesticides might be risky leading to increase in the variation of the output, while technology and labor might decrease the output risk. Other risks might increase or decrease the output. For example, currency risk in the financial sector, which is related to the risk that changes in the rate of foreign exchange will positively or negatively affect the value of the asset held in that currency (Asche and Tveteras 1999; Kumbhakar et al. 2002; Kumbhakar and Tveterås 2003).

Literatures related to production risks are mainly theoretically analyzed, whereas, only few empirical studies exist (See for example: Coppejans et al. 2007; Kumbhakar 2002a). The empirical studies were conducted based on either output price uncertainty, or based on the Just and Pope (1978) production risk framework, where the main focus is on how changes in the level of inputs affect variations in the range of output. An empirical study by Appelbaum and Ullah (1997) on the firm's production decision behavior analyzed the supply and demand decision under the price uncertainty using data of two US industries: Printing and publishing industry, and stone, clay, and glass industry. They found that uncertainty has high statistical significant effects on production decision.

Kumbhakar (2002b) estimated jointly the production technology and risk preference functions represented by variable input choice equations under output price uncertainty. He applied the model on a paned data of 28 Norwegian Salmon farms for the period 1985–1992. He found that the absolute risk aversion in the salmon farms is decreasing and all Salmon farms are risk averse. Sandmo (1971) studied the theory of competitive firm under the conditions of price uncertainty, when the firm is price taker and the demand is not known. He empirically analyzed the competitive firm's behavior under the price uncertainty and risk aversion behavior. His finding indicates that the level of production will be lowered by the presence of price uncertainty. Chambers (1983) studied some implications of price uncertainty to measure economies of scale and the rate of technical change by applying Sandmo (1971) model. He found that in the presence of risk and uncertainty about the production structure and utility function, it is not possible to measure economies of scale elasticity and the rate of technical change that can be derived from price and quantity observations.

Tveterås (1999), based on Just and Pope (1978) production risk estimated the production risk using unbalanced panel data model of Norwegian Salmon farms, focusing mainly on the measurement of the properties of risks related to input factors and productivity growth. He found that input factors of production can be used as instruments for controlling risks. Another finding was that heterogeneity in the production by using the same input factors of production will yield different level of output risk. Tveterås (2000) estimated flexible panel data models for risky production technologies by applying Just and Pope (1978) production risk and using unbalanced panel data of Norwegian Salmon farms. He showed that the empirical results were to a large extent influenced by different specifications of unobservable firm's specific effects and different functional forms underlying the production and risk specifications. In another study relying on the Just and Pope (1978) propositions, Tveteras et al. (2011) estimated the mean and variance functions of production risk separately in the presence of heteroskedasticity using a two-step procedure and second order approximation. They found that the structure of the production risk has implications in production decision for the risk averse producers.

4.6 Mean Factor Inputs and Output Variance

As discussed by Wan et al. (1992), the relationship between each input factor with the variance of the output is essential for allocating optimal input by a risk averse decision making producer. As depicted by Fufa and Hassan (2003), firms that account for risk involved in the input factors used in the production need to measure the factors that affect the distribution of return, which is the variance rather than the mean of input. For producers and policy makers in managing risk, it is essential to know which input factor increase (decrease) the risk of the production output.

According to Tveterås (1999), an important feature of production risk is that in many production sectors the input level affects the output risk (variance) level. In other words, some input factors increase the level of output risk while some others reduce the output risk. The risk feature discussed above is worthy of note when a researcher empirically studies the production and productivity change, as some firms say group A firms in a specific industry may choose the level of input for their production to be varied with the optimal level of input in other firms say group B firms in the same industry. In this regard the group A firms are usually risk averse, when they tend to adopt a new technology, they consider the properties of risks related to the adoption of that technology. Hence, they may not necessarily choose the technology that yield the highest output in average.

The deterministic setting approach is applied by many scholars in the econometric productivity studies. The idea is to estimate the basic production model or the dual Translog production model which according to Coyle (1999), is considered as less tractable under risk productions, when compared with the conventional deterministic setting. Pope and Chavas (1994) and Pope and Just (1996) argued that in addition to the shortcoming of deterministic approach in the production risk, the standard Translog production function approach is also less controllable, as it limits the production output risks to allow for increase in the level of input factors. The reason is that the explained component (deterministic part) will multiplicatively interact with the unexplained component (or the variance part).

The marginal risk of an input will tend to be positive (negative) if the increase (decrease) in the variance of the output is a result of the increase in the level of input. Just and Pope (1978) found the marginal risk and the inputs/output relationships cannot be explained precisely using the deterministic settings. They developed a risk production function version that allows for input factors to affect the mean and variance of the production output. The error component of their proposed function is modeled with input dependence heteroskedastic form. Thus, the model, in addition to accounting for risk, it also accounts for heteroskedasticity as well.

4.7 Technical Efficiency

In order to understand the importance of the output risk for implications about the efficiency and its measurement, it is important to explain the concept of technical and allocative efficiency. The technical efficiency can be represented by the equation below:

$$\pi = p \cdot f(x) - wx, \tag{4.9}$$

where p is the output price, x is a vector of inputs with price vector w, and $f(x)$ is the deterministic part of the production function. Here, the firm is trying to maximize the profit π by choosing different input combinations. It can be noticed that this relation is only valid under conditions of price certainly as the price is an exogenous factor in the relationship (Tveterås 1997).

For simplification, Fig. 4.2 illustrates a profit line for two different technologies used in the production, the profit line π^* shows the efficient technology corresponds to $f^*(x)$, while the profit line π' represents an inefficient technology corresponds to $f^*(x)$. Here one can identify two types of inefficiencies: The difference between the maximum feasible output (point A in Fig. 4.2) that corresponds to $\mathrm{y}_0^* = \mathrm{f}^*(\mathrm{x}^*)$ and the actual output (point B in Fig. 4.2) that corresponds to $\mathrm{y}_0' = \mathrm{f}'(\mathrm{x}^*)$ give level of input x^*. This type of inefficiency is called technical efficiency corresponds to the vertical distance between point A and B.

The allocated inefficiency which is the second type of inefficiency can be measured for a given technology $f(x)$ and price p and w as the difference between profit at profit maximizing input levels and profits earned at the actual inputs level.

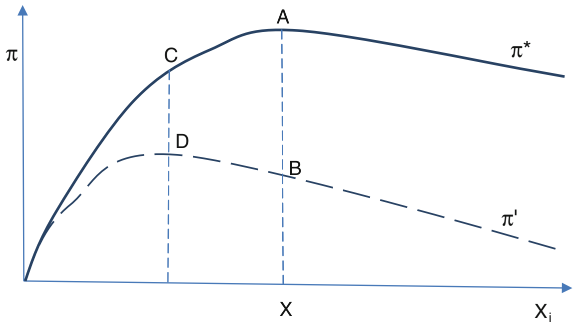

Fig. 4.2 Efficiency under price certainty

Point A in Fig. 4.2 represents the allocated efficient point for the technology $f^*(x)$, while all other points are considered allocated inefficient. Accordingly, the first order condition for allocative efficiency is equal to the first order condition for profit maximization as follows:

$$\frac{\partial \pi}{\partial x_i} = p \cdot \frac{\partial f}{\partial x_i} - w_i = 0. \tag{4.10}$$

Hence, it can be illustrated from the discussion above, and based on the Lovell and Schmidt (1987) argument, that a firm is considered both technically and allocatively efficient for the prices (p, w), and here, point A represents profit efficiency assuming that all other input factors of production are at their profit maximum level.

4.8 Critique of Previous Literature

Many scholars who applied Just and Pope (1978) implied that production risks have failed to address two main issues:

1. For simplicity the basic Cobb-Douglas production function is used in both the deterministic part and the variance part despite its weakness, which imposes high restriction on the production technology. However, using the Translog model, which is more flexible than the basic Cobb-Douglas function is more favorable in spite of its requirement to use non-linear estimation form. The choice of a generalized function form such as a Translog form compared with a simpler form is statistically testable.
2. Variations in capital and different input factors based on specific characteristics are matter in regard to producer heterogeneity, in which it has been neglected by researchers who applied Just and Pope Production function.

Tveterås (1999) argued that firms' specific effects (in the case of this study the industries' specific effects) will significantly influence the performance of the estimation in the mean and variance part if it has been accounted for in the estimated model. Hence, the traditional deterministic models estimating production growth is not sufficient in explaining the production growth in a realistic and precise way. Estimation of risk properties of energy demand in the South Korean industrial sector is provided in this empirical study.

Therefore, this study will provide empirical understanding about which input factor or group of input factors decrease the use of energy, and which factors increase the risk in production and variations in energy use. The idea is to treat the residual (the error or the disturbance part) from a production function as a measure of risk (both positive and negative). It is then modeled as a function of inputs and both observable and unobservable characteristics of the producer, market, policy, etc. A well specified generalized model will serve as a useful tool in production decision making, energy demand, and policy analysis.

In the case of this study, the same idea is applied, but in the context of energy demand. Here the meaning of risk is not the same as in the production. An increase in prices is a negative shock or risk, and technical progress in area of energy saving is a positive shock. ICT capital is another factor and might serve as either positive or negative shock to energy demand. All these factors increase changes or variability in energy demand. The methodology in this study, in similarity with the production risk approach, deals with heteroskedasticity of known form. It is to be considered as an attempt to identify and estimate the effects of determinants of variations in production and energy demand.

Many scholars provided evidence that risk affects the input in many production's cases in different sectors. Kumbhakar and Tsionas (2010) through explaining how the input factors affect the risk related to factor demand found that input factors of production influence the probability distribution of output, and thus, it has important meaning for the decision makers. Pope and Kramer (1979) argued that production uncertainty have more effects on the economy than the market uncertainty. For example as they depicted, contracting and distortion can lower the price uncertainty, but little of mechanisms are available to avoid or at least to lighten the production uncertainty. They also argued that scholars failed to properly model production uncertainty by not explicitly allowing for the fact that many factors of production have a risk reducing marginal effect on output. Griffiths and Anderson (1982) and Wan et al. (1992) proposed models of production functions with error component composed of three parts, one is time specific, the second one is firm specific, and the other one appears as heteroskedastic disturbance. The models allow for the variance of the output (the marginal risk) to take both negative and positive values when an input is increasing or decreasing.

In this study, the above mentioned shortcoming has been accounted for in the estimation procedure for production risk, by explicitly allowing for the input factors of production to vary the risk of increasing/decreasing the demand for energy. All the articles included in the literature review were found useful to formulate the models outlined in this study, through providing an understanding of the underlying theories, objectives of output maximization and cost minimization, cause and effect relationships, model specification, estimation and testing procedures, as well as how to construct relationships between the models' components.

4.9 Summary

For the specification of utility function in empirical studies, two important issues are considered: First, for the argument of the utility function should final wealth or profits be used, and second, whether the argument takes both negative and positive values or not, as it affects the choice of parametric form for the utility function. Models of producer behavior under uncertainty are mostly applying expected utility in profits instead of wealth. In such case the coefficient of relative risk aversion is identical to the coefficient of partial relative risk aversion.

Although it is desirable to have generalized theoretical model for firm behavior under production risk, some propositions and assumptions are needed for empirical conformation and analysis of the stochastic production technology. The eight propositions of Just and Pop for the stochastic production function are used in theoretical and empirical researches on production uncertainty. These propositions are reasonable on the basis of a priori theorizing and observed behavior. The proposed production function of Just and Pope (1978) and its eight propositions for the stochastic production function have introduced a theoretical framework for the modeling of production risk; it also provided consistent and asymptotically efficient estimates of the production function parameters when the production function is in the form of Just and Pope Production function.

The riskiness of alternative production technology represented by the variance of the output will be the other measure of interest for the risk averse producers. A production technology with a lower mean of output for a given input and a smaller variance of output than alternative technologies might be chosen and desirable by the risk averse producers. Hence, theoretical assumptions or priori information about the structure of risk preference and structure of the stochastic production technology are needed to study the effects of changes in production risk and changes in inputs and output prices on input demand and output supply. The methodology in this study, in similarity with the production risk approach, deals with heteroskedasticity of known form. It is to be considered as an attempt to identify and estimate the effects of determinants of variations in production and energy demand.

The production risk has illustrations for the way the technical efficiency is viewed. When two production technologies are compared for their technical efficiency and measurement of technical changes over time, the mean will be considered no longer the only measure of interest.

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Chapter 5
Econometrics of Panel Data Estimation

An issue not to be ignored in econometric modeling of production technology and firm behavior is the heterogeneity with respect to production technology and productivity, and heterogeneity with respect to input demand. Industries that use the same amount of input often experience different levels of output. The assumption of homogeneous firms in the neoclassical production theory may not be suitable for many industries. The heterogeneity should be accounted for in empirical studies with econometric modeling. The availability of panel data set makes it easy to use econometric panel data techniques to account for heterogeneity. The producer heterogeneity under risk can operate on several stages: The production process, the risk preferences, and the expectation formation with respect to price and output. However, only heterogeneity with respect to the production process is relevant for estimating production function. A two-stage approach is used to model industrial demand for energy. In the first stage, a model to determine the total demand for energy as a derived input factor of production is specified and estimated. Here, the demand for energy is considered as a dependent variable, and then a Translog production function model incorporating non-ICT capital, labor, and energy as input factors of production is estimated. Furthermore, elasticities of substitution are calculated. In this study three specifications of mean function of the risk model are specified and compared: A general production function where energy is an input, a Translog energy demand function where energy is a dependent variable, and a Translog energy demand model generalized to incorporate risk function.

5.1 Introduction

This chapter deals with issues related to estimation of models when panel data sets are available. An issue not to be ignored in econometric modeling of production technology and firm behavior is the heterogeneity with respect to production technology and productivity, and heterogeneity with respect to input demand. Industries that use the same amount of input often experience different levels of output. This can only be attributed to different outcomes of the stochastic variables in the production process. The discussion in this chapter will be focused more

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specifically on the context of production analysis and energy demand. Specific problems that are relevant to empirical applications will be also discussed. This chapter then defines the research methodology of this study. It describes the methodology selected and how it supports or rejects the research questions and their hypotheses. The chapter includes in addition to mentioned above the theoretical framework, the econometric model specification, estimation and testing procedures, population and sample selection issues, research procedures, instrument used, and statistical analysis methods.

5.2 Fixed Effect and Random Effect Models

There are in general two techniques to analyze panel data: Fixed effect and random effect techniques. Consider a linear model specified as follows:

$$Y_{it} = X_{it}\beta + \eta_i + \lambda_t + u_{it} \qquad i = 1, 2\ldots, N, \qquad t = 1, 2, \ldots.T_i \tag{5.1}$$

where i is the cross section unit, for example firm or industry, and t is the time period representation. The error component $\eta_i + \lambda_t + u_{it}$ will determine the type of the specified model. The firm (industry) specific effect is captured by η_i, while λ_t is the time specific effect. Two classes of econometric panel data models can be defined by using Eq. (5.1), these are fixed effect and random effect models. If η_i and λ_t are fixed (random) parameters then the model specified in Eq. (5.1) is described as fixed (random) model, respectively. The error component $\eta_i + \lambda_t + u_{it}$ is assumed to be homoskedastic, independent of each other and of the regressors X_{it} (See: Baltagi 2008 for more details).

The model applied in this study is a panel data model with only industry specific random effects η_i known as one way random error component model. It is possible to include the time specific effects λ_t as dummy variables. However, it is more reasonable to treat the time specific effects as fixed in a data set with a small number of periods, which is generally the case for empirical productivity studies, and particularly for the empirical application in this study. The observation specific error term u_{it} is generally assumed to be homoskedastic in estimating the panel data models in the literature. However, the u_{it} in this study is assumed to have Just and Pope heteroskedasticity property (Just and Pope 1978) as follows:

$$Var(u_{it}) = [h(u_{it}; \alpha]^2 \sigma_\varepsilon^2, \tag{5.2}$$

where σ_ε^2 is the variance of the exogenous error term ε.

5.3 Characteristics of Panel Data

5.3.1 Advantages

The panel data regression techniques have many advantages that can be summarized as bellow (For details, see: Baltagi 2008; Baltagi and Raj 1992):

- In case of having parameter heterogeneity across units of cross sectional or time series data sets, estimating models that ignore this heterogeneity will generate inconsistency in the estimated parameters of interests. For example in the case of heterogeneous intercepts in a simple linear regression model such as: $y_{it} = \beta_i + \beta_1 x_{it} + \varepsilon_{it}$. By estimating a pooled regression (a regression with homogenies intercept) $\beta_1 = \beta_2 = \cdots = \beta$ on a dataset generated by a model with heterogamous intercept will probably lead to biasedness in the estimation of the parameters β. Also the estimates of the residuals ε will be biased, in which it leads to bias estimates of the variance for β in the next stage estimation [for detailed discussion, see: Greene (2008)].
- Omitted Variable Bias: Missing explanatory variables Z_{it} that are correlated with explanatory variables X_{it} actually included in the regression model will generate biasedness in the estimates (Wooldridge 2006). In linear regression models the researcher may estimate $y_{it} = \beta_i + \beta_1 x_{it} + \varepsilon_{it}$ but the true regression model to be estimated is $y_{it} = \beta_i + \beta_1 x_{it} + \beta_2 z_{it} + \varepsilon_{it}$. This problem can be often corrected if repeated observations for a group of individuals are available (panel), in which it may allow to eliminate the effects of $\mathrm{Z_{it}}$. If the effect of the omitted variable is constant (or equal) for a given individual across time, the effects of the omitted variable can be eliminated through different techniques such as differencing the sample observations, using dummy variable, or formulating assumptions about the distribution of the unobserved variables.
- Measurement Error: A problem often called measurement error is expected to occur, and the procedure of finding remedies for errors in the variables is often difficult in case of cross sectional and time series data sets. However with panel data sets the probability of finding the remedies and obtaining consistent estimators are higher (Griliches and Hausman 1986).
- Dynamic effects can only be captured using panel data. Although time series also allows for time lag (lagged variable), but cannot provide precise estimates due to multicollinearity problems, while individual differences are used in the panel data to reduce the multicollinearity problem (Greene 2008).

5.3.2 Disadvantages and Limitations

Although there are several advantages associated with using panel data sets as mentioned previously if compared with the cross sectional and time series data sets, there are also disadvantages and limitations as described bellow (Baltagi 2008):

- Random Sample Properties: The randomness of a sample from a population is an issue for the purpose of making inferences. A sample drown from a population if it is not random, a selectivity bias will occur in the estimated parameters (Hsiao 1986). The selectivity bias results from non-randomness of the population sample may occur for different reasons (Greene 2008) as described bellow:

   a. Self-selectivity: In case of some units of individuals or firms decided not to occur in the sampling, a self-selectivity problem occurs. For this particular study the decision of some firms within an industry to integrate horizontally or vermicular which make them not eligible to participate in a national survey of collecting data is an example of self-selectivity. However, there is no evidence in the EUKLEMS Productivity Database or any documentation in EUKLEMS website that these particular industries (if exist) are structurally different form the sample population with respect to production technology.
   b. Non-response: A designated respondent may not respond to certain question (s) or decide not to participate at all. In this particular study, there is again no evidence that there are certain firms within a specific industry that did not participate in the data collection.
   c. Attrition: This means that there might be some units that are dropped out form the sample population as they are not available anymore. For this empirical study again although there is no evidence or no documentation in EUKLEMS mentioning this issue, but it is quite logical to assume that some firms have been bankrupted, for example during the two economic shocks within the dataset period covered, or a change in their proficiency for one reason or another.

- Omitted Variable Bias: The issue of omitted variable bias can be accounted for in a panel data with linear regression models. However, for the nonlinear regression modes handling the issue of omitted variable bias is more complicated. Often fixed effect and random effect approaches are applied to handle the issue but it yield different estimates (Hsiao 1986).

5.4 Industry Heterogeneity and Heteroskedasticity

In an econometric modeling of production technology and firm behavior, heterogeneity with respect to production technology and productivity is crucial (Greenaway and Kneller 2007). Firms (industries in the case of this study) that use the same input combination will usually experience different output levels, in which it might be attributed to the variability in outcomes of the stochastic variables in the production process. Some differences in the productivity across the industries are often determined by nature related to industries' unobserved characteristics. Many scholars by using econometric panel data techniques recommend that industry's heterogeneity to be accounted for in the specification of production models, arguing that ignoring heterogeneity will provide biased estimates leading to incorrect inferences, in such case the estimated model suffers from heteroskedasticity (Just and Pope 1978, 1979; Kumbhakar 1997).

In addition to heterogeneity, the issue of Heteroskedasticity is also crucial when estimating models with panel data techniques. The error component in the panel data literature that often assumed to be homoskedastic in the estimated models will be presented in the disturbance part (Baltagi 2008). The error component (as it will be described in the preceding sections) will be consisted of two parts time and random components. If the time invariant industry specific is assumed fixed, then it is called fixed effect, while it is called random effect if it is assumed random (Greene 2008).

5.5 Industry Heterogeneity and Panel Data Availability

The assumption of homogeneous firms in the neoclassical production theory may not be suitable for many industries and sectors. However, since the 1990s the availability of penal data sets that allow for accounting for heterogeneity became available for researchers. The producer heterogeneity under risk can operate on several stages: The production process, the risk preferences, and the expectation formation with respect to price and output. However, only heterogeneity with respect to production process is relevant for estimating production function (Baltagi 2008).

The heterogeneity is captured by accounting for industry or firm specific effects that can be captured in the input demand and expected output supply derived from indirect utility function. However, as illustrated by Tveterås (1997), it is difficult to separate the effects of technology heterogeneity from the risk preferences heterogeneity on the estimated firm (industry) specific effects.

5.6 The Theoretical Framework

The production risk proposed by Just and Pope (1978) is considered as a basis for many successive theoretical and empirical studies that deal with production function modeling and estimation. Just and Pope proposed a generalized production function to allow increase and decrease in the risk (or variations) of output by the use of input factors.

The general form of Just and Pope Production technology can be expressed as follows:

$$y = f(x) + u = f(x) + g(x)^{1/2\varepsilon} \tag{5.3}$$

where x is a vector of k inputs, $f(x)$ is the explained part (deterministic part) or the mean function, $g(x)$ is the risk part or the variance function, while ε is an exogenous random shocks and it is beyond the control of the producers. According to the specification in Eq. (5.3), the input vector x affects independently both the mean (output) part and the variance part (output risk). The relation in Eq. (5.4) is an illustration:

$$E(y) = f(x), \text{and } \mathrm{Var}(y) = \mathrm{Var}(u) = g(x)\sigma_{\varepsilon}^{2} \tag{5.4}$$

In addition, there is no restriction on the risk effects of inputs, i.e. $\frac{\delta \mathrm{var(y)}}{\delta \mathrm{x_k}} = g(x)$ can be either positive, negative, or zero. This is a strong assumption imposed by Just and Pope Production function, but allows the model to be less restrictive and realistic. As can be noted from Eq. (5.3), the explained component (the deterministic part) will interact multiplicatively with the unexplained component (or the variance part). Furthermore, the error term is not specified in a familiar multiplicative form such as $y = f(x)e^{u}$. It is rather an additive formula such as $y = f(x) + u$. For this reason, Just and Pope Production technology model needs to be nonlinearly estimated.

In general, only the production function approach is covered in the literature of panel data and production. However, what actually behind the production function is the utility maximization through profit and output maximization or cost minimization. The expected utility approach that can be solved by the indirect utility function is often used to model the production risk of competitive firms. The risk averse producers choose the level of inputs that maximizes the utility based on three main factors: First, the expected (or observed) level of output, second the price of the used inputs, and third, the available information of the risky production technology's structure. The indirect utility function reflects the risk averse producer's constrain about the mean and the variance of output (Tveterås 2000).

Ramaswami (1992) investigated the relationship between the production risk and uncertainty with the decision of allocating optimal inputs in the production process. He argued that risk averse producers behave differently from risk neutral producers, due to marginal risk premium, which according to his definition is the difference between the cost of inputs and the expected marginal product producing at the optimal level of inputs. If the marginal risk premium is positive, it indicates that the risk averse producers are using inputs above the optimal level (the level that risk neutral managers are choosing), while negative marginal risk premium implies decrease in the level of input relative to the optimal level. His major finding was that the marginal risk premium's sign will be positive for all risk averse producers only if the input risk is increasing, while the sign will be negative only if the input risk is decreasing. Ramaswami's finding is an adequate implication from the model which shows that the determinant of risk taker producers in using the level of input relative to risk neutral producers is the marginal risk of input (Picazo-Tadeo and Wall 2011). In other words, it will be appropriate to use the obtained information about marginal risk of input to imply whether the risk taker producers are using their level of inputs in production more or less than the risk neutral producers. Hence, it is possible to use the estimation of risk parameters obtained from Just and Pope Production technology for that purpose, namely to shed light on the heterogeneity in producers behavior by their degree of risk averseness.

In order to fully understand the methodology applied in this study, it is necessary to shed light on the relationship between the adoption of new technology and the risk and risk aversion. A study conducted by Ghosh et al. (1994) showed explicitly the separate effects of technical efficiency and risk behavior of new technology adoption. They proposed a new model that takes into account the separate effects of technical inefficiency and risk aversion on the firm's behavior to adopt new technology in production. In order to explain the model of technology adoption in a simplified manner, it is necessary to begin with specification of a deterministic production model as it simply ranks the alternative technology as follows:

Let $y_a = f_a(x)$ denote a deterministic production technology that produces a higher output than the alternative $y_b = f_b(x)$ for all input used in the production, then y_a is said to be more technically efficient than y_b and the producers will give y_a a higher rank. This will not be the case for modeling risky production function technology when $y_a = f_a(x) + g_a(x)^{1/2\varepsilon}$ produces more than the alternative $y_b = f_b(x) + g_b(x)^{1/2}.\varepsilon$. Here, the risk averse producer will rank the two alternative technologies considering the mean and the variance of the output. There are two reasons as Tveterås (2000) explained: First, the technical efficiency in the second case is not an objective measure; it is rather a subjective measure depends on the risk preferences of the production; and second, a technology with higher mean of output does not necessarily imply more technically efficient than the technology that provides less mean of output for all inputs used in the production.

5.7 The Econometric Model

In order to understand the statistical relationship between energy use and output, technology and other input factors of production, and to quantify the impact of these factors a quantitative methodology will be applied. This study tests the related hypotheses of stated research questions from chapter one through parametric regression analysis. In doing so, a demand model is estimated based on knowledge production function (Griliches 1979), incorporating research and development (in this context ICT capital is incorporated), and using panel data with time and industry dimensions. The model is estimated using both fixed and random effects models.

A two-stage approach is used to model industrial demand for energy. In the first stage, a model to determine the total demand for energy as a derived input factor of production is specified and estimated. Here, the demand for energy is considered as a dependent variable, and then a Translog production function model incorporating non-ICT capital, labor, and energy as input factors of production is estimated. Furthermore, elasticities of substitution are also calculated (Pindyck 1979).

For the specification of a stochastic production function, several requirements with respect to theoretical consistency, flexibility of the functional forms, and scientific consistency should be accounted for. In this study, in addition to the standard Cobb-Douglas production function, a Translog production function is specified for the energy demand model and its risk component. The Translog production function is more flexible than the Cobb-Douglas production function due to presence of functional forms in the former one. Lau (1986) provides some general criteria as guidelines for the choice of functional specification, these criteria are: Theoretical consistency, domain of applicability, flexibility, computational facility, and factual conformity.

To validate the theoretical consistency, the Just and Pope Production function satisfies the Just and Pope eight propositions for the stochastic production function, and hence, it is theoretically proved to be consistent. Flexibility in terms of mean production function suggests that the functional form does not impose a priori restrictions on derived elasticities of substitution and scale. The Translog function is considered as flexible in this sense, while the Cobb-Douglas production function is inflexible, as it imposes a priori restriction on the production technology (Chambers 1983).

Various empirical studies from the application of flexible functions highly recommend the use of Translog production function. However, despite the inflexibility of Cobb-Douglas production function, many studies have used it in their econometric studies of production uncertainty (See for example: Griffiths and Anderson 1982; Just and Pope 1979; Subal C. Kumbhakar and Wang 2006; Saha et al. 1997). A considerable weakness of these studies is that they did not provide any justification for not using a more flexible functional form in modeling the production technology. In this study, the Cobb-Douglas Production function is estimated along with the Translog production function. The aim is to provide additional evidence to the restrictiveness of Cobb-Douglas specification and to justify the use of more flexible specification (in this case the Translog production function). In addition to the general arguments presented above against the use of the Cobb-Douglas Production function, the returns to scale obtained from estimating the Cobb-Douglas production function is equal to the sum of the estimated parameters. This is too restrictive to examine the contribution of the scale economies to observe productivity differences.

For the domain of applicability criteria, there are some problems in using the functional forms. As mentioned by Lau (1986), the results from empirical applications are generally arguing that flexible functional forms although they are behaving well around the mean observation, the theoretical consistency requirements are violated for observations that lay far from the mean, as the production technology cannot be approximated in outlying observations. Hence the accuracy of the predicted disturbances is questionable for these observations. This will affect the estimation of the error term and as a consequence will affect the estimation of the parameters. Comparisons between the performances of different flexible functional forms are conducted in several studies. The result suggest that the Translog is more reliable in comparison with the other flexible functional forms with observations that are far from the mean, and it provides more consistency in terms of parameters estimates (Caves and Christensen 1980; Diewert and Wales 1987; Lovell and Schmidt 1987; Westbrook and Buckley 1990).

The factual conformity criterion, which implies consistency of the functional forms with known empirical facts for the South Korean industrial sector supports the use of flexible functional forms such as Translog. The empirical results of Kim and Labys (1988) and Pyo and Ha (2007) from estimating the energy demand provide solid support for the use of Translog production function estimated for the South Korean industrial sector based on time series data and panel data set, respectively. The majority of second order term coefficients in their estimation of Translog energy model were significant at 95 % confidence level, which strongly suggest that Cobb-Douglas specification is inappropriate. Another study conducted by Cho et al. (2004) using Translog cost function to estimate energy demand function for a South Korean quarterly data covers the period 1981–1997 also suggests the use of Translog function, and hence another evidence for factual conformity is provided. For the variance function, both theoretical consistency and flexibility requirements suggest that the econometric specification should allow the conditional variance of output to both increase and decrease in inputs.

To summarize the above discussion, the Just and Pope Production function satisfies the theoretical conformity criterion, but violates the flexibility criterion in the case when the restrictive Cobb-Douglas production function is applied, if the flexible functional forms is used, then the computational facility criterion is violated, as it is difficult to find the nonlinear parameter estimates that optimize the objective function.

In conclusion, it is difficult to find an econometric specification capable to fully satisfies all Lau (1986) criteria. Given the problem stated above about which econometric specification is superior, for each set of models in this study Cobb-Douglas and Translog specifications are estimated for stochastic production function. The scale elasticities as well as the elasticities of substitution and marginal input risks of the estimated models will be evaluated at the mean observation and its neighborhood in order to determine if the estimated production function is reliable.

In this study three specifications of mean function of the risk model are specified and compared. These include the general production function, where energy is an input, the Translog energy demand function, where energy is a dependent variable, and the Translog energy demand model generalized to incorporate risk function.

5.7.1 Feasible Generalized Least Square (FGLS)

In order to simplify the understanding of the concept of feasible generalized least square estimate, it is necessary to derive a simple classical linear model and then end up with the FGLS estimator. The procedure is taken from (Johnston 1984) as follows:

Suppose the simple regression model $y = \alpha + \beta X + \varepsilon$, where y is the dependent variable, α and β are the vector of parameters to be estimated, and X is the vector of explanatory variables of interest, ε is the error term, which captures those endogenous variables affecting y that cannot be exogenously specified, in other words it captures those factors that are not specified in X and have effects on y. The simple regression model specified above needs to fulfill the following conditions (so called the classical assumptions):

1. Linearity: $y = \alpha + \beta X + \varepsilon$.
2. Strict exogeneity: $E(\varepsilon|X) = 0$, in other words, the expected value (the mean) of the error term does not depend on X and it is equal to zero.
3. No multicollinearity: No linear relationships between the explanatory variables X.
4. No heteroskedasticity (no serial correlation): Var (€|X) = $\sigma^2 I$, in other words, the variance of the error term is constant and does not change across observations and samples.

These conditions above are necessary for the estimator to be the best linear unbiased estimator, or the so called BLUE (Johnston 1984). The ordinary least square (OLS) can be used to estimate such model.

Next, the focus will be on the consequence of relaxing the fourth condition $\mathrm{Var}(\varepsilon|\mathrm{X}) = \sigma^2 \cdot \mathrm{I}$, where I is an identity matrix, in which all its elements are equal to one. Suppose all the other conditions hold but the variance function is equal to $\mathrm{Var}(\varepsilon|\mathrm{X}) = \sigma^2\Omega$, where Ω is any symmetric positive defines $n \times m$ matrix. Accordingly, the model is allowing for heteroskedasticity as the elements of the diagonal of Ω are not restricted to be equal or the off diagonal elements are not equal to zero (serial correlation). In this case the estimator $\widehat{\beta}$ is no longer considered the best linear unbiased estimator; hence, there is a need to find a best linear unbiased estimator. $\widehat{\beta}$ is still linear in parameters and also unbiased estimator, but it is not efficient estimator, due to presence of heteroskedasticity (Johnston 1984).

Consider now the following transformed model $y^* = \alpha + \beta X^* + \varepsilon^*$, where $y^* = C \cdot y$, $X^* = C \cdot X$, and $\varepsilon^* = C \cdot \varepsilon$, and C is a positive matrix, such that the nonsingular matrix $\Omega^{-1} = C' \cdot C$, and C' is the transpose matrix of C. The transformed model $y^* = \alpha + \beta X^* + \varepsilon^*$ holds all conditions of the best linear unbiased estimator as follows:

$$\widehat{\beta}_{GLS} = \left(X^{*'}X^*\right)^{-1}X^{*'}Y^* = (X'C'CX)^{-1}X'C'CY = \left(X'\Omega^{-1}X\right)X'\Omega^{-1}Y \qquad (5.5)$$

This is called a generalized least square (GLS) estimator (Johnston 1984).

Now suppose that there exists an estimator for Ω which is $\widehat{\Omega}$, then

$$\widehat{\beta}_{GLS} = \left(X'\widehat{\Omega}^{-1}X\right)X'\widehat{\Omega}^{-1}Y, \tag{5.6}$$

which is called Feasible Generalized Least Square FGLS. To estimate a model using FGLS, one needs to know the form of the error structure (the variance part or the non-deterministic part) in order to propose a homoskedastic transformed model. It is worth of mentioning that most of the estimation procedures suggested for heteroskedastic models are GLS transformations of the variables which change the error terms into classical error, and thus allow for OLS estimations (Johnston 1984).

5.7.2 Cobb-Douglas Production Function

The general form of Cobb-Douglas Production function can be specified as follows (Cobb and Douglas 1928):

$$Y_t = f(L, K, t) = AL_t^{\alpha 1}K_t^{\alpha 2} \tag{5.7}$$

A model with two inputs, labor L and capital K produces a single output Y at time t. A refers to the total factor productivity. The coefficient α_1 is the labor share of output, or the output elasticity with respect to labor, α_2 is the capital share of output, or the output elasticity with respect to capital. They are constant and can be determined by the available technology used in the production process. The Cobb-Douglas function relies on a set of conditions as follows (Chilarescu and Vaneecloo 2007):

1. A constant returns to scale implies that $\alpha_1 + \alpha_2 = 1$.[1] In other words any proportional increase in capital and labor implies an equal proportional increase in producing the output.
2. Neutrality in technical progress which implies that capital and labor are increasing in their efficiency without any change in their elasticity of substitution with respect to differences in the relative prices.
3. The unity of elasticity of substitutions.

For simplicity, the Cobb-Douglas production function can be estimated using a linear relationship. By taking the natural logarithm and adding a stochastic term, the Eq. (5.7) can be written as follows:

$$ln(Y_{it}) = ln(A) + \alpha_1 ln(L_t) + \alpha_2 ln(K_t) + U_{it} \tag{5.8}$$

[1]In general production function, the returns to scale is said to be increasing if $\alpha_1 + \alpha_2 > 1$ and decreasing if $\alpha_1 + \alpha_2 < 1$.

For multiple inputs X production, the Eq. (5.8) can be rewritten as follows when there are n inputs used in the production:

$$y_{it} = \alpha_0 + \sum_{j=1}^{n} \alpha_j ln\left(X_{jit}\right) + u_{it} \tag{5.9}$$

Equation (5.9) represents a generalized pooled Cobb-Douglas production function where the lower case y indicates the logarithmic value of output Y, X_{jit} represents vector of J inputs used in the production for industry i at time t, and the $\alpha_j(j = 1,\ldots,n)$ are the coefficients to be estimated.

The error term u_{it} in Eq. (5.9) represents three different effects, and hence, it contains three elements as follows:

$$u_{it} = \mu_i + \tau_t + \varepsilon_{it} \tag{5.10}$$

where μ_i captures the unobservable industry specific effects, τ_t captures the unobservable time effects, and ε_{it} is the random error term effects. Note that the industry specific effect is interacted with the variance function. It captures the share of the residual containing the variance that is attributed to individual effects that measures the degree of inefficiency in energy use. This measure is expressed in efficiency form to rank industries by their degree of efficiency in utilization of energy in production.

It is possible to derive a factor demand function from the generalized Cobb-Douglas production function specified in Eq. (5.8). For simplicity, the derivative will be based on the original Cobb-Douglas production function with two input factors labor and capital. Taking the derivative of Eq. (5.7) with respect to L and K, and making $\alpha_1 = \alpha$ and $\alpha_2 = 1-\alpha$ for simplicity, the marginal productivity of labor Y_L and the marginal productivity of capital Y_K can be obtained, respectively, as follows (Pierre and Zylberberg 2004):

$$Y_L = \frac{\partial Y}{\partial L} = \frac{\partial Y}{\partial L} f(L, K, t) = \frac{\partial Y}{\partial L}\left(AL_t^{\alpha} K_t^{1-\alpha}\right) = \alpha \cdot A \cdot K^{1-\alpha} L^{\alpha-1} = \alpha \frac{Y}{L} \tag{5.11}$$

and,

$$Y_K = \frac{\partial Y}{\partial K} = \frac{\partial Y}{\partial K} f(L, K, t) = \frac{\partial Y}{\partial K}\left(AL_t^{\alpha} K_t^{1-\alpha}\right) = \alpha \cdot A \cdot L^{1-\alpha} K^{\alpha-1} = \alpha \frac{Y}{K} \tag{5.12}$$

By relaying on the marginal productivity theory of distribution which states that the input factors of production will be paid in accordance to the value of their marginal product in a competitive economy (Ostroy 1984), one can obtain the following relation:

$$Y = L \times w + K \times r \tag{5.13}$$

Where w is the labor wage and r is the capital price, then $w = Y_L$ and $r = Y_K$. By substituting the right hand sides of both Eqs. (5.11) and (5.12) in Eq. (5.13), the following relation will be derived:

$$Y = L \times \alpha \cdot \frac{Y}{L} + K \times (1-\alpha) \cdot \frac{Y}{K} = \alpha \cdot Y + (1-\alpha)Y \tag{5.14}$$

Thus, ($\alpha \cdot Y$) is the labor share and ($(1-\alpha) \cdot Y$) is the capital share of the production output. Finally, the factor demand function can be derived using the marginal product approach specified in Eqs. (5.11) and (5.12).

Since $w = Y_L$, then The labor demand can be derived as follows:

$$w = \alpha \cdot A \cdot K^{1-\alpha} L^{\alpha-1} \tag{5.15}$$

Taking the logarithm of Eq. (5.15), the following relation can be obtained:

$$lnw = ln\alpha + lnA + (1-\alpha)lnK + (\alpha-1)lnL \tag{5.16}$$

Equation (5.16) can be solved for more standard form of factor demand by taking the exponential of Eq. (5.15), then solving for L to obtain the following:

$$L = (\alpha.A)^{-(\alpha-1)}.K.(w)^{-\frac{1}{1-\alpha}} \tag{5.17}$$

Following the same steps above and adding energy as a third factor input of production, the energy demand using Cobb-Douglas production function is equal to the following:

$$\begin{aligned} lnE = {} & \alpha_0 + \alpha_1 lnY + \alpha_2 lnP + \alpha_3 lnK + \alpha_4 lnL \\ & + \alpha_5 lnICT + \alpha_6 lnM + \alpha_7 lnS + \alpha_8 T + \varepsilon \end{aligned} \tag{5.18}$$

where Y is the output, P is the energy price, M, S, ICT, and T are materials, value added services, ICT capital input, and time trend representing technology or technical change, respectively.

An important issue is the specification of the technical change. A deterministic trend variable is implemented in this study in order to be able to test for technical change. One question is whether the technical change is embodied in new inputs. Improvements in the quality of existing inputs, such as the energy use and the ICT capital are believed to have been important sources of productivity increase in the data period. Improvements in the quality of inputs, or factor-augmenting technical change, should thus be accounted for in the model specification. If the trend-variable is allowed to interact multiplicatively with input levels in the econometric model, it is possible to test whether technical change is a boosting factor or not.

For examining the production factor demand, it is assumed that firms will make their decision about how much quantity of output to be supplied and based on this assumption the decision on the mix of factor inputs can be made. As depicted by

Dougherty (2007), this will provide a derived demand function for each individual production factor. Here another assumption needs to be made in order to determine the demand for production factor, namely the profit maximization behavior of the firm. By this assumption, each firm is trying to maximize its profit through either maximizing output and minimize input, or minimizing the cost of producing its output.

5.7.3 The Translog Function

The Translog production function was first introduced by Christensen et al. (1973) for issues of separability and homogeneity of Cobb-Douglas and other production functions specifications. It is a generalized form of Cobb-Douglas production function with J input factors as described below:

$$lnY_{it} = \alpha_0 + \sum_k \alpha_k \cdot lnX_{k,it} + \frac{1}{2}\sum_j \sum_k \alpha_{jk} \cdot lnx_{j,it} \cdot lnx_{k,it} + u_{it} \tag{5.19}$$

In addition to input factors, components for unobservable time specific and industry specific effects can be added to Eq. (5.19) as follows:

$$\begin{aligned} lnY_{it} = \alpha_0 + \sum_k \alpha_k \cdot lnX_{k,it} + \frac{1}{2}\sum_j \sum_k \alpha_{jk} \cdot lnx_{j,it} \cdot lnx_{k,it} \\ + \sum_t \alpha_t D_t + \sum_i \mu_i D_i + u_{it} \end{aligned} \tag{5.20}$$

where $x_{k,it}$ refers to the production input variables, the subscripts j ($j = 1,\ldots,K$) and k ($k = 1,\ldots.,K$) are production inputs, i ($i = 1,\ldots.,N$) and t($t = 1,\ldots,T$) refer to industry and time, respectively, D_t and D_i are dummy variables to capture the effects of time and industry, respectively. Following the tradition, here the time represents the state of technology. Alternatively, the time dummies can be replaced by a time trend. Time dummies are preferred in capturing the year to year changes in production and energy demand, while time trend is better in picking up the trends (Knetter and Slaughter 2001).

The number of coefficients to be estimated for the Translog function in Eq. (5.20) is $(n^2 + 3n + 2)/2$, where n is the member of variables in addition to the coefficients of the dummies that capture the industries' specific effects (Christensen et al. 1973). Note that the error term will multiplicatively interact with the mean function of the Translog function in Eq. (5.20), i.e. $E(y_{it}) = f(x_{it}) * \exp(\mu_i + y_{it})$. From this regard, the Translog production specification tends to be more realistic than Cobb-Douglas production function by being less restrictive. The mean output results from the difference between two industries and the difference values of the industry specific effects are not constant. It is rather to be increased in the gap when the operation scale is increased (Tveterås 2000).

The functional form used in Translog production function does not allow for making any assumptions about the market structure such as perfect competition and assumption of perfect substitution between some input factors. It allows for non-linear relationship between the explanatory variables (input factors) and the dependent variable (output) through the presence of quadratic terms. The interaction terms also allow for analysis of substitutability and complementarity in effects. Hence, the Translog production function is considered to be more flexible function (Pavelescu 2011).

An important issue is the specification of technical change. In order to be able to test for technical change, a trend variable t has to be implemented in the deterministic part $f(.)$, the quadratic term t^2 will be included in the model (as the model is Translog and has the full functional forms) to capture the increase/decrease rate of technical change over time. Moreover, the multiplicative interactions between time trend t and the inputs factor of production allow for the possibility to test whether technical change is factor augmenting or not (Pavelescu 2011).

5.7.4 Models for Production Risk

An econometric panel data model can be specified using the generalized Just and Pope Production function technology such that it allows for production risk to be included as follows:

$$y_{it} = f(x_{it}, T, \alpha, \mu_i) + u_{it}, \quad \mathrm{Var}(u_{it}) = g(x_{it}, T, \beta) \tag{5.21}$$

where x_{it} is a vector of input for industry i at time t, The time specific effects T represent the state of production technology, α and β are vector of parameters to be estimated, μ_i is a vector of industry specific affects (industry characteristics), and u_{it} is the random error component assumed to have zero mean and constant variance.

The model specified in Eq. (5.21) is considered flexible due to the following reasons:

1. The use of functional forms: The elasticities of input and scale will be differed in mean, i.e. $f(x_{it},T,\alpha,\mu_i)$ and variance $\mathrm{Var}(u_{it}) = g(x_{it},T,\beta)$ *will be* differed according to the input levels. As mentioned before, many scholars in their empirical studies have used for simplicity the basic Cobb-Douglas production function, in which it has restrictive functional forms in the mean (deterministic) and the variance part. Hence, the second order functional form is computed and industry specific effects are estimated in this study, and sensitivity test is conducted for the choice of the functional forms. This will allow for different levels of output risk for industries that use the same amount of input quantities (Driscoll et al. 1992).
2. A Translog mean function is also estimated and different elasticities' estimates are compared. In such models, the industry specific effects on mean output will multiplicatively interact with the mean production function (Heshmati 2001;

Tveterås 2000). In other words, $E(y_{it}) = f(x_{it})* \exp(\mu_i + y_{it})$ rather than additive as in the case of linear forms. The Translog model will specify more accurately the industry specific effects. The reason is that the difference between mean outputs of industry i and mean outputs of industry j that have two different industry specific effects will tend to increase with the increase in scale operations.

3. More flexibility in pattern of technological change and responsiveness in output to changes in inputs are accounted for in this study. The rate of technical change and the input elasticities are calculated at each point of the data. As a result, they differ by year, industry, time period, and industry's characteristics. This will allow explaining the result in more detailed form.

5.7.5 Specification of the Variance

The production risk variance of Just and Pope (1978) specified in Eq. (5.21) is used, but here in the context of energy demand, which is an inverted factor demand derived from an industrial production function. The production risk function in Eq. (5.21) consists of two parts a mean production function and a variance function. In similar way, the energy demand model is generalized to incorporate the key input factors of production and variance of energy demand.

A flexible Translog functional form can be used to represent the energy demand function, when the demand for energy is a function of energy price, ICT capital, industrial production activities, quasi-fixed inputs, other control variables, and industry and time specific effects. The variance function appears multiplicatively with the demand function, it accommodates both positive and negative marginal effects of determinants of energy demand and its effect on energy consumption pattern.

Unlike in traditional models with heteroskedasticity but in unknown form, the variance function allows the energy demand model to be heteroskedastic of specified form. It is specified to be a function of the production input factors (including ICT capital) as well as energy policy and environmental variables. A multi-step procedure is used to estimate the parameters of the proposed energy demand model to estimate energy use efficiency. The energy use efficiency is defined in terms of a shift in energy demand over time and the distance from the frontier defined as the minimum energy required by an industry to produce a given level of output (For more details, see: Heshmati 2001; Kumbhakar 1997).

The approach used here is not a production function approach, it is rather an inverted energy factor demand approach (Diewert 1974), or so called a factor requirement. In addition, the energy demand is specified to incorporate variance of the demand as well. Different combinations of input factors affect both the mean and the variance of the energy demand and help to estimate the impact and identify the source of the variance representing variations in energy consumption.

A non-optimal level of energy consumption with a high dispersion has a major impact on the profitability of the industry. Certain input factors may help to reduce the dispersion in the event of unexpected and rapid changes in the energy supply (Zahan and Kenett 2013).

5.8 Model Specification

5.8.1 *Two-Stage Estimation Procedure for the Variance Function Parameters*

A two-stage estimation procedure exists for the Just and Pope Production function. It relies on the use of a consistent estimator of the variance function parameters vector β in the first stage. The least square estimate of β is consistent, and can be used in the first stage. In the second stage β is estimated relying on the specification described in Harvey (1976) as follows:

$$\widehat{\beta}_{(2)} = \widehat{\beta}_{(1)} + \Phi + 0.2804\left[\sum\nolimits_{i=1}^{n} z_i' z_i\right]^{-1} \sum\nolimits_{i=1}^{n} z_i' e^{-z_i \widehat{\beta}_{(1)} \widehat{u_i^2}} \tag{5.22}$$

where $\widehat{\beta}_{(1)}$ is the first stage (estimated by least square) estimate of the $m \times 1$ parameter vector β, z_i is the $1 \times m$ vector of regressors (with first element one), Φ is $m \times 1$ vector, in which the first element is (0.2804) and the remaining elements are zero. The second stage is to estimate $\widehat{\beta}_{(2)}$, it is considered asymptotically efficient (Tveterås 1997).

5.8.2 *Estimation of the Energy Demand Model Using Production Risk Approach*

Let the Energy demand function of South Korean industries be specified as follows:

$$e = f(y, p, q, t)e^{\varepsilon}, \varepsilon = \mu + \upsilon \tag{5.23}$$

where e is the energy demand, f represents the functional form of the consumption technology, y is the value added which is produced by using energy input, p is the price of energy, q is a vector of quasi-fixed factor inputs of production, and t represents the consumption technology. The relationship specified in Eq. (5.23) defines the consumption possibility frontier, given the level of e as depicted by Diewert (1974). The model can be viewed as the energy input requirement function.

An industry i may use energy in excess of what is technically necessary to produce a given level of output. Thus, its demand for energy depends on the following factors:

1. The functional form of the consumption technology *f*.
2. The energy use inefficiency μ.
3. Random factors v outside the control of the industries such as different types of unanticipated policies and external shocks with impact on the industry.

According to Aigner et al. (1977), the value of $\mu \geq 0$ is interpreted as energy use inefficiency or overuse of energy in this case. It represents the percentage of energy consumption in excess of the minimum amount of energy required to produce a given level of output. If $\mu = 0$ for an industry, it is said to be fully efficient in the use of energy. Since random factors can be both be favorable $v < 0$ and unfavorable $v > 0$, the error term v takes both positive and negative values, i.e. $-\infty < v < \infty$. The energy demand frontier is obtained by setting $\mu = 0$. The energy demand frontier is, therefore, stochastic because of the presence of v. In similarity with the commonly known stochastic frontier production model, the demand model here is a stochastic energy demand model.

The energy demand function can be generalized to incorporate risk according to Just and Pope (1978) and interpreted as energy demand frontier written as:

$$e = f(x;\alpha)e^{g(x;\beta)}\varepsilon \tag{5.24}$$

where $x = (y,p,q,t)$, *and* $f(x;\alpha)$ is the deterministic part, $g(x;\beta)\varepsilon$ is the variance part and can be modeled as known heteroskedasticity, where x (input factors) are the prime determinant of variance of energy use. Taking logarithm of Eq. (5.24), the model, its mean and variance can be written in linear form as follows:

$$ln(e) = ln(f(x;\alpha)) + g(x;\beta) + \varepsilon \tag{5.25}$$

$$E(e) = f(x;\alpha)e^{\frac{[g(x;\beta)]^2}{2}} \tag{5.26}$$

$$V(e) = [f(x;\alpha)^2]e^{[g(x;\beta)]^2}\left(e^{\frac{[g(x;\beta)]^2}{2}} - 1\right) \tag{5.27}$$

If $E(e) \geq f(x;\alpha)$, the marginal effect (marginal variance) with respect to input j is:

$$\begin{aligned} ME_j &= \frac{\partial V(e)}{\partial x_j} \\ &= 2 \cdot f(x;\alpha) \cdot e^{\frac{[g(x;\beta)]^2}{2}} \cdot \left(f_j(x;\alpha)e^{[g(x;\beta)]^2} - 1\right) + f(x;\alpha) \cdot g(x;\beta) \cdot g_j(x;\beta) \\ &\quad \cdot \left(2e^{[g(x;\beta)]^2} - 1\right) \end{aligned} \tag{5.28}$$

The rate of technical change from period s to period t can be specified, assuming a Translog specification as follows:

$$TC_{s,t} = (\theta_t - \theta_s) + \sum_j (\theta_{j,t} - \theta_{j,s}) \ln(x_j) \tag{5.29}$$

where the term $(\theta_t - \theta_s)$ is the pure component that is only time dependent, and the summation term is the non-neutral component depends on the level of input utilization.

In a production case, the elasticity of output with respect to input j is specified as follows:

$$E_j = \frac{\delta y}{\delta x_j} \cdot \frac{x_j}{y} = \frac{\delta lny}{\delta lnx} = \beta_j + \sum\nolimits_k \beta\, C_{kj} lnx_k + \beta\, C_{jt} \tag{5.30}$$

From Eq. (5.30), the subscripts representing industry and time periods are neglected for simplicity. The vector of parameters β is the estimated coefficients of the production model.

The rate of returns to scale RTS is the sum of j output elasticities in a production function case, it can be calculated as sum of the input elasticities as follows:

$$RTS = \sum\nolimits_j \left(E_j(x)\right) = \sum\nolimits_j \frac{\partial f}{\partial x_j} \cdot \frac{x_j}{f(x)} \tag{5.31}$$

The value of RTS determines the rate of returns to scale. If RTS is greater than one, the returns to scale is increasing; if it is less than one, it is interpreted as decreasing, and if it is equal to one, it is said that the production is subjected to constant returns to scale (Allen et al. 2009). In the case of energy demand, the returns to scale is obtained as a derivative of energy demand with respect to changes in the output. Its inverse form represents the returns to scale corresponding to the one explained in above in a case of production function.

Using a Translog functional form to approximate f in Eq. (5.24), the following relation can be obtained:

$$\begin{aligned} lne_{it} = {} & \alpha_0 + \sum_i \alpha_i lny_{it} + \alpha_p lnp_{it} + \alpha_q lnq_{it} + \frac{1}{2}\left\{\sum_i \sum_k \alpha_{ik} lny_{kt} + \alpha_{pp} lnp_{it}^2 + \alpha_{qq} lnq_{it}^2\right\} \\ & + \sum_i \alpha_{ip} lny_{it} lnp_{it} + \sum_i \alpha_{iq} lny_{it} lnq_{it} + \alpha_{pq} lnp_{it} lnq_{it} \\ & + \left\{\sum_i \beta_i y_{it} + \beta_p p_{it} + \beta_q q_{it} + \beta_t t\right\} \times [\mu_i + v_{it}] \end{aligned} \tag{5.32}$$

where e, y, p, and q are variables as defined previously (i.e. energy input, output, and vector of quasi fixed inputs). The subscripts i and t in Eq. (5.32) represent unobservable industry (i = 1, 2,...,25), and time period (t = 1, 2,...,35), respectively.

The same steps outlined in Heshmati (2001) are applied in this study which used this model in the context of labor demand. The estimation steps are as follows:

1. Ignore the variance function g(x; β) and estimate Eq. (5.32) by Oridnary Least Square (OLS) or Least Squares Dummy Variable (LSDV), where μ_i is estimated from *N-1* industry. The error term which contains the variance function parameter will be heteroskedastic (heteroskedasticity of unspecified form) (Caudill et al. 1995; Kumbhakar 1997).
2. From estimating α, and μ in step 1, the residual can be obtained as follows:

$$res_{it} = lne_{it} - \{\alpha + \sum_i \alpha_i lny_{it} + \alpha_p lnp_{it} + \alpha_q lnq_{it} + \frac{1}{2}\left[\sum_j \sum_k \alpha_{jk} lny_{jit} lny_{kit} + \alpha_{pp} lnp_{it}^2 + \alpha_{qq} lnq_{it}^2\right] + \sum_j \alpha_{jp} lny_{jit} lnp_{it} + \sum_j \alpha_{jq} lny_{jit} lnq_{it} + \sum_j \alpha_{pq} lnp_{it} lnq_{it} + \mu_i\} \quad (5.33)$$

The values of the estimated residual will be used to estimate the variance function by non-linear estimation method as follows:

$$\ln(res_{it}) = -1.2704 + ln\left\{\sum\nolimits_j \beta_j y_{jit} + \beta_p p_{it} + \beta_q q_{it} + \beta_t t\right\} + lnv_{it} \quad (5.34)$$

It should be noted that the energy demand is a flexible Translog functional form, while the variance function is in a simple formula without any interaction and square terms. The error term converges to v_{it}, which is a Chi-square statistics with one degree of freedom. Therefore, according to theorem 2 in Just and Pope (1978), the mean and the variance of lnv_{it} are (−1.2704) and (4.9348), respectively (Griffiths and Anderson 1982). The models in Eqs. (5.32) and (5.34) together form a non-linear model and therefore must be estimated in an iterative procedure accounting for heteroskedasticity by using the Generalized Least Square (GLS) estimator (Greene 2008; Wansbeek and Kapteyn 1989), in order to obtain efficient estimates of α and β. GLS is more efficient than simple least squares dummy variable estimates of the model.

Since the model is non-linear, an iterative procedure is used. Convergence will be obtained after repeated iteration process, which is equivalent of using maximum likelihood estimation method (Greene 2008).

In addition, estimates of the elasticity of energy consumption with respect to price, output, and all inputs considered as quasi fixed, and the elasticity of energy demand with respect to time (representing the rate of technical change) are provided. These measures of elasticities are corresponding to those defined for the output production. The measures of returns to scale and technical change are obtained in similar way. The measures of elasticities will be helpful in analyzing the impact of technical change on the mean input and the variance output, and for the analysis of marginal effects for mean inputs and the variance output and their properties. The rate of technical change and returns to scale are further used to compute the total factor productivity for each industry, each year, and other characteristics of the industry, and time periods (Tveterås 2000).

The marginal risk effect (ME) for *g*(.) which is analogous to the demand elasticity based on *f*(.) can be also calculated. A variable is variance increasing if $ME > 0$, and variance decreasing if $ME < 0$. The total marginal effects (sum of individual *ME*) is analogous to the scale effect in energy consumption derived from *f*(.), if the total marginal effects is greater than zero, i.e. $ME > 0$, then an expansion of output level leads to increase in energy consumption variance. The variance and *ME* can be used as policy variables (Battese et al. 2000), in which it helps to identify which factors increase or decrease the variance of the energy demand.

5.9 Sampling Distribution Properties

Although knowledge about the large sample properties of an estimator is desirable, it rarely happens when a researcher obtains a data set large enough to invoke asymptotic properties when choosing an estimator. Let θ denotes any element of the parameter vector ($\alpha_1,\ldots, \alpha_k, \beta_1,\ldots, \beta_m$). The following sampling distribution properties for the element $\widehat{\theta}$ of θ will be analyzed as follows:

- The estimated expected value is: $\mathrm{Exp}\left(\widehat{\theta}\right) = \left[\sum_{i=1}^{r} \widehat{\theta}_i\right]/r$, where $\widehat{\theta}_i$ is the parameter estimate in sample *i*, and *r* is the total number of repeated samples.
- The mean square error (MSE) of $\widehat{\theta}$ estimated by the average of the squared difference between $\widehat{\theta}$ and the true parameter value θ is:

$$MSE\left(\widehat{\theta}\right) = \left\{\sum_{i=1}^{r}\left(\widehat{\theta}_i - \theta\right)\right\}^2 \Big/ (r-1),$$

The MSE measures how much the estimator $\widehat{\theta}$ differs around the true parameter value in *r* repeated samples.

- The probability of rejecting a false null hypothesis H_0: $\theta = 0$, measures by the average estimated t-ratio is equal to: $\widehat{t}_o = (1/r)\sum_{i=1}^{r}\left(\widehat{\theta}_i/SE\left(\widehat{\theta}_i\right)\right)$, where $SE\left(\widehat{\theta}_i\right)$ is the standard error of the estimator in a sample experiment *i*.
- The probability of rejecting a true null hypothesis H0: θ = actual value is measured by the t-ratio: $\widehat{t}_o = (1/r)\sum_{i=1}^{r}\left\{(\widehat{\theta}_i - \theta)/SE\left(\widehat{\theta}_i\right)\right\}$.

5.10 Summary

This chapter discussed the econometric issues associated with the model choice for econometric estimation at a general level. The industry heterogeneity and heteroskedasticity are discussed. Heterogeneity with respect to production technology and productivity is crucial when estimating panel data sets. The heteroskedasticity in the estimated models will be presented in the disturbance part (error term). The error component will consists of three parts time, industry, and random components, if the time invariant industry specific is assumed fixed, then it is called a fixed effect, while it is called a random effect if it is assumed random.

Some important issues associated with panel data are discussed both in general level and more specifically in the context of production analysis and factor demand, focusing on specific problems that are relevant to the empirical application of this study. With the availability of panel data sets, one can account for heterogeneity in the econometric modeling.

The importance of model specification and estimator choice for empirical results are demonstrated for all the three groups of models estimated in this study, i.e. production model, energy demand without risk, and energy demand with risk incorporated in the specification. The issue of model specification involves the choice between simple and flexible functional forms for the stochastic production function and energy demand function, the fixed effects and the treatment or the industry specific effects are all discussed and demonstrated. Based on different test statistics, the flexible Translog functional form has been proved to be superior in relation with the simple nested Cobb-Douglas specification form.

The issue of industry heterogeneity specification has also been accounted for in this study. Inclusion of industry fixed effects have significant impact on the elasticities estimated based on derivation of both mean and variance functions.

The generalized form of Just and Pope Production function is considered as groundwork for this study for modeling and estimating the production risk, as it allows for increasing and decreasing the risk of output by the use of different inputs. The generalized Just and Pope Production function is utilized to study the statistical relationship between energy use and output, technology and certain other input factors of production, and to quantify the impact of these factors.

The model choice decision depends on the data availability and the complexity of the specification issues for the specific industry which is the subject for empirical analysis. The model choice depends also on the focus of the study; whether the primary interest is the structure of the production technology or input demand and output supply elasticities in prices.

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Chapter 6
The EUKLEMS Database

The data used in this study is obtained from the harmonized EUKLEMS Growth and Productivity Account database released in 2009. It includes variables that measure output and input growth, and derived variables such as multi-factor productivity at the industry level. The input measures include different categories of inputs: Capital, labor, energy, materials, ICT capital, and value added services inputs. The data sample composes a panel data of 950 observations taken from 25 South Korean industries observed for the period 1970–2007. Additional variables are also included such as the energy price, volumes, growth accounting, and some other control variables. For the models specification, explanatory variables that show higher correlation with the dependent variable are chosen. The explanatory variables that show high correlation with each other are either neglected or transformed and treated by correcting for heteroskedasticity to prevent the confounded effects estimated in the form of coefficient. The data set for the South Korean industries is classified based on different industries' characteristics such as technology level, export orientation, scale of R&D investment, industry size in terms of labor used, and labor skill. Due to the difference in the production process, some industries consume higher rate of energy per unit of output than other industries. This difference is often labeled as heterogeneity in industries' energy use. Various groups of industries are consuming energy for different purposes and activities such as space conditioning, lightening, processing, and assembly. The nature of activities explains much of the variations in energy use per unit of output. Different tests procedures for heterogeneity are offered. A test called analyses of variance (ANOVA) is performed using the generalized linear model to test for heterogeneity among the industries' level of output.

6.1 Introduction

This chapter presents the study as it was conducted according to the procedures stated in chapter five. It includes the description of the data sample, population and sampling strategy, along with a summary statistics of the raw data. The industries are classified based on different characteristics such as technology level, market

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orientation, and R&D spending. Measures for energy intensity in the industries are also provided. The issue of multicollinearity is also discussed and appropriate remedies are proposed, and finally, different empirical tests procedures for heterogeneity and heteroskedasticity are offered in this chapter.

6.2 The Data Source

The data used in this study is obtained from the harmonized EUKLEMS Growth and Productivity Account database (November 2009 released).[1] The database includes variables that measure output and input growth, and derived variables such as multi-factor productivity at the industry level (For details about the EUKLEMS Growth and Productivity Account Database, see: O'Mahony and Timmer 2009). The input measures include various categories of capital, labor, energy, materials, ICT capital, and value added services inputs.

The main objective of the EUKLEMS Growth and Productivity Account Database is to support empirical studies as well as theoretical researches in areas related to economic growth, productivity, skill formations, innovation, and technological progress (O'Mahony and Timmer 2009). The data in the EUKLEMS Growth and Productivity Account database contains varieties of basic input data series, in which it derived separately from the growth accounting assumptions methodology. Different categories and classes of capital, labor, materials, and energy inputs are provided in cooperation between the EUKLEMS consortium partners and national statistic offices in the partner countries (O'Mahony and Timmer 2009).

The provision of the data came in two stages: The first stage was to take from the national accounts databases all the most updated figures of gross output, value added, and total intermediate inputs for all the industries broken down into more industry details. The second stage was to break down the total intermediate inputs into energy, value added services, and materials (O'Mahony and Timmer 2009). The data collection is standardized across the OECD sample country's industries. It provides a clear conceptual framework, in which the interaction between variables can be analyzed in an internally consistent way.

The greatest advantage of this data set is that it provides data series for almost entire organized industries (O'Mahony and Timmer 2009). The capital compensation is derived as the difference between the value added and the labor compensation. The labor compensation variable is derived using the proportion of total hours worked by total involved persons to total hours worked by employees to compensation. Other inputs such as materials, energy, and value added services are computed from the share of each of these inputs from the national account. The

[1]The database is publicly available on http://www.euklems.net.

energy input is the aggregate of energy mining, oil refining, electricity, and gas products (O'Mahony and Timmer 2009).

The variables measures in addition to the measures mentioned above consist of measures for export/import oriented industry, industry size, R&D intensity, and labor skills category of high, medium, and low developed for 25 main industries in South Korea. The data covers the period from 1970 to 2007 and consists of 950 observations.

6.3 Population and Sampling Strategy

The data sample composes a panel data of 25 South Korean industries observed for the period from 1970 to 2007. The variables used in this study include in addition to the key input factors mentioned in the previous section values for price of energy, volumes, growth accounting, and some other control variables. The variables of monetarily measures for example intermediate inputs, gross output, and gross value added are all given in fixed 1995 prices.

The EUKLEMS Growth and Productivity Account Database provides also capital and labor compensations and their volumes, and additional variables such as skilled labor compensation and ICT capital compensation and their volumes. A detailed summary list of the complete data set and brief definitions of variables is presented in Table 6.1.

6.4 Classification of the Industries

The South Korean industries are divided into 26 industries using the international industry classification system (U.N. 2008). The EUKLEMS Growth and Productivity Account database provides subordinate structure of the industries more precisely (See Table 6.2). Even though the South Korea industries are divided in more detailed form, the database does not provide energy data. In this case, the upper classification containing sub-industries is used. An industry with the code P is excluded from the data set as the proportion is relatively small in compare to the other industries.

The figures reported in Table 6.2 reflect the fact that each industry has unique characteristics concerning concentration, technology level, scale of R&D, and the degree of export orientation. The total industry is divided into three parts in terms of technology concentration: High, medium, and low technology industries. The R&D intensity is divided according to the proportion of R&D expenditure in each industry. The labor skill is categorized into three categories: High, medium, and low skills. The technology level (denoted as tech) is derived as high, medium, and low, through the industry's international classification. Note that the number of industries under this study in terms of technology level is 12, 5, and 8 for low, medium, and high technology, respectively. The degree of export orientation (denoted as

Table 6.1 Variable used and their definitions

Variable	Definition
A. Dependent variables: output and energy demand	
GO	Gross output at fixed 1995 prices (in millions of Korean Won)
IIE	Intermediate energy inputs at fixed 1995 purchasers' prices (in millions of Korean Won)
B. Independent variables: input factors of production and energy price variables	
II	Intermediate inputs at fixed 1995 purchasers' prices (in millions of Korean Won)
LAB	Labor compensation at fixed 1995 prices (in millions of Korean Won)
CAP	Capital compensation at fixed 1995 prices (in millions of Korean Won)
IIM	Intermediate material inputs at fixed 1995 purchasers' prices (in millions of Korean Won)
IIS	Intermediate service inputs at fixed 1995 purchasers' prices (in millions of Korean Won)
Penergy	Price of energy at 1995 prices
CAPIT	ICT capital compensation at fixed 1995 prices (share in total capital compensation)
VA	Gross value added at fixed 1955 prices (in millions of Korean Won)
COMP	Compensation of employees at fixed 1995 prices (in millions of Korean Won)
C. Volume indices: 1995 = 100	
GO_QI	Gross output, volume indices
IIE_QI	Intermediate energy inputs, volume indices
GO_P	Gross output, price indices
II_P	Intermediate inputs, price indices
II_QI	Intermediate inputs, volume indices
LAB_QI	Labor services, volume indices
CAP_QI	Capital services, volume indices
IIM_QI	Intermediate material inputs, volume indices
IIS_QI	Intermediate service inputs, volume indices
VA_P	Gross value added, price indices
VA_QI	Gross value added, volume indices
CAPIT_QI	ICT capital services, volume indices
D. Other explanatory and characteristics variables	
Industry	Industry name (or code) (25 industries)
Year	Year of observation (1970–2007)
EMPE	Number of employees (thousands)
H_EMPE	Total hours worked by employees (millions)
LABHS	Hours worked by high-skilled persons engaged (share in total hours)
LABMS	Hours worked by medium-skilled persons engaged (share in total hours)
LABLS	Hours worked by low-skilled persons engaged (share in total hours)

Source EUKLEMS growth and productivity account database, November 2009 release

Table 6.2 Classification of the South Korean industries

Industry ID	Industry description	EUKLEMS code	Technology level	R&D intensity level	Market orientation
1	Agriculture, hunting, forestry and fishing	A + B	L	M	L
2	Mining and quarrying	C	L	L	L
3	Food, beverages and tobacco	15t16	L	M	M
4	Textiles, leather and footwear	17t19	L	M	H
5	Wood and cork	20	L	L	L
6	Pulp, paper, printing and publishing	21t22	L	H	M
7	Chemical, rubber, plastics and fuel	23t25	H	M	H
8	Other non-metallic mineral	26	M	M	L
9	Basic and fabricated metals	27t28	M	L	M
10	Machinery, NEC	29	H	H	H
11	Electrical and optical equipment	30t33	H	H	H
12	Transport equipment	34t35	H	M	H
13	Manufacturing NEC, recycling	36t37	H	M	H
14	Electricity, gas and water supply	E	M	H	L
15	Construction	F	H	H	H
16	Wholesale and retail trade	G	L	M	L
17	Hotels and restaurants	H	L	M	L
18	Transport and storage	60t63	M	L	L
19	Post and telecom	64	H	H	H
20	Financial intermediation	J	M	H	L
21	Real estate, renting and business activities	K	L	L	L

(continued)

Table 6.2 (continued)

Industry ID	Industry description	EUKLEMS code	Technology level	R&D intensity level	Market orientation
22	Public admin and defense; compulsory social security	L	L	H	L
23	Education	M	L	H	L
24	Health and social work	N	H	H	L
25	Other community, social and personal services	O	L	L	L
26	Private households with employed persons	P	–	–	–

Note The industry with the code P is excluded and not considered in this study due to data incompleteness in the Korean part of EUKLEMS

export) according to the industry classification as high for international market or export oriented, medium for mix of international and domestic and, low for domestic only oriented market. There are 8 industries classified as export oriented market, 14 as domestic, and only 3 as mix market. The scale of R&D activities (denoted as rdinv) is also derived and classified as high, medium, and low level scale. From the total of 25 industries, 10 industries are classified as high R&D intensive, 9 industries as medium R&D intensive, while 6 industries are classified as low in R&D intensive.

6.5 The Dependent and the Independent Variables

This study estimated three groups of models, for the first group model, the dependent variable output is correlated with composite independent variable of input factors of production and time trend. For the other two groups of models, the dependent variable of energy demand is correlated with composite independent variable of other inputs factors of production, output, and time trend.

The composite independent variables for the dependent variable output are non-ICT capital, labor, energy, materials, ICT capital, value added services, and time. The composite independent variables for the dependent variable energy are non-ICT capital, labor, materials, ICT capital, value added services, output, price of energy, and time. The independent variables represent the factors that affect the dependent variables and investigated to assess their correlations. Some control variables (or so called dummy variables) are also included as independent variables to capture the industry and time specific effects.

6.6 Multicollinearity and Validation of Results

For the specification of the production and energy demand models under this study, explanatory variables that show higher correlation with the dependent variable are selected. The explanatory variables that show high correlation with each other are either neglected or transformed and treated in the model by correcting for heteroskedasticity to prevent the confounded effects estimated in the form of coefficient (For different Hetersokedasticity tests, see: Greene 2008).

Values of correlation coefficients computed by applying the Pearson product moment and Spearman's rank order correlation found to be within the interval [0–0.3] are considered weak, between [0.3–0.7] are considered moderate, and those between the interval [0.7–1.0] are considered high correlated (Wooldridge 2006). However, an accepted interval for correlation as reported by Wheeler and Tiefelsdorf (2005) is below (0.59). In all the models under this study the correlation coefficients for the most independent variables that are reported in Table 6.3 for the production model and energy demand model without risk and Table 6.4 for the risk model are less than (0.59) and statistically significant at 99 % level of significance. This implies that multicolinearity is not a serious problem in this study. Some of the explanatory variables are positively correlated with each other, while some others have negative correlations. The only four high positive values that are above the acceptable range are labor productivity with capital intensity, materials with value added services, non-ICT capital with value added services, and labor with value added services (0.793), (0.718), (0.717), and (0.705), respectively.

The results shown in Tables 6.3 and 6.4 suggest a high complementarity between these variables in energy demand and possibility of confounded effects. However, in this study a Translog specification and various elasticities that each consist of summation of several effects are used. Hence the impact of individual components is only a small fraction of the total effect in a way that reduces the multicollinearity effects (Pavelescu 2011). Given the number of interaction terms and squared terms incorporated in all the models under this study, the problem of severe multicollinearity is expected in estimating these models. In order to avoid omission of important variables in the model, this study accounted for correcting for heteroskedasticity in all the models under estimation.

Table 6.3 Pearson correlation coefficients, output, inputs variables and time trend

	Output	Capital	Labor	Energy	Material	Service	ICT-capital	T
Output	1							
Capital	0.784	1						
Labor	0.682	0.533	1					
Energy	0.439	0.315	0.303	1				
Material	0.918	0.611	0.455	0.373	1			
Service	0.892	0.717	0.705	0.467	0.718	1		
ICT-capital	0.349	0.366	0.467	0.248	0.202	0.342	1	
T	0.490	0.361	0.513	0.491	0.365	0.555	0.262	1

Table 6.4 Pearson correlation coefficients for energy demand models

	Energy	Output	Capital	Labor	Material	Service	ICT	Tech	Export	R&D	Period	Size	Labor productivity	Capital intensity	High skilled	Medium skilled	Low skilled	Outsourcing
Energy	1																	
Output	0.5	1																
Capital	0.3	0.8	1															
Labor	0.4	0.7	0.5	1														
Material	0.3	0.9	0.6	0.5	1													
Service	0.5	0.9	0.7	0.7	0.7	1												
ICT	0.2	0.3	0.4	0.5	0.2	0.3	1											
Tech	0.0	−0.1	0.0	0.1	−0.2	−0.1	0.1	1										
Export	0.0	−0.2	0.0	0.1	−0.4	−0.1	0.1	0.7	1									
R&D	0.0	−0.1	0.1	−0.2	−0.1	0.0	−0.2	0.4	0.3	1								
Period	0.9	0.4	0.3	0.5	0.3	0.5	0.3	0.0	0.0	0.0	1							
Sze	0.0	0.3	0.2	0.4	0.2	0.4	0.2	0.1	0.0	0.1	0.0	1						
Labor productivity	0.5	0.5	0.5	0.2	0.5	0.4	0.2	−0.1	0.0	−0.1	0.4	−0.3	1					
Capital intensity	0.2	0.2	0.4	0.0	0.1	0.1	0.0	0.1	0.2	0.0	0.2	−0.3	0.8	1				
High skilled	0.3	0.2	0.3	0.5	0.0	0.2	0.3	0.0	0.3	−0.4	0.3	0.1	0.2	0.2	1			
Medium skilled	0.2	0.2	0.1	−0.2	0.3	0.2	−0.2	−0.2	−0.4	0.2	0.3	−0.1	0.2	0.0	−0.5	1		
Low skilled	−0.5	−0.3	−0.3	−0.5	−0.2	−0.4	−0.3	0.1	−0.1	0.4	−0.5	−0.1	−0.3	−0.2	−0.8	−0.1	1	
Outsourcing	0.0	0.1	0.2	0.4	0.0	0.1	0.1	0.3	0.2	0.1	0.0	0.3	−0.1	0.0	0.1	−0.1	0.0	1

6.7 Overview of Statistical Analysis

6.7.1 Summary Statistics

The data set for this study is comprised of 950 observations taken from 25 main industries in South Korea observed for the period 1970–2007. The data includes a number of variables pertaining to industry's level of input-output production data, as well as industry's level of demand for energy and industry and time period characteristics. A summary statistics for the variables and its raw data is presented in Table 6.5. As mentioned previously, the industry with the code P (industry 26) is excluded and not considered because it is missing in the Korean data.

Prior to estimation, the input levels are normalized to their sample means. This procedure will simplify the analysis of estimated elasticities particularly for the variance function (Wooldridge 2006). The data set is transformed by taking the natural logarithms of continuous and positive variables. There are many benefits when the data is transformed as described by Roberts (2008): First, it ensures that data is distributed symmetrically, second, it ensures a better equally dispersion across various levels, and third, it also benefits when constructing linear relationships between the variables. In addition to that, the main advantage of logarithmic transformation is direct interpretation of the result in form of elasticities. They correspond to percentage change in dependent variables in response to percentage change in independent variables. Prior to estimating the models, the inputs variables are normalized by dividing them by their sample means. This procedure simplifies the analysis of estimated elasticities, especially those related to the variance function.

In addition to data normalization, different variables were derived from the existing variables as follows: The real price of energy (denoted as xpenergy) is derived by dividing the intermediate energy input (denoted as IEE_QI) with the intermediate inputs price indices (denoted as II_PI), the labor productivity (denoted as labpro) by dividing the gross output with the number of employees (denoted as EMPE), the capital intensity (denoted as capint) by dividing the capital compensation (denoted as CAP) with EMPE. A variable (denoted as period) with three values is created to capture the data within the three different economic crises, period 1 is for the time before 1980, period 2 for the period 1980–1996, and period 3 for the period 1997 and above. These are corresponding to the oil crisis, before Asian financial crisis, and before global economic crisis, respectively. The variable size of industry (denoted as size) is created based on the observed year and total number of employees for each individual industry, and based on that a three size scale (small, medium, and large) measure is created. The labor productivity (labpro) and the capital intensity (capint) are derived by dividing the output by (EMPE) and the capital by EMPE, respectively (Thomas and Mathews 1986). The category of labor skills is defined as high (denoted as LABHS), medium (denoted as LABMS) and low (denoted as LABLS), while outsourcing labor (denoted as outs) is defined as the difference between the number of persons engaged in the production and the total number of employed in house.

Table 6.5 Summary statistic of the raw data, in 1995 prices, no. of obs. 950

Variable	Mean	Std. dev.	Minimum	Maximum	Coefficient of variation	t value
Industry	13.000	7.210	1.000	25.000	55.500	55.540
Year	1,988.500	10.970	1,970.000	2,007.000	0.550	5,586.20
Output	25,270,391.40	37,915,021.60	153,558.4	505,328,749.0	150.040	20.540
GO_QI	77.160	69.800	0.530	666.510	90.460	34.070
GO_P	74.110	44.090	1.910	196.310	59.490	51.810
II	14,656,346.10	25,153,285.70	6,749.000	192,260,745.0	171.620	17.960
II_QI	80.110	76.660	0.550	700.320	95.690	32.210
II_P	76.890	43.700	3.910	220.660	56.840	54.220
Labor	7,930,306.030	9,743,784.91	46,787.980	70,617,576.60	122.870	25.090
LAB_QI	83.260	52.900	2.790	430.100	63.530	48.510
Capital	2,989,091.440	5,393,115.90	0.180	53,010,075.50	180.430	17.080
CAP_QI	77.750	72.660	5.000	721.590	93.460	32.980
cenergy	1,505,701.130	3,845,394.640	7,796.820	39,412,084.10	255.390	12.070
IIE_QI	98.670	107.370	0.760	770.870	108.810	28.330
Material	9,183,631.570	18,896,083.50	25,916.900	271,959,294.0	205.760	14.980
IIM_QI	82.810	75.270	0.620	651.520	90.890	33.910
Service	3,871,294.850	6,311,234.930	17,272.150	74,636,919.70	163.030	18.910
IIS_QI	71.760	75.810	0.410	605.380	105.640	29.180
VA	9,949,715.120	15,039,148.70	9,834.560	101,237,264.0	151.150	20.390
COMP	4,948,954.930	7,696,430.470	3,882.020	46,421,526.80	155.520	19.820
EMP	673.020	914.530	16.000	5,514.0	135.880	22.680
Employed	384.950	437.780	13.000	2,646.710	113.720	27.100
Hours	1,691.290	2,271.730	40.450	14,893.530	134.320	22.950
VA_P	71.740	46.870	1.630	280.110	65.320	47.180

(continued)

Table 6.5 (continued)

Variable	Mean	Std. dev.	Minimum	Maximum	Coefficient of variation	t value
VA_QI	75.990	68.700	0.450	611.230	90.400	34.090
CAPIT	411,182.500	1,213,159.680	112.050	11,968,561.80	295.040	10.450
CAPIT_QI	97.750	106.740	0.500	786.520	109.200	28.230
LABHS	36.520	20.410	7.920	84.810	55.900	55.140
LABMS	38.470	11.390	12.240	61.460	29.610	104.110
LABLS	25.010	17.980	1.200	74.360	71.880	42.880
Penergy	47.990	26.660	10.700	113.500	55.550	55.490
Tech	2.160	0.880	1.000	3.000	40.760	75.610
Export	2.240	0.910	1.000	3.000	40.510	76.090
rdinv	1.840	0.780	1.000	3.000	42.620	72.310
Period	2.030	0.740	1.000	3.000	36.680	84.020
Size	2.030	0.820	1.000	3.000	40.540	76.040
DI: industry dummy	0.040	0.200	0.200	0.200	0.200	0.200
Shock1	0.030	0.160	0.000	1.000	608.60	5.060
Shock2	0.030	0.160	0.000	1.000	608.60	5.060
qenergy	98.670	107.370	0.760	770.870	108.810	28.330
xpenergy[a]	18,555.0	36,003.480	1,241.980	197,310.280	194.040	15.880
Outs	288.080	658.190	1.000	4,850.000	228.480	13.490
Labpro	80,675.270	84,965.640	3,609.320	688,484.740	105.320	29.270
capint	12,919.120	24,417.080	0.000	233,115.340	189.000	16.310

[a]xpenergy is a derived real price of energy calculated as (II_P divided by IIE_QI)

6.7.2 Classification of the Industries Based on Their Characteristics

The data set for the South Korean industries is further classified based on different characteristics of industries: Technology level, export orientation, scale of R&D investment, industry's size in terms of labor used, and labor skill. According to the figures reported in Table 6.6, a number of 8 industries are classified as high technology level industries with frequency data of 296 (32 % of the observations), the 5 medium tech level industries with frequency data of 185 account for 20 % of the data, while the largest portion (12 industries) is for the low technology level industries with frequency data of 444 (48 %).

The classification of industries based on export orientation in Table 6.7 shows that a number of 8, 3, and 14 industries are classified as international (export oriented), mixed (export and domestic), and only domestic oriented industries, respectively. Their frequency of data observations are 296, 111, and 518 accounting for 32, 12, and 56 %, respectively.

For the scale of R&D investment, according to Table 6.8, the number of industries with larger scale of R&D investment is 10 with frequency of data observations 370 (40 %), the number of medium scaled R&D investment is 9 with

Table 6.6 Frequency of data by industry's characteristic (technology level)

Technology	Frequency	No. of industries	Percentage	Cumulative %
High	296	8	32	32
Medium	185	5	20	52
Low	444	12	48	100
Total	925	25	100	–

Table 6.7 Frequency of data by industry's characteristic (export orientation)

Export	Frequency	No of industries	Percentage	Cumulative %
International	296	8	32	32
Mixed	111	3	12	44
Domestic	518	14	56	100
Total	925	25	100	

Table 6.8 Frequency of data by industry's characteristic (R&D Scale)

R&D	Frequency	No of industries	Percentage	Cumulative %
High	370	10	40	40
Medium	333	9	36	76
Low	222	6	24	100
Total	925	25	100	

Table 6.9 Frequency of data by industry's characteristic (size in terms of no. of employees)

Size	Frequency	No of industries	Percent	Cumulative %
Large	299	8	32	32
Medium	296	8	33	65
Small	330	9	35	100
Total	925	25	100	

Table 6.10 Frequency of data by industry's characteristic (labor skill)

Labor skill	Frequency	No of industries	Percent	Cumulative %
LABHS	339	9	37	37
LABMS	359	10	39	76
LABLS	227	6	24	100
Total	925	25	100	

frequency data of 333 (36 %), while only 6 industries are characterized by low scale in R&D investment with frequency data of 222 (24 %) observations.

The South Korean industries are classified based on the number of employees (size) for different time periods into large, medium, and small industries (see Table 6.9). During the period 1970–2007 a number of 8, 8, and 9 industries with relative frequency of 299, 296, and 330 are classified as large, medium, and small industries, respectively.

Another classification is based on the labor skills. From the figures reported in Table 6.10, the number of industries with a high skilled labor is 9 with frequency of 339 during the period 1970–2007. A number of 10 industries are classified as a medium skilled labor with frequency of 359. Only 6 industries were classified as a low skilled labor with frequency of 227.

6.7.3 *Inputs and Output Levels by Industry*

According to Table 6.11, there are differences in the mean output and input levels across the industries. The electrical and optical equipment (industry code 11) has the highest output accounting for 10 % of the total output for all industries, while the wood and cork (industry code 5) has the lowest output 0.33 % of the total output for all industries. In addition to the output level by industry, the different inputs' levels by industry are also reported.

Table 6.11 Output and input volume levels by industry

Industry	Output	Capital	Labor	Material	VA services	Energy	ICT
Agriculture, hunting, forestry and fishing	830,483,306	162,017,716	694,558,229	222,541,779	57,856,429	22,111,708	4,155,971
Mining and quarrying	85,605,552	27,568,435	21,350,800	12,086,612	13,364,916	11,991,392	80,206
Food, beverages and tobacco	1,040,515,118	81,771,495	105,746,189	725,113,513	109,935,975	20,819,104	1,599,404
Textiles, leather and footwear	822,983,369	47,038,802	138,825,435	485,112,037	99,690,952	52,241,468	709,725
Wood and cork	78,212,934	4,142,510	12,952,614	44,776,602	12,948,996	3,905,667	28,528
Pulp, paper, printing and publishing	403,038,653	26,394,968	86,258,356	207,945,238	64,230,087	18,203,058	528,977
Chemical, rubber, plastics and fuel	2,257,867,412	268,411,546	236,407,392	804,944,563	241,953,027	717,926,725	4,314,804
Other non-metallic mineral	360,656,283	44,369,320	70,039,115	130,996,989	51,307,046	62,857,861	403,285
Basic and fabricated metals	1,646,656,449	177,324,939	183,696,717	1,062,232,206	147,102,979	120,637,335	2,214,093
Machinery, NEC	505,099,954	33,469,960	96,882,533	448,757,025	101,871,689	17,905,801	871,486
Electrical and optical equipment	2,369,554,690	271,497,457	343,299,766	1,229,990,578	285,100,521	50,363,527	7,420,701
Transport equipment	1,427,903,410	82,133,106	230,334,203	922,509,346	154,684,050	40,432,842	2,033,671
Manufacturing NEC, recycling	189,971,997	11,429,454	42,182,489	95,775,766	30,431,022	10,436,722	242,289
Electricity, gas and water supply	497,422,211	155,066,151	68,598,385	82,201,663	38,975,265	152,567,111	680,316
Construction	2,096,612,682	18,540,489	894,081,906	777,060,116	371,327,847	36,662,855	235,960
Wholesale and retail trade	1,328,646,091	298,369,860	479,928,773	196,909,933	306,154,599	36,707,541	8,277,548
Hotels and restaurants	715,889,875	1,297,082	254,603,277	166,331,970	260,431,387	34,111,440	155,139
Transport and storage	1,053,123,908	83,580,116	366,248,753	168,701,586	398,101,663	46,278,819	505,041
Post and telecom	452,314,660	76,551,473	138,020,854	56,941,392	155,686,709	16,395,696	11,655,278
Financial intermediation	1,017,463,949	213,084,031	483,827,247	44,208,614	241,188,402	8,280,498	13,404,136
Real estate and business activities	1,696,633,585	598,126,465	504,237,639	203,453,584	354,648,476	30,341,402	9,138,919
Public admin and defense	862,734,453	72,531,536	626,719,076	158,250,369	130,675,194	17,495,447	730,540
Education	630,963,227	136,713,998	675,644,594	43,235,801	67,999,894	14,568,090	35,268,200
Health and social work	533,513,033	20,766,138	295,119,142	101,425,981	82,074,318	38,701,218	465,400
Other community, social and personal services	471,891,372	3,608,761	249,767,702	77,204,136	144,653,396	19,020,293	176,192

6.8 Energy Intensity in the Industries

In general, due to the difference in the production process, some industries consume higher rate of energy per unit of output than other industries. This difference is often labeled as heterogeneity in industries' energy use. Various groups of industries such as manufacturing, chemical, mining, agriculture, and fisheries are consuming energy for different purposes and activities such as space conditioning, lightening, processing, and assembly (IEA 2011). The nature of activities explains much of the variations in energy use per unit of output.

Table 6.12 shows relative energy intensity in the South Korean industries. The figures are obtained from dividing the total energy consumption by the total output for each industry and per decade multiplied by 100. The trends are obtained by differencing two consequence decades divided by the later decade. For example the trend 1970–1980 is obtained by differencing the figures of 1970s from 1980s and then dividing by 1980s figures.

According to Table 6.12, the most energy intensive industries are found to be the chemical, rubber, plastics and fuel industry (code 7), electricity, gas and water supply industry (code 14), other non-metallic minerals industry (code 8). Electricity, gas and water supply industry (code 14) has been relatively high energy intense since year 2000. Agriculture, hunting, forestry and fishing industry (code 1), machinery, NEC industry (code 10), transport equipment industry (code 12) and post and telecommunications industry (code 19) are above average use of energy. Mining and quarrying industry (code 2), hotels and restaurants industry (code 17), health and social work industry (code 24) and other community, social and personal services industry (code 25) consumed relatively less from year 2000 per unit of output. The least energy intensity Industries are public administration and defense industry (code 22), financial intermediation industry (code 20), electrical and optical equipment industry (code 11) and food and beverage industry (code 3).

The trend in energy intensity from the period 1970s to 1980s shows that the total energy intensity for all industries increased by 5.2 %. However, the trend in energy use of post and telecommunication industry (code 19) declined by 25.7 %, construction industry (code 15), other community, social and personal services industry (code 25), and education industry (code 23) declined in their energy intensity by 20.8, 18.5, and 17.0 %, respectively, during that period.

For the second period trend, i.e. 1980s–1990s, a noticeable decline in energy intensity is witnessed. The total energy intensity has decreased by 43.85 %. All industries with exception of post and telecommunication industry have declined in their energy intensity during that period. The decline in the energy consumption in that period was mainly due to introduction of new technology which allowed for some industries to produce their output with less energy input (Kim and Labys 1988), while the increase in the energy intensity for post and telecommunication industry is due to increase in the use of telecommunication services and equipment nationwide.

For the third period trend, i.e. 1990s to 2000s, a dramatic increase has been witnessed in the total energy consumption for all industries by 42.5 %. The main

Table 6.12 Energy intensity in the South Korean industries, 1970–2000

Code	Industry	Decades				Trends		
		1970	1980	1990	2000	1970–1980	1980–1990	1990–2000
1	Agriculture, hunting, forestry and fishing	2.15	2.48	2.08	3.31	15.28	−16.09	59.24
2	Mining and quarrying	26.47	27.22	8.13	7.87	2.84	−70.12	−3.23
3	Food, beverages and tobacco	2.68	2.43	1.68	2.09	−9.17	−30.73	23.83
4	Textiles, leather and footwear	8.60	7.78	5.04	6.98	−9.60	−35.24	38.46
5	Wood and cork	7.05	6.47	4.07	5.11	−8.24	−37.03	25.45
6	Pulp, paper, printing and publishing	5.96	5.47	3.62	4.91	−8.21	−33.89	35.56
7	Chemical, rubber, plastics and fuel	40.92	37.36	26.25	33.07	−8.71	−29.74	25.98
8	Other non-metallic mineral	23.86	21.70	15.09	18.36	−9.09	−30.44	21.67
9	Basic and fabricated metals	11.05	9.65	5.19	7.85	−12.72	−46.24	51.42
10	Machinery, NEC	3.32	3.38	2.57	4.12	1.75	−23.92	60.46
11	Electrical and optical equipment	2.38	2.03	1.41	2.39	−14.69	−30.35	68.72
12	Transport equipment	2.13	2.19	1.94	3.24	2.68	−11.41	66.78
13	Manufacturing NEC, recycling	7.93	7.53	4.29	5.68	−4.98	−43.11	32.56
14	Electricity, gas and water supply	30.01	27.15	22.86	33.57	−9.55	−15.78	46.85
15	Construction	3.63	2.87	1.33	1.89	−20.85	−53.62	41.43
16	Wholesale and retail trade	5.30	5.36	2.51	2.41	1.15	−53.16	−3.96
17	Hotels and restaurants	14.80	12.72	4.21	3.47	−14.08	−66.88	−17.64
18	Transport and storage	7.41	7.28	3.33	4.43	−1.78	−54.33	33.26
19	Post and telecom	3.01	2.24	2.24	4.04	−25.64	0.11	80.26
20	Financial intermediation	3.24	2.92	0.81	0.69	−10.11	−72.33	−14.28
21	Real estate and business activities	3.47	3.68	1.35	1.84	6.23	−63.39	36.56
22	Public admin and defense	1.79	1.75	1.70	2.24	−2.19	−2.94	31.99
23	Education	5.69	4.73	1.41	2.44	−16.96	−70.23	73.20
24	Health and social work	14.09	12.27	4.06	7.92	−12.89	−66.89	94.87
25	Other community, social and personal services	9.32	7.59	3.48	3.97	−18.53	−54.16	14.25
Total		**8.76**	**9.21**	**5.17**	**7.37**	**5.18**	**−43.85**	**42.50**

reason is the rapid economic development of South Korean economy. The economy is transformed to an industrialized economy. As a result, industries with high intensive energy use have grown rapidly due to structural changes in the Korean economy. Health and social work and, post and telecommunication and education industries have witnessed noticeable increase in energy intensity by 94.9, 80.2, and 73.2 %, respectively. This group of high intensive energy use Industries is followed by four other Industries including electrical and optical equipment, transport equipment, machinery, and agriculture, hunting, forestry and fishing. Their increase in energy intensity was 68.7, 66.8, 60.5, and 59.2 %, respectively.

In summary, heterogeneity in industrial energy use is observed in the South Korean industries due to differences in the production process. Some industries consume higher rate of energy than other industries. Despite large variations in energy use and intensity, the growth rates in the energy use have been relatively high and characterized as continuous process.

6.9 Empirical Test for Heterogeneity

There are varieties of techniques used to determine the heterogeneity in panel data sets. One of these techniques is based on the mean comparison between the sub-groups within the panel data (Greene 2008). The test procedure is based on comparing the sample means of different groups. This will involve testing the null hypothesis that the mean weight of a variable is equal regardless of the differences in the group.

In the case of this empirical study, the null hypothesis is that the sample mean of outputs are equal across the industries, while the alternative hypothesis is that at least two means are different, concluding that the industries' output level do not have the same sample mean and the effects of the different input combinations used in the production are differ across industries. Although some differences between sample means usually exist, the issue is whether these differences are significant or not. The aim here is not to identify which mean is different, rather it is to show whether there are significant differences across the sample means or not.

A test called analyses of variance (ANOVA) is performed using the generalized linear model (GLM) (SAS Institute Inc 1993). It involves separating the total variation in the data set into two classes: Variation due to differences among the groups, and variation due to errors (or so called disturbances), which might be caused by other factors that are not specified exogenously in the estimated model. The assumption here is that the variation in the error is relatively small, as it represents the factors that are non-controllable by the researcher. If the variations among the groups are relatively larger than the variations in the errors, then one should conclude that the group means are likely to be differed.

The results that are reported in Table 6.13 include figures for the sample mean output of each Industry with its standard deviation. The F-test statistics for the comparison between the two variations parts of means squares is equal to (14.19),

Table 6.13 Heterogeneity among the industries' level of output-analysis of variance

Industry	Mean	Std. dev	Industry	Mean	Std. dev
Agriculture, hunting, forestry and fishing	1.135	0.268	Electricity, gas and water supply	0.408	0.389
Mining and quarrying	0.129	0.024	Construction	2.142	1.477
Food, beverages and tobacco	1.097	0.536	Wholesale and retail trade	1.461	0.907
Textiles, leather and footwear	1.108	0.437	Hotels and restaurants	0.9	0.435
Wood and cork	0.102	0.042	Transport and storage	1.064	0.791
Pulp, paper, printing and publishing	0.389	0.287	Post and telecom	0.526	0.723
Chemical, rubber, plastics and fuel	1.936	1.694	Financial intermediation	0.873	0.851
Other non-metallic mineral	0.368	0.289	Real estate and business activities	1.643	1.225
Basic and fabricated metals	1.5	1.231	Public admin and defense	0.933	0.429
Machinery, NEC	0.466	0.472	Education	0.673	0.32
Electrical and optical equipment	3.717	5.229	Health and social work	0.433	0.367
Transport equipment	1.313	1.493	Other community, social and personal services	0.476	0.384
Manufacturing NEC, recycling	0.21	0.133			
Source	**DF**	**Sum of squares**	**Mean square**	**F value**	**Pr > F**
Model	24	575.018	23.959	14.19	<0.0001
Error	925	1561.295	1.688		

and it is statically significant at 99 % level of significance, indicating that the output mean is different among the different industries concluding the presence of heterogeneity.

6.10 Summary

The data in the EUKLEMS Growth and Productivity Account database contains varieties of basic input data series, in which it derived separately from the growth accounting assumptions methodology. Different categories and classes of capital, labor, materials, and energy inputs are provided in cooperation between the EUKLEMS consortium partners and national statistic offices in the partner countries.

The South Korean industries are divided into 26 industries using the international industry classification system. Each industry has unique characteristics concerning concentration, technology level, scale of R&D, and the degree of export orientation. This study estimated three groups of models, for the first group, the dependent variable output is correlated with composite independent variable of input factors of production and time trend. For the other two groups of models, the dependent variable of energy demand is correlated with composite independent variable of other inputs factors of production, output, and time trend.

According to the preliminary tests conducted in this study, the multicolinearity is not a serious problem. However, given the number of interaction terms and squared terms incorporated in all the models under this study, the problem of severe multicollinearity is expected in estimating these models. Thus, to avoid omission of important variables in the model, this study accounted for correcting for heteroskedasticity in all the models. Prior to estimate the models, the inputs variables are normalized by dividing them by their sample means. This procedure simplifies the analysis of estimated elasticities, especially those related to the variance function. Heterogeneity in industrial energy use is observed in the South Korean industries due to differences in the production process. Some industries consume higher rate of energy than other industries. Despite large variations in energy use and intensity, the growth rates in the energy use have been relatively high and characterized as continuous process.

The presence of industry heterogeneity in the data for this study has been proved and tested using ANOVA tests. This heterogeneity should be accounted for in an econometric model. Due to availability of panel data sets, using econometric of panel data techniques to account for heterogeneity and heteroskedasticity is possible.

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Chapter 7
Production Function Models Estimation

In this chapter the first group of econometric models the Cobb-Douglas production function and the Translog production function are estimated. The findings from estimating the Cobb-Douglas production function model reveal that (i) In general the South Korean industries are exhibiting increasing returns to scale, (ii) There is a slight substitution pattern between energy and ICT capital, and (iii) There is a significant and positive impact of energy use on the production level in the South Korean industries. The Translog production function allows for relaxing the assumption of perfect competition of the market and perfect substitution of some input factors, it also allows for analyzing the effects of substitutability and complementarity, and nonlinearity relationships between the explanatory variables and the dependent variable. Thus the Translog function is applied and estimated by Least Square Dummy Variables (LSDV) to formulate a regression model. Different tests have been conducted to evaluate the model performance such as regularity conditions test, which requires monotonicity and quasi concavity. The test results indicate on average positivity of logarithmic marginal products with respect to each input factor of production, and negative semi-definite value is also obtained. Based on the Translog specification of production function, the findings reveal that (i) The industries are exhibiting increasing returns to scale, (ii) The rate of technical change is decomposed into two parts: Pure technical change which depends on only time and non-neutral technical change (biased technical change) affected by changes in inputs over time. The results show negative value of pure component indicating its negative contribution to the rate of technical change. The non-neutral values although are negative in the sample mean but it started to increase positively over time to reduce its negative contribution. (ii) There is a fluctuation in the values of the total factor productivity during the sample period, and (iv) The variability of elasticity of energy with respect to output by industry indicates that industries employ different levels of energy input for their production.

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7.1 Introduction

This chapter and the next two ones present the study as it was conducted according to the procedures stated in chapter five. These three chapters cover the details of estimating three groups of models: Production function, energy demand without risk, and energy demand accounting for risk. This chapter will provide details about the estimation procedure of the production function when the energy variable is considered as one of the input factors of production. The production function is estimates by applying first the Cobb-Douglas function and then the Translog function. Different econometric tests are conducted to evaluate the estimated Translog function and it superiority in compare to the Cobb-Douglas function.

7.2 Cobb-Douglas Production Function

The first model estimated in this study is the standard Cobb-Douglas production function (Cobb and Douglas 1928). The aim of this basic procedure is to validate the relationship between output and input factors of production in accordance to the principles of the theory of production. The production technology or transformation relationship between the amount of input factor and the amount of output can be formulated using the Cobb-Douglas production function.

The production function yields a maximum possible outcome that can be produced from a combination of a given set of inputs quantities using a given technology, these inputs quantities will be different in order to obtain the optimal level of output. The analysis of production function involves the examination of the following characteristics: The elasticity of production, the rate of returns to scale, the total and average product, the marginal product, and the marginal rate of substitution.

The linear relationship of Cobb-Douglas production as a function given in Eq. (5.9) is estimated by Ordinary Least Square (OLS) regression (See Table 7.1 for the parameters estimates) as follows:

$$\begin{aligned} y_{it} = 0.526 + 0.068K_{it} + 0.328L_{it} + 0.060E_{it} + 0.344M_{it} \\ + 0.179S_{it} + 0.057I_{it} - 0.009T \end{aligned} \tag{7.1}$$

where y, K, L, E, M, S, I, and T are logarithmic values of output, non-ICT capital, labor, energy, materials, value added services, ICT capital, and time, respectively, for industry i at time t. The time trend T is added to the model to represent the technology or a shift in the production function over time due to technical progress (Felipe and Adams 2005).

Table 7.1 The Cobb-Douglas production function parameter estimates (the dependent variable Y is the level of output)

Variable	Parameter estimate	t value	Variable	Parameter estimate	t value
Intercept	0.526a	18.83	Materials	0.344a	46.49
	(0.028)			(0.007)	
Capital	0.068a	7.16	VA services	0.179a	17.78
	(0.009)			(0.010)	
Labor	0.328a	37.1	ICT	0.057a	10.43
	(0.009)			(0.005)	
Energy	0.061a	6.12	Time	−0.009a	−8.4
	(0.009)			(0.001)	
F test: 5415.120					
Root MSE:0.204					
R-Square: 0.976					
Adj. R-Square: 0.976					
Residual sum of square RSS: 38.107					

Note (1) The significant levels denoted as follows: a 99 %, b 95 %, c 90 %
(2) The standard errors are between the parentheses

The value[1] of production for industry *i* at time *t* depends on the level of technology (here represented by a time trend), the non-ICT capital, labor, values of energy used in the production, materials, value added services, and ICT capital. It must be noted that the intercept represents the technology level. According to the Cobb-Douglas function, the technology level (denoted by A) is A = exp (0.526) = 1.69.[2] However, here the time trend coefficient is added to the intercept representing yearly shifts in the production level.

The economic theory indicates that the marginal products of capital and labor are positive, and these inputs are exhibiting diminishing return. The statistical test for this hypothesis is straight forward. The coefficients of capital and labor are both less than one, indicating diminishing return. This can be tested further by using square values of the inputs, where the first order is expected to be positive, while the second order coefficient is expected to be negative. The sum of the two effects is interpreted as increasing at a decreasing rate (Allen et al. 2009). To measure the output elasticities with respect to each input, one should rely on the estimated coefficients of the inputs, for example in Eq. (7.1) the coefficient for capital is (0.068) implies that a 10 % increase in capital will lead to ~0.7 % increase in output, all other factors being held as constant (or so called ceteris paribus) (Allen et al. 2009).

In estimating the Cobb-Douglas production function, there are two strong assumptions imposed: First, a perfect competition of the market, and second, the share of all inputs is constant over time. In addition to these two assumptions, the Cobb-Douglas production

[1]All values are measured in millions of Korean Won.

[2]The antilog is calculated because the estimated function was based on logarithm values.

function assumes that the level of technology is fixed over time (captured by the intercept), and does not depend on time t (Cobb and Douglas 1928).

The sum of the estimated coefficients for the input factors will identify the returns to scale as follows:

1. If the sum is less than one, it exhibits decreasing returns to scale, which means that a proportionate increase in the inputs leads to a less than proportional increase in the output.
2. If the sum is greater than one, it exhibits increasing returns to scale, which means that a proportionate increase in the inputs leads to a more than proportional increase in the output.
3. If the sum is equal to one, it exhibits constant returns to scale.

In the model specified above, the sum of the estimated coefficients for the input factors production (0.068 + 0.328 + 0.060 + 0.344 + 0.179 + 0.05) is equal to (1.029), indicating that in general the South Korean industries are exhibiting increasing returns to scale.

Depicted by the critical values of statistical significance,[3] all the explanatory variables are significant at 99 % level. This implies that all variables are contributing to define the production model significantly. Moreover, the measure of the goodness of fit (R^2) with the value of (0. 976) indicates that approximately 98 % of variations in the data can be explained using this specified model.

Interpreting the coefficient in the Cobb-Douglas production function is straight forward. The coefficients are all positive (excluding the time trend which implies a technical regress), indicating that an increase in each input factor (for example energy) will lead to a proportional increase in the output (ceteris paribus).

The marginal rate of substitution will measure the responsiveness of the production scale with a change in the quantity of inputs (Cobb and Douglas 1928). For example, the marginal rate of substitution related to energy with one of the other input factors such as ICT capital can be obtained from the following relation:

$$MRS_{E/I} = \frac{0.060}{0.057} \times \frac{I}{E} \tag{7.2}$$

The relationship in Eq. (7.2) implies that for the same level of output it is possible to substitute 1.05 % of ICT capital for 1 % of energy (0.060/0.057 = 1.05). This indicates a slight substitution pattern between energy and ICT capital.

From this model, and according to the results reported in Table 7.1, the coefficient of the variable energy (E) is positive and statistically significant at 99 % level of significance (exceeds the critical value 0.258). This indicates that there is a significant and positive impact of energy use on the production level in the industrial sector for South Korea. Specifically a 10 % increase in the level of energy will yield approximately 0.6 % increase in the output level.

[3] The values are as follows: ($|r| > 0.258$ for 99 % level, ($|r| > 0.196$ for 95 % level, and $|r| > 0.1645$ for 90 % level).

7.3 The Translog Production Function

A generalization of the Cobb-Douglas production function is the Translog production function represented earlier in Eq. (5.19). As mentioned previously, the specification of the Translog production function is more flexible than Cobb-Douglas. It relaxes the assumption of unitary elasticity of substitution and the assumption that all firms have the same responses or production elasticities. It is also less restrictive as it uses flexible functional forms (accommodating interactions and squares of the explanatory variables). In other words, the Translog production function allows for (i) relaxing the assumptions of perfect competition of the market and perfect substitution of some input factors, (ii) analyzing the effects of substitutability and complementarity, and (iii) nonlinearity relationships between the explanatory variables and the dependent variable through the square and interaction terms, despite being linear in parameters.

For the mentioned flexibilities, the Translog production function is used to measure the elasticities of substitution and the total factor productivity (Pavelescu 2011). The nonlinear relationship of Translog production function given in Eq. (5.19) is specified and estimated by Least Square Dummy Variables (LSDV) to formulate a regression model (See Table 7.2).

The time trend *t* is included in the model to account for the effects of the rate of exogenous technical change (Heshmati 1994). The pooled model is equivalent to the least square dummy variable, as many of the explanatory variables account for industry group and time period specific effects. Before interpreting the results in Table 7.2, it is necessary to introduce measures for the model's performance in general and also in compare with the Cobb-Douglas production function as its restricted counterpart.

7.3.1 The Model's Overall Performance

The model's coefficient of determination (R^2) is equal to (0.991) indicating that more than 99 % of variations in the data can be explained using this specification. The standard deviation or the Mean Square Error (MSE) with a value of (0.129) indicates that the observations on average are little over one point away from the mean. In other words, there is a small rate of dispersion of the data around the average (mean). The model have incorporated 44 explanatory variables (the variables and their quadratic and interactions with other variables), 27 variables are statistically significant, in which 22 of them are highly significant with 99 % level of significance.

Table 7.2 The translog production function parameter estimates (the dependent variable Y is the level of output)

Variable	Parameter estimates	t value	Variable	Parameter estimates	t value
Intercept	0.304a	3.76	Capital * Services	−0.033a	−5.64
	(−0.081)			(−0.006)	
Capital	−0.041c	−1.36	Capital * ICT	0.005c	1.48
	(−0.03)			(−0.004)	
Labor	0.018	0.5	Capital * Time	0.008a	8.8
	(−0.035)			(−0.0009)	
Energy	−0.208a	−4.4	Labor * Energy	−0.011	−1.12
	(−0.047)			(−0.009)	
Material	0.447a	19.42	Labor * Material	−0.008	−0.83
	(−0.023)			(−0.009)	
Services	0.333a	10.31	Labor * Services	−0.092a	−7.77
	(−0.032)			(−0.012)	
ICT	0.170a	5.34	Labor * ICT	−0.002	−0.28
	(−0.031)			(−0.007)	
Time	−0.003	−0.59	Labor/Time	0.005a	4.63
	(−0.005)			(−0.001)	
$(\text{Capital})^2/2$	0.008b	2.31	Energy * Material	0.027	2.28
	(−0.004)			(−0.012)	
$(\text{Labor})^2/2$	0.104a	6.22	Energy * Services	−0.057a	−3.99
	(−0.017)			(−0.014)	
$(\text{Energy})^2/2$	−0.007	−0.53	Energy * ICT	0.009	1.11
	(−0.014)			(-0.008)	
$(\text{Material})^2/2$	0.032a	3.06	Energy * Time	0.008a	4.67
	(−0.011)			(−0.002)	
$(\text{Services})^2/2$	0.183a	10.13	Material * Services	−0.036a	−3.39
	(−0.018)			(−0.011)	
$(\text{Labor})^2/2$	0.021a	3.04	Material * ICT	−0.030a	−5.96
	(−0.007)			(−0.005)	
$(\text{Time})^2/2$	−0.0003c	−1.29	Material * Time	−0.005a	−5.22
	(−0.0001)			(−0.001)	
Capital * Labor	−0.092a	−10.16	Services * ICT	0.052a	9.46
	(−0.009)			(−0.006)	
Capital * Energy	−0.0346a	−3.36	Services * Time	−0.0001	−0.09
	(−0.01)			(−0.001)	
Capital * Material	0.048a	7.96	ICT * Time	−0.005a	−5.35
	(−0.006)			(−0.001)	
F test: 2759.370					
Root MSE: 0.129					
R-Square: 0.991					
Adj. R-Square: 0.991					
Residual Sum of Square RSS: 14.715					

Note (1) The significant levels are as follows: a 99 %, b 95 %, c 90 %
(2) The standard errors are between the parentheses

7.3.2 Specification Test

A specification test is constructed to compare a model with explanatory variables against a nested model (a model with only intercept) to see whether the explanatory variables are jointly explaining the variability of the dependent variable. Most of the econometric packages provide the F-test when estimating a regression model. In the case of this study, the software package SAS 9.3 is used and includes all statistical tests.

The value of F-test (2759.37) is significant at 99 % level of significance. It is large enough to reject the null hypothesis that all explanatory variables are zero. The model overall accounts for a significant portion of the variability in the dependent variable (Fai and Cornelius 1996). In comparison with the Cobb-Douglas production function specified in Eq. (7.1), an F-test is conducted based on the residual sum of squares. It is used to determine whether the Translog model (the full model) fits significantly better than the restricted Cobb-Douglas model. The test relies on a hypothesis about rejection or acceptance of the restricted model. The null hypothesis states that the restricted model is correct, while the alternative hypothesis is that the restricted model is too simple and that the full model is more appropriate. The F-test formula is given as bellow (Johnston 1984):

$$F = \frac{RSS_R - RSS_U/(DF_R - DF_U)}{RSS_U/DF_U} \tag{7.3}$$

where RSS_R, DF_R, RSS_U, DF_U are the residual sum of squares and degree of freedoms from the least square dummy variable for restricted model (Cobb-Douglas) and unrestricted model (Translog), respectively. Accordingly, the calculated F-statistic value for Eq. (7.3) is [(38.107−14.715)/(917−889)]/[(14.715/889)] = (50.47), which indicates that at 99 % level of significance, the null hypothesis cannot be accepted, and thus the full model should be used (Press et al. 1994).

7.3.3 Regularity Conditions Test

It is necessary to test for regularity conditions after estimating any model with different functional forms. The Translog function does not in general satisfy globally the two regularity conditions of monotonicity and quasi concavity. For the first property, i.e. monotonicity, the Translog function should satisfy the positivity of logarithmic marginal products with respect to each input factor of production (the input elasticities). The quasi concavity on the input factors can be checked by ensuring that the Hessian matrix H is semi-definite negative: $\mathrm{H} = \beta - \mathrm{diagonal}(\alpha) + \acute{\alpha}\alpha$ assuming that $y = \alpha_0 + \acute{\alpha}x + \frac{1}{2}\beta x$ is a Translog function (Heshmati 1994).

Curvature can be tested alternatively; it requires that the input elasticities matrix be negative semi-definite as described by Gallant (2008). The Eigen values of a symmetric real values matrix determine the definiteness of the matrix. If all Eigen values of the matrix are positive, the matrix is said to be positive definite. If the values are negative, the matrix is negative definite; while if the values have mixed signs, then the matrix is said to be semi-definite (Moss et al. 2003). The regularity conditions depend on values of inputs, the output and the estimated coefficients of the Translog production function, and hence, it is necessary to validate the regularity conditions at each data point. However there is no minimum condition for the percentage of data that verify the regularity properties.

The elasticities (denoted by σ) based on the Translog model specification is computed at each point of the data. If they are not as expected at each point, then it will result in violating the regulatory conditions. The percentage frequencies of positive marginal productivities of the estimated Translog production function are as follows (see Table 7.3): non-ICT capital σ_{YK} (0.958), labor σ_{YL} (0.943), energy σ_{YE} (0.623), materials σ_{YM} (0.985), value added services σ_{YS} (0.783), and ICT capital σ_{YI} (0.33), indicating that on average positivity of logarithmic marginal products with respect to each input factor of production is satisfied.

Furthermore, the concavity (curvature condition) in the production function is checked. The Eigen values of the input elasticity are mixed in signs, for non-ICT capital, labor, materials, value added services, energy, ICT capital, and time trend are (0.32), (0.026), (0.013), (−0.04), (−0.14), (−0.223), and (−0.34), respectively. These are indication for negative semi-definite values, and hence the second regularity condition is also satisfied.[4]

7.3.4 The Elasticities of Inputs

The estimated coefficients of the Translog production function cannot be directly interpreted due to the presence of interactions and squares in the flexible functional forms that yield correlational problem. Therefore, the total elasticities of output with respect to each input factor of production is calculated. The elasticity of output y with respect to input j can be expressed as follows:

$$E_j = \frac{\partial y_{it}}{\partial x_{jit}} = \beta_j + \sum\nolimits_n \beta_{jn} x_{nit} + \beta_{jt} t \tag{7.4}$$

[4]The curvature property cannot be fully satisfied in each point of the data, as stated by Sauer et al. (2006): "With respect to the Translog production function curvature depends on the input bundles.... For some bundles quasi-concavity may be satisfied, but not for others. Hence, what can be expected is that the condition of negative-semidefiniteness of the bordered Hessian is met only locally or with respect to a range of bundles".

Table 7.3 Percentage frequency of positive marginal productivity

Variable	Percentage frequency
σ_{YK}	0.958
σ_{YL}	0.943
σ_{YE}	0.623
σ_{YM}	0.985
σ_{YS}	0.783
σ_{YI}	0.63

Since the elasticities are computed at each point of the data, these elasticities are both industry and time specific. They can be applied for implications about allocation of resources and public policy support by industry and over time. The parameters estimates for the Translog production function and the input elasticities and returns to scale that are evaluated at the mean per year, per industry, and per industry's and period's characteristics are all reported in Tables 7.5, 7.6, 7.7, 7.8, 7.9, 7.10 and 7.11 in Appendix A, respectively.

7.3.5 *The Rate of Returns to Scale*

The rate of returns to scale (denoted by RTS) is calculated by measuring the elasticity of output with respect to total proportional changes in the inputs factors. In other words, RTS is defined as the sum of marginal elasticities of all inputs with respect to the output (Heshmati 1994). This can be expressed by the following relation:

$$RTS_i = \sum\nolimits_{j=1}^{n} E_j = \sum\nolimits_{j=1}^{n} \frac{\partial y_{it}}{\partial x_{jit}} = \sum\nolimits_{j=1}^{n} \left[\beta_j + \sum\nolimits_{n} \beta_{jn} x_{nit} + \beta_{jt} t\right] \tag{7.5}$$

where E_j is the marginal elasticity of input x_j with respect to the output y for industry i at time t. The value of RTS determines the returns to scale. If RTS of industry i is greater than one, the returns to scale for this industry is said to be increasing. If it is less than one, then the returns to scale is decreasing, and if it is equal to one then the RTS for the industry i is considered constant or unitary (equal to one).

The sample mean of RTS is found to be (1.014) with a standard deviation of (0.197), indicating on average increasing returns to scale. However, it is not statistically different than constant returns to scale. According to Fig. 7.1, The RTS during the period 1971–1978 has slightly declined over time from (1.188) to (1.045), but started to increase continuously since then. Twelve industries are characterized by decreasing returns to scale (See Table 7.6 in Appendix A), they are among industries that characterized also as low and medium technology level industries. The RTS is increasing with the decrease in the industry size. The rate of technical scale is higher for domestic market oriented and smaller industries in size. Industries that have high scale of R&D investment are exhibiting increasing returns to scale.

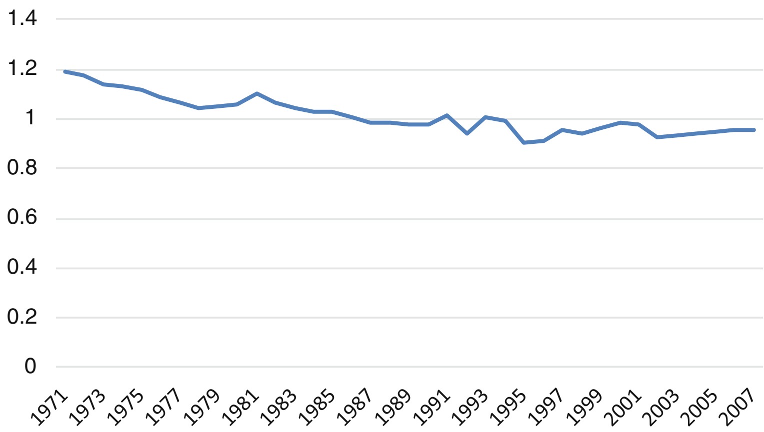

Fig. 7.1 The rate of returns to scale by year (production model)

7.3.6 The Rate of Technical Change

The rate of technical change is defined as the partial derivative of the production function with respect to time. As mentioned previously, if a true measurement tool of technology cannot be obtained, the time can be used as a representative of un-specified technology used by certain input. If the rate of technical change is positive, then any change in technology leads to increase in the output for given inputs, while it decreases if it is negative. The former indicates technical progress, while the later indicates technical regress in production (Progress refers to what is expected from technology development, while regress may result in introduction of regulations to reduce the output level for given inputs (Heshmati and Kumbhakar 2011)).

The rate of technical change can be expressed as in the following equation:

$$E_t = \frac{\partial y_{it}}{\partial t} = \beta_t + \beta_{it} t + \sum\nolimits_j \beta_{jt} x_{jit} \tag{7.6}$$

E_t is equal to the partial derivative of the production function with respect to time (it is equivalent to the partial elasticity of output with respect to time t). The rate of technical change described in Eq. (7.6) as explained by Heshmati (1994) can be decomposed into two components as follows:

1. The pure technical change (denoted as Puret in this study): It depends on only time $(\beta_t + \beta_{it} t)$. It refers to neutral shift in the production function, in which it results from equal effects of inputs by technical change (it is called a proportional change).
2. The non-neutral technical change (denoted as Nonnt in this study): It affected by changes in the inputs over time $\left(\sum_j \beta_{jt} x_{jit}\right)$. The non-neutral technical change is often called a biased technical change. The technical change is considered as

biased if the marginal rate of technical substitution between any two combinations of inputs factor of production is affected by the technical change. This will further implies that the technical change affect the contribution of each of these two inputs to the production process. The sign of interaction between the time trend and an individual input indicates input using (if positive) or input saving (if negative) biased technical change.

The time trend specified in Eq. (5.20) and the use of the flexible functional form (the interactions and quadratic terms) between the time trend t and all input factors of production allows for non-neutrality of technical change in addition to its pure term.

The sample mean value (−0.009) for the elasticity of output with respect to time shows small technical regress (Turnovsky and Donnelly 1984) during the period of study (i.e. 1970−2007). The sample mean of pure and non-neutral components are (−0.008) and (−0.002), respectively. The negative value of pure component indicates its negative contribution to the rate of technical change. The non-neutral values although are negative in the sample mean but it started to increase positively since 1982, and thus, it reduced its negative contribution since then (See Fig. 7.2).

Variability can be observed in the rate of technical change and in its non-neutral component across industries and across different characteristic of industries (See Tables 7.5, 7.6, 7.7, 7.8, 7.9, 7.10 and 7.11). Only five industries including mining and quarrying (industry code 2), food, beverage and tobacco (industry code 3), post and telecommunication (industry code 19), public administration and defense, compulsory social security (industry code 22) and education (industry code 23) on average experienced technical progress. Industries characterized by low and medium tech, large size, domestic oriented, low scale of R&D are on average experienced higher rate of technical regress. The increasing rate of non-neutral component over time indicate that changes have taken place in the input combination of production process

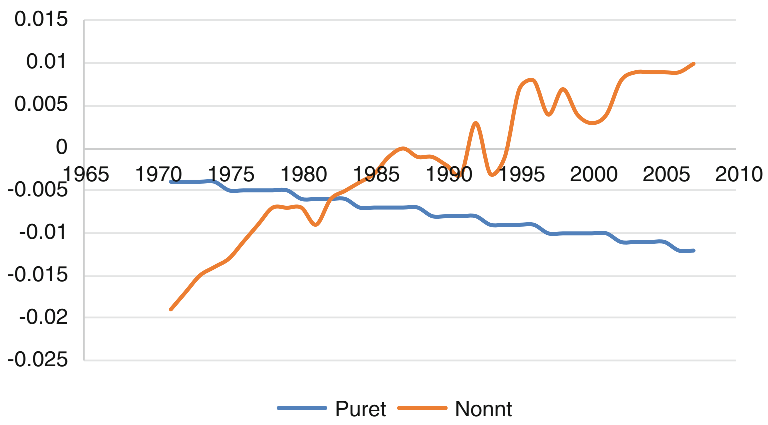

Fig. 7.2 The rate of technical change and its decomposition over time

in the industrial sector, which might be attributed to the consequence of South Korean industrial policies that targeted different industries over time.

7.3.7 The Growth in the Total Factor Productivity

The total factor productivity is the productivity involves all the input factors employed to produce the output. Using Eqs. (7.4), (7.5), and (7.6), and based on the specification given in Oh et al. (2012) and Tveterås and Heshmati (2002), one can obtain the total factor productivity growth as follows:

$$TFP = TC + (RTS - 1)^{*} gY \tag{7.7}$$

where *TC* is the rate of technical change which is equal to the sum of pure and non-neutral technical, *RTS* is the rate of returns to scale defined as the sum of the marginal elasticities of each individual input with respect to the output, and *gY* is the growth in output y which can be obtained as $\frac{y_{it} - y_{it-1}}{y_{it-1}}$, where y_{it} and y_{it-1} are the output y for the industry *i* at time *t* and *t−1*, respectively. From Eq. (7.7) one can notice that the only difference between the growth in total factor productivity and the technical change is the rate of returns to scale. Moreover, the specification in Eq. (7.7) can also be used for growth determinants in addition to TFP measure. The result of TFP in Table 7.4 indicates negative TFP growth with sample mean of (−0.003) and standard deviation of (0.031).

Table 7.4 Overall mean input elasticities (elasticity of output with respect to each input)

Variable	Mean	Std. dev.
σ_{YK}	0.183	0.123
σ_{YL}	0.266	0.18
σ_{YE}	0.046	0.056
σ_{YM}	0.368	0.094
σ_{YS}	0.13	0.126
σ_{YI}	0.021	0.04
σ_{YT}	−0.009	0.016
Puret	−0.008	0.002
Nonnt	−0.002	0.017
RTS	1.014	0.197
TFP	−0.003	0.031
Goutput	0.096	0.113

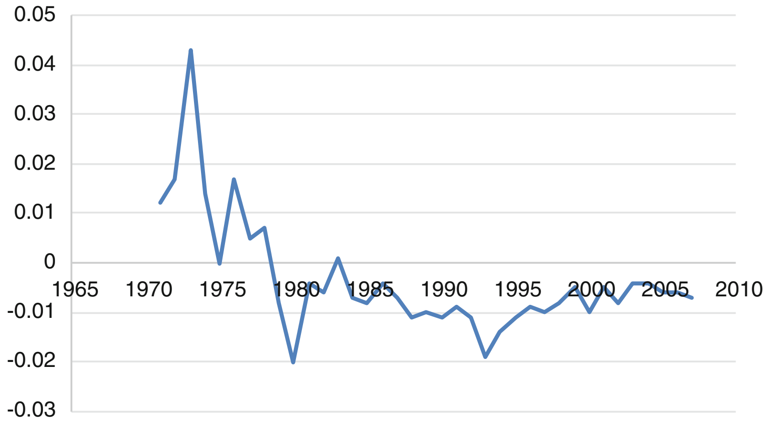

Fig. 7.3 The development of total factor productivity growth over time

A sharp increase in TFP growth observed in the South Korean industries during the period 1970–1973 until the first oil shock. Then it started to decline until 1975 and increased again for only one year. It has sharply declined after that again during the second oil shock. Since then, it fluctuated steadily but with negative decrease (See Fig. 7.3).

Positive TFP are found only in seven industries (See Table 7.6 in the Appendix A): Chemical, rubber, plastic and fuel (industry code 7), transport and storage (industry code 18), education (industry code 23), electricity, gas and water supply (industry code 14), financial intermediation (industry code 20), other community, social and personal services (industry code 25), and public administration and defense and compulsory social security (industry code 22).

It can also be noted that the TFP growth follows the same pattern of the rate of technical change since 1987 (See Fig. 7.4). This implies that a year to year shift (since 1986) in the technical change explains most of the fluctuations in the growth of TFP since 1986. The contribution from the returns to scale to TFP growth is small.

7.3.8 Hypotheses Testing

From the results reported in Table 7.2, most of the coefficients of the variable energy E with its quadratic and interactions forms are statistically significant at 99 % level of significance (exceeds the critical value 0.258). As a result, the evidence supports the hypothesis stating that there is a significant and positive impact for energy use on the production level in the industrial sector for South Korea.

As the coefficients of Translog model specification have no direct interpretation due to the presence of squares and interaction terms; therefore, the total effects of

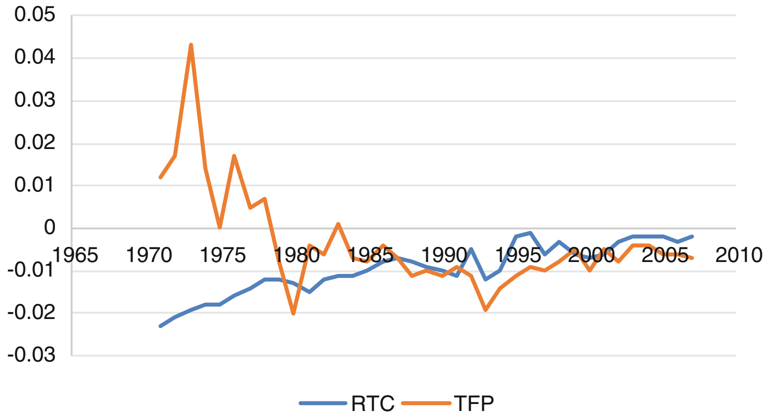

Fig. 7.4 Patterns of the rate of technical change and the total factor productivity

input elasticities are reported and interpreted (See Appendix A). The positive elasticities of energy with respect to output indicate a positive relation between output and energy, which implies that the energy factor is to be considered as a necessary input in production.

The variability of elasticity of energy with respect to output by industry indicates that different production employs different levels of energy input (See Table 7.6), the highest energy input was found in the wood and cork industry with value of (0.148), followed by the manufacturing and machinery industry with value of (0.111), and (0.100), respectively. However, perfect inelastic figures are found in three industries including the whole sale and retail trade, the transport and storage, and the real estate and renting and business activities. This indicates that any change in the level of energy use in these three industries will not affect the change in the level of output.

7.4 Summary

In this chapter, the results based on the estimated models are presented. The first model is the production model, in which it is estimated firstly by Cobb-Douglas production function then by Translog functional form. The aim of the estimated production model is to theoretically validate the explanatory variables (the input factors) that are used to estimate the demand for energy. The validation is based on the neoclassical economic theory of production which requires all variable inputs in the production function to be positive and to contribute to the final outcome.

In estimating the Cobb-Douglas production function, there are two strong assumptions imposed the perfect competition of the market and the share of all inputs is constant over time. In addition to these two assumptions, the Cobb-Douglas production function assumes that the level of technology is fixed over time (it is captured by the intercept in the estimated model), and does not depend on time t. The specification of the Translog production function is more flexible than Cobb-Douglas. It relaxes the assumption of unitary elasticity of substation and the assumption that all firms have the same responses or production elasticities. It is also less restrictive as it uses flexible functional forms (accommodating interactions and squares of the explanatory variables). For the mentioned flexibilities, the Translog production function is used to measure the elasticities of substitution and the total factor productivity.

The two models for production function (i.e. Cobb-Douglas and Translog) have been corrected for heteroskedasticity. The heteroskedasticity standard errors are reported instead of the original ones. One feature that all estimated flexible Translog functions have in common is that the determinant of the Hessian of the mean takes very small negative values. In other words, the Eigen values of the input elasticities were all mixed in signs. This indicates that the Hessian is negative semi definite, implying diminishing marginal productivity of input.

Different tests have been conducted to evaluate the Translog model performance and to show its superiority over the standard Cobb- Douglas function. The estimated coefficients of the Translog production function cannot be directly interpreted due to the presence of interactions and squares in the flexible functional forms that yield correlational problem. Therefore, the total elasticities of output with respect to each input factor of production is calculated. The elasticities are both industry and time specific. They can help for implications about resources allocation and public policy support by industry and over time.

The next two chapters deal with estimating the energy demand models (i.e. energy demand without risk, and energy demand accounting for risk). Again both Cobb-Douglas and Translog functions are applied for the estimation and different measures are introduced to analyze the estimated results.

Appendix A: Elasticities Estimates for the Translog Production Function

Table 7.5 Mean input elasticities by year (elasticity of output with respect to each input)

Year	σ_{YK}	σ_{YL}	σ_{YE}	σ_{YM}	σ_{YS}	σ_{YI}	σ_{YT}	Puret	Nonnt	RTS	TFP
1971	0.234	0.367	0.06	0.428	0.085	0.013	−0.022	−0.004	−0.019	1.188	0.012
1972	0.241	0.339	0.058	0.431	0.093	0.013	−0.021	−0.004	−0.017	1.174	0.017
1973	0.226	0.326	0.049	0.434	0.09	0.013	−0.019	−0.004	−0.015	1.138	0.043
1974	0.232	0.31	0.05	0.434	0.094	0.012	−0.018	−0.004	−0.014	1.132	0.014
1975	0.228	0.303	0.049	0.433	0.091	0.012	−0.017	−0.005	−0.013	1.116	0.000
1976	0.215	0.297	0.044	0.432	0.088	0.013	−0.015	−0.005	−0.011	1.089	0.017
1977	0.204	0.299	0.042	0.428	0.083	0.012	−0.014	−0.005	−0.009	1.069	0.005
1978	0.193	0.295	0.038	0.432	0.075	0.011	−0.012	−0.005	−0.007	1.045	0.007
1979	0.191	0.300	0.041	0.425	0.079	0.013	−0.012	−0.005	−0.007	1.048	−0.008
1980	0.200	0.311	0.047	0.419	0.073	0.012	−0.013	−0.006	−0.007	1.061	−0.020
1981	0.196	0.344	0.057	0.405	0.089	0.013	−0.015	−0.006	−0.009	1.104	−0.004
1982	0.196	0.329	0.053	0.406	0.066	0.014	−0.013	−0.006	−0.006	1.063	−0.006
1983	0.185	0.328	0.048	0.406	0.062	0.013	−0.011	−0.006	−0.005	1.041	0.001
1984	0.187	0.312	0.048	0.402	0.07	0.013	−0.011	−0.007	−0.004	1.031	−0.007
1985	0.188	0.308	0.05	0.401	0.07	0.013	−0.010	−0.007	−0.003	1.029	−0.008
1986	0.181	0.297	0.045	0.405	0.07	0.011	−0.008	−0.007	−0.001	1.009	−0.004
1987	0.179	0.276	0.043	0.400	0.076	0.014	−0.008	−0.007	0.000	0.987	−0.007
1988	0.173	0.278	0.044	0.389	0.082	0.015	−0.008	−0.007	−0.001	0.982	−0.011
1989	0.174	0.273	0.045	0.382	0.089	0.015	−0.008	−0.008	−0.001	0.979	−0.010
1990	0.163	0.256	0.035	0.354	0.15	0.019	−0.01	−0.008	−0.002	0.977	−0.011
1991	0.155	0.282	0.043	0.351	0.162	0.021	−0.011	−0.008	−0.003	1.013	−0.009
1992	0.155	0.237	0.027	0.360	0.14	0.02	−0.006	−0.008	0.003	0.939	−0.011
1993	0.155	0.278	0.045	0.332	0.172	0.024	−0.011	−0.009	−0.003	1.005	−0.019
1994	0.152	0.266	0.045	0.331	0.176	0.025	−0.01	−0.009	−0.001	0.995	−0.014
1995	0.144	0.191	0.02	0.347	0.169	0.031	−0.002	−0.009	0.007	0.902	−0.011
1996	0.136	0.207	0.025	0.336	0.176	0.034	−0.002	−0.009	0.008	0.915	−0.009
1997	0.143	0.224	0.039	0.313	0.202	0.035	−0.006	−0.010	0.004	0.956	−0.01
1998	0.172	0.201	0.038	0.332	0.171	0.028	−0.003	−0.010	0.007	0.943	−0.008
1999	0.165	0.209	0.045	0.309	0.203	0.035	−0.006	−0.010	0.004	0.966	−0.005
2000	0.163	0.222	0.055	0.295	0.215	0.036	−0.007	−0.010	0.003	0.986	−0.01
2001	0.165	0.218	0.055	0.292	0.21	0.037	−0.007	−0.010	0.004	0.978	−0.005
2002	0.167	0.179	0.042	0.308	0.194	0.035	−0.002	−0.011	0.008	0.927	−0.008
2003	0.170	0.191	0.047	0.304	0.188	0.033	−0.002	−0.011	0.009	0.933	−0.004
2004	0.176	0.194	0.053	0.301	0.186	0.032	−0.002	−0.011	0.009	0.941	−0.004
2005	0.179	0.199	0.059	0.295	0.185	0.031	−0.002	−0.011	0.009	0.947	−0.006
2006	0.183	0.205	0.066	0.290	0.183	0.029	−0.002	−0.012	0.009	0.956	−0.006
2007	0.188	0.200	0.068	0.287	0.183	0.029	−0.002	−0.012	0.010	0.956	−0.007

Table 7.6 Mean input elasticities by industry (elasticity of output with respect to each input)

Industry	σ_{YK}	σ_{YL}	σ_{YE}	σ_{YM}	σ_{YS}	σ_{YI}	σ_{YT}	Puret	Nonnt	RTS	TFP
Agriculture, hunting, forestry and fishing	0.048	0.361	0.031	0.429	0.026	0.002	0.005	−0.008	0.013	0.897	0.002
Mining and quarrying	0.18	0.268	0.039	0.449	0.003	0.000	0.014	−0.008	0.022	0.94	0.013
Food, beverages and tobacco	0.288	0.114	0.033	0.418	0.179	0.000	−0.017	−0.008	−0.009	1.031	−0.016
Textiles, leather and footwear	0.207	0.163	0.023	0.422	0.115	0.002	−0.009	−0.008	−0.001	0.932	−0.013
Wood and cork	0.348	0.384	0.148	0.406	0.011	0.000	−0.016	−0.008	−0.008	1.297	−0.002
Pulp, paper, printing and publishing	0.283	0.286	0.079	0.371	0.103	0.000	−0.019	−0.008	−0.011	1.122	−0.004
Chemical, rubber, plastics and fuel	0.250	0.092	0.009	0.407	0.189	0.017	−0.012	−0.008	−0.005	0.965	−0.010
Other non-metallic mineral	0.286	0.238	0.061	0.404	0.06	0.000	−0.011	−0.008	−0.003	1.049	−0.003
Basic and fabricated metals	0.309	0.132	0.043	0.440	0.099	0.000	−0.016	−0.008	−0.008	1.023	0.005
Machinery, NEC	0.335	0.253	0.100	0.381	0.123	0.000	−0.025	−0.008	−0.017	1.192	0.018
Electrical and optical equipment	0.241	0.157	0.034	0.399	0.170	0.028	−0.016	−0.008	−0.009	1.030	0.009
Transport equipment	0.299	0.265	0.082	0.384	0.094	0.000	−0.023	−0.008	−0.015	1.124	0.004
Manufacturing NEC, recycling	0.305	0.324	0.111	0.373	0.064	0.000	−0.018	−0.008	−0.01	1.176	−0.002
Electricity, gas and water supply	0.297	0.225	0.059	0.444	0.001	0.000	−0.002	−0.008	0.005	1.027	0.005
Construction	0.064	0.361	0.011	0.367	0.095	0.003	−0.007	−0.008	0.001	0.901	−0.015
Wholesale and retail trade	0.057	0.027	0.000	0.361	0.306	0.116	0.005	−0.008	0.012	0.868	−0.004
Hotels and restaurants	0.061	0.363	0.052	0.253	0.395	0.045	−0.021	−0.008	−0.013	1.169	−0.012
Transport and storage	0.053	0.198	0.000	0.372	0.184	0.032	0.005	−0.008	0.013	0.839	−0.008
Post and telecom	0.189	0.323	0.06	0.252	0.223	0.052	−0.019	−0.008	−0.012	1.099	0.000
Financial intermediation	0.069	0.332	0.017	0.265	0.200	0.069	−0.007	−0.008	0.000	0.952	−0.012
Real estate and business activities	0.108	0.025	0.000	0.375	0.275	0.094	0.002	−0.008	0.010	0.877	−0.008

(continued)

Table 7.6 (continued)

Industry	σ_{YK}	σ_{YL}	σ_{YE}	σ_{YM}	σ_{YS}	σ_{YI}	σ_{YT}	Puret	Nonnt	RTS	TFP
Public admin and defense	0.069	0.338	0.003	0.380	0.032	0.004	0.001	−0.008	0.009	0.825	−0.006
Education	0.011	0.527	0.065	0.232	0.096	0.057	−0.012	−0.008	−0.004	0.987	−0.012
Health and social work	0.133	0.450	0.064	0.340	0.046	0.002	−0.008	−0.008	0.000	1.036	−0.002
Other community, social and personal services	0.074	0.447	0.036	0.284	0.149	0.003	−0.010	−0.008	−0.002	0.994	−0.011

Table 7.7 Mean input elasticities by industries' characteristics: technology level (elasticity of output with respect to each input)

Technology	σ_{YK}	σ_{YL}	σ_{YE}	σ_{YM}	σ_{YS}	σ_{YI}	σ_{YT}	Puret	Nonnt	RTS	TFP
High	0.227	0.278	0.059	0.363	0.126	0.013	−0.016	−0.008	−0.008	1.065	0.000
Medium	0.203	0.225	0.036	0.385	0.109	0.02	−0.006	−0.008	0.001	0.978	−0.003
Low	0.144	0.275	0.042	0.365	0.141	0.027	−0.006	−0.008	0.001	0.995	−0.006

Table 7.8 Mean input elasticities by industries' characteristics: export orientation (elasticity of output with respect to each input)

Type	σ_{YK}	σ_{YL}	σ_{YE}	σ_{YM}	σ_{YS}	σ_{YI}	σ_{YT}	Puret	Nonnt	RTS	TFP
International	0.236	0.242	0.054	0.373	0.134	0.013	−0.016	−0.008	−0.008	1.052	−0.001
Mixed	0.293	0.177	0.052	0.41	0.127	0.000	−0.017	−0.008	−0.009	1.059	−0.005
National	0.128	0.299	0.041	0.357	0.127	0.03	−0.004	−0.008	0.004	0.983	−0.004

Table 7.9 Mean input elasticities by industries' characteristics: size (elasticity of output with respect to each input)

Size	σ_{YK}	σ_{YL}	σ_{YE}	σ_{YM}	σ_{YS}	σ_{YI}	σ_{YT}	Puret	Nonnt	RTS	TFP
Small	0.249	0.302	0.077	0.381	0.071	0.01	−0.01	−0.008	−0.002	1.091	0.002
Medium	0.218	0.23	0.041	0.381	0.125	0.013	−0.012	−0.008	−0.005	1.009	−0.004
Large	0.090	0.267	0.023	0.345	0.186	0.038	−0.006	−0.008	0.001	0.949	−0.008

Table 7.10 Mean input elasticities by industries' characteristics: R&D level (elasticity of output with respect to each input)

R&D	σ_{YK}	σ_{YL}	σ_{YE}	σ_{YM}	σ_{YS}	σ_{YI}	σ_{YT}	Puret	Nonnt	RTS	TFP
High	0.169	0.325	0.049	0.343	0.109	0.021	−0.011	−0.008	−0.004	1.017	−0.002
Medium	0.199	0.198	0.039	0.397	0.135	0.019	−0.008	−0.008	−0.001	0.987	−0.006
Low	0.180	0.270	0.053	0.368	0.155	0.024	−0.008	−0.008	0	1.05	−0.002

Table 7.11 Mean input elasticities by industries' characteristics: oil crisis shock (elasticity of output with respect to each input)

Period	σ_{YK}	σ_{YL}	σ_{YE}	σ_{YM}	σ_{YS}	σ_{YI}	σ_{YT}	Puret	Nonnt	RTS	TFP
<=1979	0.218	0.315	0.048	0.431	0.086	0.012	−0.017	−0.005	−0.012	1.111	0.012
1980−1995	0.172	0.281	0.042	0.378	0.111	0.018	−0.009	−0.007	−0.002	1.002	−0.009
>=1996	0.170	0.204	0.052	0.302	0.193	0.033	−0.004	−0.011	0.007	0.953	−0.007

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Chapter 8
Energy Demand Model I

This chapter introduces the second group of the econometric models estimation, namely the energy demand model. The model is constructed in two forms: The Cobb-Douglas and the Translog function to allow for consistency and comparability. It is worthy of mentioning that the estimated energy demand is a derived demand, the variable of energy is considered as one of the input factors of production. The energy demand is, therefore, derived from the demand for the industry's output. Since the demand for energy depends on the output level, the possible substitutability between energy and other inputs is allowed by production technology and energy price. The demand behavior and the potential policy variables are specified in short run and long run in their elasticities. In the short run, the behavioral specifications and the policy variables such as imposed taxes must consider that demand responses can only take the form of saving and alter in utilizing capital, while in the long run as the size and technological characteristics of the capital stock become variable, the characteristics and the degree of availability of new technologies as well as substitutability or complementarity become applicable. The partial derivative of the energy demand function with respect to time along with the elasticity of energy with respect to time is calculated to capture the rate of technical change. Due to presence of heterogeneity across the industries under this study, the estimated models have been corrected for heteroskedasticity. The heteroskedasticity standard errors are reported instead of the original ones. According to the results, the South Korean industrial sector exhibits a technological progress with increase in the returns to scale. Only few industries have witnessed restructuring by adopting new, more energy efficient, and productive technology. The findings reveal that although the substitutability between ICT capital and energy is feasible and proved in this model, the high technology industries still lack behind in implementing energy saving program.

8.1 Introduction

As explained in previously, the demand for energy is a derived demand. The variable of energy is considered as one of the input factors of production. The energy demand is, therefore, derived from the demand for the industry's output.

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Since the demand for the energy depends on the output level, the possible substitutability between energy and other inputs is allowed by production technology and energy price.

This chapter will provide details about the estimation procedure of the energy demand function not accounting for risk. The model is estimates by applying first the Cobb-Douglas function and then the Translog function. Different econometric tests are conducted to evaluate the estimated Translog function and it superiority in compare to the Cobb-Douglas function.

8.2 The Energy Demand Model not Accounting for Risk

The energy demand model is constructed based on the Eq. (3.2) and specified in two forms: The Cobb-Douglas and the Translog function. This will allow for consistency and comparability with the production function part described in Chap. 7. The Translog production function is more flexible than the Cobb-Douglas for many reasons as follows (Pavelescu 2011):

(1) It relaxes the assumption of unitary elasticity of substation.
(2) It relaxes the assumption that all industries have the same production elasticities.
(3) It is less restrictive due to incorporating flexible functional forms, in which it relaxes the assumptions about the market structure.
(4) It allows for investigating the possible substitution between the inputs.
(5) It allows for implementing nonlinear relations between the explanatory variables and the dependent variable through the use of square and interaction terms.

Thus, the Translog production function is used to measure the elasticities of substitution, technical change, and the total factor productivity growth. For the mentioned reasons the Cobb-Douglas function will not be considered for the energy demand analysis. The only reason of reporting it is to show the robustness of the Translog function and its superiority relative to Cobb-Douglas specification.

The parameter estimates for the pooled energy demand model not accounting for risk reported in Table 8.1. Note that the first part of the table reports the estimated parameters of Cobb Douglas function, whereas the second part (the right side of the table) is the Translog function parameter estimates.

Due to the presence of functional forms, it is difficult to directly interpret the estimated coefficients, thus, different measures will be provided to interpret the estimated coefficients such as input and output elasticities and the rate of technical change measures.

Table 8.1 Parameter estimates for pooled energy demand model (dependent variable is e (energy))

Cobb-Douglas			Translog		
Variable	Parameter estimate	t-value	Variable	Parameter estimate	t-value
Intercept	0.174	0.75	Intercept	0.267	1.07
	(0.233)			(0.249)	
Price	−0.260a	−11.29	Price	−1.410a	−8.44
	(0.023)			(0.249)	
Output	1.152a	9.26	Output	−1.732a	−3.72
	(0.125)			(0.466)	
Capital	0.002a	0.17	Capital	0.433a	5.56
	(0.013)			(0.078)	
Labor	−0.312a	−6.38	Labor	−0.749a	−4.77
	(0.049)			(0.157)	
Material	−0.227a	−4.95	Material	0.989a	6.19
	(0.046)			(0.159)	
Services	0.002	0.04	Services	1.892a	8.8
	(0.052)			(0.215)	
ICT	−0.068a	−4.68	ICT	0.035	0.53
	(0.015)			(0.068)	
Time	0.031a	5.4	Time	−0.073a	−4.1
	(0.006)			(0.018)	
Mid tech	−0.238a	−2.77	(Price^2)/2	0.424a	8.01
	(0.086)			(0.053)	
Low tech	−0.067	−1.01	(Outout^2)/2	−0.025	−0.03
	(0.067)			(0.005)	
Mixed market	−0.265a	−3.6	(Capital^2)/2	0.031a	6.19
	(0.074)			(0.005)	
Domestic market	0.541a	5.92	(Labor^2)/2	−0.566a	−4.16
	(0.091)			(0.136)	
Medium R&D	-0.081c	−1.28	(Material^2)/2	−0.596a	−6.5
	(0.064)			(0.092)	
Low R&D	0.015	0.23	(Services^2)/2	0.486a	3.46
	(0.065)			(0.140)	
1980–1995	0.287a	3.48	(ICT^2)/2	0.067a	4.47
	(0.083)			(0.015)	
1996–2007	0.491a	4.15	(Time^2)/2	0.004a	6.5
	(0.118)			(0.001)	
Medium size	−0.396a	−6.53	Price * Output	−0.195	−1.09
	(0.061)			(0.179)	
Small size	−0.363a	−4.44	Price * Capital	−0.181a	−4.49
	(0.082)			(0.040)	
Labor productivity	0.172a	5.75	Price * Labor	−0.089	−1.22
	(0.029)			(0.072)	
Capital intensity	−0.133a	−6.36	Price * Material	0.145a	2.34
	(0.021)			(0.062)	

(continued)

Table 8.1 (continued)

Cobb-Douglas			Translog		
Variable	Parameter estimate	t-value	Variable	Parameter estimate	t-value
High skilled labor	−0.018a	−6.83	Price * Services	−0.124c	−1.41
	(0.003)			(0.088)	
Medium skilled labor	−0.020a	−7.36	Price * ICT	0.106a	3.43
	(0.003)			(0.031)	
Labor outsourcing	−0.032a	−2.83	Price * Time	0.046a	8.15
	(0.011)			(0.006)	
1974	−0.099	−0.75	Output * Capital	−0.065	−0.74
	(0.133)			(0.088)	
1980	−0.091	−0.82	Output * Labor	0.466a	1.58
	(0.110)			(0.296)	
F test: 151.1600 **Root MSE** :0.4943 **R-Square**: 0.8078 **Adj. R-Square**: 0.8025 **Residual Sum of Square RSS**: 219.7360			Output * Material	0.320	1.19
				(0.269)	
			Output * Services	−1.05a	−2.76
				(0.382)	
			Output * ICT	0.045	0.51
				(0.088)	
			Output * Time	0.064a	4.29
				(0.015)	
			Capita l* Labor	−0.005	−0.13
				(0.038)	
			Capital * Material	0.122a	4.66
				(0.026)	
			Capital * Services	0.035c	1.37
				(0.026)	
			Capital * ICT	−0.031a	−5.79
				(0.005)	
			Capital * Time	−0.015a	−4.39
				(0.003)	
			Labor * Material	−0.138c	−1.36
				(0.102)	
			Labor * Services	0.073	0.67
				(0.109)	
			Labor * ICT	−0.031	−0.95
				(0.032)	
			Labor * Time	0.011b	2.07
				(0.005)	
			Material * Services	0.589a	5.55
				(0.106)	
			Material * ICT	−0.103a	−3.03
				(0.034)	
			Material * Time	−0.037a	−5.74
				(0.006)	

(continued)

Table 8.1 (continued)

Cobb-Douglas			Translog		
Variable	Parameter estimate	t-value	Variable	Parameter estimate	t-value
			Services * ICT	0.093a (0.033)	2.78
			Services * Time	−0.046a (0.005)	−8.5
			ICT * Time	−0.009 (0.002)	−0.38
			F test: 130.9700 **Root MSE**: 0.414 **R-Square**: 0.867 **Adj. R-Square**: 0.860 **Residual Sum of Squares RSS**: 151.474		

Note The significant levels are as follows: a 99 %, b 95 %, c 90 %
The standard errors are between the parentheses

8.3 The Overall Performance

The model's coefficient of determination (R^2) is equal to (0.867) (compare to 0.80 in case of Cobb-Douglas), it implies that more than 86 % of variations in the data can be explained using this model. The standard error (MSE), as another measure of goodness of fit with a value of (0.414) indicates that the observations on average are little over 4 point away from the mean. In other words, there is relatively not high rate of dispersion of the data around the mean. The model consists of 45 explanatory variables (the intercept, the variables and their quadratic and interactions with other variables), in which, 34 variables (76 %) are statistically significant, 26 of them are highly significant with 99 % level of significance.

The value of F-test statistics (equal to 130.97) is large and statistically significant at a 99 % level. It is large enough to reject the null hypothesis that all explanatory variables are zero, and the overall model accounts for a significant portion of the variability in the dependent variable (Fai and Cornelius, 1996). The F-test statistics, according to Johnston (1984) for comparing the Cobb-Douglas and the Translog based on Eq. (7.3) is equal to (14.335), which is larger than the critical value at 99 %. This implies the superiority of Translog over Cobb-Douglas form (Press et al. 1994).

8.4 Regularity Conditions Test

To test for the regularity conditions monotonicity and quasi concavity, the Translog function must satisfy the positivity of logarithmic marginal products with respect to each input factor of production (the input elasticities). In addition to the own price

Table 8.2 Percentage frequently of positive marginal productivity

Variable	Percentage Frequency
σ_{EP}	(Negative values) 0.881
σ_{EY}	0.615
σ_{EK}	0.846
σ_{EL}	0.330
σ_{EM}	0.506
σ_{ES}	0.792
σ_{EI}	0.191

elasticity, in case of the factor demand the property of convexity is required to have negative values of own price elasticities (Morey 1986). In the case of energy demand, the curvature can be tested. It requires that the other inputs and the output elasticity matrix be negative semi-definite as described in Gallant (2008).

The percentage frequency of positive marginal productivities of the estimated Translog energy demand function are as follows (See Table 8.2): Output (0.615), non-ICT capital (0.846), labor (0.330), materials (0.506), value added services (0.792), and ICT capital (0.191), indicating the on average positivity of logarithmic marginal products with respect to output and each input factor of demand is satisfied. The convexity of own price elasticity is also satisfied with (0.881) indicating that more than 88 % of the data points satisfies the convexity condition of own price elasticity in the energy demand model.

The Curvature condition in the energy demand model is also evaluated. The Eigen values of the elasticities are mixed in sign. The sample average elasticities for price, output, non-ICT capital, labor, materials, value added services, ICT capital, and time trend are (−2.71), (2.16), (−0.73), (1.05), (−0.12), (0.03), (0.081), and (0.038), respectively, indicating negative semi-definite values. As a result, the second regularity condition is also satisfied (Moss et al. 2003). However, the sign of ICT capital does not alter with the sign of time variable, indicating that the curvature property does not hold globally for all bundle of inputs (Sauer et al. 2006).

8.5 The Elasticities of Energy Demand

The demand behavior and the potential policy variables can be classified as short run and long run in their elasticities. In the short run, the behavioral specifications and the policy variables such as imposed taxes must consider that demand responses can only take the form of saving and alter in utilizing capital, while in the long run as the size and technological characteristics of the capital stock become variable, the characteristics and the degree of availability of new technologies as well as substitutability or complementarity become applicable (Hartman 1979).

The energy demand elasticities have been estimated econometrically by many scholars aiming at specifying causal relationships between energy and economic growth (See for example: Agnolucci 2009; Apostolakis 1990; Berndt and

Wood 1975; Bhattacharyya and Timilsina 2009; Kamerschen and Porter 2004; Pindyck 1979; Polemis 2007). However, despite its importance for policy driven tools, there is little literature that estimate the elasticity of energy demand for the industrial sector using panel data set (Adeyemi and Hunt 2007; Liu 2004).

The energy demand elasticity is calculated as the derivative of energy use with respect to energy price, output, non-ICT capital, labor, materials, value added service, ICT capital, and time trend. These elasticities are short run elasticities reflecting the percentage changes in energy use in response to one percent changes in respective explanatory variables of energy price, output, and other inputs (ceteris paribus). The elasticity with respect to time indicates percentage changes in energy use when time elapses with one year. In the production theory it is labeled as the rate of technical change (Kumbhakar et al. 2000). A negative rate of technical change will suggest energy saving, whereas a positive value suggests energy using technology employment for given level of output.

The elasticities of energy with respect to various inputs are calculated at each point of the data to allow variations in the responsiveness of industries in their energy use. It should be mentioned that the individual coefficients of the Translog energy demand function does not have direct interpretation alone (Pavelescu 2011). Therefore, the total elasticity must be computed at the mean of the data or at certain levels. These elasticities vary over time and industry. The sign of elasticity of energy demand with respect to energy price rate is expected to be negative, and the output elasticity to be positive, while others depending on their sign show the substitutability (negative) and complementarity (positive) relationships with energy use.[1]

The input elasticities of substitution are evaluated at the mean per year, industry, and industry's characteristics. They are all reported in Appendix A. It is worthy of mentioning that energy demand model is an inverted factor demand model, which is very similar to a cost model.[2] However, here the dependent variable is a partial cost but the structure of the function and interpretation of the elasticities are somewhat similar. In this study, the returns to scale (which is 1/cost for elasticity of output) will not be discussed due to difficulties in interpreting technological scale.

8.6 The Rate of Technical Change

The partial derivative of the energy demand function with respect to time along with the elasticity of energy with respect to time are calculated to capture the two of the rate of technical change components, namely, the pure technical change, which depends only on time, and the non-neutral technical change which depends on changes in the input over time (Heshmati 1994). Here the non-neutral technical change is interpreted as the rate of substitutability between energy and other inputs.

[1]Due to unavailability of the inputs prices in the data set, the cross price elasticizes are not computed.

[2]For more detail description of the inverted factor demand, see Kumbhakar et al. (2000).

These measures will serve as un-specified technology used with energy inputs (Heshmati and Kumbhakar 2011).

The rate of technical change can be expressed as in the following equation:

$$E_t = \frac{\partial e_{it}}{\partial t} = \beta_t + \beta_{it} t + \sum\nolimits_j \beta_{jt} x_{jit} \tag{8.1}$$

This is equal to the partial derivative of the energy demand function with respect to time. The pure technical change which represents the effect of knowledge advancement over time is considered as an indicator of knowledge development. It refers to the shift in the energy requirement function over time. The non-neutral component suggests that a shift in the energy use over time is not neutral. The magnitude of the rate of change is affected by utilizing other factors of production and their relationships with energy such as complementarity (positive sign) and substitutability (negative sign). Furthermore, the non-neutral component captures the cost reduction effects by applying inputs price changes and substitution. A possible interpretation is that industries replace energy with other production factors.

The sample mean value for the rate of technical change as shown in Table 8.3 is equal to (0.037) with the standard deviation of (0.056). It is an evidence of small technical progress (Turnovsky and Donnelly 1984) during the period of study (1970–2007). It can be interpreted as follows: On average, a year later, by the same amount of energy input the output can be produced by 3.7 % more.

The sample mean of pure and non-neutral components are equal to (0.015) and (0.067), respectively. The positive value of pure component indicates its positive contribution to the rate of technical change. As can be noticed in Fig. 8.1, the pure technical change follows a linear trend, indicating that the demand for energy has increased systematically over time. It reflects the fact that the South Korean economy with its continuous growth over time lead to increase in the demand of energy for its industrialization process. The non-neutral values have decreased dramatically over time indicated its decrease in the positive contribution, which reflects energy saving technology development and change (See Fig. 8.1).

Variability can be observed in the rate of technical change in its non-neutral component across industries and across different characteristic of industries (See Tables 8.4, 8.5, 8.6, 8.7, 8.8, 8.9 and 8.10). Only five industries are exhibiting technical regress, these are mining and quarrying (industry code 2), food, beverage and tobacco (industry code 3), wood and cork (industry code 5), machinery and NEC (industry code 10), and manufacturing, NEC and recycling (industry code 13).

The trend in energy saving is shown only in four industries during the period of the study. The non-neutral technical change for food, beverage and tobacco (industry code 3), electrical and optical equipment (industry code 11), wholesale and retail trade (industry code 16), and real estate, renting and business activities (industry code 21). Important implications can be drawn here as follows:

Table 8.3 Overall mean energy elasticities (elasticity of energy with respect to output and other inputs)

Variable	Mean	Std. Dev.
σ_{EP}	−0.591	0.532
σ_{EY}	0.499	0.433
σ_{EK}	0.175	0.190
σ_{EL}	−0.175	0.410
σ_{EM}	0.068	0.596
σ_{ES}	0.349	0.483
σ_{EI}	−0.172	0.191
σ_{ET}	0.037	0.056
Puret	0.015	0.047
Nonnt	0.067	0.126
RTS	2.938	1.279
TFP	0.015	0.098
Growth of output	0.096	0.113

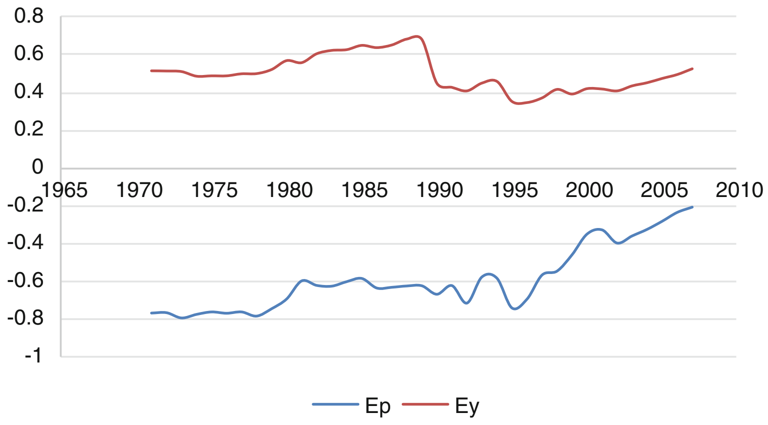

Fig. 8.1 Rate of technical change and its decomposition for energy use

1. The results imply that in these industries the restructure by adopting new, more energy efficient, and productive technology are taken place.
2. Only electrical and optical equipment industry is considered as a high technology industry among the four industries mentioned above. This implies that the high technology industries still lack behind in implementing energy saving program although the substitutability between ICT capital and energy is feasible and already proved by estimating the energy demand model in this chapter.
3. The high rate of energy saving technical change implies that these industries have experienced strong competitive pressure within the industries or encounter competition against countries with cheaper energy supply.

8.7 Hypotheses Testing

The following research questions with their hypotheses are tested based on this model as follows:

- R_1: What is the impact of energy use on the production level in the South Korean Industrial sector?
  From the results reported in Table 8.3, the mean elasticity of energy with respect to output is equal to (0.499) with the standard deviation of (0.433). A possible interpretation is that with a 10 % increase in output level, the energy use will be increased by 4.99 %. By looking at the figures of the mean elasticity of energy with respect to output across the industries, one can notice the variability of the level of energy used in the production level across the industries (See Fig. 8.2). As a result, the evidence supports the alternative hypothesis that there is a significant and a positive impact of energy use on the production level in the industrial sector for South Korea.
- R2: Is there any factor substitution pattern between energy and other inputs of production in the South Korean industrial sector?
  Based on the results reported in Table 8.3, one can evaluate the mean elasticities signs, the sign for the elasticity of energy with respect to each input specifies whether this input on average is substitute (negative sign) or complement (positive sign). Accordingly, the negative signs of the elasticities of energy with respect to labor and ICT capital indicate that these two inputs may substitute the level of energy use in the production. Hence, the hypothesis stating that ICT capital and labor are substituting energy in the South Korean industrial sector is accepted. However across industries, the sign of the mean elasticity of energy with respect to the different inputs are differed, indicating substitutability and complementarity of these inputs across industries.

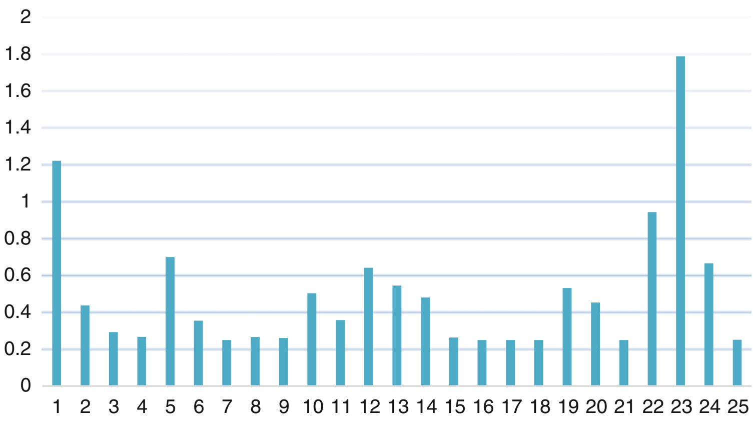

Fig. 8.2 The mean elasticity of energy with respect to output across sectors

8.8 Summary

The second group of models estimated is the energy demand model based on the inverted factor demand or input requirement function. Here again as in the previous chapter, the model is estimated firstly by the Cobb-Douglas then by the Translog functional form. Different econometric tests are conducted for the choice of the models and evaluation. It is found that the Translog function is superior to the Cobb-Douglas for its flexibility due to the use of functional forms and explanatory power.

Due to the presence of heterogeneity across the industries under the study, the two models for the energy demand (i.e. Cobb-Douglas and Translog) have been corrected for heteroskedasticity. The heteroskedasticity standard errors are reported instead of the original ones.

As mentioned previously, the estimated coefficients of the Translog specification cannot be directly interpreted due to the presence of functional forms. Therefore, the energy demand elasticity is calculated, it is calculated as the derivative of energy use with respect to energy price, output, non-ICT capital, labor, materials, value added service, ICT capital, and time trend. These elasticities are short run elasticities reflecting the percentage changes in energy use in response to one percent change in respective explanatory variables of energy price, output, and other inputs (ceteris paribus). The elasticity with respect to time indicates percentage changes in energy use when time elapses with one year. In the production theory it is labeled as the rate of technical change.

The partial derivative of the energy demand function with respect to time along with the elasticity of energy with respect to time are calculated to capture the rate of technical change The non-neutral technical change is interpreted as the rate of substitutability between energy and other inputs. These measures will serve as un-specified technology used with energy inputs. The magnitude of the rate of change is affected by utilizing other factors of production and their relationships with energy such as complementarity (positive sign) and substitutability (negative sign). Furthermore, the non-neutral component captures the cost reduction effects by applying inputs price changes and substitution. A possible interpretation is that industries replace energy with other production factors.

Appendix A: Elasticities Estimates for the Translog Energy Demand Model I

Table 8.4 Mean energy elasticities by year for pooled energy demand model (elasticity of energy with respect to output and other inputs)

Year	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
1971	−0.770	0.514	0.262	−0.049	0.182	0.525	−0.285	0.025	−0.064	0.253	2.960	0.051
1972	−0.768	0.513	0.258	−0.021	0.181	0.513	−0.276	0.024	−0.060	0.24	2.940	0.041
1973	−0.796	0.51	0.262	−0.063	0.184	0.517	−0.27	0.023	−0.055	0.221	2.970	0.123
1974	−0.777	0.485	0.26	−0.009	0.187	0.493	−0.266	0.023	−0.051	0.210	3.036	0.046
1975	−0.764	0.487	0.256	−0.032	0.165	0.500	−0.261	0.023	−0.047	0.199	3.034	0.032
1976	−0.771	0.487	0.253	−0.088	0.152	0.500	−0.253	0.025	−0.042	0.185	3.066	0.097
1977	−0.764	0.498	0.247	−0.128	0.125	0.483	−0.247	0.027	−0.038	0.174	2.946	0.057
1978	−0.786	0.499	0.251	−0.161	0.127	0.462	−0.251	0.028	−0.033	0.160	2.947	0.073
1979	−0.747	0.521	0.239	−0.169	0.091	0.440	−0.243	0.032	−0.029	0.154	2.869	0.018
1980	−0.695	0.569	0.223	−0.153	0.051	0.382	−0.246	0.037	−0.024	0.156	2.686	−0.043
1981	−0.599	0.558	0.206	−0.149	−0.019	0.359	−0.231	0.044	−0.02	0.153	2.738	−0.012
1982	−0.623	0.606	0.205	−0.170	−0.015	0.326	−0.242	0.045	−0.016	0.144	2.618	−0.011
1983	−0.627	0.624	0.204	−0.209	−0.029	0.314	−0.241	0.047	−0.011	0.132	2.56	0.023
1984	−0.603	0.628	0.195	−0.201	−0.052	0.313	−0.224	0.047	−0.007	0.121	2.547	0.007
1985	−0.586	0.651	0.189	−0.202	−0.07	0.285	−0.223	0.049	−0.002	0.113	2.445	−0.019
1986	−0.637	0.639	0.206	−0.213	−0.057	0.29	−0.236	0.045	0.002	0.096	2.439	0.027
1987	−0.633	0.653	0.204	−0.240	−0.098	0.332	−0.215	0.041	0.007	0.078	2.408	0.032
1988	−0.626	0.685	0.206	−0.287	−0.152	0.367	−0.205	0.039	0.011	0.064	2.294	0.010
1989	−0.625	0.683	0.209	−0.292	−0.17	0.384	−0.201	0.036	0.015	0.053	2.311	−0.010
1990	−0.67	0.447	0.211	−0.256	0.072	0.477	−0.165	0.025	0.02	0.032	3.044	0.032
1991	−0.624	0.425	0.2	−0.278	0.052	0.462	−0.153	0.03	0.024	0.025	3.072	0.033
1992	−0.717	0.406	0.216	−0.253	0.143	0.434	−0.180	0.024	0.029	0.011	3.177	0.012
1993	−0.578	0.448	0.185	−0.261	0.030	0.437	−0.139	0.031	0.033	0.011	3.146	0.009
1994	−0.585	0.457	0.183	−0.276	0.026	0.437	−0.133	0.03	0.038	−0.001	3.087	0.031

(continued)

Table 8.4 (continued)

Year	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
1995	−0.743	0.349	0.192	−0.239	0.280	0.408	−0.137	0.02	0.042	−0.02	3.500	0.046
1996	−0.696	0.343	0.176	−0.246	0.278	0.373	−0.127	0.025	0.047	−0.023	3.509	0.024
1997	−0.568	0.368	0.141	−0.232	0.187	0.363	−0.086	0.032	0.051	−0.024	3.445	0.004
1998	−0.547	0.414	0.133	−0.166	0.146	0.271	−0.121	0.035	0.055	−0.019	3.200	−0.079
1999	−0.46	0.389	0.104	−0.166	0.126	0.279	−0.073	0.039	0.06	−0.028	3.374	0.048
2000	−0.35	0.418	0.069	−0.190	0.065	0.258	−0.04	0.048	0.064	−0.029	3.262	0.017
2001	−0.328	0.416	0.061	−0.185	0.058	0.23	−0.042	0.05	0.069	−0.034	3.244	−0.024
2002	−0.398	0.406	0.072	−0.178	0.118	0.222	−0.058	0.045	0.073	−0.049	3.262	0.007
2003	−0.36	0.433	0.061	−0.176	0.086	0.174	−0.063	0.049	0.078	−0.05	3.115	−0.029
2004	−0.325	0.45	0.051	−0.148	0.066	0.123	−0.064	0.053	0.082	−0.054	2.993	−0.023
2005	−0.282	0.473	0.039	−0.143	0.031	0.095	−0.061	0.057	0.086	−0.058	2.906	−0.028
2006	−0.235	0.494	0.029	−0.129	0.003	0.063	−0.063	0.060	0.091	−0.061	2.816	−0.036
2007	−0.207	0.525	0.015	−0.124	−0.018	0.023	−0.056	0.064	0.095	−0.066	2.733	−0.026

Table 8.5 Mean input elasticities by sector for pooled energy demand model (elasticity of energy with respect to output and other inputs)

Sector	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
Agriculture, hunting, Forestry and fishing	−1.024	1.222	0.23	−0.931	−0.259	0.033	−0.281	0.069	0.015	0.047	0.92	−0.071
Mining and quarrying	−1.247	0.438	0.353	0.358	0.259	−0.059	−0.421	−0.009	0.015	0.108	2.65	0.015
Food, beverages and tobacco	−0.628	0.293	0.387	0.206	−0.353	0.884	−0.257	−0.024	0.015	−0.038	3.666	0.06
Textiles, leather and footwear	−0.368	0.267	0.206	−0.193	−0.098	0.718	−0.169	0.029	0.015	0.012	3.848	0.018
Wood and cork	−0.719	0.7	0.479	0.638	−0.599	0.485	−0.563	−0.035	0.015	0.1	1.959	0.062
Pulp, paper, printing and publishing	−0.373	0.355	0.239	0.036	−0.329	0.628	−0.27	0.013	0.015	0.082	3.175	0.055
Chemical, rubber, plastics and fuel	0.51	0.25	−0.271	−0.135	0.481	0.063	0.155	0.149	0.015	0.124	4.000	−0.057
Other non-metallic mineral	0.007	0.266	−0.007	0.043	0.037	0.182	−0.149	0.079	0.015	0.153	3.803	−0.003
Basic and fabricated metals	0.026	0.261	0.075	−0.003	−0.274	0.431	−0.134	0.07	0.015	0.061	3.891	0.035
Machinery, NEC	−0.349	0.504	0.366	0.035	−0.774	1.161	−0.337	−0.035	0.015	0.042	2.331	0.115
Electrical and optical equipment	−0.531	0.358	0.268	−0.202	−0.321	0.809	−0.164	0.008	0.015	−0.017	3.111	0.138
Transport equipment	−0.309	0.642	0.242	−0.118	−0.631	0.632	−0.261	0.026	0.015	0.054	2.041	0.028
Manufacturing NEC, recycling	−0.506	0.545	0.332	0.276	−0.489	0.62	−0.361	−0.012	0.015	0.09	2.239	0.06
Electricity, gas and water supply	0.013	0.481	−0.163	0.143	0.2	−0.646	−0.124	0.143	0.015	0.219	2.462	−0.087
Construction	−0.76	0.264	0.271	−0.602	0.147	0.493	−0.238	0.046	0.015	0.001	3.844	0.012

(continued)

Table 8.5 (continued)

Sector	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
Wholesale and retail trade	−1.041	0.25	0.136	−0.385	1.11	0.638	0.072	0.004	0.015	−0.023	4.000	0.049
Hotels and restaurants	−0.393	0.25	0.158	−0.062	0.771	0.798	0.019	0.023	0.015	0.02	4.000	0.013
Transport and storage	−0.947	0.25	0.187	−0.354	1.007	0.494	−0.114	0.022	0.015	0.021	4.000	0.043
Post and telecom	−0.756	0.532	0.151	−0.057	0.074	0.33	−0.073	0.008	0.015	0.113	2.552	0.076
Financial intermediation	−1.21	0.454	0.17	−0.336	0.611	−0.013	−0.071	0.03	0.015	0.07	2.709	0.038
Real estate and business activities	−1.091	0.25	0.14	−0.278	0.998	0.395	0.026	0.015	0.015	−0.012	4	0.046
Public admin and defense	−1.115	0.944	0.203	−0.806	0.046	−0.04	−0.236	0.063	0.015	0.058	1.768	−0.061
Education	−0.794	1.789	−0.024	−0.972	−0.338	−0.544	0.017	0.124	0.015	0.14	0.654	−0.163
Health and social work	−0.444	0.666	0.081	−0.416	−0.043	−0.001	−0.21	0.083	0.015	0.148	1.834	−0.058
Other community, social and personal services	−0.727	0.251	0.169	−0.264	0.475	0.233	−0.165	0.044	0.015	0.097	3.988	0.015

Table 8.6 Mean energy elasticities by sectors' characteristics: technology level for pooled energy demand model (elasticity of energy with respect to output and other inputs)

Technology	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
High	−0.393	0.47	0.18	−0.152	−0.195	0.514	−0.186	0.034	0.015	0.069	2.744	0.039
Medium	−0.422	0.343	0.053	−0.101	0.316	0.09	−0.119	0.069	0.015	0.105	3.373	0.005
Low	−0.793	0.584	0.223	−0.221	0.14	0.347	−0.186	0.026	0.015	0.049	2.886	0.003

Table 8.7 Mean energy elasticities by sectors' characteristics: export/import orientation for pooled energy demand model (elasticity of energy with respect to output and other inputs)

Export	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
International	−0.384	0.42	0.195	−0.125	−0.202	0.603	−0.181	0.027	0.015	0.052	2.996	0.049
Mixed	−0.325	0.303	0.234	0.08	−0.319	0.648	−0.22	0.02	0.015	0.035	3.577	0.05
National	−0.767	0.586	0.151	−0.259	0.306	0.14	−0.157	0.047	0.015	0.082	2.768	−0.012

Table 8.8 Mean energy elasticities by sectors' characteristics: R&D level for pooled energy demand model (elasticity of energy with respect to output and other inputs)

R&D	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
High	−0.605	−0.632	0.635	0.156	−0.318	−0.073	0.218	−0.171	0.048	0.015	0.086	2.444
Medium	−0.405	−0.478	0.443	0.16	−0.177	0.089	0.474	−0.152	0.038	0.015	0.049	3.168
Low	−0.547	−0.692	0.358	0.229	0.065	0.272	0.38	−0.206	0.018	0.015	0.062	3.415

Table 8.9 Mean energy elasticities by sectors' characteristics: industry size for pooled energy demand model (elasticity of energy with respect to output and other inputs)

Size	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
Small	−0.508	0.56	0.169	0.074	−0.098	0.178	−0.255	0.038	0.016	0.124	2.47	0.008
Medium	−0.50	0.48	0.18	−0.169	−0.097	0.427	−0.174	0.037	0.015	0.055	2.935	0.022
Large	−0.748	0.461	0.176	−0.406	0.367	0.434	−0.096	0.037	0.016	0.026	3.364	0.015

Table 8.10 Mean energy elasticities by sectors' characteristics: oil crisis shock for pooled energy demand model (elasticity of energy with respect to output and other inputs)

Period	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EI}	σ_{ET}	Puret	Nonnt	RTS	TFP
<=1979	−0.771	0.502	0.254	−0.08	0.155	0.493	−0.261	0.026	−0.047	0.199	2.974	0.06
1980–1995	−0.639	0.54	0.201	−0.231	0.016	0.375	−0.194	0.036	0.011	0.067	2.799	0.011
>=1996	−0.369	0.435	0.071	−0.167	0.079	0.191	−0.066	0.048	0.073	−0.043	3.123	−0.015

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Chapter 9
Energy Demand Model II

In this chapter the third group of the econometric model is estimated, namely the energy demand model accounting for risk. The model is constructed as in the previous models in two forms: The Cobb-Douglas and the Translog function to allow for consistency and comparability. The Just and Pop production risk function is applied. To estimate the energy demand incorporating risk, different input factors of production are included. A time trend is used to represent the exogenous rate of technical change and to capture the possible shifts in the risk function over time. Prior to estimation, it is necessary to test whether heteroskedasticity is actually presented in the data sample or not. The White test and the Breuch-Pagan test are the two tests undertaken for this purpose. The tests results indicate that heteroskedasticity is actually presented in the data. The estimated model of energy demand with risk is based on a three-stage FGLS estimator as follows: First, the model is estimated using OLS for the Translog function with a fixed effect. Second, the variance function is estimated by nonlinear least squares method. Using the estimated variances, the model is re-estimated based on transformed data in the third step. Technical inefficiency is also estimated relative to the industry with the best performance. The total variance is divided into two components output variance and input variance. Since the Translog function is applied in estimating the parameters, the monotonicity and convexity conditions are tested, the results indicate on average positivity of logarithmic marginal products with respect to output and each input factor is satisfied. The convexity of own price elasticity is also satisfied. The findings reveal that energy and capital, energy and value added services are complement, whereas labor, materials, and ICT capital have a substitutability relation with energy use. Furthermore, the negative value of total marginal effects indicating that increasing the output level will decrease the energy demand variance. The negative values for marginal of value added services and ICT capital indicate that these two factors are energy risk decreasing factors.

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9.1 Introduction

This chapter deals with empirical implementation of the theoretical framework provided by models for competitive firms under production risk. Chapter 4 presented the theoretical requirements for a stochastic production function specification, the so-called Just and Pope Propositions that have several implications for specification and estimation of econometric models of production.

Previous empirical studies applying Just and Pope Production risk have not concluded interesting results in terms of the significance of risk parameters. The reason is that these studies had limited numbers of observations available, thus producing inefficiency of the Feasible Generalized Least Square (FGLS) estimators which has been predominately applied in these studies (Saha et al. 1997; Tveterås 1997, 1999). For this reason, it has been suggested that the Maximum Likelihood (ML) estimator framework to be used in empirical studies of Just and Pope Production risk framework. The ML estimator provides asymptotically more efficient estimates of the variance function parameters (Tveterås 2000).

Saha et al. (1997) examined the finite sample performance of FGLS and ML estimator for firms that assume a simple homogenous Just and Pope Production technology specified as $y = f(x; \alpha) + h(x; \beta)$. The mean function *f*(.) had a Cobb-Douglas form, and the variance function *h*(.) was exponential in a linear function of inputs. Since firms were assumed homogeneous, firm specific effects were not included.

The current study extends Saha et al. (1997) analysis to a more flexible parameterization of Just and Pope technology. A Translog functional form is used for the mean function. This functional form as discussed in the previous chapters allows the elasticity of scale, also allows for analysis of substitution and complementarity in effects. The production technology is also characterized by firm heterogeneity in terms of firm specific effects.

9.2 The Energy Demand Model Accounting for Risk

The energy demand model accounting for risk is constructed based on the Eq. (5.24) and specified in two forms: The Cobb-Douglas and the Translog functional form. As emphasized by Tveterås (2000), the Cobb-Douglas function, although is used numerously in previous studies, imposes strong restrictions on the production technology. Hence, more flexible functional form such as Translog is desirable. The variables used in the estimation of the energy demand with risk are energy price, output, non-ICT capital, labor, materials, value added services, and ICT capital. A time trend is used to represent the exogenous rate of technical change and to capture the possible shifts in the risk function over time (Heshmati 2001).

9.3 Empirical Tests for Heteroskedasticity

Prior to estimate the energy demand model accounting for risk for the South Korean industrial sector, and before one proceeds to implement the variance function (non-constant of variance) in the estimating models, it is necessary to test whether heteroskedasticity (non-constant of variance) is actually presented in the data sample or not.

Different tests in the literature have been proposed for heteroskedasticity, they differ in generality and power. The White test, proposed by White (1980), and the Breuch-Pagan test, proposed by Breusch and Pagan (1979) are the two tests undertaken in this study. These two tests are based on the residual of the fitted model, and are performed separately for the residual of each equation. The residuals from the estimation are used to test for the presence of heteroskedasticity of the true disturbances. The White test will test the null hypothesis of homoskedasticity (the constant variance of the residuals) against the alternative hypothesis of the presence of the heteroskedasticity. The Breusch-Pagan test will test the null hypothesis of homoskedasticity, while the alternative hypothesis is that the error variance will differ with a set of regressors that are specified in the heteroskedastic part (Greene 2008).

The results of both tests are reported in Table 9.1. The parameter estimates of the Translog energy demand model reported in Table 8.1 in Chap. 8 have been used to conduct the heteroskedasticity test and to obtain the residuals. The estimates of the constant term (the intercept) and the coefficient of the variables with their squares and interactions, and their associated p-values are appeared to be different from zero, and most of them are generally at accepted levels of statistical significance. According to the results, both the White test (896.1) and the Breaush-Pagan test (404.0) reject the null hypothesis of no heteroskedasticity. Accordingly the standard errors of the parameter estimates are incorrect. Any inference that may be derived from these parameters may generate misleading results.

9.4 A Three-Stage FGLS Estimation

The estimated energy demand model accounting for risk is based on a three-stage FGLS estimator described by Just and Pope (1978). The first stage parameter estimates are the OLS estimates for the Translog function $f(x)$ with the fixed effects. The estimated parameters are those of the energy demand model without risks that

Table 9.1 Heteroskedasticity test

Type of test	Statistic	DF	Pr > ChiSq	Variables
White's test	896.1	494	<0.0001	Cross of all variables
Breusch-Pagan	404.0	44	<0.0001	Cross of all variables

Table 9.2 Cobb-Douglas energy demand with risk: feasible generalized least square parameter estimates

Variable	Parameter estimate	t value	Variable	Parameter estimate	t value
Intercept	–1.563a	–17.68	Material	–0.350a	–11.22
	(–0.088)			(–0.031)	
Price	–0.384a	–16.29	Services	0.118a	3.08
	(–0.024)			(–0.038)	
Output	1.118a	12.66	ICT capital	–0.159a	–12.51
	(–0.088)			(–0.013)	
Capital	0.037b	2.05	Time	0.041a	14.72
	(–0.018)			(–0.003)	
Labor	–0.332a	–8.33			
	(–0.039)				
SSE: 1168.1 **Root MSE(σ)**: 1.129 **R-Square**: 0.806 **Adj. R-Square**: 0.804					

Note The significant levels are as follows: a 99 %, b 95 %, c 90 %
The standard errors are between the parentheses
A summary statics for the variables used is reported in Table 9.7 in the Appendix A. The correlation coefficients for the estimated variables are reported in Table 9.8 in the Appendix A

are reported in Table 8.1 in Chap. 8. In the second stage, the variance function is estimated by nonlinear least squares method. Using the estimated variances, the model is re-estimated based on transformed data in the third step.[1]

The estimated parameters of the energy demand accounting for risk are reported in Table 9.2 for the Cobb-Douglas estimates and Table 9.3 for the Translog estimates. In the third stage, the Translog function $f(x)$ is estimated by least squares with predicted variances from the second step as weights. The estimated parameters are reported in Table 9.9 in Appendix A for both Cobb-Douglas and Translog function. The error term u_{it} from the estimated coefficients in Eq. (5.21) is treated as fixed (fixed effect error component); it is estimated based on the input variables and industries specific characteristics such as technology level, size, R&D scale, etc.

The FGLS estimator for Just and Pope Production risk with fixed industry specific intercepts will be the same as the usual FGLS estimator when the fixed effects are implemented by dummy variables (Tveterås 2000). Furthermore, technical inefficiency is also estimated relative to the industry i with the best performance (in terms of using optimal energy) in the sample. It is assumed to be fully efficient if $u_{it} = 0$. However, the reference industry might not be the best in all the years. The time variant technical inefficiency is employed and measured relative to

[1]Since the model is non-linear in parameters an iterative procedure is used. Convergence will be obtained after repeated iteration process, which is equivalent of using the maximum likelihood estimation method.

Table 9.3 Translog function energy demand with risk: feasible generalized least square parameter estimates

Variable	Parameter estimate	t value	Variable	Parameter estimate	t value
Intercept	–0.617a	–2.38	(Capital^2)/2	0.028a	4.19
	(–0.259)			(–0.007)	
Price	–1.154a	–9.8	(Labor^2)/2	–0.220b	–1.87
	(–0.118)			(–0.118)	
Output	–0.026	–0.05	(Material^2)/2	–0.428a	–6.38
	(–0.505)			(–0.067)	
Capital	0.332a	4.17	(Service^2)/2	0.499a	5.04
	(–0.079)			(–0.099)	
Labor	–1.049a	–5.91	(ICT capital^2)/2	0.067a	5.26
	(–0.178)			(–0.013)	
Material	0.383a	2.38	(Time^2)/2	0.004a	6
	(–0.161)			(–0.0006)	
Services	1.354a	6.32	Price * Output	–0.320a	–2.3
	(–0.214)			(–0.139)	
ICT capital	–0.168a	–2.73	Price * Capital	–0.068b	–2.15
	(–0.061)			(–0.032)	
Time	–0.030b	–1.83	Price * Labor	–0.122b	–1.93
	(–0.016)			(–0.063)	
(Price^2)/2	0.318a	6.5	Price * Material	0.174a	3.96
	(–0.049)			(–0.044)	
(Output)^2/2	2.282a	3.87	Price * Services	0.007	0.09
	(–0.589)			(–0.076)	
Price * ICT capital	0.080a	3.34	Capital * ICT capital	–0.028a	–4.49
	(–0.024)			(–0.006)	
Price * Time	0.034a	8.63	Capital * Time	–0.008a	–2.78
	(–0.004)			(–0.003)	
Output * Capital	–0.252a	–3.18	Labor * Material	0.134c	1.62
	(–0.079)			(–0.083)	
Output * Labor	–0.521b	–2.21	Labor * Services	0.169b	2.29
	(–0.235)			(–0.074)	
Output * Material	–0.238c	–1.4	Labor * ICT capital	0.0056	0.19
	(–0.170)			(–0.029)	
Output * Services	–1.042a	–4.96	Labor * Time	0.028a	5.31
	(–0.210)			(–0.005)	
Output * ICT capital	–0.004	–0.06	Material * Services	0.459a	7.71
	(–0.064)			(–0.0595)	
Output * Time	–0.011	–0.7	Material * ICT Capital	–0.054b	–2.21
	(–0.015)			(–0.024)	

(continued)

Table 9.3 (continued)

Variable	Parameter estimate	t value	Variable	Parameter estimate	t value
Capital * Labor	0.061b	1.73	Material * Time	–0.011b	–1.99
	(–0.035)			(–0.005)	
Capital * Material	0.137a	5.33	Services * ICT Capital	0.0518b	2.18
	(–0.026)			(–0.024)	
Capital * Services	0.029	1.13	Services * Time	(–0.029a	–4.98
	(–0.026)			(–0.006)	
			ICT * Time	0.006a	2.89
				(–0.002)	
SSE: 809.9 **Root MSE(σ)**: 0.959 **R-Square**: 0.924 **Adj R-Square**: 0.920					

Note The significant levels are as follows: a 99 %, b 95 %, c 90 %
The standard errors are between the parentheses

the industry with the best performance in each year as follows (Heshmati 2001; Lovell and Schmidt 1987):

$$TINEFF_{it} = g(x_{it};\beta)(\alpha_0 + \mu_i) - \min_t[g(x_{it};\beta)(\alpha_0 + \mu_i)] \tag{9.1}$$

$$TEFF_{it} = \exp(-TINEFF_{it}) \tag{9.2}$$

The subscripts i and t represent both industry and time specific. If the marginal variance of input j: ME_j specified in Eq. (5.24) is positive, then the input j is said to be risk increasing while it is risk decreasing if the sign is altered. The estimated variance from the Eq. (5.23) in which it is specified based on output, price, and quasi fixed inputs x_j is an increasing function of the expected mean of energy demand. The total variance is hence divided into two components output variance and input variance (Heshmati 2001).

9.5 The Overall Performance

The model's coefficient of determination (R^2) is equal to (0.924) (compare to 0.806 in case of Cobb-Douglas) implies that more than 92 % of variations in the data can be explained using this model. The model consists of 45 explanatory variables (the intercept, the variables and their quadratic and interactions with other variables), 39 variables (87 %) are statistically significant at least with 90 % level, in which 27 of them are highly significant at 99 % level of significance.

Table 9.4 Percentage frequency of positive marginal productivity

Variable	Percentage frequently
σ_{EP}	(Negative values) 0.928
σ_{EY}	0.739
σ_{EK}	0.863
σ_{EL}	0.268
σ_{EM}	0.497
σ_{ES}	0.764
σ_{EI}	0.138

9.6 Regularity Conditions Tests

The regularity conditions are tested in this model as well. The validation test requires monotonicity and concavity. The concavity can be tested by examining the matrix of the elasticities of inputs and output specified in the model in Eq. (5.30) for semi-definite negativity as explained by Gallant (2008). The percentage frequency of positive marginal productivities of the estimated Translog energy demand function with risk are as follows (See Table 9.4): Output (0.739), non-ICT capital (0.863), labor (0.268), materials (0.497), value added services (0.764), and ICT capital (0.138), indicating on average positivity of logarithmic marginal products with respect to output and each input factor is satisfied.

The convexity of own price elasticity is also satisfied with (0.928), indicating that more than 92 % of the data points satisfy the convexity condition of own price elasticity in the energy demand model with risk. The Curvature conditions in the energy demand model with risk is also tested. The Eigen values of the elasticities are mixed in sign. The sample average elasticities for price, output, capital, labor, materials, value added services, ICT capital, and time trend are (1.178), (0.805), (0.195), (0.008), (–0.066), (-0.300), (–1.122), and (–2.564), respectively. The sum is negative (–1.866) indicating negative semi-definite values, and hence the second regularity condition is also satisfied (Moss et al. 2003).

9.7 Specification Test

A specification test called Harvey test (Harvey 1976) is undertaken for the pooled energy demand model with risk. The test is based on the FGLS estimator. The null hypothesis in Harvey's test states that all coefficients of the multiplicative variance function except the intercept β_0 is zero. The Harvey's test statistic is RSS/4.9348, where RSS is the residual sum of squares of the estimated variance function, and it is asymptotically distributed as a chi-square with degrees of freedom equal to the number of regressors. For the model under this study the Harvey's test statistic is equal to (944.982) with 25 degrees of freedom for the variance function log (err).

This is noticeably higher than the chi-square value of (46.928) at the 99 % level. Thus the null hypothesis is rejected and the model with variance function is accepted.

9.8 The Energy Demand Elasticities

The elasticities of energy with respect to various inputs are also calculated for this model at each point of the data. The parameters estimated for the Translog energy demand with risk model and the input elasticities of substitution are evaluated at the mean per year, per industry, and per industry's characteristics are all reported in Tables 9.10, 9.11, 9.12, 9.13, 9.14, 9.15 and 9.16 in Appendix A. The overall mean input elasticities are reported in Table 9.5.

The own price elasticity of energy (the mean energy demand elasticity with respect to energy price) is equal to (–0.634) with the standard deviation of (0.425) See Table 9.5. It validates as expected the negative responsiveness of the energy demand with a change in the energy price. The positive value of the mean elasticity of energy with respect to capital indicates that energy and capital are complement. The mean value of (0.204) with a standard deviation of (0.170) indicates that on average a 10 % increase in the capital leads to 2.04 % increase in energy use. The mean elasticity of energy with respect to value added services is also positive and equal to (0.196) with a standard deviation of (0.391), indicating a complementarity between the energy and value added services. The negative values of the mean elasticity of energy with respect to labor, materials, and ICT capital indicate a possible substitutability between these inputs with energy use. Mean energy demand elasticity with respect to output is equal to (0.678) with a standard deviation of (0.553). It is interpreted as everything else held constant, energy use increases by about 0.5 % for every 1 % increase in output.

Table 9.5 Overall mean elasticities

Variable	Mean	Std. Dev.	Percentage frequently of positive marginal productivity
σ_{EP}	–0.634	0.425	(Negative values) 0.928
σ_{EY}	0.678	0.553	0.739
σ_{EK}	0.204	0.17	0.863
σ_{EL}	–0.26	0.51	0.268
σ_{EM}	–0.023	0.486	0.497
σ_{ES}	0.196	0.391	0.764
σ_{EI}	–0.221	0.197	0.138
σ_{ET}	0.039	0.041	–
Technical Efficiency	0.244	0.259	–

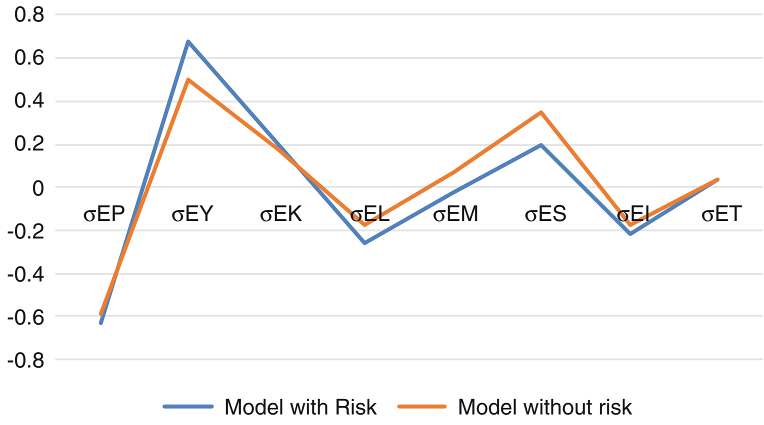

Fig. 9.1 Comparison of mean input elasticities estimated for energy demand model with and without risk

It is worth of mentioning that the mean elasticities calculated for the Translog energy demand function without risk vary somewhat (in the magnitude level and in the degree of dispersion around mean). However, they are fairly consistent in terms of the ranking of the inputs except for materials, the mean elasticity of materials shows substitutability while in the previous model shows complementarity (see Fig. 9.1). The current model is considered the favored model due to its consideration for risk and for correcting for heteroskedasticity through applying FGLS estimators. Therefore, the estimators of this model are rather more accurate than the previous model, i.e. the energy demand without risk. Looking at the model's coefficient of determination (R^2), which is equal to (0.924) in this model compared with (0.867) in the previous model based on the differences, one may be able to judge that the latter model is more consistent that the previous model.

9.9 The Marginal Risks Effects

The marginal risks effects (or so called the marginal variance) with respect to input j as in Eq. (5.28) are calculated for each input factors of production. The figures are equivalent to the total elasticity of energy with respect to output and each input. The total marginal effects are also calculated by summing up the individual marginal variances, which is equivalent to the returns to scale calculated in the previous models. If the total marginal effects are positive (negative) then expanding in the level of output will lead to increase (decrease) in the energy demand variance, respectively (Heshmati 2001). The variance is considered as an increasing function of expected value of the mean of energy demand. The variance function is specified using output, energy price, quasi fixed inputs, as well as the industries'

Table 9.6 The marginal risks (Variances)

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Price	–0.17	1.003	1980–1995	0.126	0.284
Output	0.013	1.187	1996–2007	0.859	1.332
Capital	0.041	0.388	Medium size	–0.14	0.346
Labor	0.167	0.93	Small size	–0.11	0.238
Services	–0.14	0.879	Labor productivity	–0.2	0.599
ICT capital	–0.05	0.386	Capital intensity	–0.2	0.663
Time	0.233	0.514	High skilled labor	–0.32	0.662
Mid-Tech	0.126	0.284	Medium skilled labor	–0.6	0.982
Low-Tecg	0.859	1.332	outsourcing	0.093	0.269
Mixed market	–0.05	0.099	1974 crisis	–0.07	0.118
Domestic market	–0.45	0.804	1980 crisis	–0.02	0.042
Medium R&D	0.12	0.278	Total marginal variance	–0.34	0.246
Low R&D	0.06	0.134			

characteristics. A time trend is included also in the variance function to capture the neutral shift over time. The estimated parameters are reported in Table 9.6.

The total marginal risk effect is negative, indicating that any increase in the output level will lead to decrease in the energy demand variance. Perhaps if the industry tends to expand its production level, it will more likely adopt better techniques, newer technologies and better strategies for its demand for energy. The negative values for marginal value added services and marginal ICT capital indicate that these two factors are energy risk decreasing factors. Hence, increasing the amount of value added services and the level of ICT capital will increase the stability of energy demand, in other words, reduce the risk faced by the producers for their decision for the amount of energy use in the production.

The risk reducing effects of ICT capital bodes well with the expectations, since increasing in the level of ICT capital should enable the industries to use energy and also other inputs in more efficient way, also to carry out crucial management practices more frequently. The result corroborates with the findings of Bunse et al. (2011) that ICT tools are important factors to enhance the energy efficient use in manufacturing. In addition to ICT capital, the value added service input shows risk reducing effects for energy demand. Employing more services perhaps will increase the efficiency of using energy in the production.

On the other hand, output, labor, non-ICT capital, and time are risk increasing factors of energy demand variance. Increasing the level of output and increasing the level of the capital and labor overt time will have negative impact of the stability of energy demand in the production. In terms of industries' characteristics, high technology based industries, domestic and mixed market oriented industries, high R&D scale investment, large size industries, industries with low skilled labor, and periods after the two oil hikes are risk decreasing for energy use.

9.10 Technical Efficiency

The technical efficiency component is also added to the risk model. As shown by Kumbhakar and Tveterås (2003), adding the technical efficiency effects into the risk model will prevent the estimation to be misleading, as the allocation of inputs in the production process is affected by the production risk and the presence of technical inefficiency. The mean value of technical efficiency estimates obtained from Eq. (9.2) is reported in Table 9.5. The technical efficiency estimates by year, sector, and by industries' characteristics are reported all in Tables 9.10, 9.11, 9.12, 9.13, 9.14, 9.15 and 9.16 in Appendix A. Technical efficiency is both industry and time specific.

9.11 Hypotheses Testing

From estimating the production function model and the energy demand model not accounting for risk, it was not possible to evaluate all the research questions stated in chapter one. However, in this model, all the research questions will be examined with their hypotheses as follows:

R_1: What is the impact of energy use on the production level in the South Korean industrial sector?

From the results reported in Table 9.5, the mean elasticity of energy with respect to output is equal to (0.678) with a standard deviation equal to (0.553). It implies that a 10 % increase in output level, the energy use will be increased by 6.78 %. By looking at the figures of the mean elasticity of energy with respect to output across the sectors that are reported in Table 9.5, the variability of the level of energy used in the production level across the industries can be noticed (See Fig. 9.2). As a result, the null hypothesis is rejected. The evidence supports the alternative hypothesis suggesting that there is a significant and positive impact for energy use on the production level in the industrial sector for South Korea.

R_2: Is there any factor substitution pattern between energy and other inputs of production in the South Korean industrial sector?

Using the results reported in Table 9.5, one can evaluate the mean elasticities' signs. The sign for the elasticity of energy with respect to each input specifies whether this input on average is a substitute (negative sign) or a complement (positive sign). The negative signs of the elasticities of energy with respect to labor, materials, and ICT capital indicate that these three inputs may substitute the level of energy use in the production. As a result, the null hypothesis will be rejected against the alternative hypothesis that ICT capital and labor are two factors substituting the energy in the South Korean industrial sector. However, across industries, the sign of the mean elasticity of energy with respect to the different inputs differ, indicating substitutability for some industries and complementarity for some other industries.

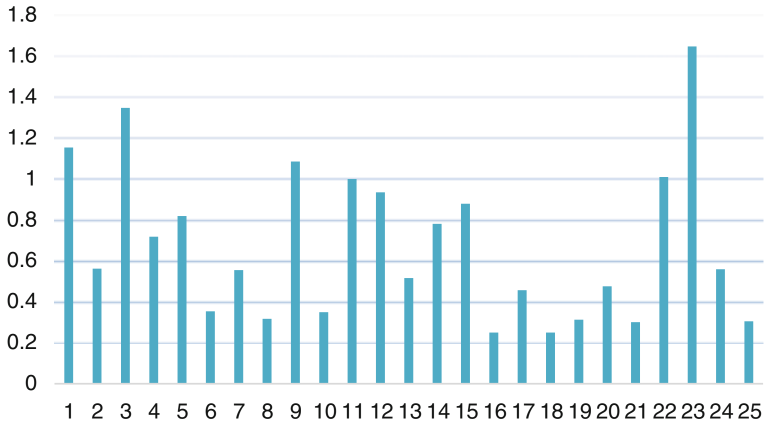

Fig. 9.2 The mean elasticity of energy with respect to output across sectors

In the risk analysis model, the research question R_3 which states that: "What factor(s) affect(s) the variability of energy demand in the South Korean industrial sector?" will be addressed through testing its null and alterative hypotheses. The null hypothesis is rejected. According to the results there are two input factors decreasing the variability of energy demand, value added services and ICT capital. Whereas, there are three input factors increasing the variability of energy demand, non-ICT capital, materials, and labor. It is believed that any increase in capital (with all other inputs held constant) should lead to a decrease in energy demand risk if the two variables are found to be substituting each other. However, the complementarity pattern between energy and capital is found in this study.

9.12 Summary

Due to the fact that standard panel data models in the literature are in general assuming homoskedastic errors, there is little evidence on the performance of different econometric panel data estimators in the presence of heteroskedasticity. This chapter provides an insight for the case of heteroskedasticity in regressors.

This study extends Saha et al. (1997) analysis to a more flexible parameterization of the Just and Pope technology. A Translog functional form is used for the mean function to allow for elasticity of scale, and for analysis of substitution and complementarity in effects.

This chapter proposed a new structure and magnitude of production risk in the South Korean industrial sector for the period 1970–2007 by means of estimating the energy demand model. Since efficiency analysis and analysis of industry behavior under risk aversion require knowledge about both conditional mean and variance of the output, this chapter investigated both the mean production function and the variance production function. This has mainly been achieved through estimating the Just and Pope Production Model.

The third group of models is concerned with the analysis of variance for the energy demand model, in which the variance (risk) is accounted for in the estimating procedure. The marginal variance (marginal effects) of each estimated parameters are presented and interpreted. A positive (negative) marginal effect indicates increasing (decreasing) the variability of the energy demand at the industrial sector level. Based on that, the necessary implications and policy recommendations may be derived.

For the third group of models, i.e. the energy demand with risk where the error variance relationships are known (heteroskedasticity of known form), the FGLS is applied with weighted on the error variance to obtain consistent estimators (SAS Institute Inc. 1993).

A natural first step in empirical analysis of production risk is to test if heteroskedasticity is present in the data set, particularly if output is heteroskedastic in input levels. Testing of heteroskedasticity is undertaken in this chapter.

The technical efficiency effects have been added into the model to prevent the estimation to be misleading, as the allocation of inputs in the production process is affected by the production risk and the presence of technical inefficiency.

Appendix A: Summary Data, Parameter Estimates, and Elasticities for the Translog Energy Demand Model II

Table 9.7 Summary statistics for the risk variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Energy	1.021	0.548	0.242	2.365
Output	1.023	1.514	0.007	19.997
Capital	1.021	1.823	0.000	17.735
Labor	1.022	1.237	0.009	8.905
Material	1.024	2.08	0.003	29.613
Service	1.025	1.645	0.005	19.28
ICT capital	1.026	2.986	0.000	29.108
Technology level	2.16	0.88	1.000	3.000
Export/Import orientation	2.24	0.907	1.000	3.000
R&D scale	1.84	0.784	1.000	3.000
Financial crisis periods	2.054	0.734	1.000	3.000
Industry size	2.034	0.824	1.000	3.000
Labor productivity	1.016	1.059	0.063	8.534
Capital intensity	1.009	1.892	0.000	18.044
High skilled labor	36.694	20.322	7.920	84.813
Medium skilled labor	38.763	11.324	12.235	61.455
Low skilled labor	24.543	17.628	1.195	72.603
Labor outsourcing	1.005	2.270	0.003	16.836

Table 9.8 Pearson correlation coefficients

Energy	Output	Capital	Labor	Material	Service	ICT	Tech	Export	R&D	Period	Size	Labor productivity	Capital intensity	High skilled	Medium skilled	Low skilled	Outsourcing
Energy	1																
Output	0.5	1															
Capital	0.3	0.8	1														
Labor	0.4	0.7	0.5	1													
Material	0.3	0.9	0.6	0.5	1												
Service	0.5	0.9	0.7	0.7	0.7	1											
ICT	0.2	0.3	0.4	0.5	0.2	0.3	1										
Tech	0	–0.1	0	0.1	–0.2	–0.1	0.1	1									
Export	0	–0.2	0	0.1	–0.4	–0.1	0.1	0.7	1								
R&D	0	–0.1	0.1	–0.2	–0.1	0	–0.2	0.4	0.3	1							
Period	0.9	0.4	0.3	0.5	0.3	0.5	0.3	0	0	0	1						
Sze	0	0.3	0.2	0.4	0.2	0.4	0.2	0.1	0	0.1	0	1					
Labor productivity	0.5	0.5	0.5	0.2	0.5	0.4	0.2	–0.1	0	–0.1	0.4	–0.3	1				
Capital intensity	0.2	0.2	0.4	0	0.1	0.1	0	0.1	0.2	0	0.2	–0.3	0.8	1			
High skilled	0.3	0.2	0.3	0.5	0	0.2	0.3	0	0.3	–0.4	0.3	0.1	0.2	0.2	1		
Medium skilled	0.2	0.2	0.1	–0.2	0.3	0.2	–0.2	–0.2	–0.4	0.2	0.3	–0.1	0.2	0	–0.5	1	
Low skilled	–0.5	–0.3	–0.3	–0.5	–0.2	–0.4	–0.3	0.1	–0.1	0.4	–0.5	–0.1	–0.3	–0.2	–0.8	–0.1	1
Outsourcing	0	0.1	0.2	0.4	0	0.1	0.1	0.3	0.2	0.1	0	0.3	–0.1	0	0.1	–0.1	0

Table 9.9 Analysis of variance—feasible generalized least square parameter estimates

Cobb-Douglas			Translog function		
Dependent variable: Log(error)			Dependent variable: Log(error)		
Variable	Parameter estimate	t value	Variable	Parameter estimate	t value
Energy	0.090b	1.63	Energy	0.168	1.25
	(–0.055)			(–0.135)	
Output	0.049	0.52	Output	–0.137	–0.67
	(–0.095)			(–0.204)	
Capital	–0.054b	–1.95	Capital	–0.076b	–1.81
	(–0.028)			(–0.042)	
Labor	0.0002	0.01	Labor	0.049	0.73
	(–0.027)			(–0.066)	
Material	–0.042	–1.12	Material	0.102	1.24
	(–0.037)			(–0.082)	
Service	0.101a	2.33	Service	0.050	0.68
	(–0.043)			(–0.074)	
ICT capital	0.027b	2.24	ICT capital	0.034b	1.97
	(–0.012)			(–0.017)	
Time	–0.021a	–4.07	Time	–0.027b	–2.28
	(–0.005)			(–0.012)	
Mid-tech	–0.427a	–5.12	Mid-tech	–0.691a	–3.8
	(–0.083)			(–0.181)	
Low-tech	–0.194a	–2.95	Low-tech	–0.229c	–1.48
	(–0.065)			(–0.154)	
Mixed- market	0.168a	2.23	Mixed- market	0.197	1.1
	(–0.075)			(–0.180)	
Domestic-market	0.405a	4.84	Domestic-market	0.500a	2.78
	(–0.084)			(–0.180)	
Medium R&D	0.255a	5.31	Medium R&D	0.382a	3.92
	(–0.048)			(–0.097)	
Low R&D	0.259a	4.51	Low R&D	0.1856b	1.84
	(–0.057)			(–0.101)	
1980–1995	0.059	0.85	1980–1995	0.214c	1.41
	(–0.068)			(–0.156)	
1996–2007	–0.071	–0.74	1996–2007	–0.145	–0.63
	(–0.095)			(–0.232)	
Medium size	0.095b	2.18	Medium size	0.189b	2.14
	(–0.044)			(–0.089)	

(continued)

Table 9.9 (continued)

Cobb-Douglas			Translog function		
Dependent variable: Log(error)			Dependent variable: Log(error)		
Variable	Parameter estimate	t value	Variable	Parameter estimate	t value
Small size	0.146a	2.39	Small size	0.294a	2.42
	(–0.061)			(–0.122)	
Labor productivity	0.022	0.44	Labor productivity	0.118	1.1
	(–0.050)			(–0.108)	
Capital intensity	0.034c	1.35	Capital intensity	0.079b	1.49
	(–0.025)			(–0.054)	
High skilled labor	0.008a	4.49	High skilled labor	0.008a	2.63
	(–0.001)			(–0.003)	
Medium skilled labor	0.006a	4.88	Medium skilled labor	0.012a	4.34
	(–0.001)			(–0.002)	
Labor outsourcing	–0.054a	–9.53	Labor outsourcing	–0.081a	–7.4
	(–0.005)			(–0.011)	
1974	0.180c	1.33	1974	–0.034	–0.34
	(–0.135)			(–0.102)	
1980	–0.047	–0.47	1980	–0.085	–0.36
	(–0.101)			(–0.237)	
SSE: 4209.9			**SSE**: 4668.3		
Root MSE(σ): 2.161			**Root MSE(σ)**: 2.277		

Note The significant levels: a 99 %, b 95 %, c 90 %
The standard errors are between the parentheses

Table 9.10 Overall mean elasticities by industrial sector

Industry	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EICT}	σ_{ET}	Efficiency
Agriculture, hunting, forestry and fishing	–1.101	1.154	0.217	–0.937	–0.165	–0.053	–0.265	0.066	0.245
Mining and quarrying	–1.084	0.562	0.331	0.452	0.214	–0.241	–0.457	0.002	0.06
Food, beverages and tobacco	–0.566	1.347	0.256	–0.159	–0.712	0.445	–0.289	–0.02	0.61
Textiles, leather and footwear	–0.41	0.718	0.214	–0.439	–0.329	0.498	–0.215	0.026	0.263
Wood and cork	–0.679	0.819	0.465	0.778	–0.615	0.128	–0.56	–0.018	0.11
Pulp, paper, printing and publishing	–0.409	0.354	0.308	0.149	–0.299	0.388	–0.296	0.03	0.231
Chemical, rubber, plastics and fuel	0.248	0.555	–0.06	–0.743	0.158	0.122	0.019	0.101	0.355
Other non–metallic mineral	–0.116	0.317	0.19	0.018	0.054	0.132	–0.218	0.072	0.114
Basic and fabricated metals	–0.1	1.085	0.142	–0.403	–0.497	0.223	–0.19	0.049	0.374
Machinery, NEC	–0.316	0.35	0.416	0.382	–0.623	0.762	–0.327	0.01	0.166
Electrical and optical equipment	–0.52	1.000	0.209	–0.419	–0.508	0.466	–0.192	0.016	0.384
Transport equipment	–0.389	0.935	0.27	–0.152	–0.628	0.333	–0.269	0.035	0.254
Manufacturing NEC, recycling	–0.509	0.516	0.367	0.459	–0.43	0.304	–0.374	0.012	0.092
Electricity, gas and water supply	–0.172	0.781	0.057	–0.153	0.181	–0.583	–0.21	0.104	0.042
Construction	–0.877	0.879	0.234	–0.891	–0.146	0.424	–0.275	0.028	0.379
Wholesale and retail trade	–0.859	0.25	0.099	–0.549	0.789	0.535	–0.04	0.017	0.265
Hotels and restaurants	–0.56	0.457	0.146	–0.428	0.273	0.728	–0.108	0.011	0.425
Transport and Storage	–0.87	0.25	0.207	–0.481	0.692	0.513	–0.211	0.02	0.41
Post and telecom	–0.749	0.313	0.193	0.251	0.266	0.101	–0.122	0.046	0.068
Financial intermediation	–1.19	0.476	0.124	–0.355	0.542	–0.106	–0.139	0.039	0.253
Real estate and business activities	–0.908	0.301	0.08	–0.549	0.658	0.271	–0.078	0.018	0.345
Public admin and defense	–1.141	1.01	0.195	–0.795	0.111	–0.097	–0.243	0.062	0.263
Education	–1.095	1.647	–0.013	–0.964	–0.024	–0.625	0.009	0.122	0.053
Health and social work	–0.632	0.559	0.218	–0.3	0.096	0.004	–0.243	0.08	0.089
Other community, social and personal services	–0.844	0.305	0.221	–0.263	0.366	0.232	–0.235	0.042	0.252

Table 9.11 Mean energy demand elasticities by year

Year	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EICT}	σ_{ET}	Efficiency
1971	–0.796	0.819	0.391	–0.157	0.017	0.175	–0.438	0.035	0.057
1972	–0.78	0.832	0.376	–0.142	0.011	0.161	–0.425	0.034	0.058
1973	–0.802	0.834	0.364	–0.198	0.005	0.173	–0.411	0.032	0.17
1974	–0.781	0.892	0.349	–0.185	–0.02	0.152	–0.405	0.029	0.167
1975	–0.768	0.869	0.342	–0.191	–0.027	0.168	–0.392	0.03	0.158
1976	–0.775	0.863	0.331	–0.239	–0.028	0.182	–0.376	0.031	0.061
1977	–0.777	0.864	0.319	–0.276	–0.043	0.178	–0.361	0.033	0.26
1978	–0.796	0.863	0.313	–0.314	–0.044	0.175	–0.359	0.033	0.319
1979	–0.773	0.879	0.3	–0.322	–0.068	0.163	–0.344	0.035	0.275
1980	–0.737	0.879	0.292	–0.294	–0.083	0.126	–0.34	0.039	0.306
1981	–0.691	0.979	0.272	–0.317	–0.155	0.115	–0.32	0.042	0.421
1982	–0.699	0.926	0.271	–0.313	–0.13	0.102	–0.322	0.043	0.366
1983	–0.707	0.921	0.263	–0.349	–0.137	0.106	–0.313	0.044	0.36
1984	–0.682	0.944	0.246	–0.347	–0.156	0.103	–0.291	0.044	0.32
1985	–0.667	0.965	0.237	–0.345	–0.164	0.089	–0.284	0.045	0.347
1986	–0.7	0.942	0.239	–0.355	–0.161	0.103	–0.289	0.041	0.419
1987	–0.687	0.946	0.224	–0.365	–0.184	0.132	–0.259	0.041	0.396
1988	–0.683	0.922	0.218	–0.381	–0.211	0.166	–0.239	0.041	0.353
1989	–0.676	0.869	0.215	–0.363	–0.215	0.187	–0.229	0.04	0.131
1990	–0.689	0.612	0.207	–0.324	–0.035	0.312	–0.204	0.031	0.351
1991	–0.676	0.637	0.194	–0.351	–0.052	0.319	–0.187	0.033	0.32
1992	–0.712	0.531	0.203	–0.307	0.031	0.312	–0.209	0.028	0.255
1993	–0.638	0.61	0.174	–0.318	–0.056	0.314	–0.163	0.034	0.139
1994	–0.637	0.57	0.166	–0.315	–0.047	0.322	–0.15	0.034	0.135
1995	–0.705	0.361	0.165	–0.271	0.168	0.33	–0.159	0.025	0.124
1996	–0.682	0.364	0.151	–0.282	0.17	0.321	–0.145	0.028	0.269
1997	–0.599	0.411	0.119	–0.275	0.103	0.307	–0.1	0.034	0.406
1998	–0.557	0.392	0.126	–0.18	0.098	0.232	–0.125	0.036	0.355
1999	–0.503	0.418	0.092	–0.202	0.076	0.243	–0.077	0.04	0.305
2000	–0.433	0.449	0.065	–0.228	0.04	0.237	–0.04	0.047	0.172
2001	–0.413	0.45	0.058	–0.212	0.045	0.226	–0.035	0.048	0.163
2002	–0.436	0.369	0.064	–0.178	0.109	0.234	–0.045	0.044	0.171
2003	–0.413	0.373	0.058	–0.167	0.096	0.208	–0.043	0.047	0.163
2004	–0.389	0.39	0.046	–0.155	0.075	0.172	–0.039	0.048	0.162
2005	–0.359	0.389	0.036	–0.144	0.055	0.157	–0.029	0.051	0.159
2006	–0.327	0.369	0.029	–0.127	0.038	0.143	–0.025	0.053	0.276
2007	–0.304	0.368	0.015	–0.121	0.03	0.115	–0.013	0.055	0.163

Table 9.12 Mean elasticities by industries' characteristics: technology level

Technology	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EICT}	σ_{ET}	Efficiency
High: 1	–0.468	0.638	0.231	–0.177	–0.227	0.315	–0.223	0.041	0.26
Medium: 2	–0.49	0.582	0.144	–0.275	0.194	0.036	–0.194	0.057	0.239
Low: 3	–0.805	0.744	0.21	–0.309	0.022	0.184	–0.231	0.03	0.223

Table 9.13 Mean elasticities by industries' characteristics: import/export orientation

Export	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EICT}	σ_{ET}	Efficiency
Inernational:1	–0.44	0.658	0.23	–0.194	–0.28	0.376	–0.219	0.034	0.245
Mixed: 2	–0.359	0.929	0.235	–0.138	–0.503	0.352	–0.258	0.019	0.405
Domestic: 3	–0.803	0.635	0.181	–0.323	0.227	0.06	–0.214	0.045	0.209

Table 9.14 Mean elasticities by industries' characteristics: R&D level

R&D	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EICT}	σ_{ET}	Efficiency
High: 1	–0.71	0.737	0.194	–0.31	–0.04	0.073	–0.204	0.054	0.293
Medium: 2	–0.508	0.671	0.195	–0.331	–0.063	0.315	–0.207	0.037	0.29
Low: 3	–0.696	0.588	0.231	–0.069	0.066	0.223	–0.271	0.017	0.261

Table 9.15 Mean elasticities by industries' characteristics: industry size

Size	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EICT}	σ_{ET}	Efficiency
Large: 1	–0.548	0.528	0.253	0.144	–0.049	0.021	–0.294	0.044	0.123
Medium: 2	–0.545	0.785	0.201	–0.296	–0.196	0.228	–0.216	0.038	0.301
Small: 3	–0.791	0.717	0.161	–0.593	0.155	0.326	–0.16	0.034	0.303

Table 9.16 Mean elasticities by industries' characteristics: oil shocks

Period	σ_{EP}	σ_{EY}	σ_{EK}	σ_{EL}	σ_{EM}	σ_{ES}	σ_{EICT}	σ_{ET}	Efficiency
<=1979	–0.783	0.857	0.343	–0.225	–0.022	0.17	–0.39	0.033	0.169
1980–1995	–0.686	0.763	0.22	–0.329	–0.083	0.203	–0.241	0.037	0.295
>=1996	–0.43	0.398	0.064	–0.181	0.07	0.207	–0.052	0.046	0.227

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Chapter 10
Discussion of the Results and Policy Implications

This chapter summarizes the findings from the estimated models. The empirical results are summarized for (i) The mean in case of production function and energy demand function without risk, and (ii) for the mean and variance function in the case of energy demand accounting for risk, in which the findings are related to the theory of the competitive firm under production risk. The empirical results are also discussed in relation to the information available about the industrial sector for the data period. Furthermore, the chapter covers the implications and policy recommendations based on the estimated models for production function and energy demand. According to the results a noticeable increase in consumption of energy in the South Korean industrial sector was observed during the 2000s due to the rapid industrialization and urbanization. The estimated mean input elasticities of energy with respect to output and other inputs were differ for the two model specifications, i.e. energy demand with and without risk, but are fairly consistent in terms of the ranking of inputs. The construction of these elasticities and their sizes reveal significant structural attributes of South Korean industrial sector. The technological progress of South Korean industrial sector leads to greater materials efficiency in the production due to recycling wastes and reusing the materials to the production process. The industries with the technological advancement were able to change their manufacturing process over time through decreasing the use of expensive materials and resources redistribution. Industries classified as high technology, largest size, domestic oriented market, and highest scale of R&D investment are those with the highest values for elasticity of energy. On the other hand, the medium technology classified industries, largest size in terms of labor, export oriented, and industries with medium scale of R&D investment are among industries with the lowest values of elasticity of energy. The elasticity of ICT capital is the smallest among all the input factors of production. In general the trend shows an increasing and fluctuating growth over time. Although South Korea is considered one of the strongest ICT producing countries, the results show relativity weak ICT usage in the industrial sector. The government's excessive regulations have lowered the productivity in the service industries. In addition to that, the South Korean public sector suffers from true competition, in which it hampers the ICT usage effects and to explore more renewable and sustainable growth. In general, all industries are exhibiting increasing returns to scale. The returns to scale measures increase in the output resulting from

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increase in the energy use, conditional on other inputs and technology. The empirical model of the energy demand with risk provides evidence of significant marginal effects in inputs which indicates that some inputs are risk increasing and some are risk decreasing factors. The value added services and ICT capital are the only two inputs decreasing risk, with ICT capital having clearly the most significant reducing effect on energy use variance. The author believes that any increase in non-ICT capital with all other inputs held fixed must lead to reduction in the level of energy demand risk if the two variables are found to be substituting each other. However, the complementarity relationship between energy and non-ICT capital is found in this study, indicating the possibility of non-ICT capital to be variance increasing input for energy. There are three input factors increasing the variability of energy non-ICT capital, materials, and labor. As for technical efficiency, the results indicate in general inefficiency in the use of energy. However, the technical efficiency is slightly increasing over time except during the period of the two oil shocks, and a large variation across the industries is observed.

10.1 Introduction

The analysis presented in Chaps. 7–9 provide an appealing perspective of the relationships between energy demand and other input factors of production, as well as between energy demand and some industries' characteristics. It also provide a general comparison between these relationships. This chapter provides insights into the implications of all the variables affecting the demand for energy, an in-depth discussion of the results is provided based on the different measures such as input elasticities, returns to scale, technical efficiency, and marginal risk. Recommendations for decision makers will be made, along with their support and justification that have emerged from the analyses and findings.

10.2 The Growth in Energy Consumption

A noticeable increase (about 42.5 %) in the energy consumption in the South Korean industrial sector was observed during the 2000s, which can be attributed to the rapid industrialization and urbanization. The chemical, rubber, plastics and fuel industry, electricity, gas and water supply industry, and other non-metallic minerals industry are the most three energy intensive industries in South Korea. Therefore, any policy intervention related to energy conservation programs should in the first place be targeting these industries.

The least energy intensive industries are public administration and defense industry, financial intermediation industry, electrical and optical equipment industry, and food and beverage industry. For these least energy intensive industries, different tax incentives schemes and tiered tariffs can be applied for further enhancement toward energy conservation.

10.3 The Elasticities of Inputs

10.3.1 The Production Function Models

For the estimated mean output elasticities in the production models See Tables 7.5–7.11 in Appendix A of Chap. 7. The most important input with respect to mean output, i.e. the highest elasticity of mean output with respect to production factor inputs is found to be the materials σ_{YM}. The average output elasticity with respect to materials is equal to (0.368). This implies that 1 % increase in the materials input is associated with 0.368 % increase in output.

In the production model, the mean elasticity of output with respect to energy σ_{YE} is equal to (0.046), while it is equal to (0.499) in the energy demand model (See Tables 7.4 and 8.3). In spite of the variation between the two models, the sign is still positive, indicating that there is a significant and positive impact for energy use on the production level in the industrial sector for South Korea. Evidence from estimating the production model shows that ICT capital and labor are substitutes in relation to energy demand.

In the production model the largest scale of elasticities is the row materials elasticity with a sample mean of (0.368) and a standard deviation of (0.094), and a strong decreasing trend moving the average value from (0.432) in 1978 to (0.287) in 2007 (See Table 7.4). The technological progress of South Korean industry leads to greater materials efficiency in the production due to recycling wastes and reusing the materials to the production process. The industries with the technological advancement were able to change their manufacturing process over time through decreasing the use of expensive materials and resources redistribution. Moreover, the policy of tariff exemption on imports of raw materials and investment goods by the South Korean government in the economic development plan after 1970s, and the import liberalization have had increased the supply of low cost materials to the industry (Lee et al. 2012).

By looking at Table 7.6 in the Appendix A of Chap. 7, where elasticities are sorted by industry type, a variation in the scale of elasticities for materials can be observed. The largest in magnitude is in the mining and quarrying (industry code 2) with the elasticity value of (0.449). The industry is classified as low technology, low investment in R&D, and domestic oriented market, hence it lacks the adequate use of resources management than other industries. The second extreme value is the electricity, gas and water supply (industry code 14) with elasticity value of (0.444). This industry classified as medium in technology use, high in R&D investment, and a domestic market oriented. Although it is considered as a high investment industry in R&D, the demand for raw materials is still high elastic. The lowest value of elasticity of materials (0.232) is observed with the education industry (industry code 23) followed by post and telecommunication (industry code 19) and hotels and restaurants (industry code 17) with value of (0.252), and (0.253), respectively.

By looking at Tables 7.8–7.11, where elasticities are sorted by industries' characteristics, i.e. by technology, size, export orientation, R&D scale, and by period when the two oil price shocks occurred. A medium level technology classified industry with relatively large size, a mix market oriented, and a medium scale of R&D has on average a higher elasticity of materials, while a low technology classified industry with smaller in size, domestic oriented market, and high investment in R&D has on average the lowest elasticity of materials. In spite of the large variations, the materials became on average much less constraining factor on production in the South Korean industrial sector.

The second largest in magnitude is the labor elasticity with the sample mean of (0.266) and a standard deviation equal to (0.080). It slightly decreased from year 1970 till year 1977, and then started to increase again till year 1981, but sharply decreased since then until year 2007. The increase in machinery and advanced technology have led to such sharp decline in the labor elasticity. The size of the industry is found to be negatively related to the elasticity of labor. There are large variations across industries due to their variability in labor requirement. The lowest labor intensity found in real estate, renting and business activities (industry code 21), and wholesale and retail trade (industry code 16). The highest labor intensity is in the education (industry code 23) followed by health and social work (industry code 24).

The high technology classified industry, smallest in size, national market oriented industry, and those with high scale investment in R&D are among the industries with largest elasticity of labor. Medium level of technology, mixed market oriented, and medium scale in R&D investment are those industries with lowest elasticity of labor.

By looking at the figures for energy elasticity of demand in Table 7.4, it can be noted that the sample mean is (0.046) and the standard deviation is equal to (0.056), and a decreasing trend moving the average values from (0.425) in year 1979 to (0.068) in year 2007 is observed. It indicates that some of the South Korean industries found their way for possible substitution of energy with the other factors of production. The second oil crisis in year 1996 has changed the energy consumption structure in the South Korean industry sector. This can be noticed from the sharp increase in elasticity since year 1997 till year 2001. The size of the industry is found to be negatively related to the energy input. In comparing these elasticities with the energy intensity figures reported in Table 6.12, the results are matching for the period 1980–1990, as the industries became less intense in energy use during that period.

For the elasticity of energy with respect to output by industry, wood and cork (industry code 5) is the highest (the elasticity is equal to 0.148) followed by manufacturing (industry code 13), and machinery (industry code 10) with the value of (0.111) and (0.100), respectively. A perfect inelastic figures for three industries: Whole sale and retail trade (industry code 16), transport and storage (industry code 18), and real estate and renting and business activities (industry code 21) indicate that any change in the level of energy use in these three industries will not have noticeable effects on changes in the level of output.

Three industries have relatively lowest elasticity of energy: Public administration and defense with the value of (0.003) (industry code 22), chemical, rubber, plastic and fuel industry with the value of (0.009) (industry code 7), and the construction industry with the value of (0.011) (industry code 15). There are different reasons for such variation, for example in the public administrative and defense industry, which is a fully publicly supported sector financed by the state, the change in the energy consumption has little effects on their output due to government's full subsidy policy. For construction industry it seems that technology has developed in this industry in a way that it tends to be less energy intensive. However, for the chemical and rubber industry, the energy consumption is essential factor of production but the figures here do not reflect the actual conditions.

Industries that are classified as high technology, largest size, domestic oriented market, and highest scale of R&D investment are those with the highest values for elasticity of energy. On the other hand, the medium technology classified industries, largest size in terms of labor, export oriented, and industries with medium scale of R&D investment are among industries with lowest values of elasticity of energy.

The sample mean for the elasticity of capital is equal to (0.183) with a standard deviation of (0.123). It declined until year 1996 and then slightly increased after that. The reason for this change might be the policy of tax incentive provided by the government to enhance the productivity. The most capital intensive industries are wood and cork (industry code 5), machinery (industry code 10), basic metals and fabricated metal (industry code 9), and manufacturing (industry code 13) with capital elasticity of (0.348), (0.335), (0.309), and (0.305), respectively. The lowest capital intensive production is in education (industry code 23). From above one may conclude that the technology level and the size of the industry are positively related to the elasticity of capital.

The sample mean of the elasticity of value added service is equal to (0.130) with a standard deviation of (0.126). It decreased until year 1983, and then started to increase slightly until year 1989 but aggressively since then. There is a noticeable variation across industries. The lowest elasticity is in the electricity, gas and water supply (industry code 14) and mining and quarrying (industry code 2), while other community, social and personal services (industry code 25), and health and social work (industry code 24) are among the industries with largest value added service elasticity. The elasticity of value added service is positively related to the size of the industry and negatively related to the R&D scale. The lowest values of service elasticity are attributed to industries with medium technology classified industry, small size, high investment in R&D, and mix market oriented industry. The highest service elasticity are related to those with low technology classified, larger in size, international market oriented industry, and low scale in R&D industry.

The elasticity of ICT capital is the smallest among all the input factors of production. The sample mean is equal to (0.021) and the standard deviation is equal to (0.040). In general the trend shows an increasing but fluctuating growth over time. It fluctuated slightly for the period 1970–1986, then started to increase aggressively till year 2001 and slowed down slightly since then. This fluctuation in some periods and the aggressive increase in another period might be attributed to several factors. South Korea is considered as one of the strongest ICT producing countries. However, the results show relativity weak ICT usage. This might be due to the excessive regulations that lowered the productivity in the service industries.

Another explanation as depicted by Fukao et al. (2009) might be that the South Korean public sector suffers from true competition, in which it hampers the ICT usage effects and to explore more renewable and sustainable growth path.

Ten industries show very low or zero elasticities, these are mining and quarrying (industry code 2), food, beverages and tobacco (industry code 3), wood and cork (industry code 5), pulp, paper, printing and publishing (industry code 6), other non-metallic mineral (industry code 8), basic metals and fabricated metal (industry code 9), machinery (industry code 10), transport equipment (industry code 12), manufacturing NEC and recycling (industry code 13), electricity, gas and water supply (industry code 14), while wholesale and retail trade (industry code 16) show highest elasticity.

Positive relation found between industry's size and elasticity of ICT capital. The low technology classified, low scale in R&D, and national oriented industries are those with highest elasticity of ICT capital, while high technology classified, medium scale in R&D, and the mixed market oriented industries are with the lowest elasticity of ICT capital.

For the rate of exogenous technical change which reflects the shift in the production function over time holding other factor unchanged (ceteris paribus), the elasticity of output with respect to time is examined. The negative sample mean value of elasticity of time shows technical regress which implies that on average the production has slowed down. The technological regress might be a result of increased competition in international market or tightened (environmental) regulations that caused lowering in the productivity.

In some industries a restructure of energy consumption is taken place by adopting new, more energy efficient, and productive technology as mentioned in the previous chapters. The high technology classified industries still lack behind in implementing energy saving programs although the substitutability between ICT capital and energy is feasible and proved in this study. The high rate of energy saving technical change in some industries implies that these industries have experienced strong competitive pressure within the industries or encounter competition against countries with cheaper energy supply.

10.3.2 The Energy Demand Models

The estimated mean input elasticities of energy with respect to output and other inputs were vary somewhat for the two model specifications, i.e. energy demand with and without risk, but are fairly consistent in terms of the ranking of inputs (See Tables 8.3 and 9.5). The construction of these elasticities and their sizes reveal significant structural attributes of South Korean industrial sector. Several important conclusions can be drawn from the reported results in Table 8.3 and Tables 8.4–8.10 in the Appendix A of Chap. 8:

1. The own price elasticity of energy (the mean energy demand elasticity with respect to energy price) is equal to (−0.591) with a standard deviation of (0.532), implies the expected negative responsiveness of the energy demand with changes in the energy price.
2. The elasticity of demand for energy use with respect to its price rate in mining and quarrying (industry code 2) is highest in absolute (it is equal to −1.247) followed by financial intermediation (industry code 20) with value of (−1.121), public administration and defense (industry code 22) with value of (−1.115), real estate, renting and business activities (industry code 21) with value of (−1.091), whole sale and retail trade (industry code 16) with value of (–1.041), and agriculture forestry, hunting and fisheries (industry code 1) with value of (−1.024). The figures indicate high elastic energy demand in respect with its price. These industries are generally low energy intensive. They are relatively more dependent on energy than other industries. On the other hand, the less responsive industries with energy price change are transport equipment (industry code 12) with value of (−0.309), machinery, NEC (industry code 10) with value of (−0.349), textile, leather and footwear (industry code 4) with value of (−0.368), pulp, paper, printing and publishing (industry code 6) with value of (−0.373), and hotels and restaurants service (industry code 17) with value of (−0.393), respectively.

   Different reasons are causing such behavior in the energy price elasticities. For example, transport equipment (industry code 12) and machinery, NEC (industry code 10) are the two industries with intense use of energy, in which it implies that the energy is an essential factor of production; therefore they are more likely to be less responsive to changes in energy price. The other three less responsive industries are classified as low technology industries; they are still unable to substitute the energy with other factors of production with lower price.
3. Complementarity can be found between energy with capital, materials, and value added services. The mean elasticity of energy with respect to capital and materials are (0.175) and (0.068), respectively, indicating slight complementarity relationship between energy with capital and materials, while relatively larger complementarity can be found between energy and value added services with mean elasticity equal to (0.349). It is interpreted as a 10 % increase in capital leads to 1.75 % increase in energy use.

   The non-ICT Capital elasticity over time is positive, but decreases continuously. The highest and lowest non-ICT capital input elasticities are found in the wood and cork, and basic metals and fabricated metal corresponding to (0.479) and (0.075), respectively. After the financial crisis it has declined toward zero level around the end of the study period. Moreover, the level varies greatly over time.
4. The energy input is found to be substituted by ICT capital and labor with mean elasticities of (−0.175) and (−0.172), respectively. That is, a 10 % increase in labor decreases energy use by only 1.72 %. All elasticities over time have negative signs. It implies that labor provides an opportunity to substitute energy but employment is not an important factor affecting the energy use. Across industries, the labor elasticities are either positive or negative. The elasticities

are varied between (−0.972) for education (industry code 23) and it is (0.638) for wood and cork (industry code 5). The results conclude that it is not sufficient to mentioning the substitution or complementarity of labor inputs for energy, but one has to look at the dispersion across industries and over time. For the ICT effects, according to the result mentioned above, a 10 % increase in investing in ICT will yield 1.75 % decrease in the use of energy. The effects look similar to the effects of labor in this study.

5. The mean energy demand elasticity with respect to output is equal to (0.499). It is interpreted as everything else held constant, energy use increases by about 0.5 % for every 1 % increase in output. The sign of the elasticity is positive as expected. It suggests that if in the industry wide more output is produced, the industries will use more energy. The positive output elasticity of energy which is less than (1.0) suggests that economic growth leads to higher energy use, but with higher energy use efficiency. Although economic growth can be helpful to productivity per unit of energy use, it makes the total energy use and the CO_2 gas emissions increase. Increasing the level of production to secure energy efficiency is a dilemma (IEA 2011). Industry wise, the output elasticities vary between (1.222) for agriculture, hunting forestry and fishing, and (0.251) for other community, social and personal services. The elasticities have changed widely overtime. The W-shaped curve emerges as time passes. It represents quite wide variation over time and across industries in the size of the elasticity reflecting variations in energy use efficiency and positive saving rates across industries.
6. Over time, no systematic pattern is observed in the development of energy price elasticity. All mean elasticities of energy price in each year are as expected negative. By looking at Table 8.4 where elasticities are sorted by year, the energy demand responsiveness for change in its own price has declined dramatically over time, although the fluctuation in the period of 1988–1996 occur due to effects of the second oil supply shock. This results cope with the findings of Kamerschen and Porter (2004), who argued that the relationship between economic growth and energy demand becomes more feasible after the industrialization.
7. The rapid development of production capacity in the South Korean industries over time have led to expansion in these industries, urbanization process, and increase in the national economy (Lee et al. 2012). As a result, the response to changes in energy price has little effects on the total demand for energy over time. The process of industrialization in South Korea has transformed its economy from agriculture dominated structure into a service based with annual GDP growth of 2.9 % (Cho et al. 2004). The high growth rate of 4–5 % have been observed during the four decades of industrialization. Hence, the increase in GDP per capita leads to significant increase in energy demand. A possible explanation might be due to the shift of industries from labor intensive to more capital and energy intensive production. In addition, the urbanization process resulted from industrialization lead to more energy demand because of expansion in services, food delivery, developing and maintenance of infrastructure (Liu 2009).

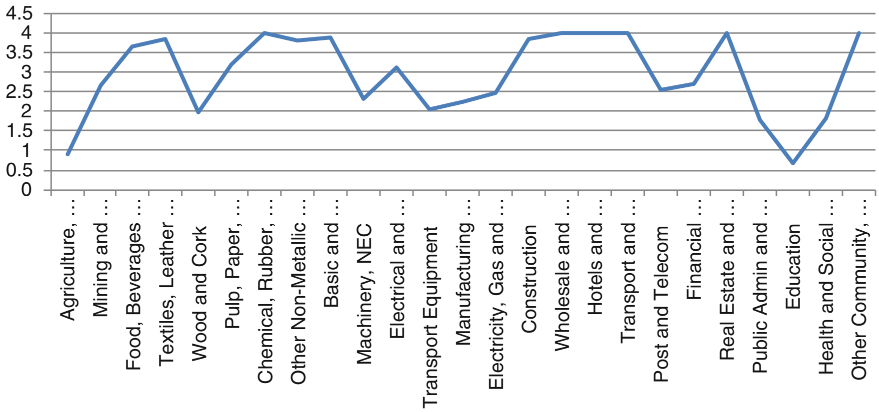

Fig. 10.1 Rate of returns to scale by industry

10.4 The Returns to Scale

The return to scale *RTS* is equal to some of all the output elasticities with respect to inputs. It measures the increasing rate in the output as a result of proportional increase in all the inputs. The overall sample mean estimated is equal to (1.014) for the production model. However it is not statistically different than constant returns to scale. There was a decline in the *RTS* during the period 1971–1978 over time from (1.188) to (1.045) but started to increase after that. A tremendous increase in the price of oil following the oil shock of 1974 hurt the economy of South Korea and took some years to recover (Benjamin and Meza 2009).

The *RTS* for energy demand model is equal to (2.938) indicating on average increasing returns to scale. It measures the increasing rate in the output resulting from the increase in the energy use conditional on other inputs and technology. By looking at Fig. 10.1, where industries are distributed based on their returns to scale, one can notice that all industries are exhibiting increase in their rate of returns to scale except agriculture, hunting, forestry and fishing (industry code 1). It implies that these industries are energy dependent for their level of production.

10.5 The Marginal Effects

The empirical model of the energy demand with risk provides evidence of significant marginal effects in inputs which indicates that some inputs are risk increasing and some are risk decreasing factors. In other words, the input risk is a function of inputs and industries' characteristics, input level then can be used as instruments to control for the level of the risk.

The value added services and ICT capital are the only two inputs decreasing risk, with ICT capital having clearly the most significant reducing effect on the energy use variance (See Table 9.6). It is believed that any increase in the non-ICT capital with all other inputs held fixed must lead to reduction in the level of energy demand risk if the two variables are found to be substituting each other. However, the complementary pattern between energy and non-ICT capital is found in this study, which indicates the possibility of non-ICT capital to be variance increasing input for energy. There are three input factors increasing the variability of energy: Non-ICT capital, materials, and labor.

By looking at the marginal effects (Table 9.6) of industries' characteristics, mixed and domestic markets are relatively risk decreasing compare to the export oriented market. The greater exports of energy intensive products could increase industrial energy intensity. It is important to investigate the role of exports on energy use intensity because it provides policy makers with the energy impact of existing and prospective export policies, in which it assist the country to fulfill its obligation in reducing the CO_2 gas emission intensity strategy (Zheng et al. 2011).

The medium and low scale investments in R&D are risk increasing factors if compared to the high level of R&D investment. Industries that invest more in R&D tend to adopt energy efficiency programs and tools. Medium and small size industries are risk decreasing compare to larger size industries. New technologies, especially micro-electronics allow small industries inexpensive means to control an entire production process (Becchetti et al. 2003).

Industries with higher rate in the labor productivity and capital intensity decrease the energy demand variability, thus, increasing the stability of energy use in the production process. Industries with more intense in capital investment are faster for adjustment toward adopting energy efficiency program (Fan et al. 2007). Limited access to capital may prevent energy efficiency measures from being implemented. Technologies that are energy efficient are often more expensive to purchase than alternative technologies. Furthermore, obtaining additional capital in order to invest in the energy efficient technology may be problematic. Apart from low liquidity, limited access to capital may also be due to problems of lending money.

The high and medium skilled labors are two risk decreasing factors if compared to the low skilled labor industries. The former can adopt new technologies which helps to efficiently use energy in production (Welsch and Ochsen 2005). The period after the first economic shock the industry's energy demand was more stable in compare to the period before the first economic shock. The two oil price hikes forced many industries to adopt saving strategy by promoting conservation measures, switching to other fuels, and raising overall energy efficiency (Tsunoda et al. 2000).

10.6 Technical Efficiency

The overall rate of technical efficiency is equal to (24.4 %) with a small standard deviation of (0.259) (See Table 9.5). It indicates that in general the industries are not efficient in the use of energy. The technical efficiency is slightly increasing over

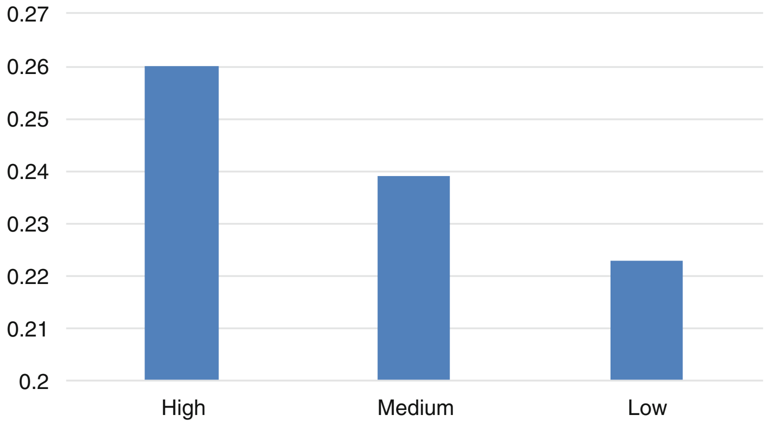

Fig. 10.2 Technical efficiency based on industries' technology level

time except during the period of the two oil shocks (See Table 9.11 in Appendix A of Chap. 9). However, a large variation across industries is observed (See Table 9.10 in Appendix A of Chap. 9). A positive relationship is observed between technical efficiency and industries' level of technology (see Fig. 10.2). The high technology level industries are most efficient in energy use than the low and medium technology level industries.

It is obvious that the available technological advance in the high technology industries allow for more efficiency and resource management, while for the low and medium technology industries these resources and technological advanced might be limited in a way that may hinder these industries to use energy in an efficient way. A positive relationship is also observed between technical efficiency and the scale of R&D investment (See Table 9.14 in Appendix A of Chap. 9). Industries with larger scale of R&D tend to use energy efficiently due to technological advance and innovation results (see Fig. 10.3).

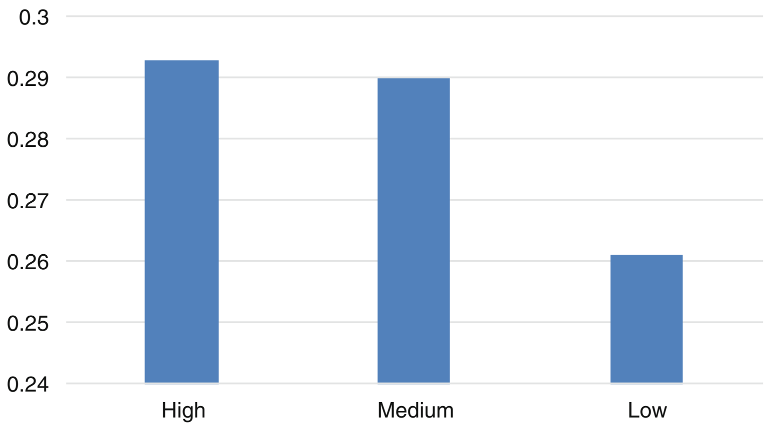

Fig. 10.3 Technical efficiency based on industries' scale of R&D investment

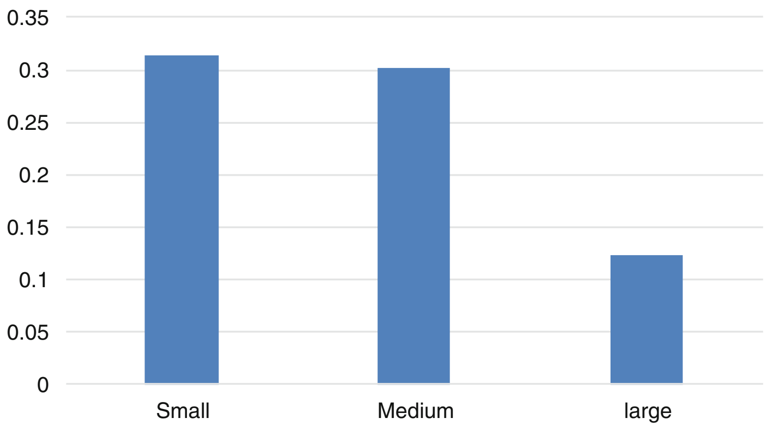

Fig. 10.4 Technical efficiency based on industries' size

There is a negative relationship between technical efficiency and industry size (See Table 9.15 in Appendix A of Chap. 9). Smaller industries operate with technically optimal level of energy inputs. There is no potential in the large and medium size industries to save energy (see Fig. 10.4). Industries classified by mixed oriented (international and domestic) market are comparatively most energy efficient than the export oriented and domestic industries (see Table 9.13 in Appendix A of Chap. 9 and Fig. 10.5). The mixed oriented industries are involved in the international market as well as domestic market. They are subjected to regulations imposed both internationally and locally.

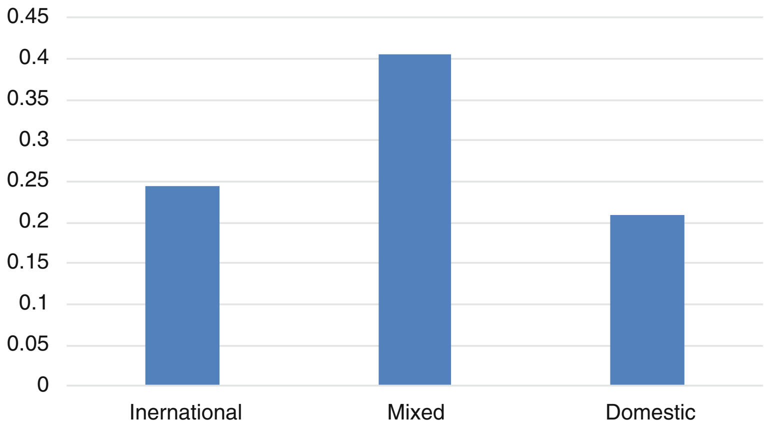

Fig. 10.5 Technical efficiency based on industries' export orientation

10.7 Conclusion About the Research Questions and Their Hypotheses

10.7.1 The Research Questions

For the sake of convenience, the three research questions examined in this study are repeated here, they were as follows R_1: What is the impact of energy use on the production level in the industrial sector for South Korea? R_2: Is there any factor substitution pattern between energy and other inputs of production in the South Korean industrial sector? R_3: What factor(s) affect(s) the variability of energy demand in the South Korean industrial sector?

The following subsections will provide insights and overall conclusion about the research questions and their related hypotheses tests as follows:

10.7.2 Overview of Analysis and Hypotheses Testing

For the regression analysis, a variable is said to be highly significant if its p-value is less than (0.010), it is said to be significant if the value is less than (0.050), while if it less than (0.100) it is said to be weakly significant. A regression analysis would determine the variables that would be included in the equation with the measure of coefficient of determination (R^2), the level of significance (<0.05), and specification tests that may vary according to model type (Greene 2008).

In this study, different specification tests are conducted in accordance to model type. They are compared and evaluated based on statistical significant levels. In the production models (i.e. Cobb-Douglas and Translog) and in the energy demand model without risk, an F-test is undertaken first to validate the individual model with its explanatory variables, whether the model as whole accounts for a significant portion of the variability in the dependent variable (Fai and Cornelius 1996), and second to compare Cobb-Douglas and Translog model specifications, whether the Translog model (the full model) fits significantly better than a restricted Cobb-Douglas model. The test relies on the hypothesis about the rejection or acceptance of the restricted model. The null hypothesis states that the restricted model is correct, while the alternative hypothesis is that the restricted model is too simple and that the full model is more appropriate (Johnston 1984).

In the energy demand model accounting for risk, Harvey specification test (Harvey1976) is undertaken. The null hypothesis in Harvey's test states that all coefficients of the multiplicative variance function except the intercept β_0 is zero. The Harvey' test statistics is RSS/4.9348, where RSS is the residual sum of squares of the estimated variance function, it is asymptotically distributed as chi-square with degrees of freedom equal to the number of regressors.

The regularity conditions are also tested for the Translog models. The conditions require monotonicity and concavity. The concavity can be tested by examining the matrix of the elasticities of inputs and output for semi-definite negativity as explained by Gallant (2008). The Curvature conditions require the Eigen values of the elasticities to be mixed in sign and the sum to be negative to imply negative semi-definite value (Moss et al. 2003).

In both specifications of the production models (Cobb-Douglas and Translog), the energy demand models (model without risk and model with risk), the overall independent variables, and the two dependent variables are found to have significant and positive impact for energy use on the production level in the industrial sector for South Korea. In both specifications of the energy demand models the overall independent variables indicate that ICT capital and labor are substituting energy in the South Korean industrial sector.

10.8 Implications for Industry and Policy Makers

It is difficult to say to what extent the risk properties of inputs have affected the industry's choice for the level of energy use in the production. This depends on the risk preference structure of the producers and industry's decision makers in the South Korean industrial sector, in which this study has not measured it due to lack of information. During the data period, the South Korean industries have increased their scale of production. This served to increase both mean of energy demand and its related risks.

There are several possible explanations for such development of mean and risk in energy demand based on the assumption that the producers and policy makers in the South Korean industrial sector are optimizing agents, these explanations are stated bellow:

- The producers and policy makers in the South Korean industrial sector are risk neutral, in which they are only concerned about the mean of energy use.
- Even if the producers and policy makers are risk averse, their risk preference structure is such that the increase in the mean of energy use associated with the increase in the scale of production is sufficient to more than compensate for the increase in energy use risk, and thus provide them with the highest level of gained utility.
- A last possible explanation is that the producers and policy makers in the South Korean industrial sector have limited knowledge about the structure of the production risk, this indicate that they know little about the effects of altering inputs levels for optimal level of energy use in the production.

The finding of this study should be of interest to the industry. This study is the first of its kind to evaluate the structure of energy demand and its related risks in the South Korean industrial sector. Furthermore, so far the data set used here is the most extensive one for productivity studies of South Korean industrial sector both with respect to the length of time period and the number of industries studied.

For individual producer and individual industry within the South Korean industries, it is difficult to estimate the effects of changing the inputs levels on the use of energy based on her productivity and energy use history. This study provides information on the structure of production risk based on a sample with 950 observations of industries over time. This implies that conclusion can be drawn with higher confidence than if one must rely on observations from an individual on aggregate industry only. However, some caution is required in the interpretation of the results due to the quality of the data.

There are number of ways industries can reduce their energy consumption, for example improving in the industrial process (especially in process heat) may lead to reduce energy waste and to recover energy. Materials recycling and fuel inputs are also considered enhancing factors for energy efficiency improvement. Policy makers and stakeholders may take these efficiency opportunities into their account for decision making.

According to the empirical results increasing in the level of ICT capital, high investment in R&D and value added services will reduce the variability of energy demand and its related risk. The findings suggest that risk averse producers should invest more in ICT and digitalization, and also invest more in R&D in order to be able to reduce the uncertainty related to their demand for energy. ICT capital has a substitutability relationship with energy input in most of the industries over time. Furthermore investing in ICT will require more high skilled labor in which this study also showed that high skilled labor reduce the risk of energy use in the production.

For public research programs aimed at industrial sector, an implication for the empirical results in this study is that one should be concerned about both mean and risk properties in research on new technologies and in investigating the possible alternative inputs for energy. The results suggest that technical progress contribute more to increasing mean of energy demand than to reduce the level of risk. However, it is an open question to what extent this development has been driven by the producers or the government sponsored research and development.

10.9 Summary

This chapter summarized the empirical results on the structure of the stochastic production technology in the South Korean industrial sector. The implications of the findings are discussed in relation to the theory of the competitive firm under production risk. It also related the results to the research questions and the related hypotheses and the information the author has collected about developments in the industry during the data period.

It is difficult to indicate the extent of risk properties of inputs that affect the industry's choice for the level of energy use in the production. It depends on risk preference structure of the producers and industry's decision makers in the South Korean industrial sector. However, this study has not measured it due to lack of information. During the data period, the South Korean industries have increased their scale of production. This served to increase both mean of energy demand and its related risks.

The empirical model of the energy demand with risk provides evidence of significant marginal effects in inputs which indicates that some inputs are risk increasing and some are risk decreasing factors. It is believed that any increase in the non-ICT capital with all other inputs held fixed must lead to reduction in the level of energy demand risk if the two variables are found to be substituting each other. However, the complementary pattern between energy and non-ICT capital is found in this study, which indicates the possibility of non-ICT capital to be variance increasing input for energy. There are three input factors increasing the variability of energy non-ICT capital, materials, and labor.

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Chapter 11
Summary and Conclusion

This study has empirically drawn the structure of the production risk in the South Korean industrial sector. The study can be considered as a first attempt to provide knowledge about the risk effects on the input factors of production and energy demand based on a comprehensive panel dataset covers 25 industries spanning over 37 years. This study contributes to the body of knowledge through its methodological contribution. The study has empirically increased the understanding of the performance of competing model specifications and estimators which can be used in econometric studies of production risk. Generally, the relative performance of different estimators for econometric models with industry specific effects and heteroskedasticity in regressors is largely unknown. It is believed that the results from this study using different specifications and estimators for models of production risk will be useful for future empirical studies in this field of research.

11.1 Overall Summary

This study explored the impact of different input factors of production, and market, consumer, and producer characteristics on the energy demand in the industrial sector for South Korea during the period 1970–2007. The study aimed at formulating an energy demand structure for the South Korean industrial sector as a tool to enable producers and policy makers to evaluate different alternatives toward reducing energy consumption and using energy in an efficient way. This book was concerned with the estimation of the following factors:

- The overall energy demand.
- The rate of technical change that may shifts the demand for energy over time.
- The variance of energy demand and its determinants and industries' characteristics.

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- The Estimation of efficiency in the use of energy, given production output and characteristics of the South Korean industrial sector.
- The total factor productivity: The measures of productivity with a single factor, such as labor or capital productivity have the advantage of simplicity. However, these measures ignore the substitution between factors of production, and can generate interpretation problems. The total factor productivity (TFP) is a measure of overall productivity change, which is a weighted average of each single factor of productivity growth. Hence, this study uses the TFP as a measure of productivity and decomposes the TFP growth for the South Korean industrial sector. The TFP growth is estimated parametrically and decomposed into neutral and non-neutral technical change components, the technical emphases are on the modeling and explaining the variations in the demand for energy, and the effects of different input factors of production on the level of energy use.

Furthermore, this book aimed at developing a better relationship between various input factors of production and energy demand. Since some energy types such as electricity and natural gas cannot be stored, this might help to identify optimal investment in these input factors of production, and better optimization of energy consumption.

The objective of this book can be summarized in two points: First, to formulate an energy demand structure by examining the energy use in the production process in the industrial sector. Special attention is given to the factors that increase the risk or variations of using more energy input in production. The second objective was to investigate to what extent the energy input is a complement or a substitute to other input factors of production such as labor, non-ICT capital, materials, value added services, and ICT capital in the production process. The pattern of substitutability or complimentarity will be useful to assess and determine the level of energy demand.

South Korea imports all its primary energy, leading to high dependency and vulnerability related to energy supply. Efficiency in the use of energy is a way to reduce the dependency and emissions. This quantitative study provided empirical results of the stochastic production process in energy use. A dynamic panel model is specified and applied to 25 Korean industries over the period 1970–2007.

In Chap. 3 a derivation of energy as an input factor demand function (or factor requirement function) is offered and the factors that derive the demand for energy by industries and over time are determined based on the production theory with a priori expected outcome. The cost minimization approach is applied for firm's profit maximization, as the energy is considered an input factor of production.

Chapter 4 provided the theoretical motivation for analyzing the structure of risk in stochastic production technologies. In addition to that, it motivates the use of a primal approach in econometric productivity analyses instead of the popular dual approaches. This chapter demonstrated that the dual approach loose much of its attractiveness when production risk is introduced into the neo-classical production function. A primal model framework which is tractable for econometric implementation is also presented.

Chapter 5 discussed the econometric issues associated with the model choice for econometric estimation at a general level. The industry heterogeneity and heteroskedasticity are discussed. Heterogeneity with respect to production technology and productivity is crucial when estimating panel data sets. The heteroskedasticity in the estimated models is presented in the disturbance part (error term). The error component consisted of three parts: Time, industry, and random components, if the time invariant industry specific are assumed fixed, then it is called fixed effect, while it is called random effect if they are assumed random.

Moreover, some important issues associated with panel data are discussed both in general level and more specifically in the context of production analysis, focusing on specific problems that are relevant to the empirical application of this study. With the availability of panel data sets one can account for heterogeneity in the econometric modeling.

The generalized form of Just and Pope Production function is considered as groundwork for this study in modeling and estimating the production risk, as it allows to increase/decrease in the risk of output by the use of different inputs. The generalized Just and Pope Production function is utilized to study the statistical relationship between energy use and output, technology and certain other input factors of production, and to quantify the impact of these factors. The model choice decision depends on the data availability and the complexity of the specification issues for the specific industry which is the subject for most of empirical analyses. The model choice depends also on the focus of the study; whether the primary interest is the structure of the production technology or input demand and output supply elasticities in prices.

The proposed production function of Just and Pope and its eight propositions for the stochastic production function have introduced a theoretical framework for the modeling of production risk. It has also provided consistent and asymptotically efficient estimates of the production function parameters when the production function is in the form of Just and Pope Production function. In Chap. 5 the determinants of energy use are identified and their effects in forms of elasticities of energy use are estimated. In addition the structural changes in energy demand pattern is explored. The stochastic production technology is applied in this study to estimate two groups of models: A production model, where the energy is a determinant of output and an energy demand model, which is based on an inverted factor demand model where the demand is a key determinant of the level of energy use.

The data collected for this study is presented in detail in Chap. 6. The data used in this study is obtained from the harmonized EUKLEMS Growth and Productivity Account database. The database includes variables that measure output and input growth, and derived variables such as multi-factor productivity at the industry level. The input measures include various categories of capital, labor, energy, materials, ICT capital, and value added services inputs. The presence of industry heterogeneity and heteroskedasticity in the data for this study has been proved and tested using ANOVA and heteroskedasticity tests. The heterogeneity and heteroskedasticity should be accounted for in an econometric model. Due to availability of panel data sets, using econometric of panel data techniques to account for heterogeneity and heteroskedasticity is possible.

Chapters 7–9 discussed the empirical application for the South Korean industrial sector. Chapter 7 provided a description of the production process. It provided details about the estimation procedure of production function when the energy variable is considered as one of the input factors of production.The aim of the estimated production model was to theoretically validate the explanatory variables (input factors) that are used to estimate the demand for energy. The validation was based on the neoclassical economic theory of production that requires all inputs in the production function to be positive and to contribute to the final outcome.

In Chap. 8, the energy demand model without risk consideration is constructed and specified in two forms: Cobb-Douglas and Translog functional to allow for consistency and comparability in terms of model specification and estimates. The Translog production function is used to measure elasticities of substitution, technical change, and total factor productivity growth. The Translog functional form is more flexible due to the following:

(1) The assumption of unitary elasticity of substitution is relaxed.
(2) The assumption that all industries have the same production elasticities is also relaxed.
(3) It is less restrictive due to incorporating flexible functional forms, in which it allows to relax assumptions about the market structure.
(4) It allows for investigating the possible substitution between the inputs.
(5) It allows for implementing nonlinear relations between the explanatory variables and the dependent variable through the use of square and interaction terms.

Chapter 9 discussed the structure of risk in the South Korean industrial sector. It proposed a new structure and magnitude of production risk in the South Korean industrial sector for the period 1970–2007 by means of estimation of energy demand models. Since efficiency analysis and analysis of industry behavior under risk aversion require knowledge about both the conditional mean and variance of output, this chapter investigated both the mean production function and the variance production function. This has mainly been done through estimation of the Just and Pope Production model.

Chapter 10 has summarized the finding from the estimated models. The empirical results are summarized for the mean in case of production function and energy demand function without risk, and for the mean and variance function in case of energy demand accounting for risk, in which the findings are related to the theory of the competitive firm under production risk. The chapter provided implications and policy recommendations based on the estimated models for production function and energy demand.

11.2 Overall Findings of the Empirical Study

The findings of the estimated models can be summarized as follows:

1. There are large variations in the degree of overuse or inefficiency in energy use among the individual industries and over time.
2. The information and communication technology (ICT) capital and labor are substituting energy.
3. The ICT capital and value added services are two input factors decreasing the variability of energy demand, while non-ICT capital, materials and labor are increasing the variability of energy demand.
4. The result suggests that technical progress contributes more to increase the mean of energy demand than to reduce the level of risk.

It is recommend that industries to increase the level of ICT capital and digitalization and invest more in R&D activities and value added services to reduce the uncertainty related to their demand for energy.

This study formed the structure of the stochastic production technology and the energy demand of South Korean industrial sector. The public research programs aimed at industrial sector should be concerned about both mean and risk properties in research on new technologies and in investigating the possible alternative inputs for energy.

11.3 Conclusions and Practical Recommendations

This study provided empirical evidence on the structure of energy demand and its related risk in the South Korean industrial sector for the period 1970–2007. It is the first study to provide knowledge on the risk effects of inputs based on a comprehensive panel data set covered 25 main industrial sectors with 950 observations. This study provided evidence that the introduction of risk has implications for efficiency analysis. A risk averse producer will be concerned about both the mean input of energy and its variance when considering alternative input factors in the production process. This mean-variance tradeoff is represented by the producer's utility function.

It is believed that the results from this study by using different specifications and models for production and for energy demand function will be useful for future empirical studies in this field of research. The empirical results considering the flexible energy requirement function have made it possible to evaluate how well energy conservation can be achieved in each industry and to suggest guidelines concerning policy formulation and evaluations to further enhance the industry level energy use efficiency.

Energy prices and environmental problems are the major constraints on the development in different industries. Maximizing energy efficiency should be consistent with the public industrial development strategies. However, it is always not clear which choice will be made between pursuing greater intensive developments or less intensive strategies. This study will help to shed lights on how differently a certain policy affects each industry.

11.4 Recommendations for Further Research

Based on the finding from this study, it is believed that this quantitative study increases the reader's knowledge about the structure of the stochastic production technology in general, and the energy demand structure of South Korean industrial sector in particular. In addition this study has contributed to the discussion of model specification and estimator choice for empirical modeling of energy demand. However, this study has its limitations. In the course of the research work, several interesting paths were not entirely investigated, as the scope of the analysis would otherwise be too wide and perhaps less accurate.

For future researches on energy demand and related risks within the Just and Pope Framework, other parameterizations of the mean function such as generalized Leontief should be examined. The focus should be in addition to flexibility, global properties and effect on variance function estimates. A Translog function seems to have limited consistency region, the estimated elasticities took extreme values as one move from the mean observation. If a functional form is not reliable at data points far from the mean, then this may also have consequences for variance function estimates. It should be then examined in future researches what effects outliers may have had on variance function estimates. In estimating the South Korean industry-wide level of energy demand, one might employ a model of dynamic energy requirement frontier accounting for the risk. Such a model allows for each industry to choose its own individual risk behavior parameters to catch up with their industry-wide global energy use requirement function and to formulate their production risk structure.

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