An Industry and Country Analysis of Technical Efficiency in the European Union, 1980-2005

by

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To my husband, Dr. George M. Korres

for all those smiles, seen and unseen

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Author’s Declaration

I declare that the thesis does not include any work-forming part of a thesis presented successfully for another degree. I declare that the thesis represents my own work except where referenced to others.

Abbreviations

AE	Allocative Efficiency
AIC	Akaike information criterion
BCC	Banker, Charnes and Cooper (1984)
BIC	Bayesian – Schwarz information criterion
CD	Cobb Douglas
CDF	Cumulative Density Function
CCR	Charnes, Cooper and Rhodes (1978)
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DFA	Deterministic Frontier Approach
DMU	Decision Making Unit
DRS	Decreasing Returns to Scale
EUI	Efficient Unit Isoquant
EU	European Union
FE	Fixed Effects
FGLS	Feasible Generalized Least Squares
GLS	Generalized Least Squares
GMM	General Methods of Moments
HQIC	Hannan – Quinn information criterion
ICT	Information and Communication Technologies
IRS	Increasing Returns to Scale

LM	Lagrange Multiplier
LSDV	Least Squares with Dummy Variables
MFP	Multi – factor productivity
MLE	Maximum Likelihood Estimation
NDRS	Non Decreasing Returns to Scale
NIRS	Non Increasing Returns to Scale
OE	Overall Efficiency (Technical And Allocative)
OECD	Organization of Economic Cooperation and Development
OLS	Ordinary Least Squares
PDF	Probability Density Function
PPF	Production Possibility Frontier
R&D	Research and Development
RE	Random Effects
SBM	Slack - based Measure
SE	Scale Efficiency
SF	Stochastic Frontier
SFA	Stochastic Frontier Analysis
SPF	Stochastic Production Frontier
TE	Technical Efficiency
TFP	Total Factor Productivity
VRS	Variable Returns To Scale

Research Background

One of the most important hypotheses in modern economic theory is based on the assumption of optimising behaviour, either from a producer or a consumer approach. As far as producer behaviour is concerned, economic theory assumes that producers optimise both from a technical and economic perspective:

- From a technical perspective, producers optimise by not wasting productive resources.
- From an economic perspective producers optimise by solving allocation problems involving prices.

However, not all producers succeed in solving both types of this optimisation problem under all circumstances. In real economic life, it is unlikely that all (or possibly any) producers operate at the full efficiency frontier, with failure to attain the efficiency frontier implying the existence of technical or allocative inefficiency (Reifschneider and Stevenson, 1991).

More precisely, as described in Levitt and Joyce (1987), as well as Worthington (2001), respectively, for a producer to be efficient, there are three requirements to hold:

1. The first requirement of technical efficiency is that the maximum possible amount is produced with the resources used, or in other words, it must be impossible to reduce the volume of any input without reducing the volume of output. Technical efficiency may then refer to the physical relationship between the inputs used (i.e. capital, labour and equipment) and output. These outcomes may either be defined in terms of intermediate outputs or final output.
2. The second requirement is that the cost of any given level of output is minimized by combining inputs in such a way that one input cannot be substituted for another without raising the total cost. This is allocative efficiency, where an allocatively efficient producer would produce that output using the lowest cost combination of inputs.
3. The third requirement is that the mix of outputs of different goods and services produced form the given resources maximizes the benefit to consumers.

For these reasons, it is important to analyse the degree to which producers fail to optimise and the extent of any resulting distances from the frontier of full technical and economic efficiency, mainly due to the following reasons:

1. First, only by measuring efficiency, and by separating the associated effects from those of the operating environment, it is possible to explore hypotheses concerning the sources of efficiency, essential to improve performance.
2. Second, efficiency measures are success indicators by which producers are evaluated and the ability to quantify efficiency provides a control mechanism with which to monitor the performance of a production unit.
3. In addition, if policy and planning is to concern itself with the performance of a particular economic unit, it is important to know to what level a given producer may be expected to increase output by simply increasing efficiency, without absorbing any further resources.

Efficiency measures can be defined as relative productivity over time or space, or both. For instance, it can be divided into intra- and inter-firm efficiency measures. The former involves measuring the use of the firm's own production potential by computing the productivity level over time relative to a firm-specific production frontier, which refers to the set of maximum outputs given the different level of inputs. In contrast, the latter measures the performance of a particular firm relative to its best counterpart(s) available in the industry (Lansink et al, 2001).

More specifically, a measure of evaluating the performance at producer level is productive efficiency through production frontier, a concept which compares the transformation process of converting input into output. As Reifschneider and Stevenson (1991) declared, if the occurrence of inefficiency is not totally random, then it should be possible to identify factors that contribute to its existence. In this case, estimating these efficiency measures involves estimating the unknown production frontier. Each production process involves a production frontier: the current state of technology in the industry, representing the maximum output attainable from each input level is called the efficiency frontier (Coelli et al., 2005). A producer operating on the efficiency frontier is productively efficient.

As noted by Greene (2007a) the literature on stochastic frontiers is rapidly growing and a great number of methodological innovations in the econometric estimation techniques were proposed. The main research assumption is that inefficiency is defined as the extent to which producers fail to achieve a theoretical ideal (Greene, 2007a). One important aspect of the recent empirical literature on efficiency measurement is the analysis of production frontiers, the relationship between input and output and the adjoining sources of efficiency. Better understanding of the process of generating efficiency requires studying the deeper determinants and factors which explain the differences in efficiency growth. In response to this most important research issue, and with the increase in data availability, economic literature has shown a resurgence of interest in testing and quantifying various theories of explaining efficiency growth and examining the corresponding relationships has attracted a lot of interest with the main research questions arising could be summarized into:

1. What are the reasons for diverging efficiency in a production industry?
2. Which factors contribute to production industries efficiency differences?
3. How the efficiency of a production industry evolves over time, with respect to technical progress and other related determining factors?

One of the application approaches of stochastic frontier analysis is the estimation of productive efficiency in manufacturing industries, and specifically medium and high technology manufacturing industries.

More recently the role of manufacturing industries to the economy is even more important taking into consideration the slowdown in the world economy, and the effects on the business environment created by the financial crisis. Thus, medium and high technology manufacturing industries have a very important role in creating opportunities making an important contribution to economic growth and development (Coviello and McAuley, 1999). Nonetheless, high technology manufacturing industries have shortages of different types of resources necessary to develop and implement their business strategies. These shortages may include financial, marketing, technological and managerial resources, or skilled personnel (Buckley, 1989). Overcoming those shortages and increasing productive efficiency has become critical for their long term survival and profitability.

However, due to their nature, these industries are characterized by being very heterogeneous since they differ in their endowments of resources as well as on the risks involved in their productive activities. For this reason, it is of great importance, on the one hand to analyze their efficiency level and potential, and on the other hand, to analyze the factors which determine their efficiency potential. This analysis is the main aim of this thesis. As in Baten et al. (2009), it is generally believed that resources in the manufacturing industries are being utilized inefficiently. Recently, there ia a major literature in estimating stochastic frontier production and consequently dealing with technical inefficiency in manufacturing industries production have been undertaken (Samad and Patwary, 2002, 2006; Baten et. al. 2006, 2007). Thus, this thesis is expected to provide meaningful insights into the level of industry-specific technical efficiency along with factors determining and affecting efficiency.

Thesis aim

This thesis focuses on the manufacturing industries and seeks to obtain the empirical results by specifying the translog functional form and the model for the technical inefficiency effects in the stochastic frontiers. Estimation of technical efficiencies and the identification of determinants of technical efficiencies for the model are also of interest (Baten et al., 2009).

The research aim of this research is to identify and examine key resources, a conceptual framework drawing on the application of stochastic frontier models in obtaining measures of efficiency that enable a comparison of performance across industries and countries, explaining why, in the same country, some industries achieve superior efficiency performance. The important task is to relate efficiency to a number of factors that are likely to be determinants, and measure the extent to which they contribute to the presence of inefficiency.

More specifically, the first step of this thesis is to review the literature concerned with techniques of efficiency estimation. This will facilitate an understanding of both the theoretical and application part of the research. The second step of this thesis is to highlight the pitfalls of the different relevant models and methodologies. The third and most important goal and contribution of this thesis is to suggest a concrete method to estimate industrial efficiency, avoiding the inherent problems. Within this framework, the problem to be examined in this thesis can be broken down into two major parts:

1. the theoretical part of the study which deals with stochastic parametric frontier methodology,
2. the applied part of the study which focus on examining the magnitude and impact of the efficiency in different manufacturing industries.

This thesis considers a European Union perspective efficiency analysis to increase the information base and derive broader conclusions about European Union productive performance within selected countries. This issue is of particular research relevance because empirical evidence shows that even though European Union industries are widely analyzed with respect to performance, yet little attention has been paid to the estimation of technical efficiency. In particular, the objective of this thesis is to employ Stochastic Frontier Analysis to examine the industry-specific technical efficiency performance for 13 manufacturing industries in 8 selected European Union countries. The countries selected are: Austria, Denmark, Finland, France, Germany (or Western Germany prior to 1991), Italy, Netherlands, Spain, and United Kingdom, in order to create a data set including both countries with strong industrial productive base, such as United Kingdom, Germany, Netherlands and France, as well as countries with low industrial productive base, such as Spain. Within this sample, it is of great importance to examine which determinants are significant, however, it is also important, to examine whether the interactions between technical progress, ICT investment, ICT investment share, R&D stock and economy openness, namely the process of the integration into the world economy, has any implications for technical efficiency. Special emphasis is given to the review of two of the main heterogeneity determining factors, namely innovation investments (as a proxy of knowledge creation) and economy openness (as a proxy of knowledge dissemination).

This thesis tries to fill a gap in the economic literature by exploring and studying various dimensions of the interaction between one of the most important economic aspects, namely technical change and innovation and the integration into the world economy, namely economy openness, and links them to efficiency growth. In particular, this thesis explores whether the interactions between these factors have any implications for efficiency growth, and whether there are any complementarities between them and fostering technical efficiency growth. More specifically, this thesis aims to distinguish between the two main factors which affect total factor productivity, namely technical progress and technical efficiency, as well as what determines the production frontier itself and what determines the inefficiency term (both theoretically and empirically).

Value of Research and Expected Contribution

This thesis contributes with an inter-industry and inter-country approach to estimate production inefficiency using the Battese and Coelli (1992, 1995) model, which allows technical inefficiency to vary over time, and allows inefficiency to depend on a set of covariates (Yu, 2008) and explore the effects of innovation-related investment on production, allowing for simultaneous estimation of the parameters of the stochastic frontier and the inefficiency model using the one-step, maximum-likelihood estimation method.

This thesis empirically examines the implication of the interrelationship and the complementarities between value added, capital, labour and technical change and the contribution of additional determining factors to technical efficiency and attempts to highlight the characteristics of alternative models specification and suggest a concrete method to estimate technical efficiency in industrial level, giving emphasis on the efficiency convergence among countries.

More specifically, the empirical application of the thesis estimates the Transcendental Logarithmic Production Function of manufacturing industries in these selected European Union member-states, considering a panel data model for inefficiency effects in stochastic production frontiers based on the Battese and Coelli (1992, 1995) models, providing translog effects, as well as industry effects. This modeling decomposes productivity growth into two components: technological growth (essentially, a shift of production possibility frontier, set by best-practice producers) and inefficiency changes (deviations of actual output level from the production possibility frontier). That is, modeling accommodates not only heteroscedasticity but also allows the possibility that a producer may not always produce the maximum possible output, given the inputs (Movshuk, 2004).

The thesis main findings suggest the great importance of the interaction between the different determining factors and estimate any implication for productive efficiency. The empirical evidence reported in this thesis supports the hypothesis and shows that technical change, ICT investment, ICT investment share, R&D stock and economy openness have a positive impact on technical efficiency in the examined industries, playing a significant role in determining the contribution of innovation in efficiency, productivity and, consequently, economic growth.

Over all, the major contribution of this thesis is that it provides a better understanding of the contribution of technical change; ICT investment and economy openness to technical efficiency taking into account the interrelationships and the complementarities between innovation and efficiency. The purpose is to study these countries' experience in an effort to determine the potential productive efficiency determining factors and to investigate various aspects of the relationship between productive efficiency and determining factors in an attempt to reach a better understanding of the contribution of alternative factors to technical efficiency growth. Especially, this thesis aims to:

1. develop a model of efficient producer behaviour and investigate possible types of departure from full technical efficiency level
2. emphasize and discuss the empirical application with special focus on the comparability of different structures of models
3. analyze the level and the development of an industry's productive efficiency along with the determining factors
4. distinguish between the two main factors which affect total factor productivity, namely technical progress and technical efficiency, as well as what determines the production frontier itself and what determines the inefficiency term (both theoretically and empirically)
5. develop an analytical econometric technique for examining the above
6. demonstrate the obtained results and come to safe conclusions as far as modelling producer behaviour (applied production analysis) is concerned.

The findings of this thesis are of value for practitioners, policy makers and the academic community:

1. For industries the purpose of this thesis is to make recommendations to firms on identifying, developing and deploying their resources that may influence their technical efficiency, competitiveness and consequently their performance.
2. For policy makers the value of this thesis stems for a better identification and understanding of the key resources to the internationalization of high technology industries. This will allow government entities to formulate and implement programs, which will leverage areas of high technology industries, which require further development.
3. Last but not least, the value for the academic community mainly lies on an increased knowledge about the impacts of different determining factors on technical efficiency estimation.

Finally, at policy level, the findings of this thesis suggest the need to establish assistance programs to develop the technology-base, at all levels, as well as to augment technology-base, which are more detailed in the thesis along with the limitations and suggestions for further research.

Thesis structure

To achieve the research aims, the thesis was designed to include six core chapters in addition to a concluding chapter:

Chapter 1 provides an overview on the definition and alternative approaches of efficiency (technical or productive efficiency, allocative or pricing efficiency, scale efficiency, as well as economic efficiency). Moreover, Chapter 1 deals with the review of measurement of Efficiency, distinguishing between: technical or allocative oriented approach, the input-oriented and output-oriented approach, the Parametric and non – parametric approach, the Frontier and non – frontier approach.

Chapter 2 studies the alternative methods for productive efficiency estimation which served as research base for the model application. More specifically, Chapter 2 analyses the alternative estimation methods of efficiency, namely, the Koopmans and Debreu methods, the Farrell method, the distance fucntion method, as well as the Data Envelopment Analysis method. Moreover, Chapter 2 explores the theory of Stochastic Production Frontiers, and alterantive approaches, as the Deterministic Production Frontiers, iinvestigating the alternative variants of the Stochastic Frontier Models, focusing on the distinction between time varying and time invariant efficiency, fixed and random effects, as well as Battese and Coelli (1992, 1995) model specifications.

Chapter 3 examines technical change and it presents the empirical model specification and methodology, along with the underlying hypotheses.

Chapter 4 deals with the industrial context of Stochastic Frontier Models and the main assumptions on efficiency estimation and analyses the efficiency estimation in industrial aggregate and disaggregate level, the inefficiecny and frontier determining factors, as well as the industrial and innovation policy context of the European Union.

Chapter 5 deals with the Stochastic Frontier Model Application, estimating the Inefficiency component. The chapter begins with the model Description and the parameter estimation procedure. In the second part, this chapter describes the data set, the variables included in the empirical model, as well as the main model assumptions.

Chapter 6 estimates the DEA model and compares the two alternative set of results. Chapter 6 applies the deterministic nonparametric approach Data Envelopment Analysis (DEA), and extensions to capture specific characteristics of the production process. Chapter 6 reports the main findings, which address the research questions and the stated specific set of hypotheses, for each research question.

Based on the obtained results, the concluding chapter 7 introduces comparative results, leading to improvements in efficiency estimation. The chapter assesses the significance of the obtained results and the possible channels of impact and it concludes the thesis, highlighting the main findings and stating their academic significance and their policy implications. Finally, chapter 7 addresses implications and contributions for academics, practitioners and public policy. A presentation of the study's limitations and suggestions for further research closes the chapter.

The general overview of the thesis sructure is as follows:

Summary of Thesis Chapters

Chapter 1. The productive efficiency theory

1. Defining concepts of efficiency
2. Defining theoretical perspectives
3. Defining key characteristics
4. Address the interrelationship between productivity and efficiency, as well as the alternative approaches to productivity and efficiency estimation

Chapter 2. Productive efficiency: Estimation methods

1. Reviewing alternative methods of efficiency measurement:
2. Reviewing strengths and weaknesses
3. Present a range of different nonparametric and parametric approaches and frameworks in the literature, discussing and comparing them in detail.

Chapter 3. Stochastic frontier models: empirical model specification and methodology

1. Defining the empirical model
2. Methodology
3. Hypotheses testing

Chapter 4. Stochastic frontier models: Industrial context

1. Inefficiency and frontier determining factors
2. Heterogeneity and aggregation
3. Industrial and Innovation policy in European Union

Chapter 5. Stochastic Frontier model: Empirical results

1. Modeling
2. Estimation method
3. Empirical results

Chapter 6. Data Envelopment model: Empirical results

4. Modeling
5. Estimation method
1. Empirical results

Chapter 7. Conclusion

1. Conclusions
2. Discussion
3. Policy Implications
4. Limitations and suggestions for further research
5. Perceived value and contribution of this study in relation to practitioners and academic community

References

Appendix

Chapter 1

The Productive Efficiency Theory

Abstract

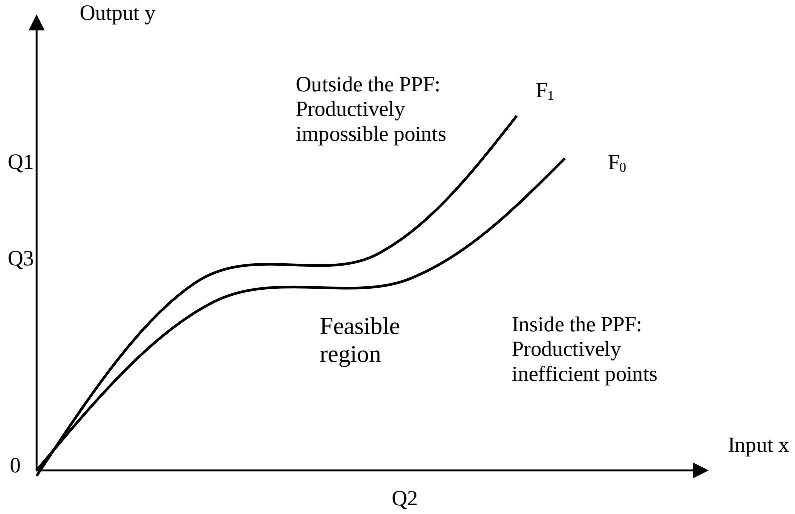
A definition of efficiency is that efficiency is the relationship between what an organization produces and what it could feasibly produce. In other words, efficiency of a production unit represents a comparison between observed and optimal values of its output and input. This comparison comes in two forms. The first is the ratio of observed to maximum potential output obtainable from a given level of input. The second is defined by considering first the given level of input, and is measured as the ratio of minimum potential to observed input required producing the given output. By the efficiency of a producer, we have in mind a comparison between observed and optimal values of its output and input. The optimum is defined in terms of production possibilities, and efficiency is technical. This chapter provides the definition and characteristics of productive efficiency, a term which is in the core place of this thesis analysis. This chapter describes the characteristics and the different aspects of production efficiency and gives the distinction between them. Finally, this chapter reviews the main methods of efficiency measurement, distinguishing between parametric and non – parametric approaches, as well as between frontier and non frontier approaches. More specifically, Chapter 1 provides an overview on the definition and alternative approaches of efficiency (technical or productive efficiency, allocative or pricing efficiency, scale efficiency, as well as economic efficiency). Moreover, Chapter 1 deals with the review of measurement of efficiency, distinguishing between: technical or allocative oriented approach, the input-oriented and output-oriented approach, the Parametric and non-parametric approach, the frontier and non-frontier approach. Moreover, this chapter also reviews the main research approaches on stochastic frontier analysis, analysing Koopmans (1951) and Debreu (1951), as well as Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) and Farrell (1957), making also an evaluation of these methods.

1.1. Introduction

Stochastic production frontiers indicate the maximum expected output for a given set of inputs. They are derived from production theory and are based on the assumption that output is a function of the level of inputs and the efficiency of the producer in using those inputs. This function defines the output associated with the best practice use of the inputs, while also recognizing the stochastic nature of the data arising from mis- or un-measured determinants of production.

The difference between actual output and the potential output is generally attributed to a combination of inefficiency and random error (i.e. the stochastic element in production). Methods have been developed to separate out the random component from the efficiency component, so that a more realistic assessment of potential output can be achieved. That is, large levels of output that may have occurred through chance rather than as a consequence of normal practice do not overly influence the estimates. When one considers productivity comparisons through time, an additional source of productivity change, called technical change is possible. This involves advances in technology that may be represented by an upward shift in the production frontier. This is presented in the following figure by the movement of the production frontier from $0F_0$ to $0F_1$ in period 1:

Figure 1.1. Production frontiers and Technical Efficiency



Source:Based on Coelli et al (2005), p. 6

In period 1, all firms can technically produce more output for each level of input, relative to what was possible in period 0. When we observe that a producer has increased productivity from one period to the next, the improvement need not have been from efficiency improvements alone, but may have been due to technical change or the exploitation of scale economies, or from some combination of these three factors (Coelli et al., 2005).

This chapter provides the definition of productive efficiency, a term which is in the core place of this thesis analysis. This chapter begins with analyzing inefficiency regarding decomposing productivity into the Production Possibility Frontier and (in)efficiency, describing the characteristics and the different aspects of this decomposition and providing the distinction between them. Finally, this chapter reviews the main methods of efficiency measurement, distinguishing between parametric and non – parametric approaches, as well as between frontier and non frontier approaches.

This chapter also reviews the main research approaches on stochastic frontier analysis. The chapter reviews the work by Koopmans (1951) and Debreu (1951) who were the first to technically combine production inputs with production outputs and to introduce the approach of distance function in order to estimate the differences between the actual output levels compared to the maximum potential output level. This chapter focuses also mainly on the stochastic frontier methodology developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), greatly influenced by Koopmans (1951), Debreu (1951) and Farrell (1957), who introduced a method to decompose the overall efficiency of a production unit into its technical and allocative components, providing the main characteristics of each approach, making also an evaluation of each one of these methods.

1.2. Inefficiency and Frontier Determining Factors

In the modern knowledge economy, growth depends extensively on the presence or the formation of a network and environment favorable to innovation, which is based on the endogenous development capabilities. Even though the producer-specific factors are important determinants of innovation activity, technological opportunities and favorable entrepreneurial environment have a positive effect on innovation activity, as well. Technological change, innovation and technology creation and diffusion are an important factor to economic progress[1].

Combining the production functions in order to create and disseminate innovations leads to improvements in productivity and efficiency. However, at a given moment of time, when technology and production environment are essentially the same, producers may exhibit different productivity levels due to differences in their production efficiency. Within growth process, therefore, efficiency of production resources becomes a critical element in growth, through utilizing the available, yet scarce, resources more productively. Within this framework, productivity represents the estimation of how well a producer uses the available resources to produce outputs from inputs. However, the productivity theory literature has emphasized factors such as productive efficiency, mainly through technological spillovers, increasing returns, learning by doing, und unobserved inputs (e.g. human capital quality), whereas the empirical industrial organization literature has emphasized the degree of openness of countries to imports and industry structure (Koop, 2001).

There is a huge literature on factors influencing productive efficiency and productivity growth. In this literature, it is widely accepted that decision making units are not homogeneous producing units and, therefore, not all units are operating at the same level of efficiency (Caves, 1989).

Bos et al. (2010) investigate the sources of output growth for a panel of manufacturing industries. They propose a flexible model beyond the division of output growth applied in the conventional growth accounting and cross-country growth regression literature, as well as the strong assumptions they typically rely upon (efficient use of resources, constant returns to scale). Bos et al. (2010) focus on the use of technology, the sources of output growth, technology spillovers and catch-

[1] This topic has been broadly examined in: Kokkinou A. (2010b) Economic Growth, Innovation and Collaborative Research and Development Activities. *Management & Marketing*, Vol. 5, No. 1, pp. 111-126.

up, as well as policy implications. To decrease the aggregation bias that may occur when these issues are considered at the country-level (Bernard and Jones, 1996 a,b), Bos et al. (2010) focus on manufacturing industries. Traditionally, the growth accounting literature has referred to the unexplained part of output growth as the 'productivity residual' or 'technical change' (Solow, 1957). This interpretation, however, depends, among other things, on the strong assumption that economic units (countries or industries) are always efficient. In reality, however, economic units may well use the best-practice (frontier) technology with varying degrees of efficiency. If this is the case, part of what is measured as technical change is in fact an improved use of the best-practice technology. Put differently, inefficient industries increase output by becoming more efficient in the use of the best-practice technology, whereas efficient industries increase output through technical change. In addition, not controlling for possible inefficient use of inputs may also result in underestimating the productivity of outputs for the best-practice technology. Bos et al. (2010) account for inefficiency and estimate a stochastic production frontier, which is the empirical analog of the theoretical production possibility frontier. This modelling strategy adds structure to the unexplained residual. Under reasonable assumptions, it disentangles the residual into inefficiency and measurement error. Technical change is modelled as a shift of the stochastic frontier, whereas efficiency change is a movement towards or away from the frontier. This framework decomposes output changes into three types of change: technical, efficiency and input change. Empirical literature carries out efficiency analyses along lines similar to Bos et al. (2010), although using different modelling approaches, considering that output change is also decomposed into technical, efficiency, and input change. Even though the attention has largely been at decomposing aggregate (country-level) output, a number of studies have investigated the role of efficiency in explaining growth differentials for a panel of manufacturing industries in the OECD countries (Bos et al., 2010).

As in Consoli (2008), research agrees that: first, strong emphasis is placed on the sources and the effects of technological change; second, great attention is paid to the dynamics generated by the interaction between business firms and their environment, including other firms and key institutional players (Malerba and Orsenigo, 1996; Antonelli, 2003; Metcalfe, 2001).

The heterogeneity in the inefficiency model can be expressed by a shift in the underlying mean of u_i or heteroscedasticity. Battese and Coelli (1995) established a model where producer-specific attributes are incorporated in the inefficiency distribution. Heterogeneity is expressed in the location parameter, the mean, of the underlying distribution of inefficiency u_i.

This model specification became popular to explain efficiency differences across producers. Reifschneider and Stevenson (1991) and Simar et al. (1994) established a SFA model incorporating heterogeneity in the variance of u_i or v_i, allowing for heteroscedasticity. Applications of the heteroscedastic SFA model can be found in Hadri (1999), Hadri et al. (2003 a,b) and Caudill et al. (1995).

Unobserved heterogeneity means that heterogeneity is not reflected in measured variables but expressed in the form of effects (Greene, 2007a). Several models attempt to separate unobserved heterogeneity from inefficiency and it became more important to model both heterogeneity in the stochastic part and producer-specific heterogeneity in the production or cost function of the underlying production process.

Kumbhakar (1991), Polachek and Yoon (1996) and Greene (2005b) have suggested to extend the original stochastic frontier model by adding an individual time-invariant random or fixed effect. These models are called “true” models because they include two stochastic terms for unobserved heterogeneity: one for the time-variant factors and one for the producer-specific constant characteristics (Farsi et al., 2003). The basic assumption is the existence of producer-specific and time-invariant factors that cannot be captured by efficiency explanatory variables due to the variation of the latter over time and/or omitted variables.

Unobservable individual effects also play an important role in the estimation of panel stochastic frontier models. In contrast to the conventional panel data literature, however, studies using stochastic frontier models often interpret individual effects as inefficiency (Schmidt and Sickles, 1984), such as technical inefficiency in a stochastic production frontier model.

Time-invariant inefficiency assumption has been relaxed, as in Kumbhakar (1990) and Battese and Coelli (1992). These studies specify inefficiency (u_{it}) as a product of two components. One of the components is a function of time and the other is an individual specific effect so that $u_{it} = f(t)u_i$. In these models, however, the time-varying pattern of inefficiency is the same for all individuals, so the problem of inseparable inefficiency and individual heterogeneity remains. In all these models, the inability to separate inefficiency and individual heterogeneity is likely to limit their applicability in empirical studies (Greene, 2005), who argues that the (in)efficiency effect and the time-invariant country-specific effect are different and should be accounted for separately in the estimation. If, for example, the country-specific heterogeneity is not adequately controlled for, then the estimated inefficiency may be picking up country-specific heterogeneity in addition to or even instead of inefficiency. In this way, the inability of a model to estimate individual effects in addition to the inefficiency effect poses a problem for empirical research (Wang and Ho, 2010).

As a management tool, stochastic frontier analysis focuses on the variables which are under the decision-makers' control. However, efficiency may be influenced by factors beyond the control of the managers. In stochastic frontier model analysis it is acknowledged that the estimation of production functions must respect the fact that actual production cannot exceed maximum possible production given input quantities.

Consequently, one of the main questions is to investigate the relationship between inefficiency and a number of factors which are likely to be determinants, and measure the extent to which they contribute to the presence of inefficiency. These factors are neither inputs to the production process nor outputs of it but nonetheless exert an influence on producer performance. Such factors are widely referred to as efficiency explanatory variables[2].

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[2] In many cases, the distinction between decision-maker controlled and efficiency explanatory variables is not always distinct. As in McMillan and Chan (2006), efficiency explanatory variables include purely exogenous variables as well as producer-specific variables representing production methods and output characteristics.

In this context, the term 'efficiency explanatory variables' is used to describe factors that could influence the efficiency of a producer, where such factors are not traditional inputs and are not under the control of the producer (Fried et al., 1999). However, they may influence productive efficiency. In particular, in order to investigate the determinants of the productive efficiency we distinguish between producers or industry -specific and efficiency explanatory factors (Caves and Barton, 1990) [3].

Efficiency explanatory factors are not under direct control of the producer, at least in the short-run, and they may be industry-affiliated, such as producer location characteristics, managerial restrictions, slow adoption to changes of the market environment and/or to technological developments, or asymmetric information in the labour market, social aspects, geographical or climatic conditions, as well as regulatory and institutional constraints, ownership differences (public/private), and government regulations (Coelli et al, 1998, Stephan et al. 2008). Producer-specific factors, on the other hand, refer to characteristics that can be influenced by the producer in the short-run, as producer size, R&D intensity and degree of outsourcing.

This section connects the discussion of theory in the thesis to the empirics. The empirical analysis focuses on productive efficiency of industries and national economies. In line with the empirical framework based on stochastic frontier analyses (SFA) and data envelopment analyses (DEA), productivity is decomposed into the production possibility frontier and technical (in) efficiency. For this reason, the discussion on theory clearly indicates what should determine the frontier and what affects efficiency.

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[3] Caves and Barton (1990) and Caves (1992) suggested that several studies have developed a strategy for identifying the determinants of efficiency, which can be grouped into three categories (Stephan et al. 2008):

1. factors external to the industry ;
2. factors internal to the industry; and
3. Ownership structures (e.g. public versus private).

Specifically, in line with the empirical framework, based on stochastic frontier analyses (SFA) and data envelopment analyses (DEA), productivity is decomposed into the production possibility frontier and technical (in) efficiency. For this reason, there should be a distinction on what should determine the frontier and what affects efficiency. This cannot be satisfactorily achieved by drawing only on theories of exogenous and endogenous growth. Both of these relate to production technology, which lies in the domain of the frontier. On the other hand, technical efficiency relates to neo-Schumpeterian ideas of catching-up with the leaders (technology diffusion and absorption) and forge-ahead through investments in R&D (innovation creation). However, this cannot be satisfactorily achieved by drawing only on theories of exogenous and endogenous growth, both of which relate to production technology, which lies in the domain of the frontier. Also, efficiency depends on the effectiveness of the institutional environment, which is closely related to evolutionary and institutional approaches. Recent contributions to the literature clearly emphasize the connection with theory, of empirical models for the production possibility frontier (or production function) and efficiency and they are also examined. More specifically, contributions to the literature (Kneller and Stevens, 2006, Bhattacharjee et al., 2009, and Eberhardt and Teal, 2011) clearly emphasize the connection with theory, of empirical models for the production possibility frontier (production function) and efficiency.

As stated in Bhattacharjee et al. (2009), the empirical models and inference methods can be categorized into two key methodologies: (a) the OLS regression based approach and the associated interpretation of the Solow residual as a measure of total factor productivity (TFP), and (b) frontier production function estimation where the distance from the highest achievable levels of productivity is interpreted as a measure of productive efficiency. The OLS approach supports the neoclassical concept of exogenous technology and the resulting view that deviations from the production frontier, either positive or negative, reflect only idiosyncratic productivity shocks. By contrast, negative skewness of the distribution of TFP is consistent with the combination of neo-Schumpeterian and neoclassical approaches, where frontier technology is viewed as a pool of knowledge accumulated through the innovative action of leaders and available to any productive unit. However the capacity to use such technology depends on a costly and time consuming effort to catch up with the leaders (Bhattacharjee et al., 2009). In order to present these issues, Bhattacharjee et al. (2009) examine the following approaches:

1. Neoclassical growth theory (Bhattacharjee et al., 2009)

Neoclassical growth models attempt to explain long run economic growth by looking at productivity, capital accumulation, population growth and technological progress. The neoclassical model of exogenous growth (Solow 1956, 1957; Swan 1956) considers the accumulation of physical capital, associated with a permanent flow of technical progress, as the driver of economic growth. Neoclassical growth model assumes the Cobb-Douglas production function. Growth is considered to be either an exogenous process or either achieved through exogenous technical innovations, embodied in capital goods (Solow, 1960). (Solow (1956) argued that countries that differ in terms of initial productivity levels but not in terms of other aspects (population growth and saving propensities) tend to converge towards the same level and the same rate of growth of productivity. This is the result of a theoretical perspective in which technology is considered as a public good, freely available to everyone, and its dynamics is largely unexplained.

Neoclassical growth consider that capital is an immobile factor accumulated through an endogenous investment process, while technology is either completely mobile or totally endogenous [Temple (2003), Keller (2004)]. Neoclassical growth models also assume diminishing returns to capital, constant savings rate and constant growth of labour, assumptions which imply a steady state growth rate depending only on the rate of exogenous technical progress. Inputs such as human capital or R&D investment imply that TFP depends on these factors, which is more in line with endogenous growth theory (Romer, 1986, 1990). Technology is assumed to be a private good which is produced by dedicated inputs and accumulated by economic systems as a stock of ideas. If the accumulation of ideas is not restricted by the law of diminishing returns, a steady state growth process can be derived, under which TFP increases at a rate depending on the growth of labour force dedicated to innovation and on the extent to which labour is used efficiently.

Limitations of the model include its failure to take account of entrepreneurship (which may be a catalyst behind economic growth) and strength of institutions (which facilitate economic growth). In addition, it does not explain how or why technological progress occurs. This failing has led to the development of endogenous growth theory, which endogenizes technological progress and/or knowledge accumulation.

Alternative models developed by Lucas (1988) assume the existence of a pool of exogenous technology combined with different endogenous capacities, dependent on the average level of human capital, accumulated either through formal learning or through learning-by-doing. On the other hand, the distinction between an exogenous technological frontier, at global level, and efficiency, at local level, measured as a TFP gap in relation to the frontier is not clearly made, unless by neo-Schumpeterian theory of growth.

2. Neo-Schumpeterian theory of growth (Bhattacharjee et al., 2009)

Even though endogenous growth theory may be used in order to describe diverse development processes according distinct divergence levels, the assumption of immobile technology in Romer (1986, 1990) and the lack of clear distinction between technological frontier and efficiency in Lucas (1988) prevent the consideration of technological catching-up through diffusion mechanisms (Keller 2004). On the other hand, according to Aghion and Howitt (2006), endogenous growth theory is not suitable to derive inferences and policy regarding technical progress, leading to growth and convergence attainment.

According to the neo- Schumpeterian approach, economic growth is mainly the outcome of a permanent attempt to forge ahead, rather than being driven by factor accumulation. This idea is directly related to the concept of an upward moving technological frontier, combining the most advanced technical knowledge with best practice. However, the assumption of a production possibility frontier which every productive unit seeks to achieve (in other words, a ceiling frontier production function) is only valid for public good technology. Neo-Schumpeterian theory of growth focuses on creative destruction as the basic process leading to the upward movement of the technological frontier (Aghion and Howitt, 1992). International flows of technology arise from the attempt to catch-up with the best practices (Grossman and Helpman, 1991), a process which depends on the technology and innovation absorptive capacity (Abramovitz, 1986; Fagerberg, 1988).

According to Bhattacharjee et al. (2009), the interaction between forging ahead and catching up process defines the upward movement of the technological frontier and the national, regional or firm heterogeneity, respectively, with respect to the capacity to reach the frontier. This interaction depends on two factors: (i) the levels of investment in human capital and R&D activities (Aghion and Howitt, 2006), and (ii) the relative importance of codified technology, technology embodied in capital goods and tacit knowledge embodied either in individuals or in organizations (Nelson, 1980).

3. Technology diffusion (Bhattacharjee et al., 2009)

Technology diffusion involves the dissemination of technical information and know-how and the subsequent adoption of new technologies and techniques. Diffused technologies can be embodied in products and processes. Although classic models of technological development suggest a inear relationshop from basic research and development to technology commercialization and adoption, in practice technology diffusion is a complex process. Technology can diffuse in multiple ways and with significant variations, depending on the particular technology, across time, over space, and between different industries. Moreover, the effective use of diffused technologies frequently requires organizational and technical changes. Technology also diffuses through the internal "catch-up" efforts of firms, the transfer and mobility of skilled labor, the activities of professional societies and the trade and scientific press, varied forms of informal knowledge trading, and such practices as reverse engineering. Import of technology embodied in capital goods (Solow, 1960; Caselli and Wilson, 2004), as well as disembodied technological spillovers are the two main channels through which technology diffuses. In both cases, the efficiency of technology diffusion depends on the availability of human capital and on the investment in specific forms of R&D which enhance the absorptive capacity of productive system (Aghion and Howitt, 2006). Coe and Helpman (1995) measure the effect of R&D spending of trade partners on the TFP of developed countries, while Funke and

Niebuhr (2005) use a model of R&D workforce to measure knowledge spillovers across regions. These models are based on the implicit assumption of a constant absorptive capacity, informing about how embodied and mobile disembodied technology contribute to form a global benchmark frontier. An alternative procedure is to assume an invariant capacity to access exogenous technology and measure different absorptive capacities.

4. Evolutionary and institutional approaches (Bhattacharjee et al., 2009)

The evolutionary approach developed by Nelson and Winter (1982) and Dosi et al. (1988) considers that innovation creates mainly technological paradigms, rather than a universal benchmark, defining a technological frontier. Technological paradigms combine a set of established routines with a shared knowledge base, which determines the opportunities of future technical advances (Dosi, 1997). Dosi (1997) defines a technological paradigm as a set of procedures, or a definition of the relevant problems and of the specific knowledge related to their solution. Such paradigms are shared by all productive units and provide the basis for the development of specific learning processes (Nelson and Winter, 2002). Technological paradigms promote learning processes at industrial level, generating industrial trajectories which are both driven by specific capacities to absorb, enhance and apply scientific and technical knowledge, as well as by changes in demand. Inside each industry, specific firms compete with each other, trying to perform better than the common benchmark determined by the floor technological standard, forging ahead through innovation.

Evolutionary approach asserts that technology has a strong tacit, private good component, it is more reasonable to assume a benchmark level of productivity given by a technological floor. Over this base level, each productive unit builds its own comparative advantage using proprietary techniques and tacit knowledge. The dominance of the public-good or private-good component defines the sign of skewness in the distribution of TFP, and thus determines whether the ceiling or the floor representation of technology is more appropriate.

Productivity and innovation performance depends on the availability of skilled workforce and on the synergies arising from interactions between firms and supporting organizations. On the other hand, entrepreneurial behavior is shaped by the combination of social and political factors stressed by the new institutional economics (Furobotn and Richter, 1992), such as legal system to ensure property and intellectual rights, and the existence of a cultural and institutional framework which lowers transaction costs (Williamson, 1996).

Within this framework, based on Wang (2007), since R&D is one of the most crucial elements in promoting growth, it is argued that any production unit that uses R&D resources inefficiently may be subjected to a growth penalty in the form of a much smaller benefit from R&D investment. If R&D resources are not used effectively, additional investment may be of little help in stimulating economic growth. Literature has already been devoted to investigating the economic aspects and effects of R&D investment. It has been considered that R&D could result in better production technology and also raise the productivity as well as the rates of return on investment at both the producer and industry levels. Griliches (1986) and Griliches (1990), Mansfield (1988), Goto and Suzuki (1989), Meliciani (2000), Timmer (2003) and Gonzalez and Gascon (2004) have provided theoretical arguments as well as empirical evidence from various industries in many countries. The positive effects of R&D investment on productivity as well as on rates of return are clearly identified. In addition, there are many other issues related to R&D, such as patenting, patent quality and business strategies that have been discussed in the economic literature. Griliches (1990), Ginarte and Park (1997) and Penin (2005) examined the economic aspects of patents. Patent quality and examination procedures were also discussed in King (2003). The relationship between the protection of patents and product standardization strategies was explored by Blind and Thumm (2004)[4].

[4] However, the existing literature has focused primarily on efforts to engage in new investment and comparatively little attention has been paid to the effective use of R&D resources once they are in place. This is a potentially important omission, since the very conditions responsible for economic backwardness may operate through the poor management of the means of engaging in R&D. Therefore, knowing the nature of R&D performance by examining its relative efficiency across production units is the first required step for designing policies that intend to improve resource allocation.

Technology and innovation play an important role in economic growth and technology has become one of the most important factors in the models of growth (Geroski and Machin, 1993, Barro and Sala-i-Martin, 1995, 1997, Freeman and Soete, 1997, and Sternberg, 2000)[5]. The role of innovation is multiple: as motive force it directs the producers to ambitious and long-term objectives, it leads to the renewal of methods of production, supply and distribution, and management and marketing, as well as industrial structures and the appearance of new industries of economic activity, achieving a wider spectrum of products and services, as well as relative markets. Inputs affect the intermediate inputs, which consequently affect and define the productivity and competitiveness level. Technological change, innovation and technology creation and diffusion are an important factor to economic progress. While innovation may lead to divergence between producers or nations, imitation through diffusion and dissemination tends to erode differences in technological competencies, and hence lead to convergence (Fagerberg and Verspagen, 2002). On the other hand, combining the production functions in order to create and disseminate innovations leads to improvements in productivity and economic development (Malecki and Varaia 1986; Malecki 1991, Fagerberg and Verspagen, 2002)[6].

1.3. Technical Efficiency and knowledge creation

Technological change refers to the creation and successful market implementation of a new or improved product or production process. Technological change is a term

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[5] Arrow (1962) was the first to systematically appreciate the importance of innovation and technological change in the capital formation and economic growth. He observed that increases in income per capita couldn't be explained by increases in capital to labour ratio, and concluded that the power behind the increase in productivity is the acquisition of knowledge and learning experience created and acquired during the production procedure.

[6] This topic has been broadly examined in: Kokkinou A. (2008) *Innovation Policy, Competitiveness, and Growth: A Strategy towards Convergence of European Regions,* 48th European Congress of the Regional Science Association, Liverpool, U.K.

which includes the search for, discovery, development, improvement, adoption, commercialization of new processes, new products, and new organizational structures and procedures and it is a process that involves uncertainty, risk taking, probing, re-probing, experimenting, and testing (Jorde and Teece, 1989).

In economic theory, technology is usually represented as a set of factor combinations which relate to a certain output level; technological change simply shifts the production possibility curve to a higher output level given the same quantity level in input factors. The endogenous element of this shift is called innovative activity, an activity which we partially attribute to some economic incentive when referring to the "market pull" approach, and partially ascribe to the "technology push", an autonomous factor in technology itself. Dosi (1982) defines technology as a set of pieces of knowledge, both directly 'practical' (related to concrete problems and devices) and 'theoretical' (but practically, applicable although not necessarily already applied), know-how, methods, procedures, experience of successes and failures and also, of course, physical devices and equipment (Dosi, 1982).

According to Mansfield (1968), the main sources of economic growth are:

1. Increase in the productive base in order to increases the productive possibilities of the economy within a time period (as, for example though increases in total work force or Gross Fixed Capital formation)
2. Economies of scale that are related with increase in the factors of production
3. Technological progress

However, despite these significant contributions, the systematic analysis and the theoretical framework of the effects of innovation on economic efficiency, productivity and growth is based on endogenous growth theory developed by Solow (1957) and extended by Arrow (1962), Romer (1986, and 1990), Lucas (1990 and 1993). Endogenous growth theory claimed that not only the accumulation of capital, but mainly the development and accumulation of knowledge and technological change leads to sustainable growth.

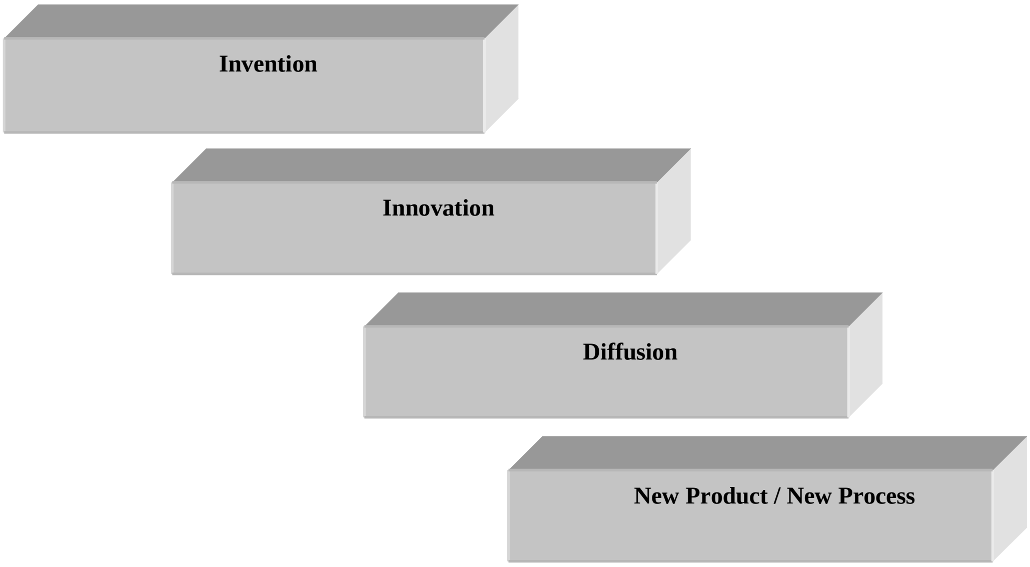
The main contribution of endogenous growth theory was the incorporation of a general concept of technology by broadening the conception of capital or explicitly introducing technology as a production factor, suggesting that there is a three-way complementarity between physical capital, human capital, and technical progress.

More specifically, according to Solow (1957) there is a close correlation between technological development and productivity, since technological change affects the use of inputs engaged in the production process. Innovative capacity is one of the main factors which determine the production level [Fagerberg et al. (1997), Freeman & Soete (1997)] and technological variables are able to explain a significant part of the diverging trends in the economic growth [Fagerberg & Verspagen (1996)] and productivity [Abramovitz (1986), Fagerberg (1988 a,b, 1994)].

Endogenous growth theory takes innovation as an endogenous variable which can explain the different growth rates. The reason is that the long-run productivity decrease is avoided, due to capital accumulation through the qualitative-technological improvements of natural and human capital. According to Romer (1986, 1990), technological progress is the main engine of economic dynamism and the economy grows endogenously through the accumulation and spillover of knowledge. Industry growth rate depends on the amount of technological activity within the economy and on the ability to exploit external technological achievements (Martin and Ottaviano, 1999, Grossman and Helpman, 1994, Coe and Helpman, 1995). Increasing returns and technical change are incorporated within the production function as determinants of the endogenous growth rate (Romer 1986, Lucas 1988, Grossman and Helpman 1994, Barro and Sala-i-Martin, 1997) and economic growth is sustained because of the continuous creation and diffusion of technological advances.

Developments in the theory of economic growth have renewed the interest for the role of innovation in the development process, underlining the interaction between the investment in innovative activities, technological change and economic growth. Technological change, innovation and technology creation and diffusion are an important factor to economic progress, as illustrated in the figure that follows:

Figure 1.2. Innovation and Industrial Growth



Source: Own elaboration

The economic processes that create and diffuse new knowledge are critical in the development process and there are powerful contacts between the investment in human capital, technological change and productive efficiency (Acs, Anselin and Varga, 2002) [7]. The reason is that the new technologies lead to increase of productivity of factors of production, contributing in the long-term improvement of efficiency (Griliches, 1980). For example, new equipment invested in requires a well-trained workforce for efficient operation. While human capital in the form of general education is a key factor for developing countries, the effect of this is expected to be less strong for more developed countries, as they already have relatively high levels of general education and the marginal productivity of an additional year of primary-level schooling is quite low. For developed economies, human capital is made more productive through better skills and in-company training. An increase in the quality of workers would allow increased efficiency in capital use and in turn increase output

[7] Under this approach, Fagerberg (1987, 1988a,b) created a model of endogenous technological change, focusing on the importance of innovation on economic growth. According to Fagerberg (1987, 1988a,b) economic growth is explained as the combined result of three factors, namely the potential for innovation creation, the potential for innovation diffusion and the exploitation of these potentials.

growth. Another issue is that some types of capital may matter more than others. Some studies have suggested that investment in machinery and equipment is more important than investment in buildings and structures, while others have argued that investment in infrastructure is an important prerequisite for productivity growth and have attributed high payoffs to investment in such capital stock[8].

1.4. Technical Efficiency and knowledge dissemination

As broadly described in Gallié and Poux (2010), in the last two decades, R&D cooperation has attracted a considerable amount of attention. Many empirical studies, in economics or in management, have investigated the motives for and potential benefits of cooperation as compared to internal R&D. Cooperation enables firms to internalize knowledge spillovers, facilitates knowledge transfers between them (in particular between firms and universities), helps them gain access to complementary knowledge and technologies, generates scale economies of research, enables firms to speed the commercialization of new products or technologies, to avoid duplicative R&D efforts, to share costs and risk, to gain access to foreign or new markets. Since R&D collaboration, cooperation was most often captured as a homogenous object (i.e. R&D cooperation vs. internal R&D)[9].

At a given moment of time, when technology and production environment are essentially the same, producers may exhibit different productivity levels due to

[8] This topic has been broadly examined in: Kokkinou A. (2011a) Innovation Policy, Competitiveness, and Growth: Towards Convergence or Divergence? *in* Patricia Ordonez de Pablos, W.B. Lee and Jingyuan Zhao (editors) *Regional Innovation Systems and Sustainable Development: Emerging Technologies*, Information Science Reference, Hershey, New York, pp. 187 – 201.

[9] This topic has been broadly examined in: Kokkinou A. (2009b) Economic Growth, Innovation and Collaborative Research and Development Activities, στο *ICBE 2009,* 4th edition.

differences in their production efficiency[10]. Within economic growth process, therefore, efficiency of productivity of resources becomes a critical element in economic growth, through utilizing the available, yet scarce, resources more productively.
Within this framework, productivity represents the estimation of how well a producer uses the available resources to produce outputs from inputs. However, the productivity theory literature has emphasized factors such as productive efficiency, mainly through technological spillovers, increasing returns, learning by doing, und unobserved inputs (e.g. human capital quality), whereas the empirical industrial organization literature has emphasized the degree of openness of countries to imports and industry structure (Koop, 2001)[11].

Innovation and technology is an important source of industry competitiveness through facilitating cooperation. In particular, they can improve collective processes of learning and the creation, transfer and diffusion of knowledge, critical for innovation. Such cooperation and the networks that are formed help to translate knowledge into economic opportunity, while at the same time building the relationships between organizations which can act as a catalyst for innovation.

Following the main findings from literature survey, there are two complimentary sets of conditions need to be satisfied for industries to sustain productivity and efficiency in competitive environment. The first is that they must have suitable levels of both physical infrastructure and human capital. The second is that, in the new knowledge-based economy, they must have the capacity to innovate and to use both existing and new technologies effectively. Industrial and innovation policy is aimed at strengthening the competitiveness of producers by promoting competition, ensuring access to markets and establishing an environment which is conducive to R&D. As

[10] Variation in productivity, either across producers or through time is thus a residual which Abramovitz (1956) characterized as ‘a residual of our ignorance’.

[11] This topic has been broadly examined in: Kokkinou A. (2009a) Strategy for Entrepreneurship and Innovation Activities in the knowledge Economy in *Women Participation and Innovation Activities: Knowledge Based Economy*, Women’s Press, New Delhi, India.

recognized, lack of innovative capacity stems not only from deficiencies in the research base and low levels of R&D expenditure but also from weaknesses in the links between research centers and businesses, and slow take-up of information and communication technologies. Knowledge and access to it has become the driving force of productivity, much more than natural resources or the ability to exploit abundant low-cost labor, have become the major determinants of economic competitiveness since it is through these that industries can increase their productive efficiency. Innovation, therefore, holds the key to maintaining and strengthening efficiency which in turn inessential for achieving sustained economic development.
These environmental factors are spatially confined externalities with different scales of influence. Some factors, such as the legal and cultural framework or large research institutes, operate mainly at national level, generating national systems of innovation (Lundvall, 1992), other factors, such as skilled labour supply and networks linking firms and support institutions have a more limited territorial span, and are the basis of regional systems of innovation (Braczyk et al., 1998).

As far as empirical modelling is regarded, estimation of production functions using OLS methods correspond closely with the neoclassical approach. Here, all producers use the best purpose technology, and any deviation in their output, positive or negative, is attributed solely to idiosyncratic productivity shocks. This leads to the interpretation of the Solow residual as a measure of TFP (Solow, 1957). By contrast, neo-Schumpeterian theory has generated a rich variety of empirical studies that attempt to identify both the evolution of the frontier and the catching up capacity of different countries and regions. These studies treat investment in physical capital as an exogenous process and thus, rather than looking at the dynamics of capital accumulation, they are centred on comparative analyses of TFP levels. Neo-Schumpeterian empirical studies can be divided into two main approaches, according to the econometric techniques used: The first approach is inspired by the work of Färe et al. (1994), who applied Data Envelopment Analysis (DEA) to a sample of OECD countries over a 10-year period. Kumar and Russell (2002) develop a related methodology, where the evolution of labour productivity is decomposed into physical capital accumulation (movement along the frontier) and increase of TFP; rise in TFP results from a combination of technical progress (upward movement of the frontier) and catching up (movement towards the frontier).

The second approach is Stochastic Frontier Analysis (SFA), which decomposes the residuals of an estimated production function into an efficiency component, corresponding to a negative valued random effect having a skewed distribution, and an idiosyncratic zero mean zero skewness random error. SFA is relatively robust to random noise arising from measurement errors and erratic variations in the level of TFP, and can accommodate idiosyncratic productivity shocks. Further, by explicitly modeling departures from the frontier as a combination of inefficiency and idiosyncratic shocks, SFA offers unique and useful interpretation combining the neo-Schumpeterian and neoclassical approaches.

Because of these advantages, as in Bhattacharjee et al. (2009), SFA has emerged as the most popular methodology to study TFP at the firm level, either for crosssection comparison of efficiencies (Green and Mayes 1991), or analysis of efficiency dynamics using panel data (Tsionas, 2006), or for analyzing spatial influences on the efficiency of firms in specific industries (Coelli et al., 1999). SFA has also been applied to study TFP at the macroeconomic level, although less frequently. For example, Kneller and Stevens (2006), using panel data on manufacturing industries of OECD countries, analyzed the skewed component of the error term, representing the distance to the technological frontier, as a function of the levels of investment in R&D and human capital, which in turn are related to the absorptive capacity of the economic system. Neo-Schumpeterian theory applied to SFA implies a negative skewness in the distribution of TFP (Carree, 2002), while standard OLS assumes a symmetrical distribution. Therefore, the empirical observation in several studies that the cross-sectional distribution of TFP is positively skewed (Green and Mayes, 1991, Fritsch and Stephan, 2004) casts serious doubts about the validity of the theoretical approaches adopted and the consistency of the estimation methods[12].

[12] These seemingly contradictory results have been explained as arising either from weakness of the frontier methodology, mainly concerning the lack of robustness with respect to violation of normality and measurement of skewness (Simar and Wilson, 2005), or from a notion of superefficiency (Green and Mayes,1991).

Bhattacharjee et al. (2009) explore the idea that the productivity enhancing positive component captures innovative activity raising certain industries above common productivity standards at specific times. In addition, there may be an omitted variables problem (Temple, 1999) where common shocks, like the global business cycle or new technology developed by the leaders, can drive spillovers across countries or regions. In so far as technology transfer depends on technology gap with the leaders (Lucas, 2000 and Hultberg et al., 2004) which is in turn driven by technological progress in leading regions, technology transfer can be characterized by time-specific common factors. Moreover, according to Bhattacharjee et al. (2009), more explicit modeling of innovation, particularly investment in R&D, human capital, international technological spillovers and spatial diffusion are also to be considered.

Even though the vast majority of empirical approaches limit cross-country heterogeneity in production technology to the specification of total factor productivity (TFP), Eberhardt and Teal (2011) present two general empirical frameworks for cross-country growth and productivity analysis and demonstrate that they encompass the various approaches in the growth empirics literature of the past two decades. Solow (1956, 1970) makes clear that the stylized facts for which this model was developed were not interpreted as universal properties for every country in the world. In contrast, the current literature imposes very strong homogeneity assumptions on the cross-country growth process as each country is assumed to have an identical aggregate production function. (Durlauf *et al.*, 2001). Eberhardt and Teal (2011) argue that there are a number of important reasons why the standard cross-country growth regression framework needs to be reconsidered. Intuitively, the heterogeneity in production technology could be taken to mean that countries can choose an 'appropriate' production technology from a menu of feasible options. Further, the cross-country heterogeneity in TFP relates to differences both in the underlying processes that make up TFP and in the impact of those processes on output.

Following Mankiw et al. (1992) most empirical studies put this down to the failure to account for forms of intangible capital (human capital, social capital) in the regression model. This belief has led to a growth empirics literature that for the most part neglects technology-parameter heterogeneity across countries and simplifies dynamics. The mainstream literature favours ever more sophisticated statistical devices (Sala-i-Martin et al., 2004; Moral-Benito, 2009) and 'general-to-specific' automatic model selection algorithms (Hendry and Krolzig, 2004; Ciccone and Jarocinski, 2008) – to pick out the 'relevant' variables in an augmented Solow regression model with time-averaged variables, so-called 'Barro regressions'. At the last count no fewer than 145 variables have been investigated in their impact on growth (Durlauf et al., 2005) and most were found to matter in at least some studies. A number of papers, however, question this paradigm and have integrated considerations of parameter heterogeneity into their cross-country empirics, also considering the time-series properties of the data, an issue largely ignored in the standard cross-country growth regression framework. Their regression results and diagnostic tests for variable non-stationarity and parameter heterogeneity confirm their importance in the empirical analysis (Pedroni, 2007; Canning and Pedroni, 2008).

Martin and Mitra (2002) estimate industrial production functions for agriculture and manufacturing using Crego et al. (1998) data for 1967 to 1992. Martin and Mitra (2002) allow for differential TFP levels and growth rates across countries, modelled via country-specific intercepts and linear trend terms in a pooled panel estimation using annual data for around 50 countries. TFP growth is captured by the country trends and thus assumed to be constant over time and heterogeneous across countries (and industries). Martin and Mitra (2002) results indicate considerable variation in TFP growth rates between industries and across countries, with TFP growth rates in agriculture commonly in excess of those in manufacturing.

Martin and Mitra (2002) address the issue of heterogeneity in TFP levels and growth rates in a static pooled fixed effects model, which imposes common technology parameters across countries. However, the estimation equations for agriculture and manufacturing are static and no investigation of error correlation is undertaken to justify this choice.

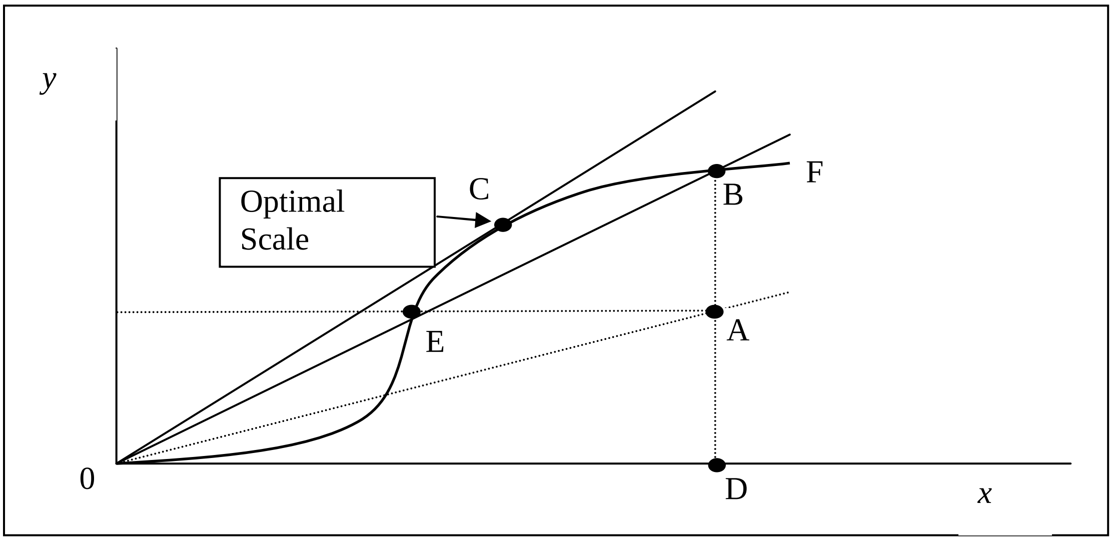
Keeping production technology constant across countries may be seen as a less restrictive assumption when investigating more homogeneous sets of economies, such as the group of OECD countries. Arnold et al. (2007) empirically compare two rival growth models, the human-capital-augmented Solow model with two industries, using annual panel data from 21 OECD countries over the 1971–2004 period. Their empirical specification allows for flexibility in the short-run dynamics across countries, while imposing common long-run production technology. The latter is consistent with the idea that the OECD countries have access to common technologies and have intensive intra-industry trade and foreign direct investment (Arnold et al., 2007). Using annual data for 20 Italian regions from 1970 to 2003, Pedroni (2007) and Canning and Pedroni (2008) estimate their empirical model by industry, comparing results for the heterogeneous parameter group mean. However, given the relatively recent emergence of cross-section correlation issues in macro panels only a small number of empirical papers combine cross-section correlation in macro panel data with heterogeneous production technology, including work by Bhattacharjee et al. (2009) and Fleisher et al. (2010) on production in Danish regions and Chinese provinces, respectively, as well as work by Cavalcanti et al. (2009) investigating the 'natural resource curse' in a panel of 53 countries. Moreover, Eberhardt and Teal (2009a, b) analysed cross-country macro data for the manufacturing (48 countries, 1970–2002; UNIDO, 2004) and agricultural (128 countries, 1961–2002; FAO, 2007) industries, respectively.

1.5. Reviewing the productive efficiency

A definition of efficiency is that efficiency is the relationship between what an organization produces and what it could feasibly produce. In other words, efficiency of a production unit represents a comparison between observed and optimal values of its output and input. This comparison comes in two forms. The first is the ratio of observed to maximum potential output obtainable from a given level of input. The second is defined by considering first the given level of input, and is measured as the ratio of minimum potential to observed input required producing the given output. By the efficiency of a producer, we have in mind a comparison between observed and optimal values of its output and input.

The optimum is defined in terms of production possibilities, and efficiency is technical. It is also possible to define the optimum in terms of the behavioral goal of the producer. As in Wang et al. (2002), productivity and efficiency are the two most important concepts in measuring performance. However, the terms productivity and efficiency have been used frequently interchangeably, even though they are not precisely the same things (Coelli et al, 2005). The difference between efficiency and productivity can be simply illustrated, as shown in the following figure. As in Coelli et al. (2005), to illustrate the distinction between these two terms, it is useful to consider a simple production process in which a single input (x) is used to produce a single output (y). Points A, B and C refer to three different producers. The productivity of point A can be measured by the ratio DA/0D according to the definition of productivity where the x-axis represents inputs and the y-axis denotes outputs.

Figure 1.3. Efficiency and Productivity



Source: Wang et al. (2002), p.4 and Coelli et al. (2005), p. 5

In this figure we use a ray through the origin to measure productivity at a particular data point. The slope of this ray is y/x and hence provides a measure of productivity. If the firm operating at point A were to move to the technically efficient point B, the slope of the ray would be greater, implying higher productivity at point B. However, by moving to the point C, the ray from the origin is at a tangent to the production frontier and hence defines the point of maximum possible productivity (exploiting scale economies). The point C is at the technically optimal scale. Operation in any other point of the production frontier results in lower productivity.

Given the same input, it is quite clear that productivity can be further improved by moving from point A to point B. The new level of productivity is then given by BD/0D. Clearly, productivity can be represented, therefore, by the slope of the ray through the origin which joins the specific point under study. The efficiency of point A, on the other hand, can be measured by the ratio of the productivity of point A to that of point B, i.e., $\frac{AD/0D}{BD/0D}$.

The above efficiency is normally termed *Technical Efficiency*, and includes output- and input-oriented technical efficiencies, i.e., the producer can either improve output given the same input (output-oriented, point A to B) or reduce the input given the same output (input-oriented, point A to E) by improving technology. The curve 0F in the figure is the so-called production frontier. All the points on the production frontier are technically efficient, whilst all the points below or lying to the right of the efficient frontier are technically inefficient (Wang et al., 2002).

Central to frontier productivity analysis is the determination of the efficient production technology, identification of those efficient decision-making producers on the technological frontier and of those inefficient producers not on the frontier and, for the latter, determination of the degree and sources of their inefficiency. Estimation and quantification of efficiency measures is useful for several reasons: Relative measures of efficiency facilitate comparisons across similar production units (Lovell, 1993) [13].

[13] A wide range of efficiency approaches and frameworks exist in the literature (see Jamasb and Pollitt, 2001, ; Farsi et al., 2003).

As rigorously described in Kumbhakar and Lovell (2000), productive efficiency represents the degree of success producers achieve in allocating the inputs at their disposal and the outputs they produce, in an effort to meet specific set productive objectives. Thus, in order to measure productive efficiency it is first necessary to specify producers' objectives and then to quantify their degrees of success.

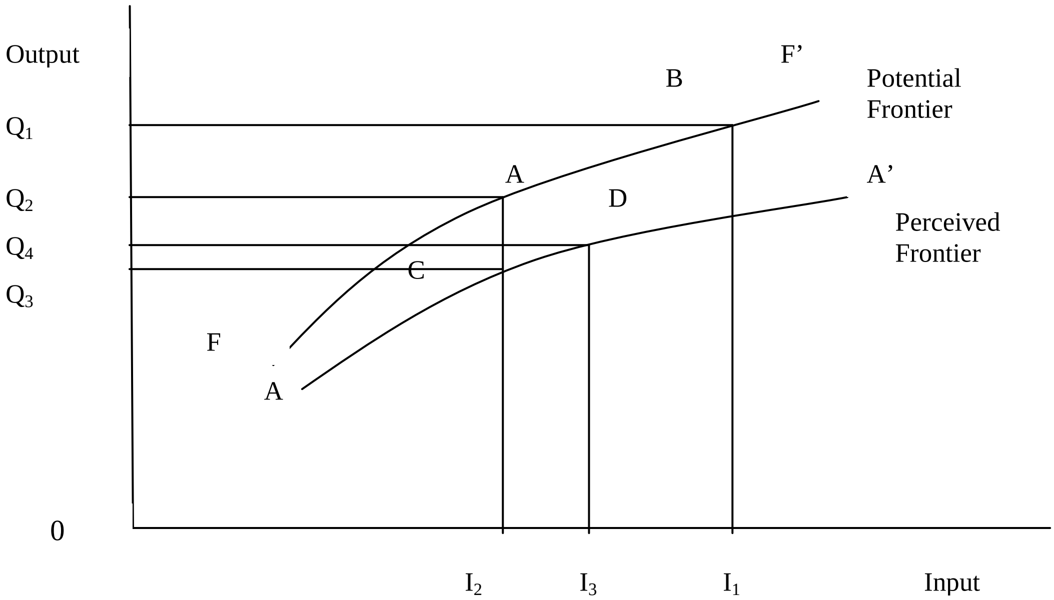
Efficiency performance is conventionally judged utilising the concept of economic efficiency, which is generally assumed to be made up of two components: technical efficiency and allocative efficiency. The former is defined as the capacity and willingness of an economic unit to produce the maximum possible output from a given bundle of inputs and technology level. The latter concept is defined as the ability and willingness of an economic unit to equate its specific marginal value product with its marginal cost.

Allocative efficiency reflects the ability of an organization to use these inputs in optimal proportions, given their respective prices and the production technology. In other words, allocative efficiency is concerned with choosing between the different technically efficient combinations of inputs used to produce the maximum possible outputs. Since different combinations of inputs are being used, the choice is based on the relative costs of these different inputs (assuming outputs are held constant).

Allocative inefficiency is input-oriented and occurs when the mixture of inputs used is not the mixture with the lowest possible cost for producing a given amount of outputs.

As analytically described in Kalirajan and Shand (1999), while the concept of technical efficiency is as old as neoclassical economics, interest in its measurement is not. This is probably explained by the fact that neoclassical production theory presupposes full technical efficiency. Then, the question raises as to why should one measure technical efficiency. There are two principal arguments for its measurement (Bauer, 1990 a,b; Kalirajan and Shand, 1992). Technical efficiency becomes central to the achievement of high levels of economic performance at the producer level, as does its measurement. The basic concept underpinning the measurement of technical efficiency starts with the description of production technology. Production technologies can be represented using isoquants, production functions, and cost functions or profit functions. These four models provide four different tools for measuring technical efficiency. Although analyses based on these models appear to be distinct, they constitute the same basic approach and ideally their results should converge:

Figure 1.4. The concepts of technical efficiency, allocative efficiency and economic efficiency



Source: Kalirajan and Shand (1999), p. 151

In neoclassical theory, all producers are assumed to operate at potential technical efficiency at points along the frontier *FF'*. Any inefficiency will be solely allocative. Thus, if a producer is operating on its frontier *FF'*, its point of economic efficiency may be at B, the point of tangency with its price line. If it operates at *B,* with inputs I_1 and output Q_1 there will be maximum profits π_1 and no allocative or economic inefficiency. It should be noted that, provided producers are operating on their technical frontiers, allocative (in) efficiency will be the same as economic (in) efficiency (they are used synonymously in the literature) because of the theoretical assumption of potential technical efficiency. Thus if a producer is operating at point *A* on its frontier, using I_2 inputs and producing Q_2 output, its profits may be π_2, and its allocative / economic inefficiency will be measured as π_2/π_1. In practice, with a new technology, producers operate at less than potential technical efficiency owing to incomplete knowledge of best technical practices or to other organisational factors that prevent it from operating on its technical frontier. Thus, a producer will operate on an actual or perceived production function which is below the potential frontier, e.g. on *AA'*. At I_2 inputs, it operates at point *C*, produces Q_3 output and earns π_3 profits. On this actual production function, point *C* is allocatively inefficient. To maximise its profits (π_4) it would have to operate at point *D*, use I_3 inputs and produce Q_4 output. At *D*, however, it would not achieve potential economic efficiency, for by definition, potential economic efficiency can only be achieved with potential technical efficiency.

To be consistent with neoclassical production theory, efficiency should only be measured in relation to the frontier production function *FF'*. Thus if a producer is operating at *C* on its actual or perceived production function, its economic inefficiency would be measured in profit terms by the ratio $\pi 3/ \pi 1$, or in output terms by the ratio Q_3/Q_1. Now, it can easily be seen that this economic inefficiency comprises two components, technical and allocative inefficiencies. In profit terms, the total loss in economic inefficiency in operating at point C is π_1 - π_3. Of this, the loss from technical inefficiency is π_3 - π_2, and the loss due to allocative inefficiency is π_1 - π_2. In output terms, the losses are Q_2 - Q_3 and Q_1 - Q_2 respectively. The various models for measurement that follow are based upon this conceptual framework.

If the analyzed industry exhibits variable returns-to-scale, then another component of economic efficiency, scale efficiency, is present. The scale efficiency measure, determines how close an observed production unit is from the most productive scale size (Førsund and Hjalmarsson, 1979; Banker and Thrall, 1992). A production unit may be scale inefficient if it exceeds the most productive scale size (therefore experiencing decreasing returns-to-scale) or if it is smaller than the most productive scale size (therefore failing to take full advantage of increasing returns-to-scale).

Scale inefficiency of a production unit is defined with respect to those production units in the sample which operate where average and marginal products are equal (Førsund et al., 1980). The analyzed industry might also exhibit scope efficiency. This measure relates to the benefits which are realized by production units that produce several products compared to specialized ones (Chavas and Aliber, 1993).

Finally, when taken together, allocative efficiency and technical efficiency determine the degree of `economic efficiency' (also known as total economic efficiency). Thus, if an organization uses its resources completely allocatively and technically efficiently, then it can be said to have achieved total economic efficiency.

Alternatively, to the extent that either allocative or technical inefficiency is present, then the organization will be operating at less than total economic efficiency.

1.6. Koopmans (1951) and Debreu (1951) approach

Koopmans (1951) defined a feasible input – output vector to be technically efficient if it is technologically impossible to increase any output and /or to reduce any input without simultaneously reducing at least one other output and / or increasing at least one other input. While Koopmans offered a definition and characterization of technical efficiency, it was Debreu who first provided a measure or an index of the degree of technical efficiency with his coefficient of resource utilization. When there is no such feasible reduction, the production unit is said to be technically efficient with score one. In any other case, production unit is characterized as inefficient and has a technical efficiency score lower than one.

Debreu (1951) introduced distance functions into economics. Distance functions introduce the distance from some observed input – output combination to the frontier of technology (Fried et al, 2008). Distance functions allow one to describe a production technology without the need to specify a behavioural objective (such as cost – minimisation or profit – maximisation). Distance functions describe technology in a way that makes it possible to measure efficiency and productivity. The concept of a distance function is closely related to production frontiers. The basic idea underlying distance functions involves radial contractions and expansions in defining these functions. Distance functions are functional representations of multiple-output, multiple-input technology that require only quantity data of those inputs and outputs. Thus, distance functions allow modelling the production frontier as well as deviations from it. Those deviations represent technical inefficiency while shifts in the frontier represent technological change (Grosskopf, 1993).

Debreu (1951) and Koopmans (1951) were concerned mainly with the measurement of efficiency and although they produced careful measurements of some, or all, of the inputs and outputs used in the production process of a decision-making unit, they failed to combine these measurements into any satisfactory estimate of efficiency.

In the following years, applications using distance functions [Shephard (1970)] have begun to be very usual [Färe et al. (1993), Simar et al. (1994), Coelli and Perelman (1996) or Grosskopf et al. (1997)]. In turn, it is only required to assume that technical efficiency be time invariant (Schmidt and Sickles, 1984). On the other hand, Cornwell, Schmidt and Sickles (1990), Kumbhakar (1991), Battese and Coelli (1992) and Lee and Schmidt (1993) have proposed time-varying technical efficiency panel data models. The first of these models allows for producer specific patterns of temporal change in technical efficiency and it models technical efficiency through the intercept of the production frontier. The rest of these models adopt a different approach in that they model technical efficiency through an error component but assume that efficiency change is the same for all producers.

The advantages of these quantity-based functions over value-based functions are that they do not require either input prices or output prices in their construction, and they do not rely on assumptions regarding economic behaviour, such as revenue maximization or cost minimization (Zofio and Lovell, 2001)**.**

1.7. Farrell (1957) approach

Farrell (1957) extended the work initiated by Koopmans (1951) and Debreu (1951) by noting that production efficiency has a second component reflecting the ability of producers to select the right technically efficient input- output vector in light of prevailing input and output prices. This led Farrell (1957) to define overall productive efficiency as the product of technical and allocative efficiency.

Farrell (1957) first obtained a partial decomposition of efficiency into technical and allocative components and he also proposed indexes of technical, allocative and overall efficiency[14]. However, Farrell (1957) reminds of the empirical necessity of treating Koopmans definition of technical efficiency as a relative notion, relative to the best observed practice in the reference set or comparison group. This provides a way of differentiating efficient from inefficient production states, but it offers no guidance concerning either the degree of inefficiency of an efficient vector or the identification of an efficient vector or combination of efficient vectors with which to compare an efficient vector. If the theoretical arguments as to the relative efficiency of different economic systems are to be subjected to empirical testing, it is essential to be able to make some actual measurements of efficiency. Equally, if economic planning is to concern itself with particular industries, it is important to know how far a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources.

Farrell (1957) proposed that the economic efficiency of a producer consists of two components: *technical or productive efficiency*, (which reflects the ability of a producer to produce maximum output from a given set of inputs), and *allocative or pricing efficiency* (which reflects the ability of a producer to use the inputs in optimal proportions, given their respective prices and production technology)[15]. When a producer is technically efficient, the *maximum output* is generated from a given level of inputs. An allocatively efficient producer would produce that output using the lowest cost combination of inputs. Therefore, technical efficiency illustrates a comparison of actual output and the maximum output, while allocative efficiency deals with the relationship between the minimum cost and actual cost bundles of inputs. Together they help to identify the potential for reducing the costs of producing a given level of output.

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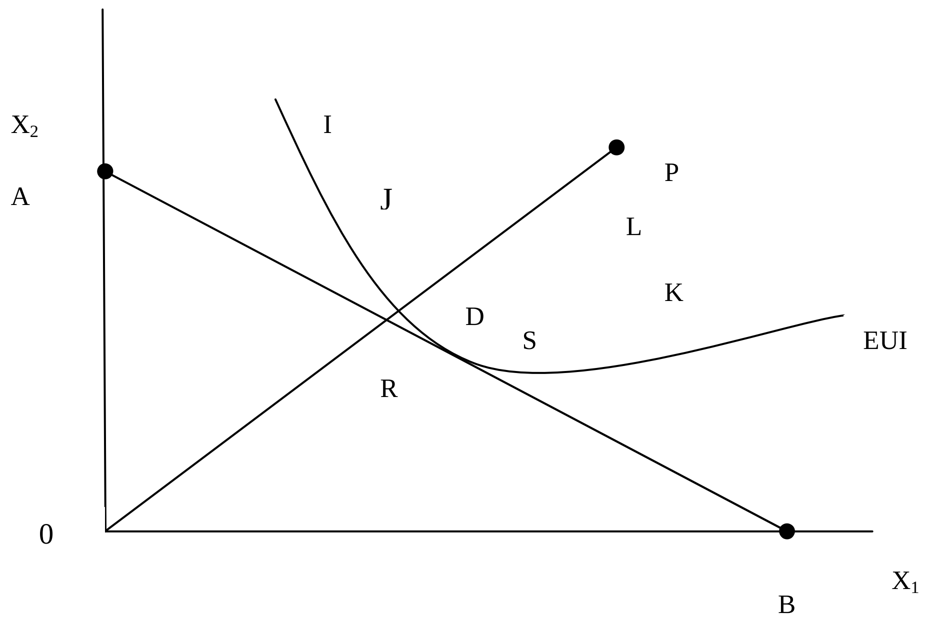
[14] However, Farrell (1957) confined his attention to a single – output production technology having strong scale, monotonicity and curvature properties, and these properties rule out the possibility of structural inefficiency.

[15] A detailed treatment on efficiency measurement and the related concepts is provided by Färe, Grosskopf and Lovell, 1985, 1994 and Lovell, 1993.

Moreover, Farrell (1957) was the first to measure productive efficiency empirically. In measuring technical efficiency, Farrell (1957) assumed inputs to be strongly (freely) disposable and that the technology exhibits constant returns to scale. Moreover, his use of linear programming techniques influenced the development of data envelopment analysis (DEA) by Charnes, Cooper and Rhodes (1978). The basic ideas underlying the Farrell (1957) approach to efficiency measurement are illustrated in Figure (1.5):

Figure 1.5. Farrell Efficiency Measures



Source: Farrell (1957), p. 254

This diagram shows the efficient unit isoquant *(EUI)* for a group of producers constructed from the input bundles of producers *I, J,* and *K* which use the least amounts of inputs to produce a unit of output. These producers constitute the technically efficient subset in this group and the remaining producers (*L* and *P*) are deemed technically inefficient. Farrell proposed that *EUI* should provide a set of standards for measuring both allocative and technical efficiency.

The technical efficiency (TE) standard for producer *P* is that point on *EUI* which uses inputs in the same proportions as *P* and the measured TE of *P* is *OQ/OP*. Given relative input prices, the isocost line AB indicates the minimum cost of producing one unit of output and this suggests that overall economic efficiency is highest at point *S* on *EUI.* Note that point *R* has the same level of costs as *S*.

Farrell proposed that overall economic efficiency (OE) be measured as *OR/OP*. These measures are input-based in so far as they measure differences in input use between producers for standardised (unit) output. This defines the TE standard as a point on *EUI* having identical input proportions to the producer whose efficiency is being measured and allows a simplified cost interpretation of the AE measure. Farrell also proposed an output-based measure which focuses on differences in output between producers when input levels are standardised.

Farrell (1957) argued that the measurement of productive efficiency is of theoretical and practical importance, a satisfactory efficiency measure allows both empirical testing of theoretical arguments and economic planning to improve the productivity of particular industries. He first developed a better-founded theoretical method for measuring efficiency, the so-called efficiency frontiers, which have been widely used in applied studies. In this approach, it is necessary to create a standard or benchmark for the measurement of efficiency. Defining the standard against which to measure efficiency is at the core of every study related to measuring productive efficiency. Farrell (1957) focused this discussion by defining a simple or partial measure of producer efficiency that could be readily extended to multiple inputs.

From the description of Farrell's method it should be clear that the technique involves constructing a frontier from the observed best practice in the sample. Thus the efficient unit isoquant will only depend on a subset of the full sample of observations. In this sense the technique may be described as inefficient because it does not make full use of all the information available, the main consequence of this being that it will be sensitive to measurement errors and extreme observations.

Of greater significance in the present context is the influence Farrell's work exerted on Aigner and Chu (1968), Seitz (1970), Timmer (1970), Afriat (1972) and Richmond (1974), for it was the work of these writes that led directly to the development of Stochastic Frontier Analysis models (Kumbhakar and Lovell, 2000).

The pioneering work of Farrell (1957) focused attention on the concept of productive efficiency and the consequences of its recognition for the modelling of production processes. Moreover, a considerable volume of applied work has been undertaken since the original studies by Farrell (1957), Farrell and Fieldhouse (1962), Aigner and Chu (1968) and Afriat (1972) pioneered the work on frontier production functions, while Seitz (1970) and Timmer (1970) are examples of specific efficiency studies.

Aigner, Lovell, and Schmidt (1977); Schmidt and Lovell (1979); Meeusen and van den Broeck (1977); and Greene (1980) introduced refinements of the frontier approach and the modelling of production processes explicitly recognizing the existence of productive inefficiency.

1.8. Aigner et al. (1977) and Meeusen and van den Broeck (1977) approach

Aigner et al. (1977) and Meeusen and van den Broeck (1977) developed a statistically and theoretically sound method for measuring efficiency, known as stochastic frontier analysis. In this case, a stochastic frontier is defined as the production of best performing agents within a data set. The other data points of the other producers are located "below" this estimated frontier. The relative distance measured between this best performance and the other data points is interpreted as inefficiency[16]. Following Farrell (1957), researchers applying frontier estimation techniques represent technology by a bounding function that reflects best-practice production, defined in terms of the maximum real output technologically possible to produce given available inputs (Førsund, Lovell, and Schmidt, 1980; Varian, 1985; Bauer, 1990 a,b).

The stochastic frontier model pioneered by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) has attracted a great deal of attention in the literature since its introduction (Bera and Sharma, 1999), Førsund, Lovell and Schmidt (1980), Schmidt (1986), Bauer (1990 a,b), and Greene (1993). Within this framework, several models for estimating technical efficiency have been

[16] This is true if random noise is ignored. The innovativeness of the Stochastic Frontier Analysis is the separation of noise from inefficiency.

progressively developed, extending the stochastic frontier methodology to account for different theoretical and empirical issues (Coelli et al., 1998; and Kumbhakar and Lovell, 2000), who suggested the basic frontier statistical models, based on an econometric specification of a production frontier.

If the frontier has a functional form, that is, if a parametric model for the frontier can be formulated, then several parametric approaches have been developed in the literature for obtaining measurement of efficiency. The type of parametric technique employed will depend on whether the frontier model is deterministic (no random error in the model) or stochastic (random error in the model). However, it has been clearly established that stochastic frontier models are superior to deterministic frontier models (Aigner, Lovell and Schmidt, 1977, Fried et al, 1993; Kumbhakar and Lovell, 2000; Jacobs, Smith and Street, 2006).

Following Aigner, Lovell and Schmidt (1977), a stochastic frontier model can be formulated in terms of a general production function for the ith production unit. This function defines a production relationship between inputs, x, and an output y, where, for any given x, the observed value of y, must be less or equal to $f(x)$.The basic model includes a composite error term that sums a two-sided error term, measuring all effects outside the producer's control, and a one-sided, non-negative error term, measuring technical inefficiency. A producer can lie on or within the frontier, and the distance between actual output and the frontier output represents technical inefficiency.

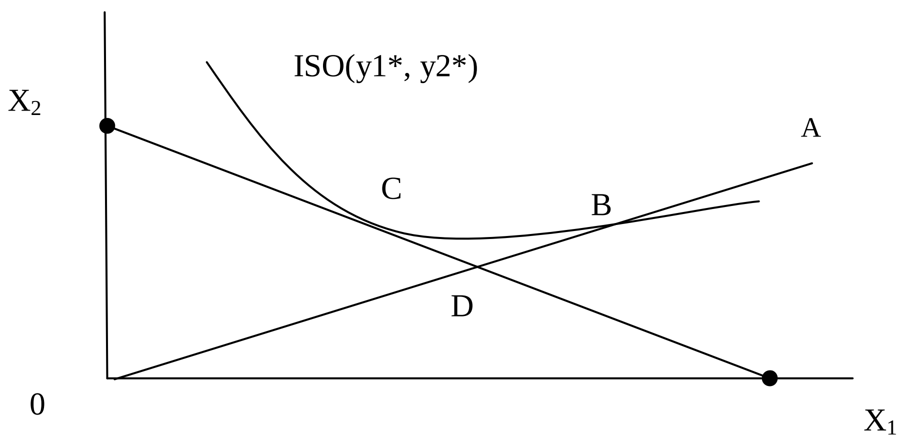
According to Battese and Coelli (1995), the stochastic frontier production function postulates the existence of technical inefficiencies involved in producing a particular output. The stochastic production frontier model allows: technical inefficiency and input elasticities to vary over time in order to detect changes in the production structure; and inefficiency effects to be a function of a set of explanatory variables the parameters of which are estimated simultaneously with the stochastic frontier. The approach is stochastic and producers may be off the frontier because they are inefficient or because of random shocks or measurement errors. Efficiency is measured by separating the efficiency component from the overall error term.

1.9. Input-oriented and output-oriented efficiency

Measures of efficiency can be input-oriented or output-oriented. When input quantities are fixed so that output varies across producers, the efficiency measure is output-oriented because the objective of producers is to maximize output. When output quantities are fixed so that inputs vary across producers, the efficiency measure is input-oriented because the objective of producers is to best allocate input quantities and minimize input usage.

As analytically described in Herrero and Pascoe (2002), these concepts can be illustrated graphically using a simple example of a two input (x_1, x_2)-two output (y_1, y_2) production process. Efficiency can be considered in terms of the optimal combination of inputs to achieve a given level of output (an input-orientation), or the optimal output that could be produced given a set of inputs (an output-orientation).

Figure 1.6. Input oriented efficiency



Source: Herrero and Pascoe (2002), p. 3

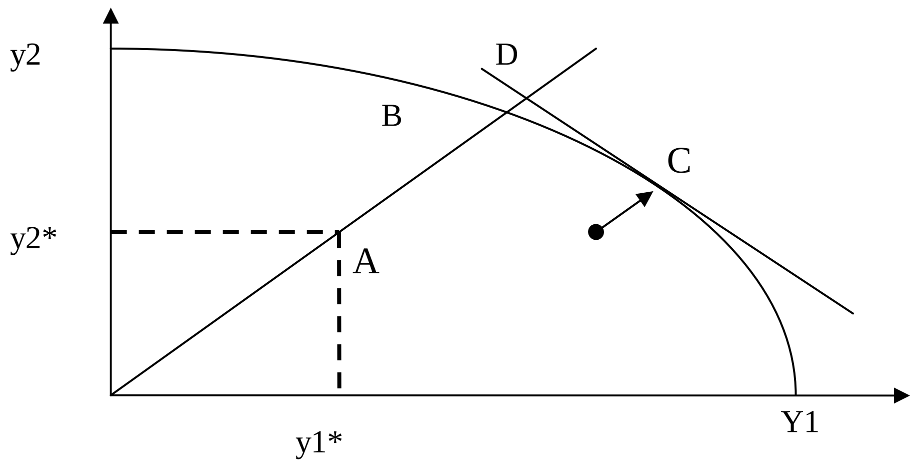
In the above figure, the producer is producing a given level of output (y_1^*, y_2^*) using an input combination defined by point *A*. The same level of output could have been produced by radially contracting the use of both inputs back to point *B*, which lies on the isoquant associated with the minimum level of inputs required to produce (y_1^*, y_2^*). The input-oriented level of technical efficiency ($TE_I(y,x)$) is defined by *0B/0A*.

However, the least-cost combination of inputs that produces (y_1^*, y_2^*) is given by point *C*.

To achieve the same level of cost (i.e. expenditure on inputs), the inputs would need to be further contracted to point *D*. The cost efficiency (CE(y,x,w)) is therefore defined by *0D/0A*. The input allocative efficiency (AE_I(y,w,w)) is subsequently given by CE(y,x,w)/TE_I(y,x), or *0D/0B* (Kumbhakar and Lovell 2000).

The production possibility frontier for a given set of inputs is illustrated in the above figure (i.e. an output-orientation):

Figure 1.7. Output oriented efficiency



Source: Herrero and Pascoe (2002), p. 3

If the inputs employed by the producer were used efficiently, the output of the producer, producing at point A, can be expanded radially to point *B*. Hence, the output oriented measure of technical efficiency (TE_O(y,x)), can be given by *0A/0B*. This is only equivalent to the input-oriented measure of technical efficiency under conditions of constant returns to scale. While point *B* is technically efficient, in the sense that it lies on the production possibility frontier, a higher revenue could be achieved by producing at point *C*. In this case, more of y_1 should be produced and less of y_2 in order to maximise revenue. To achieve the same level of revenue as at point *C* while maintaining the same input and output combination, output of the producer would need to be expanded to point *D*. Hence, the revenue efficiency (RE(y,x,p)) is given by *0A/0D*. Output allocative efficiency (AE_O(y,w,w)) is given by RE(y,x,w)/TE_I(y,x), or *0B/0D* in the above figure (Kumbhakar and Lovell 2000).

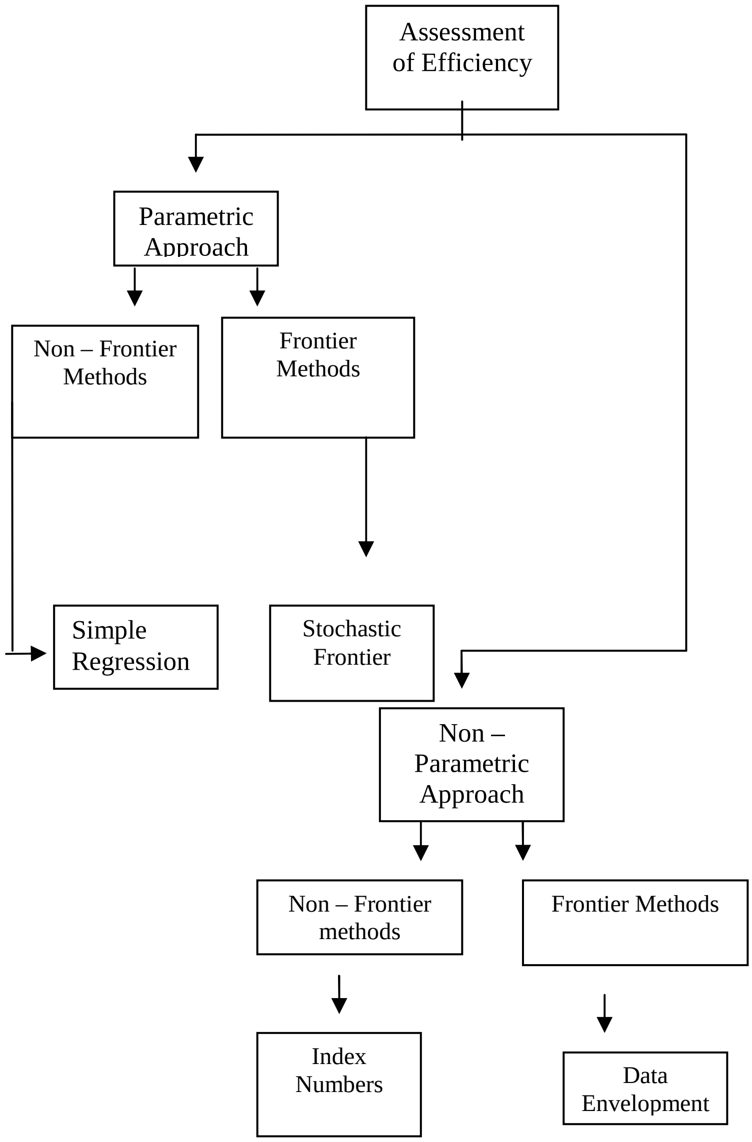
1.10. Efficiency Estimation: Parametric and non – parametric approach

Approaches to efficiency measurement are broadly divided between: parametric analysis, which involves econometric analysis, and nonparametric analysis, which employs mathematical programming methods[17]. An alternative distinction is that by Grosskopf (1993) who divided productivity measurement approaches into two primary different categories: a) non-frontier and b) frontier[18]. The flowchart in the following figure shows the main efficiency measuring methods under these two approaches.

[17] For a broad overview, see del Hoyo et al. (2004) and Kortelainen (2008).

[18] Even though the measurement of productivity growth and of the various efficiency types can be implemented with various approaches: non-frontier and frontier, econometric and nonparametric, frontier approaches strictly dominate non-frontier ones due to their ability to differentiate technological change from producer's inefficiency.

Figure 1.8. Alternative Efficiency Estimation Approaches



Source: Own elaboration, based on Mahadevan (2002), p. 6 and Sarafidis (2002), p. 3.

Non-parametric models (regarding Data Envelopment Analysis), initially developed by Farrell (1957) and Charnes et al. (1978) which are robust with respect to the particular functional form and distribution assumptions. This method does not posit any explicit functional form for the frontier and constructs it from the observed input-output ratios using linear programming techniques. On the other hand, nonparametric approaches do not impose parametric restrictions on the underlying technology. The level of optimal producer performance is determined by constructing an efficiency frontier, which consists of the best performing producers[19]. Therefore, random fluctuation in production, for example due to climatic conditions, may lead one to underestimate the technical efficiency[20].

Parametric models (regarding Deterministic Frontier Analysis and Stochastic Frontier Analysis), initially developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), which are analytical functions with an a priori fixed number of parameters. In this case, the frontier is represented through a functional form (i.e. a Cobb-Douglas or a Translog function), derived with econometric techniques (Greene, 1993). The first approach examined was the construct of the deterministic statistical frontier (Barrow, 1991; Cubbin & Zamani, 1996). Using statistical techniques, a deterministic frontier is derived such that all deviations from this frontier are assumed to be the result of inefficiency. That is, no allowance is made for noise or measurement error. Parametric approaches, assume a functional approximation to the underlying technology. By this assumption, they derive parameters for the model[21]. The parametric approach relies on a parametric specification of the production function that fits to the data (i.e. Førsund et al., 1980; Bauer, 1990a). Parametric specification of the production function is mostly performed by the Stochastic Frontier Analysis (SFA), which accounts for both inefficiency and random noise

[19] Thus, no (direct) accommodation is made for the types of bias resulting from producer heterogeneity, external shocks, measurement error, and omitted variables. Consequently, the entire deviation from the frontier is assessed as being the result of inefficiency. This may lead to either an understatement or an overstatement of the level of inefficiency and, as a non-stochastic technique, there is no possible way in which probability statements of the shape and placement of this frontier can be made (Battese and Coelli, 1992; Coelli and Battese, 1996).

[20] Thus, it is essential to use a time series or panel data that contains observations for a few numbers of years, in order to eliminate annual random effects and to estimate actual producer efficiency and productivity (Fraser and Hone, 2001).

[21] For a survey on the theoretical literature see e.g. Cooper et al. (2004) for the nonparametric and Kumbhakar and Lovell (2000) for the parametric approaches. For the theoretical background for production, cost and distance function derivation see Chambers (1988).

effects. Parametric frontier models are particular analytical functions with an a priori fixed number of parameters.

1.11. Efficiency Estimation: Frontier and non-frontier approach

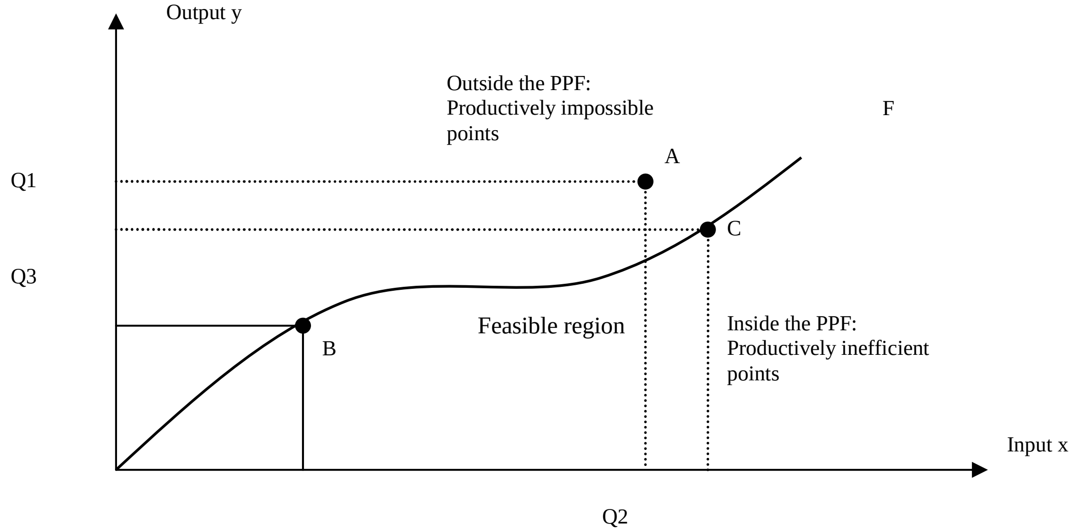
A quite important distinction between these approaches lies in the definition of the 'frontier'. A frontier refers to a bounding function, or more appropriately, a set of best obtainable positions.

Thus, a production frontier traces the set of maximum outputs obtainable from a given set of inputs and technology, and a cost frontier traces the minimum achievable cost given input prices and output. The production frontier is an unobservable function that is said to represent the 'best practice' function as it is a function bounding or enveloping the sample data.

According to frontier approach, observed output and potential output might differ due to the presence of technical inefficiency in productive processes. This implies the adoption of a new perspective with respect to non-frontier methodologies, since estimated TFP will now explicitly result from a decomposition of productivity growth in technological change and efficiency change.

Figure (1.9) represents a simple production process. *A* single input *(x)* is used to produce a single output *(y).* The production frontier is *OF* showing the relationship between input and output, namely the maximum output attainable from each input level, regarding the state of technology.

Figure 1.9. Production frontiers and Technical Efficiency



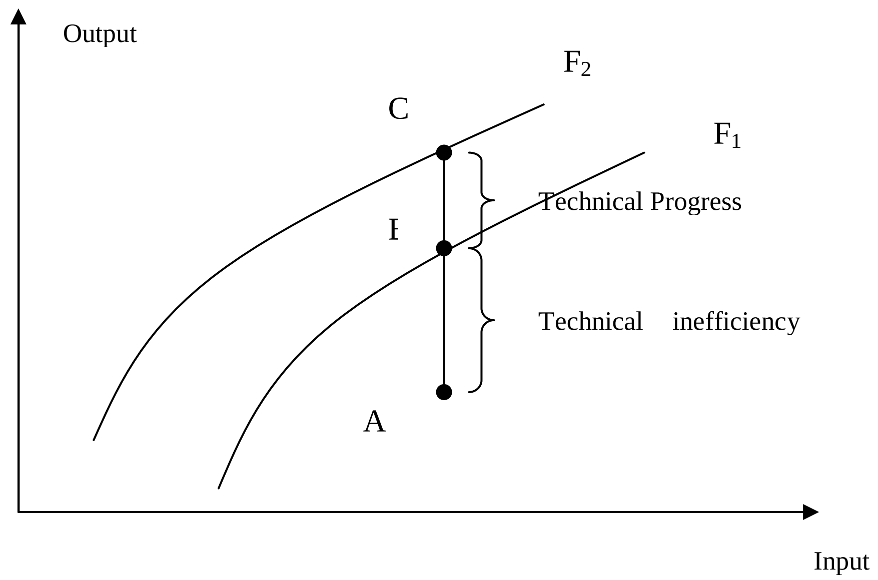
Source:Based on Coelli et al (2005), p. 4

The feasible production set is the set of all input- output combinations which are feasible. It consists of all points between production frontier OF and the x-axis. The production frontier is a graph of maximum feasible output producible given fixed resources. Hence a production frontier envelopes producer outputs from above. If what a producer actually produces is less than what it could feasibly produce than it will lie below the frontier. The distance by which a producer lies below its production frontier or above its cost frontier is a measure of the producer's inefficiency (Bera and Sharma, 1999). The further below the production frontier a producer lies, the more inefficient it is. The points along the production frontier define the efficient sub-set of this feasible production set and they show the technically efficient combinations of input and output. On the other hand, the points beneath the production frontier show the non-technically efficient combinations, respectively. In this figure, e.g. point *(A)* is inefficient; points *(B)* and *(C)* are efficient points.

The type of efficiency that can be measured using a production frontier is technical efficiency. The level of technical efficiency of a particular producer is characterized by the relationship between observed production and some ideal or potential production (Greene 1993). The measurement of producer specific technical efficiency is based upon deviations of observed output from the best production or efficient production frontier. If a producer's actual production point lies on the frontier it is perfectly efficient. If it lies below the frontier then it is technically inefficient, with the ratio of the actual to potential production defining the level of efficiency of the individual producer (Herrero and Pascoe, 2002).

Technological progress is assumed to push the frontier of potential production upward, while efficiency change will change the capability of productive units to improve production with available inputs and technology. The following figure (1.10) illustrates this idea:

Figure 1.10. The frontier and non-frontier TFP growth measure



Source: Mahadevan (2002), p. 7

As illustrated in the above figure, F_1 and F_2 are production frontiers in periods 1 and 2, respectively. Technical efficiency, which is represented by a movement towards the frontier from *A* to *B*, refers to the efficient use of inputs and technology due to the accumulation of knowledge in the learning-by-doing process, diffusion of new technology, improved managerial practices, etc. Thus *AB* shows technical inefficiency in period 1. The absence of technical inefficiency in the non-frontier approach is related to the implicit assumption of long-term equilibrium behavior whereby producers are said to be fully efficient as they have had time to learn and adjust their input and technology use appropriately. Thus the non-frontier TFP growth measure is only made up of the movement from *B* to *C*, which represents technical progress due to technological improvements incorporated in inputs. Hence technical progress and TFP growth are used synonymously when the non-frontier approach is used. Unlike the non-frontier approach, the frontier approach is able to decompose output growth not just into input growth and TFP growth; it goes a step further to decompose TFP growth into various efficiency components such as technical progress and gains in technical efficiency.

The frontier TFP growth measure, on the other hand, consists of outward shifts of the production function resulting from technical progress as well as technical efficiency related to movements toward the production frontier. The frontier approach to total factor productivity (TFP) measurement makes it possible to distinguish between shifts in technology from movements towards the best-practice frontier. By estimating the best-practice production function (an unobservable function) this approach calculates technical efficiency as the distance between the frontier and the observed output. However, a different technique has also been used to measure technical efficiency under the frontier approach that differs in the assumptions imposed on the data: nonparametric linear programming technique or Data Envelopment Analysis (DEA).

The main disadvantage of the non-frontier approach is that all deviations in the observed ratio of inputs / outputs of an agent from the production frontier are exclusively due to inefficiency assuming that all the errors in the measurement of the variables or random fluctuates in the luck of agents are captured as part of the inefficiency term. This assumption can produce upward biased estimations of the inefficiency. However, this is not to say that the non-frontier TFP growth measure would always be lower than the frontier TFP growth measure as gains in technical efficiency may well be negative and cause the frontier TFP growth measure to be lower (Mahadevan and Kalirajan, 2000).

One feature shared by the frontier and non-frontier approach is that they can both be estimated using either the parametric or the non-parametric method. The parametric technique is an econometric estimation of a specific model and since it is based on the statistical properties of the error terms, it allows for statistical testing and hence validation of the chosen model. However, the choice of the functional form is crucial to model the data as different model specifications can give rise to very different results. The non-parametric technique, on the other hand, does not impose any functional form on the model but has the drawback that no direct statistical tests can be carried out for validation. The main weakness of the first class of techniques is due to the fact that they are solely based on input and output data and to their deterministic nature, which implies that any discrepancy between actual and potential output is attributed to inefficiency. Any other feasible sources of technical inefficiency, i.e., omitted variables; unobserved measurement errors and stochastic noise are neglected, resulting in a possible upward bias of inefficiency scores (Førsund et al., 1980).

Last, but not least, it may be helpful to broadly distinguish between the different types of efficiency measures. Measures of efficiency can be input-oriented or output-oriented. When input quantities are fixed so that output varies across producers, the efficiency measure is output-oriented because the objective of producers is to maximize output. When output quantities are fixed so that inputs vary across producers, the efficiency measure is input-oriented because the objective of producers is to best allocate input quantities and minimize input usage.

1.12. Concluding Remarks

This chapter defines the two main approaches on which this thesis analysis is based, namely efficiency and productivity. More specifically, this chapter provides the definitions of these two terms, the main categories in which they are divided, along with the main distinctions between them. Moreover, this chapter reviews the main methods of efficiency measurement, distinguishing between parametric and non – parametric approaches, as well as between frontier and non-frontier approaches. The selection of any particular approach is likely to be subject to both theoretical and empirical considerations. The emphasis here is not on selecting a superior theoretical approach, since different approaches provide different mathematical programming and econometric approaches, which address different questions, serve different purposes, and have different informational requirements. If the frontier has a functional form, then several parametric approaches have been developed in the literature for obtaining measurements of efficiency. The type of parametric technique employed will depend on whether the frontier model is deterministic (no random error in the model) or stochastic (random error in the model). Data Envelopment Analysis (DEA) as a nonparametric approach and Stochastic Frontier Analysis (SFA) as a parametric framework are the most commonly used. The nonparametric method of Data Envelopment Analysis determines the reference technology by means of linear programming methods whereas the parametric method of Stochastic Frontier Analysis assumes a functional relationship for the production process and determines the reference technology based on econometric methods. These methods are broadly analysed in the next chapter.

Chapter 2

Productive Efficiency: Estimation Methods

Abstract

The empirical estimation of production functions had begun arguably with Cobb and Douglas (1928). However, until the 1950s, production functions were largely used as devices for studying the functional distribution of income between capital and labor at the macroeconomic level. Consequently, until 1950s, efforts were made to measure efficiency by interpreting the average productivity of inputs. However, this method suffered from no allowance for random noise in measurement and little or no knowledge about the functional form of production and the values of the parameters of the underlying technology. In the 1950s, economists found that this method of measuring efficiency was unsatisfactory as it ignored other inputs used in the process of production. The historical discussion concerning the measurement of productivity and efficiency in the economic literature started with contemporaneous papers by Debreu (1951) and Koopmans (1951). Koopmans (1951) and Debreu (1951) made the first systematic efforts in the investigation of efficiency and its measurement. However, the standard efficiency measurement literature was started by Farrell (1957), built upon Debreu (1951) and Koopmans (1951). Farrell (1957) proposed to measure the efficiency of a productive unit in terms of the realized deviations from an idealized frontier isoquant. The empirical identification of such a benchmark is the main issue of the literature on efficiency measurement. Farrell (1957) extended this work in an attempt to operationalize the measurement of productivity and efficiency. From Farrell's work, we define the productivity of an economic agent as the scalar ratio of outputs to inputs used by the agent in its production process. Finally in the 1970's, with the seminal papers of Aigner et al. (1977) and Meeusen and van den Broeck (1977), econometricians developed a statistically and theoretically sound method for measuring efficiency, a method now known as stochastic frontiers. In this case, a stochastic frontier is defined as the locus of best performing agents within a data set. The other data points of the other producers are located "below" this estimated frontier. The relative distance measured between this best performance and the other data points is interpreted as inefficiency.

Chapter 2 studies the alternative methods for productivity estimation which served as research base for the application of stochastic frontier analysis. This chapter reviews these main research approaches on stochastic frontier analysis and introduces the approach of distance function in order to estimate the differences between the actual output levels compared to the maximum potential output level. The analysis of distance functions was the basis of Data Envelopment Analysis, as a major approach of efficiency measurement, which is also analysed. Then, the chapter provides the main characteristics of

Deterministic and Stochastic Frontier Analysis. Finally, Chapter 2 provides a detailed analysis of the main approaches in estimating efficiency in frontier analysis making also an evaluation of these approaches – methods. This chapter analyses the deterministic and the stochastic frontier approach and explains the reasons for which the stochastic frontier approach is the most comprehensive analytical and estimation method, providing the main features which characterise this method, as well as the main hypotheses related.

2.1. Introduction

The empirical estimation of production functions had begun arguably with Cobb and Douglas (1928). However, until the 1950s, production functions were largely used mainly as devices for studying the functional distribution of income between capital and labor at the macroeconomic level. Consequently, until 1950s, efforts were made to measure efficiency by interpreting the average productivity of inputs. However, this method suffered from no allowance for random noise in measurement and little or no knowledge about the functional form of production and the values of the parameters of the underlying technology. In the 1950s, economists found that this method of measuring efficiency was unsatisfactory as it ignored other inputs used in the process of production.

The historical discussion concerning the measurement of productivity and efficiency in the economic literature started with contemporaneous papers by Debreu (1951) and Koopmans (1951). Koopmans (1951) and Debreu (1951) made the first systematic efforts in the investigation of efficiency and its measurement[22]. However, the standard efficiency measurement literature was started by Farrell (1957), built upon Debreu (1951) and Koopmans (1951).

Farrell (1957) proposed to measure the efficiency of a productive unit in terms of the realized deviations from an idealized frontier isoquant. The empirical identification of such a benchmark is the main issue of the literature on efficiency measurement[23]. Farrell (1957) extended this work in an attempt to operationalize the measurement of productivity and efficiency. From Farrell's work, we define the productivity of an economic agent as the scalar ratio of outputs to inputs used by the agent in its production process.

[22] Both only studied technical inefficiency.

[23] Introductions to this literature are provided by Fried, Lovell and Schmidt (1993) and Coelli, Rao and Battese (1998).

Finally in the 1970's, with the seminal papers of Aigner et al. (1977) and Meeusen and van den Brock (1977), econometricians developed a statistically and theoretically sound method for measuring efficiency, a method now known as stochastic frontiers. In this case, a stochastic frontier is defined as the locus of best performing agents within a data set. The other data points of the other producers are located "below" this estimated frontier. The relative distance measured between this best performance and the other data points is interpreted as inefficiency.

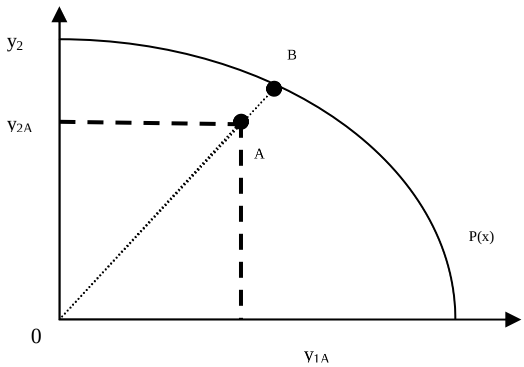
2.2. Output and Input Distance functions

Output Distance Functions characterize a production technology by looking at the maximum proportional expansion of outputs given the input vector. An input distance function characterises the production technology by looking at a minimal proportional contraction of the input vector, given an output vector. An output distance function considers a maximal proportional expansion of the output vector, given an input vector (Coelli et al, 2005).

The Input Distance Function characterizes a production technology by looking at the maximum proportional contraction of the input vector given the output vector. An output distance function takes an output – expanding approach to the measurement of the distance from a producer to the boundary of production possibilities. It gives the minimum amount by which an output vector can be deflated and still remain producible with a given input vector (Kumbhakar and Lovell, 2000).

The following figure illustrates the input and output distance functions. On the left side, the output distance function is presented. The production possibility set is bounded from above by the production possibility frontier and the y_1 and y_2 axis. The value of the output distance function of producer *A* is estimated by the ratio $\delta=0A/0B$. In the case of producer *B*, the value of the output distance function is equal to one. The output distance function is the inverse of the factor by which the production of all output quantities could be increased while still remaining within the feasible production possibility set of a given input level[24]. On the right hand side of the figure, the input distance function is represented. The input set is the area bounded from below by the frontier of L*(y)*. The value of the input distance function for producer *A*, is $\delta = 0A/0B$, while producer *B*, has a value of input distance function equal to one.

Figure 2. 1. Output Distance function

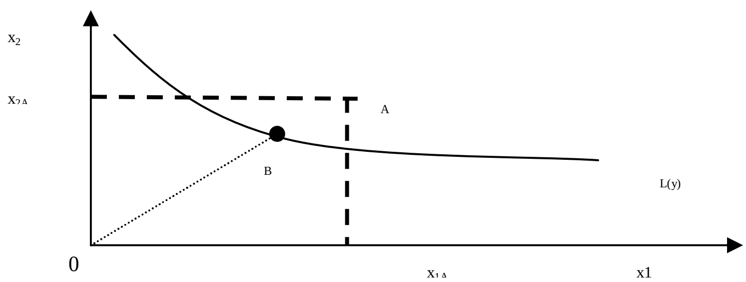


$$Dt(x,y) \equiv \inf[\delta \mid \delta > 0, y/\delta Pt(x)]$$

Properties:

1. Non-increasing in y and increasing in x; Linearly homogeneous in y;
2. If y belongs to the input set of x *(i.e.* $y \in P^t(x)$*)*, then $D^t_0(x, y) \leq 1$
3. Distance is equal to unity *(i.e.* $D^t_0(x, y) = 1$*)* if y belongs to the 'frontier' of the output set. (Coelli et al., 1998)

Figure 2.2. Input Distance function



$$Dt(x,y) \equiv \sup[\delta \mid \delta > 0, x/\delta Lt(y)]$$

[24] This factor is actually the measure of the Farrell output-oriented technical efficiency.

Properties:

1. Non-increasing in x and increasing in y; Linearly homogeneous in x;
2. If x belongs to the input set of *y (i.e.* $x \in L^t(y)$*)*, then $D^t_i(x, y) \geq 1$*;*
3. Distance is equal to unity *(i.e.* $D^t_i(x, y) = 1$*)* if x belongs to the 'frontier' of the input set. (Coelli et al., 1998)

Source: Own elaboration, based on Coelli et al. (2005), p. 48 and 50

The input distance function is the inverse of the factor by which all input quantities could be decreased while still remaining within the feasible input set for the given output level[25]. Additionally, if technology exhibits global constant returns to scale, then the input distance function is the reciprocal of the output distance function.

2.3. Data Envelopment Frontiers (DEA)

As described in Coelli et al. (2005), the piece – wise – linear convex hull approach to frontier estimation, proposed by Farrell (1957), Shephard (1970) and Afriat (1972) who suggested mathematical programming methods that could achieve frontier estimation, but the method did not receive wide attention until the paper by Charnes, Cooper and Rhodes (CCR) (1978), in which the term DEA was first presented. Charnes, Cooper and Rhodes (1978) proposed a model that had an input orientation and assumed constant returns to scale (CRS). Subsequently, Färe and Logan (1983) and Banker, Charnes and Cooper (BCC) (1984) proposed variable returns to scale (VRS). The term DEA and the CCR model were first introduced in 1978 (Charnes et al, 1978) and were followed by a phenomenal expansion of DEA in terms of its theory, methodology and application over the last few decades (Førsund and Sarafoglou, 2003, Seiford (1996), Charnes et al (1994).

As in Wang et al. (2002), DEA can be roughly defined as a nonparametric method of measuring the efficiency of a Decision Making Unit (DMU) with multiple inputs and/or multiple outputs. DEA is concerned with the efficiency of the individual unit, which can be defined as the *Decision Making Unit* (*DMU*) (Charnes et al, 1978) that

[25] This factor is actually the measure of the Farrell input-oriented technical efficiency.

is responsible for controlling the process of production and making decisions at various levels including daily operation, short-term tactics and long-term strategy. DEA is used to measure the relative productivity of a DMU by comparing it with other homogeneous units transforming the same group of measurable positive inputs into the same types of measurable positive outputs.

Apart from the DEA CCR model and BCC model are the other two DEA models that are widely studied and applied. The main difference between these two models is that the former allow variable returns-to-scale to be assumed, while the latter is limited solely to a constant returns-to-scale assumption. Accordingly, the production frontiers in these models are different. The basic information derived from the above three DEA models, i.e. the CCR model, the BCC model, is whether or not a DMU can improve its performance relative to the set of DMUs to which it is being compared. The different set of DMUs is likely to provide different efficiency results because of the possible movement of the production frontier.

Charnes et al. (1978) and Banker et al. (1984) extended Farrell's ideas by imposing returns to scale properties. The nonparametric approach relies on a production frontier defined as the geometrical locus of optimal production plans (Simar and Wilson, 1998, 2007). The production frontier can be estimated non parametrically from a set of observed production units, based on different envelopment techniques. A Common nonparametric measure is the Data Envelopment Analysis (DEA)[26]. Nonparametric DEA shows how one can apply simulation methods, to conduct statistical inference to obtain more reliable and robust results.

In DEA the inefficiency is defined as the distance from the frontier of a convex envelope of the data; therefore, due to the convexity assumption, a company might be compared to an unobservable and fictitious linear combination of efficient observations (Coelli et al., 2005). Thus, the efficiency score is the point on the frontier

[26] All nonparametric calculations in this dissertation are presented using an input orientation assuming that the outputs are fixed and the inputs must be minimized to be efficient.

characterized by the level of inputs that should be reached to be efficient (Simar and Wilson, 1998, Simar and Wilson, 2007).

Many studies have further developed the DEA methodology, including those by Färe, Grosskopf and Lovell (1985). Data Envelopment Analysis (DEA) is, in fact, a mathematical programming approach for the construction of production frontiers and the measurement of efficiency relative to the constructed frontiers. The basic idea of this approach consists of enveloping the data (the observed input-output combinations) in order to obtain an approximation of the production frontier (best-practice frontier) and using this to identify the contribution of technological change, technological catch-up, and inputs accumulation to productivity growth.

DEA can be used to measure efficiency when there are multiple inputs and outputs, but there are no generally acceptable weights for aggregating inputs and aggregating outputs. DEA permits the use of multiple inputs and outputs, but does not impose any functional form on the data, nor does it make distributional assumptions for the inefficiency term DEA overcomes some of the specific weaknesses of the other methods, such as a particular functional form for technology, particular assumptions on market structure, and the hypothesis that markets are perfect. DEA is usually handled with linear programming techniques. The analysis assumes that there is a frontier technology (in the same spirit as the stochastic frontier production model) that can be described by a piecewise linear hull that envelopes the observed outcomes. Some (efficient) observations will be on the frontier while other (inefficient) individuals will be inside. The technique produces a deterministic frontier that is generated by the observed data, so by construction, some individuals are efficient.

On the other hand, DEA is based on a concept of efficiency very similar to the microeconomic one; the main difference is that the DEA production frontier is not determined by some specific functional form, but it is generated from the actual data for the evaluated producers. As a consequence, the DEA efficiency score for a specific productive unit is not defined by an absolute standard, but it is defined relative to the other units in the specific data set under consideration. This feature differentiates DEA from the parametric approaches, which require a specific prespecified functional form of the modelled production or cost function (Charnes, Cooper, Lewin & Seiford 1994, Cooper, Seiford & Tone 2000, Cooper, Seiford & Zhu 2004). This could be a limitation in some contexts because it is possible that all producers in a sample may be technically inefficient to some extent when compared with a conceptual frontier, and even the best practice producers in a sample may still be some distance from being 'fully efficient'.

It should be noted, however, that DEA identifies two or more producers that represent the best practice of a set of entities. This means that it will always choose a couple or more producers as being 100 per cent technically efficient. This could be a limitation in some contexts because it is possible that all producers in a sample may be technically inefficient to some extent when compared with a conceptual frontier, and even the best practice producers in a sample may still be some distance from being 'fully efficient'. With DEA, the best practice producers are defined only relative to other producers in the given dataset, and do not necessarily produce output at the potential production frontier[27].

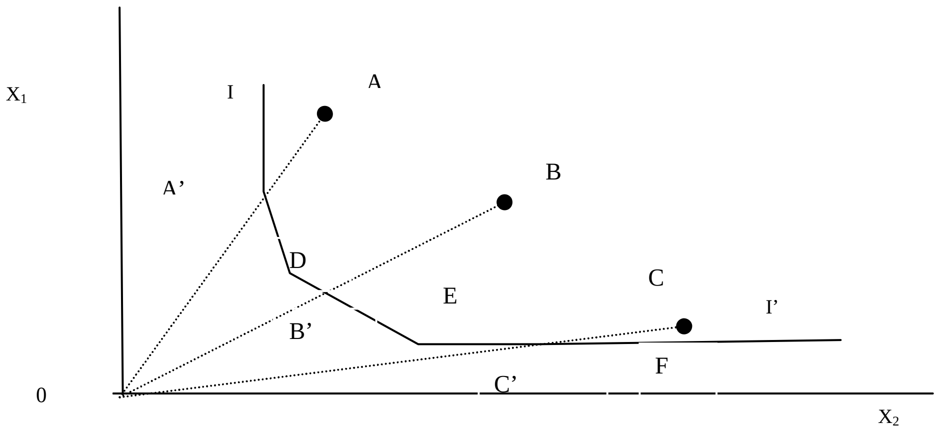
One important feature related to DEA, is slack variables. DEA method, projects the points of inefficient production units to the production frontiers and by doing so, it suggests a combination of inputs that maximize the technical efficiency of the specific producer.

The problem of slack variables arises from the fact that a part of the production frontier is parallel to the axis. Because the DEA method calculates the distance of a producer from the production frontier supposing equiproportional decrease of all inputs, it is possible that a production unit may lie upon the part of the production frontier that is parallel to the axis. In this case, the production unit is technically efficient according to Farrell, but not Pareto efficient. The latter, demands that, keeping output level constant, there is no feasible reduction of any input without the increase of at least one other input.

[27] DEA (Farrell, 1957; Charnes et al., 1978) can be seen as an attempt to overcome some of the specific weaknesses of the growth accounting approach: a particular functional form for technology, particular assumptions on market structure, and the hypothesis that markets are perfect.

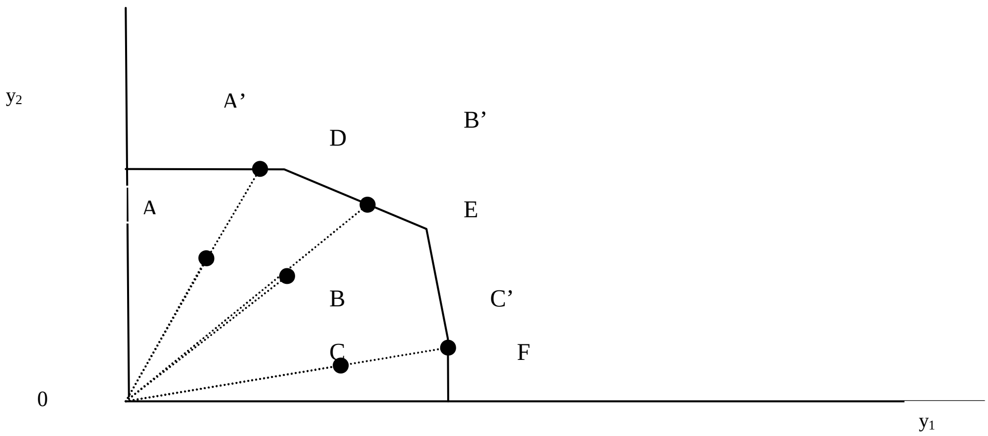
Looking at the following figures, producer *F*, can decrease input x_2 keeping output level constant:

Figure 2.3. Input Efficiency Slacks



Source: Based on Coelli et al. (2005), p. 165

Figure 2.4. Output Efficiency slacks



Source: Based on Coelli et al. (2005), p. 181

Producers *A* and *C*, could equiproportionately decrease their inputs until they reach points *A'* and *C'* respectively. But again, it is possible to reduce inputs x_1 and x_2 respectively, keeping output level constant. So, only the equiproportionate reduction of producer B inputs (reaching point *B'*) is enough to satisfy both the Farrell and Pareto criteria. Equiproportionate reduction of inputs in the case of producers *A*, *C* and F can satisfy only the Farrell criterion. In those cases, slack variables are called input slacks.

DEA is used to obtain efficiency measures based on the aggregated, or 'virtual', inputs and outputs. As described in McMillan and Chan (2006), let there be n producers using varying amounts of inputs to produce outputs. There are s inputs xi (i = 1, …, s) and m outputs yr (r = 1, …, m). For each producer, such as producer $_j$ (j = 1, …, k, …, n), the problem is to:

$$\max_{u,v} \quad h_j = \frac{\sum_r u_{rj} y_{rj}}{\sum_i v_{ij} x_{ij}} \tag{2.1}$$

subject to

$$\frac{\sum_r u_{rj} y_{rj}}{\sum_i v_{ij} x_{ij}} \leq 1 \qquad for \qquad j = 1,..., \quad n \tag{2.2}$$

$$u_r \;, v_i \geq 0$$

where u_{rj} is the weight assigned each unit of output r from producer $_j$ and v_{ij} is the weight assigned each unit of input i used by producer$_j$. That is, solutions are sought to maximize the ratio of weighted output to weighted input for each producer (the ratio of virtual output to virtual input). By normalization, the efficiency scores range from zero to one. The same weights (virtual multipliers) that maximize h_j for producer $_j$ are applied to the inputs and outputs of all producers in the solution to the problem for producer $_j$. This solution process is repeated for each producer. Hence, because the weights can vary for each solution, the efficiency scores determined are those most favourable to each producer.

As far as the DEA characteristics are concerned, DEA can be specified as either an output-maximizing problem or an input-minimizing problem. Input models measure efficiency in terms of the potential (proportional) reduction in input use while output models measure efficiency in term of the potential (proportional) output increase. While the efficient and inefficient units do not change, the efficiency scores can differ between the two orientations in the variable returns to scale case[28]:

Table 2.1.The basic DEA models

Orientation	Constant Returns to Scale	Variable Returns to Scale
Input Oriented	$\min \theta, v\lambda\theta$ $s.t. - yi + Y\lambda \geq 0$ $\theta xi - X\lambda, v \geq 0$ $\lambda \geq 0$	$\min \theta\lambda, \theta$ $s.t. - yi + Y\lambda \geq 0$ $\theta xi - X\lambda \geq 0,$ $N_1'\lambda = 1$ $\lambda \geq 0$
Output Oriented	$\max \phi\lambda, \phi$ $s.t. - \phi yi + Y\lambda \geq 0$ $xi - X\lambda, v \geq 0,$ $\lambda \geq 0$	$\max \phi\lambda, \phi$ $s.t. - \phi yi + Y\lambda \geq 0$ $xi - X\lambda \geq 0,$ $N_1'\lambda = 1$ $\lambda \geq 0$

Source: Own elaboration

The input based measure considers how inputs may be reduced relative to a desired output level. The output-based measure indicates how output could be expanded given the input levels. There is also a non-orienting DEA measure in which the frontier output and various concepts of technical and economic efficiency may be determined without being conditional on input or output levels being held constant.

The variable returns to scale (VRS) approach assumes that scale inefficiencies in the industry are present (Banker et al., 1984 first allow for VRS). Within the VRS

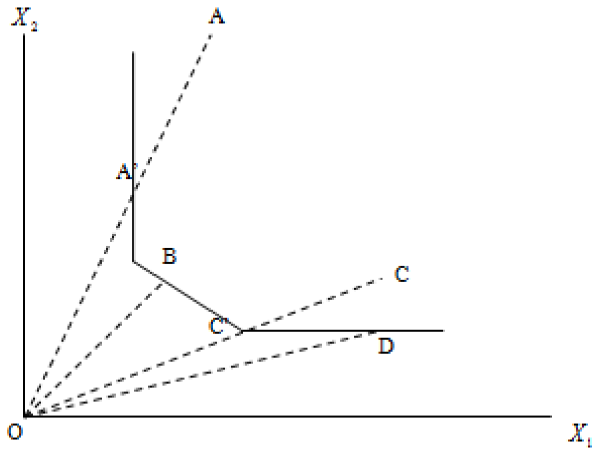
[28] McMillan and Datta (1998) comparisons of input-oriented and output-oriented DEA analyses suggested that the results were not sensitive to orientation.

assumption we can distinguish between decreasing returns to scale (DRS), increasing returns to scale (IRS), non-increasing returns to scale (NIRS), and non-decreasing returns to scale (NDRS), modifying the restrictions in the linear optimization problem (see Cooper et al., 2006, for a summary of assumptions). All calculations can also be done using an output-orientation (Simar and Wilson, 2007)[29].

Before assessing each industry's efficiency, DEA compares the relative efficiency among industries. Since efficiency evaluation in DEA is based on the concept of Pareto optima, there may be more than one industry judged as efficient. In DEA, efficiency is computed on the basis of the envelope or efficient frontier, formed by all values near the original point *0*:

[29] In empirical application it is necessary to investigate the statistical properties of the DEA estimators. First it can be shown that both are biased by construction (Simar and Wilson, 2007). Considering the consistency of the estimators we note that in the nonparametric framework it is often difficult to prove convergence and derive the rate of convergence (Simar and Wilson, 2002, 2007). Korostelev et al. (1995) provide the first systematic analysis of the convergence properties of DEA estimators for one input and multiple outputs. They find that incorporating the convexity constraint improves the rate of convergence if the true set is convex; otherwise the DEA-VRS estimator is inconsistent. They also find that the rates of convergence depend heavily on the dimensionality of the problem (the number of outputs in his analysis). It can be shown that if the number of outputs increases, a much larger sample size is required to obtain precise results; otherwise the imprecision arises in large bias, large variances and large confidence intervals for the individual efficiency scores (Simar and Wilson, 2007).

Figure 2.5. DEA efficiency values



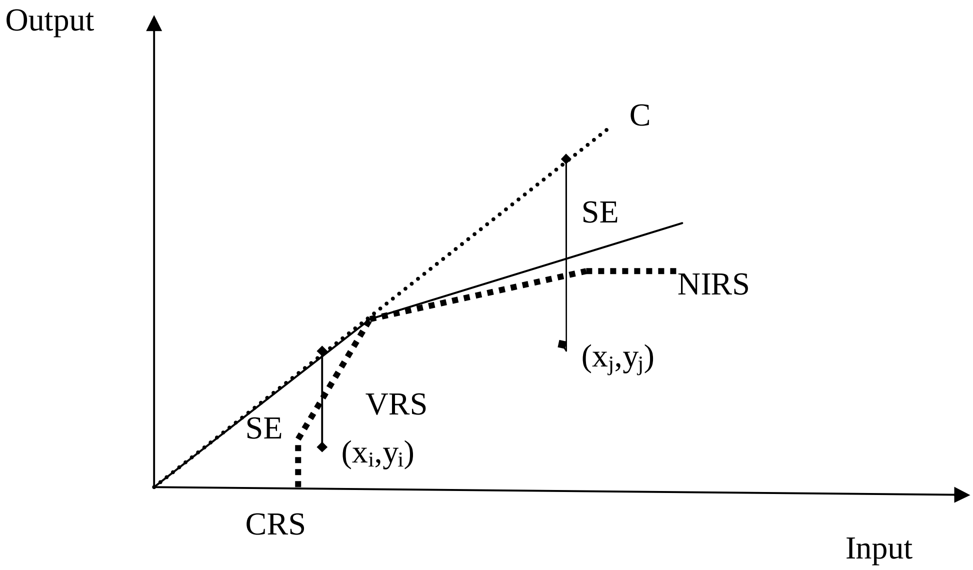
Source: Chen (2011)

DEA involves the use of linear programming methods to construct a non – parametric piece – wise frontier over the data, so as to be able to calculate efficiencies relative to this surface. The two principal model options are:

1. Standard CRS and VRS DEA model which involve the calculation of technical and scale efficiencies (where applicable) (Färe et al., 1994).
2. Panel data DEA model which refers to calculating indices of TFP change: technological change, technical efficiency change, and scale efficiency change (Färe, Grosskopf, Norris and Zhang, 1994).

DEA is based on either constant returns to scale (CRS), also called CCR for Charnes, Cooper, and Rhodes (1978), or variable returns to scale (VRS), also called BCC for Banker, Charnes, and Cooper (1984). Charnes, Cooper and Rhodes (1978) proposed a model which had an input orientation and assumed CRS. Banker, Charnes and Cooper proposed a VRS model. In each case a linear programming problem is solved to envelop the data in a convex area bounded by straight lines. Under CRS, only as many DMUs as outputs can be efficient. Under VRS, many DMUs can be efficient. Under VRS, scale efficiency refers to operating at the scale of operation, or linear sum of outputs, which maximizes the ratio the linear sum of outputs to the linear sum of inputs. An economically efficient business is both technically efficient and scale efficient. Under CRS, output-oriented technical efficiency and input-oriented technical efficiency are the same, but under VRS, they are different, because the efficient frontier is not just one line (or hyperplane) emanating from the origin.

Figure 2.6. Output – oriented technical and scale efficiency



Notes:

CRS: Constant returns to scale
NIRS: Nonincreasing returns to scale
VRS: Variable returns to scale
SE: Scale efficiency

Source: SpringerImages (2011)

The above figure presents hypothetical one-input one-output production processes with three different technologies: Constant returns to scale (CRS), Variable returns to scale (VRS) and Nonincreasing returns to scale (NIRS). The vertical distance from an observation (either (x_i, y_i) or (x_j, y_j)) to the CRS/VRS/NIRS best-practice frontier stands for output-oriented technical efficiency under CRS/VRS/NIRS assumptions, respectively. Scale efficiency in DEA is calculated as in Banker et al. (1984): $TE(CRS)/TE(VRS)$.

The methods are available in either an input or an output orientation. Efficiency in DEA is generally defined as the weighted sum of outputs divided by the weighted sum of inputs. The set of weights for a DMU is computed in DEA with the objective to give the highest possible relative efficiency score for the DMU, while keeping the efficiency scores of other DMUs in the range of 0 to 1 under the same set of weights. Efficient DMUs have the score of 1; the other DMUs which score less than 1 are considered as inefficient. Graphically, efficiency is obtained from the ratio between the distance from the original point to the relative point of the envelope and the distance from the original point to the observation point (optimal value=1).

Coelli et al. (2005) declare that input and output oriented DEA models estimate exactly the same frontier and identify the same set of producers as being efficient. It is only the efficiency measures associated with the inefficient producers that many differ between the two methods. In applied research, the choice of input or output orientation has both theoretical and practical implications. Generally, input-orientated DEA models are commonly used. This is because many producers have particular orders to fill, so it seems that the input quantities are of main importance. However, a producer's objective may be the maximization of output subject to a fixed level of inputs. In such cases, output-orientated DEA models would be more appropriate. Essentially, one should select the orientation according to which quantities (inputs or outputs) the managers have most control over. An important point to mention is that the output- and input-orientated models will estimate exactly the same frontier and therefore by definition, will identify the same set of producers as efficient. It is only the efficiency measures associated with the inefficient producers that may differ between those two methods.

2.4. Deterministic Production Frontiers

In deterministic frontiers analysis, it is assumed that each of N producers faces the same production technology represented by the conversion of a vector X of inputs into a single output y. For simplicity, and following Aigner and Chu (1968), assume that efficient production can be represented by a Cobb–Douglas production function with two inputs:

$$y = Ax_1^{\beta_1} x_2^{\beta_2} \tag{2.3}$$

This production function, showing the maximum output from given input usage, will serve as the basis for efficiency measurement. Allowing inefficiency, production function becomes:

$$y = Ax_1^{\beta_1} x_2^{\beta_2} u \tag{2.4}$$

where $u \leq 1$represents inefficiency. Models that seek to estimate u are considered deterministic because measurement error and other statistical noise are assumed away.

In addition, it is generally regarded as a disadvantage that the distribution of the technical inefficiency has to be specified (i.e., half-normal, normal, exponential, log-normal, etc.). Ideally, this would be based on knowledge of the economic forces that generate such inefficiency, although in practice this may not be feasible.

One method for estimating a production frontier is to envelop the data points using a function. Aigner and Chu (1968) considered a Cobb-Douglas production frontier at the form[30]:

$$\ln y_i = x_i \beta - u_i, i = 1,2,...I \tag{2.5}$$

where y_i is the output of the *ith* producer, $\boldsymbol{x_i}$ is a (kx1) vector containing the logarithms of inputs, β is a vector of unknown parameters, and u_i is a non – negative random variable associated with technical inefficiency. Technical efficiency of the *i*-th observational unit is the ratio of observed output to maximum feasible output:

$$TE_i = y_i / f(x_i, \beta) \tag{2.6}$$

[30] Deterministic frontiers fall into two categories -- either non-parametric (e.g., Farrell 1957) or parametric, and in the latter case, either non-statistical (e.g., Aigner and Chu 1968, and Timmer 1970) or statistical (e.g., Afriat 1972, and Richmond 1974).

If the observed output yi reaches its maximum obtainable value $f(xi, \beta)$ then $TEi = 1$. That is, the producer is operating at the frontier of production and is 100% efficient. Values of $TEi < 1$ measure the shortfall of observed output from maximum feasible output. Note that this model is *deterministic* (contains no statistical noise). Letting:

$$TE_i = \exp\{-u_i\}, u_i \geq 0 \tag{2.7}$$

will ensure that $0 \leq TEi \leq 1$ and that observed output yi for the i-th producer will lie below the frontier $f(xi, \beta)$ that is $yi \leq f(xi, \beta)$.

Equation $\ln y_i = x_i\beta - u_i, i = 1,2,...I$ can then be rewritten as:

$$y_i = f(x_i\beta)\exp\{-u_i\}, u_i \geq 0 \tag{2.8}$$

where ui represents the shortfall of output from the frontier for each observational unit. If productive technology takes a log-linear Cobb- Douglas form.

This production frontier is deterministic insofar as y_i is bounded from above by the non –stochastic (deterministic) quantity $exp(x_i\ \beta)$. Therefore, any shortfall in output yi from maximum feasible output $f(xi, \beta i)$ is solely attributable to the inefficiency of the producer. The goal is to estimate the unknown parameters of the model[31].

Nevertheless, in this case, no account is taken of any measurement errors and any statistical noise (all deviations from the frontier are assumed to be the result of technical inefficiency. Introducing a random variable representing statistical noise, the resulting frontier is a stochastic production frontier.

In a deterministic production frontier model, output is bounded from above by a deterministic production function. Any deviation from the best performance is imputed to inefficiency, which means random noise is not accounted for.

[31] Aigner and Chu (1968) used linear programming in estimating the unknown parameters of the model.

However, the possible influence of measurement errors and other statistical noise upon the shape and positioning of the estimated frontier is not accounted for. More specifically, deterministic models assume that any deviation from the frontier is solely due to inefficiency, since they do not accommodate for stochastic shocks to production.

2.5. Stochastic Production Frontiers

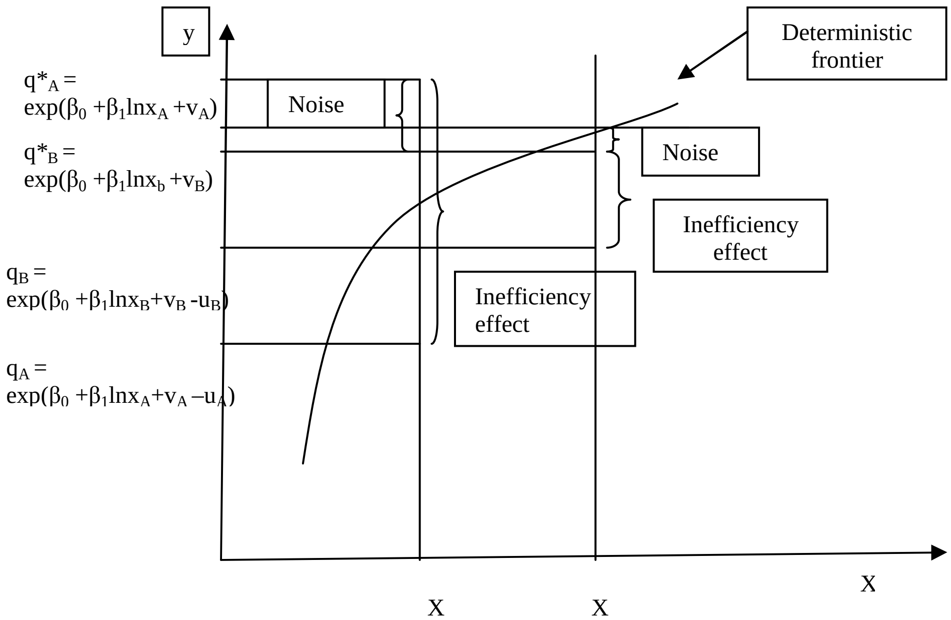
Stochastic production frontier may be seen as an answer to the deterministic parametric frontier models, where deviations of a producer from the theoretical maximum are allocated exclusively to inefficiency. The type of efficiency that can be measured using a production frontier is technical efficiency. At this stage, the main advantage of the stochastic frontier is that it can decompose the deviation from the frontier into stochastic noise and technical inefficiency in production. The maximum output which producers can obtain is determined by two parts: the production function as well as random external factors. Thus, deviations from the production frontier might not be completely under the control of producer (Greene, 2007a).

The following figure presents the inputs and outputs of two producers *A* and *B*. The deterministic component of the frontier model has been drawn to reflect the existence of diminishing returns to scale. Values to the input are measured along the horizontal axis and outputs are measured on the vertical axis. Producer *A* uses the input level x_A to produce the output q_A, while Producer *B* uses the input level x_B to produce the output q_B. if there where no inefficiency effects (if $u_A = 0$ and $u_B = 0$), then the so-called frontier outputs for producers A and B would be:

$$q^*_A = \exp(\beta_0 + \beta_1 \ln x_A + v_A) \quad (2.9)$$

$$q^*_B = \exp(\beta_0 + \beta_1 \ln x_B + v_B) \quad (2.10)$$

Figure 2.7. The stochastic production frontier



Source: Coelli et al (2005), p. 244.

It is clear that the frontier output for producer *A* lies above the deterministic part of the production frontier only because the noise effect is positive $(v_A > 0)$, while the frontier output for producer *B* lies below the deterministic part of the frontier because the noise effect is negative $(v_B < 0)$. It can also been seen that the observed output of producer *A* lies below the deterministic part of the frontier because the sum of the noise and inefficiency effects is negative $(v_A – u_A < 0)$[32].

As it has already reviewed, the original model specification involves a production function with an error term incorporating two components, one to account for random effects (v_i) and one to capture the unobservable inefficiency factor (u_i)[33]. This model can also be expressed in the following form:

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[32] These features of the frontier model generalise to the case of several inputs. Specifically, unobserved frontier outputs tend to be evenly distributed above and below the deterministic part of the frontier. However, observed outputs tend to lie below the deterministic part of the frontier. Indeed, they can only lie above the deterministic part of the frontier when the noise effect is positive and larger than the inefficiency effect ($q^*_i > exp(\mathbf{x}_i'\boldsymbol{\beta})$ *iff* $\varepsilon_i = v_i – u_i >0$). Much of stochastic frontier analysis is directed towards the prediction of the inefficiency effects.

[33] In this model specification, there are two ways to estimate technical efficiency (Kumbhakar and Lovell, 2000). The first is to hypothesize that $v_i=0$ and estimate a non-stochastic parametric production

$$Y_{it} = x_{it}\beta + (V_{ti} - U_{it}) \qquad (2.11)$$

where:

- i=1,…., N, t = 1, …., T
- Y_{it} is (the logarithm of) the production of the ith producer in he tth time period
- X_{it} is a k×1 vector of input quantities of the ith producer in the tth period
- β is a vector of unknown parameters
- V_{it} are the random variables which are assumed to be iid. $N(0,\sigma_v^2)$ and independent of the $U_{it} = \left(U_i \exp\left(-\eta\left(t-T\right)\right)\right)$
- U_i are non – negative random variables which are assumed to account for technical inefficiency in production, and assumed to be iid. as truncations at zero of the $N(\mu,\sigma_u^2)$.

The prediction of the technical efficiencies is based on its conditional expectation, given the observable value of (V_{it}-U_{it}), as in Jondrow et al. (1982) and Battese and Coelli (1988). Technical efficiency index is equal to one if the producer has an inefficiency effect equal to zero and it is less than one otherwise. The errors u_i are assumed to be negative and are due to truncation of the normal distribution with zero mean and positive variance σ_u^2 represents a producer's technical efficiency of production. Errors vi are assumed to have normal distribution with zero mean and positive variance σ_v^2, representing measurement error associated with uncontrollable factors related to the production process. Thus an industry that operates on the frontier is said to produce its potential or maximum output by following the best practice techniques, given the technology. In the stochastic frontier model, the error term, which is composed of two parts, v_i and u_i, allows the statistical noise to be distinguished from inefficiently. The random error v_i is associated with measurement errors, other statistical noise and random factors (weather, industrial actions, etc.) not

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function through maximum likelihood estimation method. The second is to allow that $v_i \neq 0$ and estimate a stochastic production function, using the maximum likelihood estimation method.

under the control of industry, whereas, u_i captures technical inefficiency and is associated with industry – specific factors.

Statistical noise arises from the unintended omission of relevant variables from the vector $\boldsymbol{x_i}$, as well as from measurement errors and approximation errors associated with the choice of functional form. The model is called stochastic frontier production function because the output values are bounded from above by the stochastic (random) variable exp $(\boldsymbol{x_i \beta} + v_i)$. The random error v_i can be positive or negative and so the stochastic frontier outputs vary about the deterministic part of the model, $exp(\boldsymbol{x_i \beta})$. The component *(v)* is a symmetric normally distributed error term that represents factors that cannot be controlled by production units, measurement errors, and left-out explanatory variables. On the other hand, the component *(u)* is a one-sided non-negative error term representing the stochastic shortfall of producer *i's* output from the production frontier due to technical inefficiency. In the stochastic frontier model, the error term, composed of *vi* and *ui*, allows the statistical noise to be distinguished from inefficiency. The random error *vi* is associated with measurement errors, other statistical noise and random factors (whither, industrial actions, etc.) not under the control of industry, whereas, *ui* captures technical inefficiency and is associated with industry-specific factors.

In this context, technical efficiency reveals the maximum amount by which output can be increased using the same level of inputs and technological conditions. The most common output – oriented measure of technical efficiency is the ratio of observed output to the corresponding stochastic frontier output:

$$TE_i = \frac{y_i}{\exp(x_i\beta + v_i)} = \frac{\exp(x_i\beta + v_i - u_i)}{\exp(x_i\beta + v_i)} = \exp(-u_i) \qquad (2.12)$$

where β are the production function parameters and TE is technical efficiency ($0 < TE(y_i, x_i) \leq 1$). Technical efficiency is defined as:

$$TE_i = \frac{y_i}{\exp(x_i\beta + v_i)} = \frac{\exp(x_i\beta + v_i - u_i)}{\exp(x_i\beta + v_i)}) \qquad (2.13)$$

and is measured using the conditional expectation of:

$$\exp(-u_i) \tag{2.14}$$

given the composed error term.

The parameter $u_i>0$ is a measure of technical inefficiency, thus, $u_i = -\ln TE_i \approx 1 - TE_i$, where $TE_i = e^{-u_i}$. The Jondrow et al. (1982) estimator of *E[u|v-u] is* the standard estimator. This is:

$$E[u_i \mid \varepsilon_i] = \left[\frac{\sigma\lambda}{1+\lambda^2}\right]\left[z_i + \frac{\phi(z_i)}{\Phi(z_i)}\right] \tag{2.15}$$

where:

$$z_i = \frac{-\varepsilon_i \lambda}{\sigma} \tag{2.16}$$

and

$$\varepsilon = v \pm u \tag{2.17}$$

This is an indirect estimator of *u*, as it is not possible to estimate u_i directly from any observed sample information.

This measure of technical efficiency takes a value between zero and one. It measures the output of the *ith* producer relative to the output that could be produced by a fully – efficient producer using the same input vector. The first step in predicting the technical efficiency TE_i, is to estimate the parameters of the stochastic production frontier model.

Estimation of u_i is the central focus of the analysis. With the model estimated in logarithms, u_i would correspond to $1\text{-}TE_i$. Individual specific efficiency is typically estimated with $\exp(-\hat{u}_i)$. Alternatively, $\hat{u}_i$ provides an estimate of proportional inefficiency.

Inefficiency, as a measure of the magnitude of sub-optimal performance, is represented by the asymmetric error term in the stochastic frontier model. The model assumes that each v_i is distributed independently of each u_i and that both errors are uncorrelated with the explanatory variables in x_i. In addition, it is assumed that:

- $E(v_i) = 0$ (zero mean)
- $E(v_i^2) = \sigma_n^2$ (homoskedastic)
- $E(v_i v_j) = 0$, for all i ≠ j (uncorrelated)
- $E(u_i^2)$ = constant
- $E(u_i u_j) = 0$, for all i ≠ j (uncorrelated)

A large number of variants of the stochastic frontier model with regard to the distributional specifications of the inefficiency component ui have been proposed: the truncated-normal (Stevenson, 1980), the exponential and the gamma (Greene, 1990). An extensive survey of the different models appears in Kumbhakar and Lovell (2000) who also provide the likelihood functions for estimation purposes. The main purpose of the stochastic frontiers is the analysis of technical inefficiency. It is an essential result that the inefficiency component is observed indirectly (Greene, 2007a) since the data and estimates only deliver estimates of the combined error term $i = v_i - u_i$. Jondrow et al. (1982) establishes a conditional mean estimator to disentangle the inefficiency component from the combined error term, which is largely used to determine the (in) efficiency levels (Kim and Schmidt, 2000).

2.6. Estimating Efficiency

The stochastic frontier model postulates that the error term ε_i is made up of two independent components $\varepsilon_i = v_i - u_i$, where u_i measures technical inefficiency in the sense that it measures the shortfall of output y_i from its maximal possible value. However, when a model of this form is estimated, one readily obtains residuals

$\hat{\varepsilon}_i = y_i - g\left(x_i - \hat{\beta}\right)$, which may be regarded as estimates of the error terms ε_i (Jondrow et al., 1982). The average technical inefficiency (the mean of the distribution of the u_i) is easily calculated. Average technical inefficiency can be estimated by the average of the $\hat{\varepsilon}_i$. But it is also clearly desirable to be able to estimate the technical inefficiency u_i for each observation. Indeed this was Farrell's (1957) original motivation for introducing production frontiers and the ability to compare levels of efficiency across observations remains the most compelling reason for estimating frontiers. Intuitively, this should be possible because $\varepsilon_i = v_i - u_i$ can be estimated and it obviously contains information on u_i. However, Jondrow et al. (1982) proceeded by considering the conditional distribution of u_i given ε_i. In other words, $E[u|\varepsilon]$ is the mean productive efficiency. Under each of the assumed possible distributional forms for the inefficiency term in a model, this mean that this distribution contains whatever information ε_i yields about u_i. This section describes the stochastic frontier production functions of Battese and Coelli (1992, 1995) and notes the cases of these formulations which can be estimated (and tested for).

2.6.1. The Battese and Coelli (1992) specification

Even though, stochastic frontier approach originated with the pioneer papers by Meeusen and van den Broeck (1977) and Aigner, Lovell and Schmidt (1977), the stochastic frontier production model methodology was developed by Battese and Coelli (1992). They defined a stochastic frontier production function model for panel data, in which technical efficiencies of producers may vary over time, with a simple exponential specification of time – varying producer effects[34]. The model may be expressed as:

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[34] Alternative time-varying models for producer effects have been proposed by Cornwell, Schmidt and Sickles (1990) and Kumbhakar (1990). Cornwell, Schmidt and Sickles (1990) assumed that the producer effects were a quadratic function of time, in which the coefficients varied over producers according to the specifications of a multivariate distribution. Kumbhakar (1990) assumed that the non-negative producer effects, U_{it}, were the product of a deterministic function of time, $\gamma(t)$ and non-negative time-invariant producer effects, U_i. Löthgren (1997) extend the stochastic frontier analysis by introducing a stochastic ray frontier model to accommodate the case of multiple outputs.

$$Y_{it} = x_{it}\beta + (V_{ti} - U_{it}) \tag{2.18}$$

$$Y_{it} = f(x_{it};\beta)\exp(V_{ti} - U_{it}) \tag{2.19}$$

and

$$U_{it} = \eta_{it}U_i = \{\exp[-\eta(t-T]\}U_i \tag{2.20}$$

where:

- i=1, …., N, t = 1, …., T
- Y_{it} is (the logarithm of) the production of the i^th^ producer in he t^th^ time period
- X_{it} is a k×1 vector of input quantities of the i^th^ producer in the t^th^ period
- β is a vector of unknown parameters, where β_k stands for the output elasticity with respect to the *k-th* input
- V_{it} are the random variables which are assumed to be iid $N(0, \sigma_v^2)$, and distributed independently of the U_{it} which are non – negative random variables, accounting for technical inefficiency in production and has the specification: $U_{it} = (U_i \exp(-\eta(t-T)))$
- U_i is a non-negative random variable which is assumed to account for technical inefficiency in production and are assumed to be iid as truncations at zero of the $N(\mu,\sigma_\mu^2)$ distribution
- η is a parameter to be estimated and
- the panel of data need not be complete (i.e. unbalanced panel data).

The model utilised the parameterization of Battese and Corra (1977) who replaced σ_U^2 and σ_V^2 with $\sigma^2 = \sigma_V^2 + \sigma_U^2$ and $\gamma = \sigma_U^2 / \left(\sigma_V^2 + \sigma_U^2\right)$. This is done with the calculation of the maximum likelihood estimates. The parameter, γ, must lie between 0 and 1[35].

The predictions of individual producer technical efficiencies from the estimated stochastic production frontiers are defined as:

$$TE_{it} = exp(-U_{it}) = E[exp(-U_{it})/E_i] = \left\{ \frac{1-\Phi\left[\eta_{it}\sigma_i^* - (\mu_i^* / \sigma_i^*)\right]}{1-\Phi\left[-\mu_i^* / \sigma_i^*\right]} \right\} \exp\left[-\eta_{it}\mu_i^* + \frac{1}{2}\eta_{it}^2\sigma_i^{*2}\right] \quad (2.21)$$

where E_i represents the (T_i x 1) vector of E_{it} 's associated with the time periods observed for the *i* th producer, where $E_{it} = V_{it} - U_{it}$.

If the producer effects are time invariant, then the technical efficiency is obtained by replacing $\eta_{it} = 1$ and $\eta = 0$. This model is such that the non-negative producer effects, Uit, decrease, remain constant or increase as t increases, if $\eta > 0$, $\eta = 0$ or $\eta < 0$, respectively[36]. If $\eta > 0$, the inefficiency term, U_{it}, is always decreasing with time, whereas $\eta < 0$ implies that U_{it} is always increasing with time. If $\eta = 0$, then the level of inefficiency remain constant. That could be one of the main problems when using this model, technical efficiency is forced to be a monotonous function of time[37]. In order

[35] The log-likelihood function of this model is presented in the appendix in Battese and Coelli (1992).

[36] The model assumed for the producer effects, Ui, was originally proposed by Stevenson (1980) and is a generalization of the half-normal distribution which has been frequently applied in empirical studies.

[37] As described in Coelli (1995), the imposition of one or more restrictions upon this model formulation can provide a number of the special cases of this particular model which have appeared in the literature. Setting η to be zero provides the time – invariant model set out in Battese, Coelli and Colby (1989). Furthermore, restricting the formulation to a full (balanced) panel of data gives the production function assumed in Batesse and Coelli (1988). The additional restriction of μ equal to zero reduces the model to model One in Pitt and Lee (1981).

to permit greater flexibility in the nature of technical efficiency, a two-parameter specification would be required. An alternative two-parameter specification, which is being investigated, is defined by:

$$\eta_{it} = 1 + \eta_1 (t - T) + \eta_2 (t - T)^2 \quad (2.22)$$

where η_1 and η_2 are unknown parameters. This model permits producer effects to be convex or concave, but the time-invariant model is the special case in which $\eta_1 = \eta_2 = 0$. In the Battese and Coelli (1992) model, the last period ($t=T_i$) for producer i contains the base level of inefficiency for that producer ($U_{it} = U_i$) and the efficiencies are measured relative to a frontier that may be regressing over time.

2.6.2. The Battese and Coelli (1995) specification

Battese and Coelli (1995) propose a model which is equivalent to the Kumbhakar, Ghosh and McGukin (1991) specification, with the exceptions that allocative efficiency is imposed, the first-order profit maximizing conditions removed, and panel data is permitted. The Battese and Coelli (1995) approach models both the stochastic and the technical inefficiency effects in the frontier, in terms of observable variables, and estimating all parameters by the method of maximum likelihood, in a one-step analysis[38].

One may add a forth restriction of T = 1 to return to the original cross sectional, half - normal formulation of Aigner, Lovell and Schmidt (1977). Obviously, a large number of permutations exist. For example, if all these restrictions excepting $\mu = 0$ are imposed, the model suggested by Stevenson (1980) results. Furthermore, if the cost function option is selected, we can estimate the model specification in Schmidt and Lovell (1979) specification, which assumed allocative efficiency.

These latter two specifications are the cost function analogues of the production functions in Battese and Coelli (1988) and Aigner, Lovell and Schmidt (1977), respectively.

[38] Battese and Coelli (1995) suggested that under the assumption of truncated normal one-sided error term, the mean of the truncated normal distribution could be expressed as a function of certain covariates, a closed form likelihood function can be derived, and the method of maximum likelihood may be used to obtain parameter estimates, and provide inefficiency measures.

According to Battese and Coelli (1995), the explanatory variables can include intercept terms or any variables in both the frontier and the model for the inefficiency effects, provided the inefficiency effects are stochastic. Battese and Coelli (1995) also suggested that under the assumption of truncated normal one-sided error term, the mean of the truncated normal distribution could be expressed as a function of certain covariates, a closed form likelihood function can be derived, and the method of maximum likelihood may be used to obtain parameter estimates, and provide inefficiency measures[39]. The Battese and Coelli (1995) model also overcomes the contradiction of the 'two – step' models and allows the simultaneous estimation of the parameters of the stochastic frontier and the inefficiency model (Puig-Junoy, 2001)[40].

The original Battese and Coelli's (1995) specification involved a production function with an error term incorporating two components, one to account for random effects (v_i) and one to capture the unobservable inefficiency factor (u_i).
The model consists of two equations, one to represent the production frontier and a second to measure technical inefficiency:

$$Y_{it} = \exp(x_{it}\beta + V_{ti} - U_{it}) \tag{2.23}$$

and

(2.24)

[39] As in Movshuk (2004), while early stochastic frontier models were devised form cross – sectional data, Battese and Coelli (1995) model is formulated for panel data, which may also be unbalanced. The model not only estimates inefficiency levels of particular industries, but also explains their inefficiency in terms of potentially important explanatory variables, decomposing TFP growth into two components: technological growth: a shift of production possibility frontier set by best – practice industries, and inefficiency changes: deviations of actual output level form the production possibility frontier.

[40] The two-stage analysis of explaining levels of technical efficiency (or inefficiency) was criticized by Battese and Coelli (1995) as being contradictory, in the assumptions made in the separate stages of the analysis.

where:

- i =1, …., N, t = 1, …., T
- Y_{it} is (the logarithm of) the production of the i^{th} producer in the t^{th} time period.
- x_{it} is a k×1 vector of input quantities of the i^{th} producer in the t^{th} period
- β is a vector of unknown parameters
- V_{it} are random variables which are assumed to be iid. $N(0, \sigma_V^2)$ and independent of the U_i which are non – negative random variables which are assumed to account for technical inefficiency in production, and assumed to be iid. as truncations at zero of the $N(\mu, \sigma_U^2)$ distribution $m_{it} = zi_t\delta$ where:
- z_{it} is a p×1 vector of variables which may influence the efficiency of a producer, and
- δ is a 1×p vector of parameters to be estimated.

The parameterisation used in this model form is the one by Battese and Corra (1977) who replaced σ_U^2 and σ_V^2 with $\sigma^2 = \sigma_V^2 + \sigma_U^2$ and $\gamma = \sigma_U^2 / \left(\sigma_V^2 + \sigma_U^2\right)$.

In the first equation, Y_{it} represents output of the *i-th* producer at time t. X_{ijt} is a vector of productive inputs and indicator variables for the *i-th* producer at time t.

Following Battese and Coelli (1995), the U_{it}s are assumed non-negative random variables that represent the stochastic shortfall of outputs from the most efficient production. It is assumed that U_{it} is defined by truncation of the normal distribution with mean:

$$\mu_{it} = \delta_0 + \sum_{j=1}^{J} \delta_j Z_{jit} \tag{2.25}$$

and variance, σ^2, where Z_{jit} is value of the j-th explanatory variable associated with the technical inefficiency effect of country i in year t; and δ_0 and δ_j are unknown parameters to be estimated.

The output-based measure of technical efficiency may be estimated as[41]:

$$TE_{it} = \frac{f(x_{it}, \beta_t)\exp(V_{it})}{yi_t} = \exp(-U_{it}) = \exp(-z_{it}\delta - W_{it}) \tag{2.26}$$

To obtain an observation – specific estimate of technical inefficiency (u), we use the Jondrow et al. (1982) result; that is, estimate u from $\hat{u} = E(u \mid v - u)$ in which $(v - u)$ is replaced by the residuals of the production function. Because estimation procedures yield merely the residuals ε rather than the inefficiency term u, this term in the model must be observed indirectly (Greene, 1993, Cullinane and Song, 2003). Jondrow et al. (1982) suggest the conditional expectation of uit, conditioned on the realized value of the error term ε_{it} = (v_{it}-u_{it}) as an estimator of uit and, in other words, E[u_{it}|ε_{it}] is the conditional mean productive inefficiency for the ith industry at any time t. Measures of technical efficiency (TE_i) for each producer can be calculated as[42]:

$$TE_i = \exp[E(u_i \mid \varepsilon_i)] \tag{2.27}$$

so that

$$0 \le TE_i \le 1 \tag{2.28}$$

Here, Z_{it} is a vector of demographic and socioeconomic characteristics that might be correlated with inefficiency and which might vary over time. The inefficiency model's

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[41] Jondrow et al. (1982) provided an initial solution by deriving the conditional distribution of *[-u_i| (v_i – u_i)]* which contains all the information (v_i – u_i) contains about u_i. This enabled to derive the expected value of this conditional distribution, from which they proposed to estimate the technical efficiency of each producer: $T\hat{E}_0(x_i, y_i) = \{\exp\{E[-\hat{u}_i \mid (v_i - u_i)]\}\}^{-1} \ge 1$, which is a function of the MLE parameter estimates. Later, Batesse and Coelli (1988) proposed to estimate the technical efficiency of each producer from: $T\hat{E}_0(x_i, y_i) = \{E[\exp\{-\hat{u}_i\} \mid (v_i - u_i)]\}^{-1} \ge 1$, which is slightly different function of the same MLE parameter estimates.

[42] The Batesse and Coelli model (1992, 1995) is modelling the time varying inefficiency in which time trend is specified to inefficiency term written as u(i,t)=exp(eta(t-T)| u(i)|.

random component, *w*, is not identically distributed nor is it required to be non-negative (Battese and Coelli, 1995) [43], [44].

A crucial issue concerning the model being estimated is what comprises the vector z. The results obtained suggest that efficiency levels in different industries were not always the result of homogeneous influences. Factors that influence efficiency include scale effects, foreign – ownership, plant age, the proportion of workers in non – manual occupations, capital intensity and population density. The emphasis is on modelling inter-industry differences in (relative) efficiency. Typically, variables are included to reflect competitive factors in the industry such as market share and profitability (Caves, 1990, Hay and Liu, 1997), investment in new technology, industry dynamics and product differentiation, as well as the importance of scale economics (Harris, 1993). The distribution in efficiency across time is considered, as is the question of whether efficiency levels were converging over time.

Battese and Coelli (1995) model has become popular thanks to its computational simplicity as well as its ability to examine the effects of various producer-specific variables on technical efficiency in an econometrically consistent manner, as opposed to a traditional two-step procedure, which is inconsistent with the assumption of independently and identically distributed technical inefficiency effects in the stochastic frontier.

[43] As referred to Coelli (1996), this model specification also encompasses a number of other model specifications as special cases. If we set T = 1 and z_{it} contains the value one and no other variables (i.e. only a constant term), then the model reduces to the truncated normal specification in Stevenson (1980), where δ_0 (the only element in δ) will have the same interpretation as the μ parameter in Stevenson (1980). It should be noted, however, that the two above mentioned models are not special case one to each other. Thus these two model specifications are non – nested and hence no set of restrictions can be defined to permit a test of one specification versus the other.

[44] This model specification also encompasses a number of other model specifications as special cases. Particularly, the model of Stevenson (1980) is a particular case of the Battese and Coelli (1995) model that can be obtained for the cases in which *T* is equal to 1 (for cross-sectional data).

The main advantage of this technique over the two-stage technique is that it incorporates producer specific factors in the estimation of the production frontier because these factors may have a direct impact on efficiency.

2.6.3. Time invariant versus time varying efficiency

Early panel data models were based on the assumption of time – invariant efficiency. Eventually this assumption was relaxed (Cornwell, Schmidt, Sickles (1990), Kumbhakar (1991) and Battese and Coelli (1992)). If efficiency varies across producers or through time, it is natural to seek determinants of efficiency variation, in order to estimate stochastic frontiers and predict producer-level efficiencies using these estimated functions, and then regress the predicted efficiencies upon producer - specific variables (such as managerial experience, ownership characteristics, etc) in an attempt to identify some of the reasons for differences in predicted efficiencies between producers. Studies adopted a two – stage approach, in which efficiencies are estimated in the first stage and estimated efficiencies are regressed against a vector of explanatory variables in a second stage.

Kumbhakar et al (1991), Reifschneider and Stevenson (1991), Huang and Liu (1994) and Battese and Coelli (1995) have adopted a single-stage approach in which explanatory variables are incorporated directly into the inefficiency error component. In this approach, either the mean or the variance of the inefficiency error component is hypothesised to be a function of the explanatory variables.

The most early panel data models related to efficiency measurement were based on the assumption of time – invariant efficiency (Pitt and Lee, 1981; Schmidt and Sickles, 1984; Kumbhakar, 1987, 1988; Battese and Coelli, 1988). These papers adopt a two-stage approach, in which the first stage involves the specification and estimation of the stochastic frontier production function and the prediction of technical inefficiency effects, under the assumption that these inefficiency effects are identically distributed. The second stage involves the specification of a regression model for the predicted technical inefficiency effects, which contradicts the assumption of identically distributed inefficiency effects in the stochastic frontier. However, the two-stage estimation procedure is unlikely to provide estimates which are as efficient as those that could be obtained using a single-stage estimation procedure (Coelli, 1996). A problem with the two-stage procedure is the inconsistency in the assumptions about the distribution of the inefficiencies. In the first stage, the inefficiencies are assumed to be independently and identically distributed (iid) in order to estimate their values. However, in the second stage, the estimated inefficiencies are assumed to be a function of a number of producer specific factors, and hence are not identically distributed unless all the coefficients of the factors are simultaneously equal to zero (Coelli et al., 1998).

Several SFA models for panel data have been proposed in the literature. Early models define the random or fixed effect as the inefficiency component, meaning that the models deduce the efficiency estimates from the individual producer-specific effects. Schmidt and Sickles (1984) propose a fixed effects SFA model that does not require the assumption that the producer-specific effects are uncorrelated with the input variables. If the assumption of independence is fulfilled, then a random effects SFA model is preferred for precision and efficiency of the estimates. Pitt and Lee (1981) established the model framework for the random effects SFA widely applied in the literature. In contrast to the fixed effects SFA model it allows time invariant producer-specific attributes entering in the econometric model. A fundamental question concerns the modeling of inefficiency over time. In the first models the individual inefficiency effects were modeled time-invariant. Extensions have been proposed by Lee and Schmidt (1993), Battese and Coelli (1992) and Kumbhakar (1990) that incorporate the variation of efficiency over time as a deterministic function that is similar across producers. However, the random component is still time-invariant, which remains a substantive restriction.

As broadly described in Wang and Schmidt (2002), it is widely agreed that the first step of the two-step procedure is biased if x and z are correlated (Kumbhakar and Lovell, 2000, Caudill and Ford, 1993).

Basically, the first-step regression that ignores z suffers from an omitted variables problem, since $E(y \mid x, z)$ depends on z but the first-step regression does not allow for this. Standard econometric theory for least squares regression says that the estimate of β will be biased by the omission of z, if z affects y and if z and x are correlated[45].

We now proceed to calculate the usual estimate of u, namely $u^* = E(u \mid \varepsilon = e)$, as in Jondrow et al. (1982) or Battese and Coelli (1988). This is a "shrinkage" estimator, where shrinkage is toward the mean, and this is intuitively reasonable because large positive ε will on average contain positive noise v, and should be shrunk downward toward the mean, while large (in absolute value) negative ε on average contain negative noise v, and should be shrunk upward toward the mean. The precise nature of the shrinkage depends on the distribution of u, and more importantly on the relative variances of v and u.

Once again this is a shrinkage estimator, and ignoring the dependence of σ_u^2 on z leads to estimates that are under dispersed. So a second-step regression of some function of r^* on z will suffer from the same downward bias as was discussed in the previous paragraph. This bias in the second-step regression, due to under dispersion in the estimates of u that do not take into account the effect of z on u, does not seem to be systematically discussed in the literature (Kumbhakar and Lovell, 2000)[46].

Two-step procedures to estimate the determinants of technical inefficiency suffer from a fundamental contradiction. In the first stage, a deterministic or a stochastic

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[45] As pointed out by Caudill and Ford (1993), the direction of the bias depends on the direction of the effect of z on u, and on the sign of the correlation between $h(z, \delta)$ and x. For example, if z is positively related to u (inefficiency), and if $h(z, \delta)$ is positively correlated with x, then neglecting z will cause the coefficient of x to be biased downward. Larger z will, other things equal, be associated with lower y and higher x, and thus the effect of x on y, not controlling for z, will appear smaller (less positive, or more negative) than it would if we controlled for z. A second and less widely recognized problem is that the first-step technical efficiency measures are likely to be seriously under dispersed, so that the results of the second-step regression are likely to be biased downward. This is true regardless of whether x and z are correlated.). To explore this point more precisely, suppose that x and z are independent, so that the first-step regression is unbiased. Thus, loosely speaking, the residual e is an unbiased estimate of the error $\varepsilon = v - u$.

[46] This discussion, as broadly described in Wang and Schmidt (2002), regarding the bias of the two-step estimator is described in Wang and Schmidt (2002).

frontier is estimated and then, in the second stage, producer technical efficiency elements are regressed on the relevant exogenous factors. The two-stage formulation presumes that the elements of Zi are uncorrelated with the elements of the input vector for this procedure to be consistent in its assumption that the inefficiency effects are independent in the two stages. The second stage involves the specification of a regression model for the predicted technical inefficiency effects which contradicts the identical distribution assumption of the first stage. In the first step, one estimates the stochastic frontier model and the producers' efficiency levels, ignoring *z*. In the second step, one tries to see how efficiency levels vary with *z*, perhaps by regressing a measure of efficiency on *z*. However, such a two – step procedure is both econometrically inefficient and is known to contradict the assumption of identically distributed technical inefficiency effects that is required to obtain predictions for their unknown values (Harris, 1999), assuming a common technology/frontier encompassing every sample observation. This may be inappropriate in the sense that the estimated technology is not likely to represent the "true" technology for all observations. Thus, the estimate of the underlying technology may be biased. In addition, as unobserved heterogeneity was not accounted for in the econometric models, parameter estimates also may have been biased. Moreover, since all time invariant heterogeneity was covered by the inefficiency part, these models show a tendency to underestimate a producer's performance (Farsi et al., 2003; Filippini et al., 2008). Hence, the modeling of heterogeneity in stochastic frontier function models has become increasingly important.

Eventually this assumption was also relaxed with the contribution of the papers by Cornwell, Schmidt, Sickles (1990), Kumbhakar (1991) and Battese and Coelli (1992), who were the first to propose a stochastic production frontier model with time varying technical efficiency. Finally, technical efficiency of production has been modeled by applying a time varying stochastic error components approach (Kumbhakar et al. 1991, Reifschneider and Stevenson 1991, Battese and Coelli 1995, Kumbhakar and Lovell 2000) using the flexible functional form of a translog production function.

For this reason, subsequent researchers allowed the technical efficiency to vary over time, but they model efficiency as a systematic function of time (Kumbhakar, 1990;

Cornwell, Schmidt and Sickles, 1990; Battese and Coelli, 1992; Lee and Schmidt, 1993). The assumption maintained in time – invariant stochastic efficiency models (Fried et al. 1993, Greene 1993) that efficiency is constant through time is a relatively unrealistic modeling restriction with respect to a competitive production environment. None of these models is formulated in a dynamic framework thereby meaning that an inefficient producer is not allowed to correct its inefficiency from the past. The problem with this approach is that, in most econometric models using time series data, technical change is also specified as an explicit function of time. As a result, in these models, one cannot distinguish between technical change and efficiency change. A number of studies have also attempted to estimate time-varying inefficiency. Cornwell, Schmidt and Sickles (1990) replaced the firm effect by a squared function of time with parameters that vary over time. Kumbhakar (1990) allowed a time-varying inefficiency measure assuming that it was the product of the specific firm inefficiency effect and an exponential function of time (Coelli, Rao and Battese 1998). We used a time-varying inefficiency effects measure assuming truncated at zero of normal distribution by Battese and Coelli (1992).

More specifically, Cornwell, Schmidt and Sickles (1990) were the first to propose a generalization of the Schmidt and Sickles (1984) model to account for time-varying inefficiency effects within a stochastic frontier panel data framework. The model used in their paper can be specified as:

$$Y_{it} = \beta_{0t} + \sum_{n=1}^{N} \beta_n X_{nit} + v_{it} - u_{it} = \beta_{it} + \sum_{n=1}^{N} \beta_n X_{nit} + v_{it} \tag{2.29}$$

where β_{0t} indicates the common production frontier intercept to all cross sectional productive units in period t and $\beta_{it} = \beta_{0t} - u_{it}$ is the intercept of unit i in period t. Cornwell, Schmidt and Sickles (1990) model the intercept parameters for different cross-section productive units at different time periods as a quadratic function of time in which the time variables are associated to producers' specific parameters. This yields the following specification for the technical inefficiency error term:

$$u_{it} = \beta_{1i} + \beta_{2i} t + \beta_{3i} t^2 \tag{2.30}$$

where the *βs* represent cross-section producer specific parameters. Moreover, several estimation strategies, including a fixed-effect approach and a random-effects approach are described in Cornwell, Schmidt and Sickles (1990) and again the jump from fixed effects approaches to random-effects approaches is made on the basis of allowing for the inclusion of time-invariant regressors.

On the other hand, if independence and distributional assumptions are available, Maximum Likelihood techniques can also be applied to the estimation of stochastic frontier panel data models where technical inefficiency depends on time. Kumbhakar (1990) suggests a model in which the technical inefficiency effects assumed to have a half-normal distribution vary systematically with time according to the following expression:

$$u_{it} = \delta(t)u_i = \left[1 + \exp\left(\gamma t + \rho t^2\right)\right]^{-1} ui \tag{2.31}$$

where γ and ρ are unknown parameters to be estimated.

According to Kumbhakar (1991) efficiency measurement in the panel data models often fails to distinguish technical inefficiency from producer specific effects, especially when technical inefficiency is assumed to be time – invariant. Most of these models also ignore time – specific effects separate from exogenous progress. Consequently, determinants of technical inefficiency are introduced by allowing its mean to be a function of exogenous variables that can explain technical inefficiency.

The model of Kumbhakar (1991) considers estimation of production function parameters and technical inefficiency for each producer using panel data. The distinguishing features of the model are:

1. technical inefficiency is separated from producer-specific and time-specific effects
2. determinants of technical inefficiency is introduced by allowing its mean to be a function of exogenous variables that explain the deterministic components of technical inefficiency, and

3. estimation methods are developed to accommodate either fixed or random treatment of producer – and time – specific effects.

This issue was addressed mainly by Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991) who propose stochastic frontier models in which the inefficiency effects (u_i) are expressed as an explicit function of a vector of producer-specific variables and a random error. Kumbhakar et al (1991), Reifschneider and Stevenson (1991), Huang and Liu (1994) and Battese and Coelli (1995) have adopted a single-stage approach in which explanatory variables are incorporated directly into the inefficiency error component. In this approach, either the mean or the variance of the inefficiency error component is hypothesised to be a function of the explanatory variables. The parameters of the stochastic frontier and the inefficiency model are estimated simultaneously, given appropriate distributional assumptions associated with cross-sectional data on the sample producers. A one-step model specifies both the stochastic frontier and the way in which u depends on z, and can be estimated in a single step. This is in contrast to a two-step procedure, where the first step is to estimate a standard stochastic frontier model and the second step is to estimate the relationship between (estimated) u and z (Wang and Schmidt, 2002).

Specifically, Kumbhakar et al. (1991) proposed a model for the technical inefficiency effects where the parameters of the stochastic frontier and technical inefficiencies are estimated simultaneously given the appropriate distributional assumptions. Kumbhakar *et al.* (1991) first raised concerns about the two-stage process in the stochastic frontier context. Instead, they incorporate the estimation of the determinants of inefficiency with estimation of the production frontier. In their composed error term ($ek = uk + vk$), they make the one-sided inefficiency component a function of z and w such that $uk(\mathbf{z},w) = \mathbf{z}\delta + wk$ where $\mathbf{z}$ is a vector of determinants of producer efficiency, δ is the vector of parameters to be estimated, and w is the random error of the inefficiency component u. As before, v is the random error of the composed error term[47].

[47] Wang and Schmidt (2002) compare one-step and two-step procedures for a stochastic model and found the two-step procedure led to biased results, and therefore recommend against that approach.

To avoid the estimation problem, the stochastic frontier and inefficiency effects may be estimated simultaneously in a one-step procedure (Wang and Schmidt, 2002), namely, all of the parameters are estimated in one step. Model used simultaneously determines the causes of inefficiency, rather than using a second-step procedure whereby efficiency estimates (obtained from step-one) are then regressed on a set of determinants[48]. As a result, the two stage approach has been dismissed as inconsistent when technical inefficiencies are used as a dependent variable in the second stage analysis[49]. This is in favour of the one stage approach where the parameters of the stochastic frontier and technical inefficiencies are estimated simultaneously. The inefficiency effects are defined as a function of the producer specific factors (as in the two-stage approach) but they are then incorporated directly into the MLE[50].

Lee and Schmidt (1993) propose an alternative formulation, in which the technical inefficiency effects for each productive unit at a different time period are defined by the product of individual technical inefficiency and time effects:

$$u_{it} = \delta_t u_i \tag{2.32}$$

where the δts are the time effects represented by time dummies and the ui can be either fixed or random producer-specific effects.

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[48] Wang and Schmidt (2002) then provide a lengthy argument why conventional estimators of the production parameters and the JLMS estimates of *ui* will be seriously biased. The same arguments apply to estimates of TEi = exp(-ui).

[49] However, using the estimated technical inefficiencies and parameters of the model to compute a measure of efficiency and then using it as dependent variable in the second stage analysis as used by Reinhard *et al.* (1999) is consistent.

[50] Although it is widely recognized that two-step procedures are biased, there seems to be little evidence on the severity of this bias. For example, Caudill and Ford (1993) provide evidence on the bias of the estimated technological parameters, but not on the efficiency levels themselves or their relationship to the explanatory variables *z*.

This is possible following the maximum likelihood estimation methodology proposed by Coelli *et al*. (1998). When the explanatory variables for the technical inefficiency effects model are producer-specific variables only, this results to Battese and Coelli (1995) production frontier model, but when both inputs and producer-specific variables are included as explanatory variables for the technical inefficiency effects model, this results to production frontier model originally proposed by Huang and Liu (1994).

2.6.4. Fixed and Random Effects

The central feature of the Battese and Coelli estimator is a fixed effects linear regression model. It is argued that this approach brings gains in statistical efficiency while obviating assumptions about the distribution of technical inefficiency.

However, heterogeneous production environments, which are not under the producer's control, may influence the production process and incurred costs. These differences when observed or measured by observed proxies, can be incorporated in the estimation methods. One of the most important issues in stochastic frontier models is adjusting for the unobserved heterogeneity among producers functioning in different production environments. Individual producers face different external factors that could influence their production costs but are not under their control. Some of these factors are observed and can be controlled for in the analysis. However, in many cases the data are not available for all these variables. Moreover, the relevant factors are often too complex to be quantified by simple indicators. In panel data where an individual producer is observed several times, the producer-specific unobserved variations can also betaken into account through fixed or random effects[51].

The first use of panel data models in stochastic frontier models goes back to Pitt and Lee (1981) who interpreted the panel data random effects as inefficiency rather than heterogeneity. This tradition continued with Schmidt and Sickles (1984) who used a

[51] Panel data may have group effects, time effects, or both. These effects are either fixed effect or random effect. Consequently, panel data are analyzed to investigate group and time effects using fixed effect and random effect models.

similar interpretation applied to a panel data model with fixed effects. The basic panel data formulation, introduced by Schmidt and Sickles (1984), is a model in which the producer-specific stochastic term is interpreted as inefficiency. This term can be alternatively identified as a fixed intercept for each producer (FE model) or as an *iid* random term (RE model). In case where the unobserved heterogeneity is correlated with some of the explanatory variables, while the random effects estimators can be biased the fixed effects model may overestimate inefficiency scores.

A main shortcoming of these models is that any unobserved, time-invariant, producer-specific heterogeneity is considered as inefficiency. In more recent papers random effects model has been extended to include time-variant inefficiency (Cornwell, Schmidt and Sickles, 1990, Battese and Coelli, 1992). However, in both these models producer-specific effects are considered as inefficiency. Another problem arises when the producer-specific effects are correlated with the explanatory variables. A common feature of all these models is that they do not fully separate the sources of heterogeneity and inefficiency at the producer level. An alternative approach is to consider two separate stochastic terms for efficiency and producer-specific heterogeneity.

Basically, there are two methods of estimation in the literature. In the first, the estimation of the parameters of the production frontier is done conditionally on fixed values of the u_i's which leads to the fixed effects model and the within estimator of the frontier coefficients. In the second, the estimation is carried out marginally on the producer specific effects u_{it}'s which leads to the random effects model and either the Generalised Least Squares (GLS) or the LM estimation of the parameters (Puig-Junoy, 2001)[52].

[52] As described in Coelli (1996), the imposition of one or more restrictions upon this model formulation can provide a number of the special cases of this particular model which have appeared in the literature. Setting η to be zero provides the time – invariant model set out in Battese, Coelli and Colby (1989). Furthermore, restricting the formulation to a full (balanced) panel of data gives the production function assumed in Batesse and Coelli (1988). The additional restriction of μ equal to zero reduces the model to model One in Pitt and Lee (1981). One may add a forth restriction of $T = 1$ to return to the original cross sectional, half - normal formulation of Aigner, Lovell and Schmidt (1977). Obviously, a large number of permutations exist. For example, if all these restrictions excepting $\mu = 0$ are imposed,

A fixed effect model (Schmidt and Sickles, 1984) examines if intercepts vary across groups or time periods, whereas a random effect model (Pitt and Lee, 1981) explores differences in error variances[53]. The fixed effect model asks how group and/or time affect the intercept, while the random effect model analyzes error variance structures affected by group and/or time. Slopes are assumed unchanged in both fixed effect and random effect models. The following table compares the fixed effect and random effect models:

Table 2.2. Fixed Effect and Random Effect Models

	Fixed Effect Model	Random Effect Model
Functional form	$y_{it} = (\alpha + \mu_i) + X_{it}^{'}\beta + v_{it}$	$y_{it} = \alpha + X_{it}^{'}\beta + (\mu_i + v_{it})$
Intercepts	Varying across groups and/or times	Constant
Error variances	Constant	Varying across groups and/or times
Slopes	Constant	Constant
Estimation	LSDV, within effect method	GLS, FGLS
Hypothesis test	Incremental F test	Breusch-Pagan LM test

Notes:

1. The parameter estimate of a dummy variable is a part of the intercept in a fixed effect model and a component of error in the random effect model. Slopes remain the same across groups or time periods.

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the model suggested by Stevenson (1980) results. Furthermore, if the cost function option is selected, we can estimate the model specification in Schmidt and Lovell (1979) specification, which assumed allocative efficiency. These latter two specifications are the cost function analogues of the production functions in Battese and Coelli (1988) and Aigner, Lovell and Schmidt (1977), respectively.

[53] In both cases, inefficiency effects are assumed to be time invariant.

2. $v_{it} \sim iid\left(0, \sigma_v^2\right)$ indicates that errors are independent identically distributed

Source: Park (2009), p. 2

Group effect models create dummies using grouping variables (e.g., country, producer, and race). A *one-way model* includes only one set of dummy variables (e.g., producer), while a *two – way model* considers two sets of dummy variables (e.g., producer and year). If one grouping variable is considered, it is called a one-way fixed or random group effects model. Two-way group effect models have two sets of dummy variables, one for a grouping variable and the other for a time variable.

This variation has two important restrictions. First, any time invariant heterogeneity will be pushed into α_i and ultimately into $\hat{u}_i$. Second, the model assumes that inefficiency is time invariant. For short time intervals, this may be a reasonable assumption. But, this is to be questionable. Both of these restrictions can be relaxed by placing country specific constant terms in the stochastic frontier model – we call this a 'true' fixed effects model:

$$y_{it} = \alpha + x_{it}^{'}\beta + v_{it} - u_{it} \tag{2.33}$$

where u_{it} has the stochastic specifications noted earlier for the stochastic frontier model.

In the fixed effects, the production function is denoted:

$$y_{it} = \alpha + x_{it}\beta + v_{it} - u_i \tag{2.34}$$

where y_{it} is the (log of the) output of the system, $\boldsymbol{x}_{it}$ is (logs of) the set of inputs, v_{it} is the random component representing stochastic elements as well as any country (and time) specific heterogeneity, u_i is the inefficiency in the system, and i and t denote country and year, respectively.

Assuming that $u_i > 0$, the equation is rewritten:

$$y_{it} = (\alpha - u_i) + x_{it}^{'}\beta + v_{it} = \alpha_i + x_{it}^{'}\beta + v_{it} \quad (2.35)$$

Assuming that v_{it} has the familiar stochastic properties of a regression model and is uncorrelated with other components of the model, the parameters can be estimated by least squares, using the "within," or dummy variable estimator. The country specific constants embody the technical inefficiency. The inefficiencies are estimated in turn by shifting the function upward so that each constant term is measured as a deviation from the benchmark level:

$$\hat{u}_i = \max_i(\hat{\alpha}_i) - \hat{\alpha}_i \geq 0 \quad (2.36)$$

The narrow assumption of half normality is viewed as significant drawback in this model. This feature leads to the extension of the model to a truncated normal model by allowing the mean of U_i to be nonzero (Stevenson, 1980). The major shortcoming here is that the strict assumption suppresses individual heterogeneity in inefficiency that is allowed, for example, by the fixed effects formulation.

Superficially, this amounts simply to adding a full set of country dummy variables to the stochastic frontier model. The model is still fit by maximum likelihood, not least squares.

The true fixed effects model places the unmeasured heterogeneity in the production function: with a loglinear model, it produces a neutral shift of the function, specific to each country. One might, instead, have the heterogeneity reside in the inefficiency distribution. This could be accomplished with the formulation:

$$\mu_i = \delta_{0i} + h_i^{'}\delta \quad (2.37)$$

that is, by placing the country specific dummy variables in the mean of the truncated normal distribution, rather than in the production function. Once again, in a moderate sized sample, this is a minor reformulation of the familiar model.

Although the fixed effects models have the advantage of following correlation between the inefficiency term and the independent variables, and of allowing no distributional assumption on efficiency, the results should be interpreted carefully. The possibility that the producer – specific effects would include the influence of variables that vary across producers but are invariant over time may be not ruled out. Simar (1992) has shown that the fixed effects model appears to provide a poor estimation of the intercepts and of the slope coefficients of frontier production functions and consequently unreasonable measures of technical efficiency.

On the other hand, as referred in Greene (2003 a,b), the random effects model is obtained by assuming that u_i is time invariant and also uncorrelated with the included variables in the model:

$$y_{it} = \alpha + X_{it}^{'}\beta + \left(\mu_i + v_{it}\right) \tag{2.38}$$

In the linear regression case, the parameters are estimated by two step generalized least squares (Greene, 2003 a,b). Random effects model has a significant drawback: there is no implied estimator of inefficiency in this model, that is, no estimator of TE_i as in the fixed effects case.

Pitt and Lee (1981) showed how the time invariant composed error model could be extended to a panel data version of the stochastic frontier model. The direct extension would be of limited usefulness here, first because of the assumption of uncorrelatedness of u_i and $\boldsymbol{x}_i$ and, because of the assumption of time invariance of the inefficiency. The first of these can be remedied in the same fashion as suggested earlier. Estimation of the random effects model with heterogeneity in $E[U_i]$ is straightforward.

The heterogeneity may also enter the distribution of u_{it} which can, as before, have mean μ_i or, in principle, even μ_{it} with time variation in the covariates. Country specific estimates of inefficiency are computed using the Jondrow et al. (1982) formulation, though simulation methods are needed to integrate out the unmeasured random effects.

In the random effects model, the stochastic nature of the efficiency effects is explicitly taken into account in the estimation process. The GLS estimation provides consistent and unbiased estimates of the parameters, if the regressors xit are not correlated with the technical efficiency effects uit. A relative major advantage of the GLS estimator relative to the within estimator is its flexibility to include the time – invariant regressors. In the fixed effects model, the coefficients of time – invariant regressors, even though they may vary across producers, cannot be estimated because these time – invariant regressors will be eliminated in the within transformation, as shown in the equation:

$$(y_{it} - \bar{y}_i) = \beta'(x_{it} - \bar{x}_i) + v'_{it} \qquad (2.39)$$

In this case, the producer – specific technical efficiency effects will include the influence of all variables that are time – invariant at the producer level within the sample. This would make technical efficiency comparisons difficult unless the excluded fixed regressors influence all producers in the sample equally (Kumbhakar, 1987).

Summarising, with fixed effects models, all statistical inference can only be made on the cross – section unit used for estimation. In other words, the findings from a fixed effects model cannot be generalised. An alternative is the random effects model, in which the error components are assumed to be random variables drawn from a normal distribution and independently and identically distributed, with the assumption that these error components are uncorrelated with the explanatory variables.

In the RE framework, it is assumed that the producer-specific effects are uncorrelated with the explanatory variables in the model. Therefore, all the extensions of the RE model are prone to heterogeneity bias due to such correlation. However, the refinement of the model to separate different sources of heterogeneity may improve the performance of the model, especially regarding the inefficiency estimates.

The core difference between fixed and random effect models lies in the role of dummy variables. If dummies are considered as a part of the intercept, this is a fixed effect model. In a random effect model, the dummies act as an error term. A fixed group effect model examines group differences in intercepts, assuming the same slopes and constant variance across entities or subjects. Since a group (individual specific) effect is time invariant and considered a part of the intercept, u_i is allowed to be correlated to other regressors.

A random effect model, by contrast, estimates variance components for groups (or times) and errors, assuming the same intercept and slopes. $u\ i$ is a part of the errors and thus should not be correlated to any regressor; otherwise, a core OLS assumption is violated. The difference among groups (or time periods) lies in their variance of the error term, not in their intercepts.

A random effect model is estimated by generalized least squares (GLS) when the Ω matrix, a variance structure among groups, is known. The feasible generalized least squares (FGLS) method is used to estimate the variance structure when Ω is not known. A typical example is the groupwise heteroscedastic regression model (Greene 2003 a,b). There are various estimation methods for FGLS including the maximum likelihood method and simulation (Baltagi and Cheng 1994).

Fixed effects models are not without their drawbacks. The fixed effects models may frequently have too many cross-sectional units of observations requiring too many dummy variables for their specification. Too many dummy variables may sap the model of sufficient number of degrees of freedom for adequately powerful statistical tests.

Moreover, a model with many such variables may be plagued with multicollinearity, which increases the standard errors and thereby drains the model of statistical power to test parameters. If these models contain variables that do not vary within the groups, parameter estimation may be precluded. Although the model residuals are assumed to be normally distributed and homogeneous, there could easily be country-specific (groupwise) heteroskedasticity or autocorrelation over time that would further plague estimation (Yaffee, 2003).

The one big advantage of the fixed effects model is that the error terms may be correlated with the individual effects. If group effects are uncorrelated with the group means of the regressors, it would probably be better to employ a more parsimonious parameterization of the panel model.

Conventional panel data models such as fixed-effects or random-effects models can be employed to account for unobserved heterogeneity (Pitt and Lee, 1981; Schmidt and Sickles, 1984). A major limitation of these models is the treatment of the inefficiency term as time-invariant, which raises a fundamental identification problem. Not only must the model distinguish noise from the inefficiency effects, but also the unobserved, time-invariant, producer-specific heterogeneity becomes difficult to distinguish from the inefficiency component (Greene, 2005). Some authors have extended the random-effects model to include time-variant inefficiency (Cornwell *et al.*, 1990; Battese and Coelli, 1992, 1995). However, a drawback in these models is that the producer-specific effects are still considered as inefficiency, which may result in biased estimates (Greene, 2005). Moreover, when producer-specific effects are correlated with the explanatory variables, the random-effects estimators are affected by heterogeneity bias. As pointed out by Greene (2002b), while fixed-effects estimators are still consistent with regard to the production frontier slopes, inefficiency variations are overestimated. Thus, an obvious drawback of all these models is their inability to separate fully the sources of heterogeneity and inefficiency at the producer level.

In a recent development, Greene (2005) demonstrated how a stochastic frontier model can be extended to panel data models by including a random effect in the model. He refers to this extension as the ‘true’ random-effects model.

The ‘true’ random-effects model is basically a random-constant frontier model that is obtained by combining a conventional random-effects model with a skewed stochastic term representing inefficiency.

However, since most of the unobserved factors, in particular those relating to efficiency explanatory conditions, are most likely to be correlated with the output and some of the explanatory variables, the ‘true’ random-effect estimators of the production function coefficients could still be biased.

2.7. Concluding Remarks

The discussion concerning the measurement of productivity and efficiency in the economic literature started with contemporaneous papers by Debreu (1951) and Koopmans (1951). Koopmans (1951) and Debreu (1951) made the first systematic efforts in the investigation of efficiency and its measurement. However, the standard efficiency measurement literature was started by Farrell (1957), built upon Debreu (1951) and Koopmans (1951). Farrell (1957) proposed to measure the efficiency of a productive unit in terms of the realized deviations from an idealized frontier isoquant. The empirical identification of such a benchmark is the main issue of the literature on efficiency measurement. Farrell (1957) extended this work in an attempt to operationalize the measurement of productivity and efficiency. From Farrell's work, we define the productivity of an economic agent as the scalar ratio of outputs to inputs used by the agent in its production process. Finally in the 1970's, with the seminal papers of Aigner et al. (1977) and Meeusen and van den Brock (1977), econometricians developed a statistically and theoretically sound method for measuring efficiency, a method now known as stochastic frontiers. In this case, a stochastic frontier is defined as the locus of best performing agents within a data set. The other data points of the other producers are located "below" this estimated frontier. The relative distance measured between this best performance and the other data points is interpreted as inefficiency.

The approach to frontier estimation, proposed by Farrell (1957), was also considered by Shephard (1970) and Afriat (1972) who suggested mathematical programming methods that could achieve frontier estimation, but the method did not receive wide attention until the paper by Charnes, Cooper and Rhodes (CCR) (1978), in which the term DEA was first presented. Charnes, Cooper and Rhodes (1978) proposed a model that had an input orientation and assumed constant returns to scale (CRS). Subsequently, Färe and Logan (1983) and Banker, Charnes and Cooper (BCC) (1984) proposed variable returns to scale (VRS). The term DEA and the CCR model were first introduced in 1978 (Charnes et al, 1978) and were followed by a phenomenal expansion of DEA in terms of its theory, methodology and application over the last few decades (Førsund and Sarafoglou, 2003, Seiford (1996), Charnes et al (1994).

Charnes et al. (1978) and Banker et al. (1984) extended Farrell's ideas by imposing returns to scale properties. The nonparametric approach relies on a production frontier defined as the geometrical locus of optimal production plans (Simar and Wilson, 1998, 2007). The production frontier can be estimated non parametrically from a set of observed production units, based on different envelopment techniques. A Common nonparametric measure is the Data Envelopment Analysis (DEA). Nonparametric DEA shows how one can apply simulation methods, to conduct statistical inference to obtain more reliable and robust results. In DEA the inefficiency is defined as the distance from the frontier of a convex envelope of the data; therefore, due to the convexity assumption, a company might be compared to an unobservable and fictitious linear combination of efficient observations (Coelli et al., 2005). Thus, the efficiency score is the point on the frontier characterized by the level of inputs that should be reached to be efficient (Simar and Wilson, 1998, Simar and Wilson, 2007). Then the analysis proceeds on deterministic, where deviations of a producer from the theoretical maximum are allocated exclusively to inefficiency, and stochastic production frontiers, where the deviation from the frontier is decomposed into stochastic noise and technical inefficiency in production. Chapter 2 analyses the Deterministic and Stochastic Production Frontiers and explains the reasons for which the stochastic frontier approach is the most comprehensive analytical and estimation method, providing the main features which characterise this method, as well as the main hypotheses related. Then, Chapter 2 deals with the literature survey on Stochastic Frontier Models and the main assumptions on efficiency estimation and analyses the Battese and Coelli (1992) specification as opposed to the Battese and Coelli (1995) specification. More specifically, as far as the stochastic frontier models are concerned, this chapter focuses on the Battese and Coelli (1992) and Battese and Coelli (1995) models, providing a detailed analysis of the specifications of these two approaches. Then, this chapter analyses the characteristics and differences between time invariant and time varying efficiency, as well as the related fixed and random effects analysis.

Chapter 3

Empirical Model Specification and Methodology

Abstract

In stochastic frontier analysis, early models were based on the assumption of time – invariant efficiency. Eventually this assumption was relaxed (Cornwell, Schmidt, Sickles (1990), Kumbhakar (1991) and Battese and Coelli (1992)). If efficiency varies across producers or through time, it is natural to seek determinants of efficiency variation, in order to estimate stochastic frontiers and predict producer-level efficiencies using these estimated functions, and then regress the predicted efficiencies upon producer-specific variables (such as managerial experience, ownership characteristics, etc) in an attempt to identify some of the reasons for differences in predicted efficiencies between producers. Studies adopted a two-stage approach, in which efficiencies are estimated in the first stage and estimated efficiencies are regressed against a vector of explanatory variables in a second stage. The assumption maintained in time-invariant stochastic efficiency models (Fried et al. 1993, Greene 1993) that efficiency is constant through time is a relatively unrealistic modeling restriction with respect to a competitive production environment. A number of studies have also attempted to estimate time-varying inefficiency. Cornwell, Schmidt and Sickles (1990) replaced the firm effect by a squared function of time with parameters that vary over time. Kumbhakar (1990) allowed a time-varying inefficiency measure assuming that it was the product of the specific firm inefficiency effect and an exponential function of time (Coelli, Rao and Battese 1998). Later papers adopted a two-stage approach, in which the first stage involves the specification and estimation of the stochastic frontier production function and the prediction of technical inefficiency determinants, under the assumption that these inefficiency effects are identically distributed. The second stage involves the specification of a regression model for the predicted technical inefficiency effects, which contradicts the assumption of identically distributed inefficiency effects in the stochastic frontier. However, the two-stage estimation procedure is unlikely to provide estimates which are as efficient as those that could be obtained using a single-stage estimation procedure (Coelli, 1996).

Chapter 3 provides an overview of alternative empirical model specifications and different sets of methodologies and instruments available allowing a justification to the chosen methodology. Then it conducts a comparison between the one-step versus two-step estimation procedure and concludes with the main Hypotheses tests and the case of panel data within the Stochastic Frontier Models. Finally, Chapter 3 analyses the empirical model and the underlyimg assumptions, it describes the econometric analysis methofdology and the related hypotheses testing.

3.1. Introduction

In stochastic frontier models, output is assumed to be bounded from above by a stochastic production function. Therefore, the error term in stochastic frontier models has two parts: the first representing randomness or statistical noise, and the second representing technical inefficiency. In this case, each producer faces a production frontier which is randomly due to stochastic shocks outside the producer's control. Moreover, this method enables to distinguish between shifts in technology from movements towards the best-practice frontier. On the other hand, frontier approaches provide a technology frontier constructed by the best-performing producers of the industry. The performance of all producers is then compared against that frontier, which enables the analyst to evaluate each producer's behavior. A frontier function represents a best-practice technology, against which the efficiency of the producers within the industry can be measured (Coelli, 1995). If a producer belongs to the frontier, it is efficient. If a producer is beneath the efficiency frontier, then it is inefficient and further analysis identifies the sources and extent of the inefficiency. There are different alternative methods, in order to estimate this frontier function, as well as to estimate any deviations from it. Literature distinguishes between parametric and nonparametric efficiency measurement and considers the characteristics of each method. Parametric estimation concepts involve strong assumptions about the functional forms describing the production process or the distribution functions of the stochastic part in the model. Nonparametric approaches assume no parametric restrictions for any features of the probability model and the frontier is not described by a specific analytical function (Simar and Wilson, 2007). One of the main approaches of parametric econometric approach of efficiency measurement is stochastic production frontier. Then, this chapter aims to employ a translog production frontier model following Battese and Coelli (1992, 1995) stochastic production frontier model, by including a time variable in the deterministic kernel of the stochastic production frontier to capture the effect of technical progress, as the translog function is a flexible function, presenting both linear and quandratic terms with the ability of using more than two factor inputs. The translog model assumes that there are no technical inefficiencies hence excludes u_i from the regression equation, estimating the level of output of a technically efficient industry, also imposing the symmetry restriction is imposed a priori to be able to identify the coefficients ($\beta_{ij} = \beta_{ji}$).

Provided the inefficiency effects are stochastic, the model permits the estimation of both technical change in the stochastic frontier and time-varying technical inefficiencies. A base model is estimated, using the traditional input and output variables, and then variations are added to this model. The base models include labor, capital and time (as the proxy for technical change) as inputs, and value added as output. In the extended models, additional input variables are introduced: ICT investment, ICT investment share, R&D stock and economy openness.

3.2. Empirical model

This chapter considers a panel data stochastic model for inefficiency effects in stochastic production frontier based on the Battese and Coelli (1992, 1995) models, providing translog effects, as well as industry effects[54].

The estimated model accommodates not only heteroscedasticity but also allows the possibility that an industry may not always produce the maximum possible output, given the inputs available.

We estimate efficiencies as industry specific fixed effects. Technical inefficient component is treated as time – varying hence a time – varying decay model is estimated. Our model is a stochastic frontier model of one output (value added) and three inputs (capital, labour, time). Following Battese and Coelli (1992, 1995), a stochastic frontier production function is defined for panel data on industries, in which the non-negative technical inefficiency effects are assumed to be a function of producer-specific variables and time.

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[54] In our analysis we will use a panel-data approach because we have a small number of countries available and by pooling industry and country data in a multi-country panel our data have a sufficient size of observations.

The inefficiency effects are assumed to be independently distributed as truncations of normal distributions with constant variance, but with means which are a linear function of observable variables. We model both the stochastic and the technical inefficiency effects in the frontier, in terms of observable variables, and estimating all parameters by the method of maximum likelihood, in a one-step analysis[55], as developed by Battese and Coelli (1992, 1995)[56].

A range of functional forms for the production function frontier are available, with the most frequently used being a translog function, which is a second order (all cross-terms included) log-linear form[57]. We use a translog function, which is a second order

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[55] Battese and Coelli (1995) suggested that under the assumption of truncated normal one-sided error term, the mean of the truncated normal distribution could be expressed as a function of certain covariates, a closed form likelihood function can be derived, and the method of maximum likelihood may be used to obtain parameter estimates, and provide inefficiency measures.

[56] When employing regression analysis in the second step to explain the variation of the efficiency scores, it is likely that the included explanatory variables fail to explain the entire variation in the calculated efficiencies and the unexplained variation mixes with the regression residuals, adversely affecting statistical inference. The use of a stochastic frontier regression model allows for the decomposition of the variation of the calculated efficiencies into a systematic component and a random component.

[57] Some literature focused on stochastic frontier model with distributional assumptions by which efficiency effects can be separated from stochastic element in the model and for this reason a distributional assumption has to be made. Among others, an exponential distribution (Meeusen and van den Broeck 1977); a normal distribution truncated at zero (Aigner, Lovell and Schmidt 1977); a half-normal distribution truncated at zero (Jondrow *et al.* 1982) and a two-parameter Gamma or Normal distribution (Greene 1990). However, these are computationally more complex, there are no priori reasons for choosing one distributional form over the other, and all have advantages and disadvantages (Coelli, Rao and Battese 1998). There are no a priori reasons for choosing one distributional form over the other, and all have advantages and disadvantages (Coelli, Rao and Battese, 1998). For example, the exponential and half-normal distributions have a mode at zero, implying that a high proportion of the producers being examined are perfectly efficient. The truncated normal and two-parameter gamma distribution both allow for a wider range of distributional shapes, including non-zero modes. However, these are computationally more complex (Coelli, Rao and Battese, 1998). Empirical analyses suggest that the use of the gamma distribution may be impractical and undesirable in most cases. Ritter and

(all cross-terms included) log-linear form. This is a relatively flexible functional form[58], as it does not impose assumptions about constant elasticities of production nor elasticities of substitution between inputs. It thus allows the data to indicate the actual curvature of the function, rather than imposing *a priori* assumptions[59].

We adopt the standard flexible translog functional form to represent technology, including the time variable *time* in order to account for technical change effects[60] used as a regressor along with the input variables, in order to capture evolution and differences in technical progress (Oh et al. 2009). To do so the model is extended by adding the term β_T, where β_T denotes an industry specific parameter and t is a time trend, $t = 1, \ldots Ti$ allowing for industry – specific (linear) changes in productive efficiency over time (Kumbhakar, Heshmati and Hjalmarsson, 1999). The parameter β_T indicates whether a producer's efficiency increases $(\beta_T > 0)$ or decreases $(\beta_T < 0)$ with time t. All of the variables are as defined before except for *time* and $time^2$, which controls for the linear and quadratic time trends, respectively. Technical change may be biased towards a particular input. A positive (negative) value of β_i implies that

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Simar (1997) found that the requirement for the estimation of two parameters in the distribution may result in identification problems, and several hundreds of observations would be required before such parameters could be determined. Further, a maximum of the log-likelihood function may not exist under some circumstances. Bhattacharyya et al. (1995), however, offer one approach for selecting the distribution to reflect technical inefficiency; they suggest the use of a data generating process.

[58] As broadly described in Khalil (2005), the translog function is an attractive flexible function. This function has both linear and quadratic terms with the ability of using more than two factor inputs.

[59] In terms of output y and inputs X, this can be expressed as: $\ln y_{it} = \beta_0 + \sum_i \beta_i \ln X_{jit} + \frac{1}{2}\sum_i \sum_k \beta_{ik} \ln X_{jit} \ln X_{jkt} - u_{jt} + v_{jt}$ where $y_{j,t}$ is the output the industry j in period t and $X_{j,i,t}$ and $X_{j,k,t}$ are the variable and fixed inputs (i,k) to the production process. As noted above, the error term is separated into two components, where $v_{j,t}$ is the stochastic error term and $u_{j,t}$ is an estimate of technical inefficiency.

[60] The translog function has become more prevalent because the Cobb-Douglas functional form imposes severe restrictions on the technology by restricting the production elasticities to be constant and the elasticities of input substitution to be unity.

technical change is relatively i[th] input – using (saving). A zero value of β_i indicates that technical change is not biased towards any particular input, i.e. technical change is neutral (Kumbhakar and Hjalmarsson, 1995, Kumbhakar and Hesmati, 1996, and Oh et al., 2009).

Our analysis is based on industry data[61] regarding estimating productive efficiency at industry level of selected countries within European Union, during 1980 – 2005.

Our model is a stochastic frontier model of one output (value added: *lnva*) and three inputs (capital: *cap,* labour: *lab,* time: *time*). We model both the stochastic and the technical inefficiency effects in the frontier, in terms of observable variables, and estimating all parameters by the method of maximum likelihood, in a one - step analysis, as developed by Battese and Coelli (1992, 1995) [62]:

$$\ln va = \alpha_0 + \beta_K \ln cap + \beta_L \ln lab + \beta_T time + \tfrac{1}{2}\beta_{KK} \ln cap^2 + \tfrac{1}{2}\beta_{LL} \ln lab^2 + \tfrac{1}{2}\beta_{TT} time^2 +$$

$$\beta_{KL} \ln cap \ln lab + \beta_{KT} \ln cap time + \beta_{LT} \ln lab time + \sum_{j=1}^{m-1} \alpha_j * Ind_j * input_{it} + (v_{it} - u_{it}) \qquad (3.1)$$

where:

- $input_{it}$ equals either capital, labor or time
- α_0 is the intercept of the constant term
- β_K, β_L, β_T are first derivatives
- β_{KK}, β_{LL}, β_{TT} are own second derivatives
- β_{KL}, β_{KT}, β_{LT} are cross second derivatives[63]

[61] Industry level data are today more easily available (see reviews by Caves, 1998, Harris, 1999, 2001, 2005).

[62] This topic has been broadly examined in: Kokkinou A. (2010e) A note on Theory of Productive Efficiency and Stochastic Frontier Models, *European Research Studies Journal,* Vol. XIII, Issue 4, 2010.

[63] Alternative specifications of the production function can be examined by testing various restrictions on the parameters of the general translog function (Jaforullah and Whiteman, 1999). The translog is

For this analysis, the output is the dependent variable while the explanatory variables are the factors of production which are inputs into the production process. We also impose symmetry restriction on parameters:

$$\begin{aligned} &\beta_{KL} = \beta_{LK} \\ &\beta_{KT} = \beta_{TK} \\ &\beta_{TL} = \beta_{LT} \end{aligned} \qquad (3.2)$$

For constant returns to scale, we impose the following restriction:

$$\begin{aligned} &K + L + T = 1 \\ &\beta_{KK} + \beta_{LK} + \beta_{TK} = 0 \\ &\beta_{KL} + \beta_{LL} + \beta_{TL} = 0 \\ &\beta_{KT} + \beta_{LT} + \beta_{TT} = 0 \end{aligned} \qquad (3.3)$$

And for weak separability, we check whether the linear separability restrictions are satisfied:

$$\beta_{LT} = \beta_{TK} = 0 \qquad (3.4)$$

Technical efficiency $TE_{i,t}$ of the i^{th} industry in year t equals the ratio of observed output level to estimated frontier output:

$$TE_{i,t} = \frac{Y_{i,t}}{\exp(f(X_{i,t};\beta))} = \exp(-u_{i,t}) \qquad (3.5)$$

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homogeneous if $\beta_{LL} + \beta_{LK} = 0$ and $\beta_{KK} + \beta_{LK} = 0$. If in addition, $\beta_L + \beta_K = 1$, the translog is linearly homogeneous. Alternatively, the production function is a (homogeneous) Cobb – Douglas function if $\beta_{LL} = \beta_{KK} = \beta_{LK} = 0$.

To obtain an observation – specific estimate of technical inefficiency (u), we use the Jondrow et al. (1982) result; that is, estimate u from $\hat{u} = E(u \mid v-u)$ in which $(v-u)$ is replaced by the residuals of the production function[64]:

$$TE_i = \exp[E(u_i \mid \varepsilon_i)] \tag{3.6}$$

so that

$$0 \le TE_i \le 1 \tag{3.7}$$

The information on the technical inefficiency (efficiency) of production units (contained in the compound disturbance term) can be obtained using the predictor developed by Jondrow et al. (1982) which is based on the conditional distribution of u given ε^2. We estimate efficiencies as producer-specific fixed effects as proposed by Schmidt and Sickles (1984)[65]. Following Movshuk (2004), the model not only estimates inefficiency levels of particular producers, but also explains their inefficiency in terms of potentially important explanatory variables.

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[64] The model can be estimated using standard ML techniques. Maximum likelihood estimation (MLE) is a popular statistical method used for fitting a mathematical model to real world data. The concept of maximum likelihood (ML) estimation is underpinned by the idea that a particular sample of observations is more likely to have been generated from some distributions than from others. The maximum likelihood estimate of an unknown parameter is defined to be the value of the parameter that maximizes the probability (or likelihood) of randomly drawing a particular sample of observations. ML approach requires distributional assumptions about the disturbances v and u. to assess the sensitivity of our estimates to the choice of distributional assumptions; we consider two alternative specifications for the one – sided variable u:

1. a one – parameter exponential distribution
2. a half – normal distribution

The random term v is unbounded, so we assume that it is normally distributed with zero mean and constant variance. The industry-specific estimates of technical efficiency are estimated from the conditional mean of u, given v – u, as in Jondrow et al. (1982).

[65] However, several studies focus either on industry characteristics (e.g. Roudaut, 2006) or size effects (e.g. Oczkowski and Sharma, 2005; Söderbomand and Teal, 2004).

Because estimation procedures yield merely the residuals ε rather than the inefficiency term u, this term in the model must be observed indirectly (Greene, 1993, Cullinane and Song, 2003). Jondrow et al. (1982) suggest the conditional expectation of u_{it}, conditioned on the realized value of the error term $\varepsilon_{it} = (v_{it}-u_{it})$ as an estimator of u_{it} and, in other words, $E[u_{it}|\varepsilon_{it}]$ is the conditional mean productive inefficiency for the i^{th} industry at any time t. Measures of technical efficiency (TE_i) for each producer can be calculated as[66]:

$$TE_i = \exp[E(u_i \mid \varepsilon_i)] \tag{3.8}$$

so that

$$0 \leq TE_i \leq 1 \tag{3.9}$$

The estimated coefficients of a translog production function can be more readily interpreted in the form of output elasticities for individual inputs calculated from the frontier production function coefficients estimation. Nevertheless, the estimates of the first order coefficients of the variables in the translog function cannot be directly interpreted as elasticities[67]. Thus, we may build a system of equations from

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[66] The Batesse and Coelli model (1992, 1995) is modelling the time varying inefficiency in which time trend is specified to inefficiency term written as u(i,t)=exp(eta(t-T)| u(i)|.

[67] In a translog frontier model, output elasticities can be calculated from the translog estimates using the formula: $\varepsilon_{yi} = \dfrac{\partial \ln y}{\partial \ln x_i} = \beta_i + \beta_{2i} \ln x_i + \sum_{i \neq j} \beta_{ij} \ln x_j$. These estimates can also be expressed as: $\varepsilon_{yi} = \lambda_j \hat{\beta}$ where $\hat{\beta}$ is the full vector of the ML estimators of the parameters and λ_j is a row vector of the same dimension, which has zero entries everywhere except when corresponding to the elements of β involving β_j and β_{jh}. The reported standard errors of the elasticities are: $\hat{V}(\lambda_j \hat{\beta}) = \lambda_j \hat{V}(\hat{\beta}) \lambda'_j$, where $\hat{V}(\hat{\beta})$ is the estimated covariance matrix for β. The sum of the elasticities of output with respect to the three inputs generates an estimated scale elasticity which

differentiating the translog production function with respect to capital and labour factor inputs, as well as time, as follows:

$$\partial \ln va/\partial \ln cap = \beta_K + \beta_{KK} \ln cap + \beta_{KL} \ln lab + \beta_{KT} time + \sum_{i \neq j} \beta_{ij} \ln x_j \qquad (3.10)$$

and

$$\partial \ln va/\partial \ln lab = \beta_L + \beta_{LL} \ln lab + \beta_{KL} \ln cap + \beta_{LT} time \qquad (3.11)$$

and

$$\partial \ln va/\partial \ln time = \beta_T + \beta_{LT} \ln lab + \beta_{KT} \ln cap + \beta_{TT} time \qquad (3.12)$$

Under perfect competition assumption, output elasticity with respect to input equals to the cost share of that input, so:

- β_K represents the average cost share of capital
- β_L represents the average cost share of labour
- $\beta_{KK}, \beta_{KL}, \beta_{KT}$ represent constant capital share elasticity with respect to capital
- $\beta_{LL}, \beta_{LK}, \beta_{LT}$ represent constant labour share elasticity with respect to labour, and
- $\beta_{LT}, \beta_{KT}, \beta_{TT}$ represent constant elasticity with respect to capital, labour, and time.

Output elasticities are estimated by substituting all input values at their variable sample means[68]. More specifically, as far as the time variable is concerned, output

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indicates the presence of increasing or decreasing returns to scale at all output deciles. The elasticity of scale (returns to scale) is defined as: $k = \sum_i \varepsilon_i (x,t)$.

[68] Boisvert (1982) shows that for non-homogeneous functions such as the translog, the function coefficient is not invariant with respect to initial input levels. The function coefficient, ε, is the sum of the elasticities: $\varepsilon = \sum_{j=1} e_j = \sum_{j=1}^{J} \beta_j + \sum_{j=1}^{J} \sum_{h=1}^{H} \beta_{jh} \ln x_j$

calculated at the mean, from the MLEs and used to test for returns to scale. The function coefficient may also be expressed as:

$$\varepsilon = \sum_{i=1}^{n} \lambda_i \hat{\theta} = \lambda \hat{\theta} \text{ where } \lambda = \sum_{j=1}^{n} \lambda_j$$

elasticity with respect to time indicates technical progress. Moreover, as in Becchetti et al. (2003), since any industry may have in principle a different production function we add to the specification *m-1* intercept dummies for the industries aggregated. More specifically, the model is extended in order to include industry specific effects (by employing industry composite dummies), so as to examine differences in efficiency level among different industries. For this reason, our model is estimated including the industry – specific composite dummies, as created above:

$$Y_{it} = \alpha_0 + \sum_{j=1}^{m-1} \alpha_j * Ind_j + \beta_1 cap_{it} + \beta_2 lab_{it} + \beta_3 time_{it} + v_{it} - u_{it} \qquad (3.13)$$

We therefore estimate the model including the products of industry dummies, as well as the first input products with the industry dummies, multiplying the first products by the industry dummies[69]. However, this solution is not completely satisfactory as industry production functions may also differ in input marginal productivities. We therefore estimate the model including the cross products of industry dummies, as well as the first input products with the industry dummies. So the model becomes:

$$Y_{it} = \alpha_0 + \sum_{j=1}^{m-1} \alpha_j * Ind_j \sum_{j=1}^{m-1} \alpha j * Ind * input + \beta_1 cap_{it} + \beta_2 lab_{it} + \beta_3 time_{it} + v_{it} - u_{it} \qquad (3.14)$$

We multiply the first and the cross – products by the industry dummies. In order to allow for industry – specific effects in the computation of the output elasticity for inputs, we have provided for the industry dummies to interact with the first – order terms. There are two goals, first to account for different industry production function (ind_1 – ind_{12}), and second to account for different marginal input productivities (cross

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Then ε minus unity, is divided by the square root of the covariance, which is calculated as $V(\varepsilon) = \lambda V(\theta)\lambda'$ in order to give $S = \frac{\varepsilon - 1}{\sqrt{V(\varepsilon)}}$ which has a t distribution. If this value is significantly smaller than unity, then there are decreasing returns to scale (DRS) and if significantly greater, there are increasing returns to scale (IRS).

[69] In order to allow for industry – specific effects in the computation of the output elasticity for inputs, we have provided for the industry dummies to interact with the first – order terms.

– products with industry dummies). The ind_1 – ind_{12} dummies actually enter the equation by multiplying *lncap* to *time* by these variables and then entering these composite dummies to investigate whether factor inputs differ by industry. Furthermore, in order to analyze the determinants of productive efficiency, we relate the estimated productive efficiency to a number of explanatory variables[70].

As described in Coelli et al. (2005), the ability of a producer to convert inputs into outputs is often influenced by exogenous variables which characterize the environment in which production takes place. When accounting for these variables, it is useful to distinguish between non stochastic variables that are observable at the time key production decisions are made, and unforeseen stochastic variables which can be regarded as sources of production risk.

Furthermore, one of the underlying objectives is to examine how efficiency explanatory performance of the industries has an impact on the industry's technical efficiency. It is therefore important to explore what happens to the estimated model in the presence of efficiency explanatory performance dummy variables. In order to analyze the determinants of productive efficiency, we relate the estimated productive efficiency to a number of explanatory variables and this is achieved when efficiency explanatory performance dummy variables are included in the estimation. Under this model specification, we estimate different variations, so to investigate alternative model specifications.

Moreover, as in Becchetti et al. (2003), since any industry may have in principle a different production function we add to the specification *m-1* intercept dummies for the industries aggregated. More specifically the model is extended in order to include industry specific effects (by employing industry composite dummies), so as to examine differences in efficiency level among different industries. For this reason, our model is estimated including the industry – specific composite dummies. We therefore estimate the model including the products of industry dummies, as well as

[70] This topic has been broadly examined in: Kokkinou A. (forthcoming) Productive Efficiency: An Industry Approach through Stochastic Frontier, *International Journal of Economic Research.*

the first input products with the industry dummies, multiplying the first products by the industry dummies[71]. The two goals, first to account for different industry production function (*ind_1 – ind_{12}*), and second to account for different marginal input productivities (the *ind_1 – ind_{12}* dummies actually enter the equation by multiplying *lncap* to *time* by these variables). Furthermore, in order to analyze the determinants of productive efficiency, we relate the estimated productive efficiency to a number of explanatory variables[72].

Under these model specifications, we estimate three different model variations, so to investigate alternative model specifications[73]:

1. Time-invariant technical efficiency
2. Time-variant technical efficiency (Battese and Coelli, 1992), with only time as efficiency explaining variable
3. Time-variant technical efficiency (Battese and Coelli, 1995), with alternative factors as efficiency explaining variables

Time invariant inefficiency models are restrictive, since we would expect industries to learn from experience and for their technical efficiency levels to change systematically over time and would expect these changes to become more noticeable as *time* gets larger. For these reasons, we need to impose some structure on the inefficiency effects and consider time – varying technical efficiencies, incorporating 'learning-by doing' behaviour (e.g. Pitt and Lee, 1981, Schmidt and Sickles, 1984,

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[71] In order to allow for industry – specific effects in the computation of the output elasticity for inputs, we have provided for the industry dummies to interact with the first – order terms.

[72] This topic has been broadly examined in: Kokkinou A. (forthcoming) Productive Efficiency: An Industry Approach through Stochastic Frontier, *International Journal of Economic Research.*

[73] A relevant topic has been broadly examined in: Kokkinou A. (2009f) Stochastic frontier analysis: empirical evidence on Greek productivity, 4th Hellenic Observatory PhD Symposium on Contemporary Greece & Cyprus, LSE, London.

Kumbhakar, 1987, Battese and Coelli, 1988, Cornwell, Schmidt and Sickles, 1990, Kumbhakar, 1990, Lee and Schmidt, 1993, Battese and Coelli, 1992)[74].

a. A first method (standard model) for dealing with observable efficiency explanatory variables is to allow them to directly influence only the stochastic component of the production frontier (Kumbhakar, Ghosh and McGuckin, 1991):

$$Y_{it} = x_{it}\beta + v_{ti} - u_{it} \tag{3.15}$$

and

$$u_{it} \sim N\left(z_{it}\gamma, \sigma_u^2\right) \tag{3.16}$$

b. A second method (extended model) to account for non-stochastic efficiency explanatory variables is to incorporate them directly into the non-stochastic component of the production frontier:

$$Y_{it} = x_{it}\beta + z_{it}\gamma + v_{ti} - u_{it} \tag{3.17}$$

and

$$u_{it} \sim N\left(z_{it}\gamma, \sigma_u^2\right) \tag{3.18}$$

where z_{it} is a vector of efficiency explanatory variables and γ is a vector of unknown parameters.

To conclude, these two primary model specifications considered are an error components specification with time-varying efficiencies permitted (Battese and Coelli, 1992), and a model specification in which the producer effects are directly influenced by a number of variables (Battese and Coelli, 1995). Furthermore, we

[74] This topic has been broadly examined in: Kokkinou A. (2010f) *Productive efficiency differentials: An empirical approach across industries.* European Network on Industrial Policy International Conference (EUNIP), 2010, Spain.

distinguish between two variable groups used in the econometric analysis, following a value added approach: a) core input variables, b) optional efficiency determining variables[75], as explained in the methodology analysis which follows.

3.3. Methodology

In order to take the efficiency determining variables into consideration, we have to accommodate them into the stochastic frontier model. There are several methods for this. One method suggests the efficiency comparison of a producer with those producers in the sample that have equal or less value of the efficiency explanatory variable. In order to be able to apply this method, the efficiency explanatory variable should be ordered from the least to the most detrimental effect upon efficiency (categorical variable) (Coelli et al., 1998). An alternative method can also be used to include the efficiency explanatory variables, directly into the stochastic frontier model formulation. The efficiency explanatory variables may be included either as inputs, outputs or neutral variables and they may be assumed to be discretionary (under the control of the manager) or not (see Coelli et al, 1998, pps. 168-170, for further discussion). Finally, the two-stage method can be applied. This method involves the computation of a stochastic frontier problem in the first-stage analysis, involving only the traditional inputs and outputs. In the second-stage analysis the efficiency scores from the first-stage are regressed upon the efficiency explanatory variables. The sign of the coefficients of the efficiency explanatory variables indicate the direction of the influence, and standard hypothesis tests can be used to assess the strength of the relationship (Coelli et al., 1998). One disadvantage of the two stage method is that if the variables used in the first-stage are highly correlated with the second-stage variables, then the results are likely to be biased due to multicollinearity. Another disadvantage is that it is only considers radial inefficiency and ignores the slacks[76].

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[75] This topic has been broadly examined in: Kokkinou A. (2010g) *Inside to the Productive Efficiency: Theory and Models*, European Asian Economics, Finance, Econometrics and Accounting Science Association, 2010, Beijing.

[76] Despite of these disadvantages, Coelli et al. (1998), recommend the two-stage method in most cases, because:

(a) It can accommodate more than one variable;

Analyzing the sign and magnitude of technical change is parametrically accomplished by including a time indicator in the time varying frontier model. By linking the stochastic approach to a time trend specification we are able to disentangle the effect of technical change from that of technical efficiency change (Kumbhakar 1990, Battese and Coelli 1992). In the literature a Hicks neutral technical change specification is differentiated from a non – neutral or biased technical change model specification.

The latter allows for the specification investigation of the assumption that technical change is biased in favor of certain input(s) with respect to a single output production framework. By following this non – neutral modeling specification we consequently include beside first and second order time related terms *time* and $time^2$ also terms involving the interactions of the variable inputs and time. As in Helvoigt and Adams (2009), the inclusion of *time* and $time^2$ in the production function is intended to measure the rate of neutral technical change over the data.

Likewise, the coefficients on the interaction terms between time and each of the inputs in the frontier production function are intended to measure the rate of biased technical change. Helvoigt and Adams (2009) also assert that, whereas, the time variable in the frontier production function captures technical change over time (i.e., shifting of the production frontier), in the inefficiency equation the time variable is intended to capture inefficiency change (i.e., changes in the distance from the industry production frontier). The negative (positive) sign on the coefficient of the time variable in the inefficiency equation indicates that the distance of the typical production unit from the technical frontier decreased (increased).

(b) It can accommodate both continuous and categorical variables;

(c) It does not make prior assumptions regarding the influence direction of the categorical variable;

(d) Hypothesis tests may be applied to see if the variables have a significant influence upon efficiencies;

(e) It is simple and therefore transparent.

Nevertheless, there are other competing specifications with respect to the measurement of technical change and total factor productivity available (Baltagi et al. 1995, Kumbhakar and Heshmati 1996, Kumbhakar et al. 2000, Baltagi and Rich, 2003, Baltagi et al., 2005, Kumbhakar 2004), which are based on Baltagi and Griffin (1988).

Later, Kumbhakar (2004) extended this general index specification by adding the definition of TFP growth as an additional equation to be simultaneously estimated with the production system. Kumbhakar (2004) explicitly included the square term of the index $\alpha(time^2)$ corresponding to the second order approximative nature of the translog production function.

In the parametric specification of technology using production/cost/profit functions, a widely used practice has been to use quadratic function of time trend to represent technical change. Baltagi and Griffin (1988) has shown that if a panel data set is available, we could estimate a time specific parameter referring to the state of technology (general index of technical change) instead of using time trend.

The popularity of time trend model comes from the fact that it is adequate in revealing long-run trends in technical change (which may be caused by economy wide, industry-specific or producer -specific product or process innovations and demand or supply shocks). In both approaches technical change is modeled entirely in terms of time and they fail to account for determinants of technological change and productivity growth. If two producers have the same inputs then their technical change will also be the same. In a general index model determinants of technical change are not directly used in the model. These are used in a second stage regression, therefore fails to take into account their direct or interactive effects with the traditional inputs. In an attempt to remedy the above limitations, our model is concerned with specification and estimation of technical efficiency.

The results obtained suggest that efficiency levels in different industries were not always the result of homogeneous influences. The distribution in efficiency across time is considered, as is the question of whether efficiency levels were converging over time.

Thus, our approach undertakes a (one-step) estimation of the stochastic frontier model in conjunction with the parameters of the variables included to explain efficiency, allowing for balanced panel data, as developed by Battese and Coelli (1993, 1995), which is the only model allowing for one-step analysis[77].

The inefficiency effects are defined as a function of the producer specific factors (as in the two-stage approach) but they are then incorporated directly into the MLE. Consequently, in this approach, either the mean or the variance of the inefficiency error component is hypothesised to be a function of the explanatory variables. More specifically, the model decomposes TFP growth into two components: technological growth (essentially, a shift of production possibility frontier, set by best-practice enterprises) and inefficiency changes (i.e., deviations of actual output level from the production possibility frontier). That is, the model accommodates not only heteroscedasticity but also allows the possibility that a producer may not always produce the maximum possible output, given the inputs[78].

In our model, factors that influence efficiency include ICT capital effects, ICT capital share effects, as well as economy openness, Research and Development stock, and capital intensity effects. To analyze these effects, we assume a standard stochastic

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[77] Bhattacharyya et al. (1997) pointed out that when employing regression analysis in the second step to explain the variation of the efficiency scores, it is likely that the included explanatory variables fail to explain the entire variation in the calculated efficiencies and the unexplained variation mixes with the regression residuals, adversely affecting statistical inference. They propose the use of a stochastic frontier regression model, which allows for the decomposition of the variation of the calculated efficiencies into a systematic component and a random component.

[78] However, several studies focus either on industry characteristics (e.g. Roudaut, 2006), or size effects (e.g. Oczkowski and Sharma, 2005; Söderbomand and Teal, 2004). However, using the stochastic possibility frontier approach at an industry level gives a better understanding of inefficiencies emerging from inefficiencies in using factor inputs.

frontier model in which the distribution of technical inefficiency may depend on exogenous variables[79], examining the following alternative variations[80]:

Table 3.1. Models with alternative variables in inefficiency effects

Model	Efficiency determinants	Model
a. Time invariant		
	none	[1]
b. Battese and Coelli (1992)		
	time	[2]
c. Battese and Coelli (1995)		
	ICT capital	[3]
	Economy Openness	[4]
	Capital Intensity	[5]
	R&D stock	[6]
	time, ICT capital	[7]
	time, Economy Openness	[8]
	time, Capital Intensity	[9]
	time, *R&D stock*	[10]

[79] Regarding panel data, in contrast to other stochastic frontier frameworks, the major advantage of this approach is that it does not require any *a priori* assumption regarding the distribution of efficiency across decision making units, as in the approach followed by Stephan et al. (2008)[79]. Unlike most studies, we estimate efficiencies as producer-specific fixed effects as proposed by Schmidt and Sickles (1984).

[80] Empirical evidence shows that accounting for heterogeneity has substantial impacts on the measured efficiency levels. The traditional models tend to underestimate the efficiency as the time-invariant unobserved factors are pushed into the inefficiency component of the model. However, later models treat most of the time-invariant factors as unobserved heterogeneity in the producer-specific random or fixed effect. Greene (2007a) notes that the truth lies somewhere between the two extremes. Farsi et al. (2006) note that the specification of inefficiency and heterogeneity relies on non-testable assumptions. In summary, there is no conclusive evidence in favor of either specification leading to the conclusion that alternative panel data models (the traditional and the more recent models accounting for heterogeneity) can be used to obtain approximate lower and upper bounds for producers' efficiency scores (Farsi et al., 2006).

	ICT capital and Economy Openness	[11]
	ICT capital, Economy Openness, and Capital Intensity	[12]
	time, ICT capital, and Capital Intensity	[13]
	ICT capital, Economy Openness	[14]
	Capital Intensity, ICT capital	[15]
	Economy Openness, R&D Stock	[16]

Source: Own elaboration

In Battese and Coelli (1992) time - varying inefficiency model, a monotonic time trend is specified to inefficiency term. In Battese and Coelli (1995) model considers the possible impact of producer – specific factors in the variances of inefficiency (heteroskedasticity). The translog production frontier used in this study follows Battese and Coelli (1995) stochastic production frontier model by including a time variable in the deterministic kernel of the stochastic production frontier to capture the effect of technical progress. According to Battese and Coelli (1995), the explanatory variables can include intercept terms or any variables in both the frontier and the model for the inefficiency effects, provided the inefficiency effects are stochastic[81].
According to Coelli et al. (2005) it is convenient for estimation purposes, a problem with assuming u_{it} are independently distributed. However, for many industries the independence assumption is unrealistic – all other things being equal, it is expected that efficient producers to remain reasonably efficient from period to period and it is suggested that inefficient producers improve their efficiency levels over time. On the other hand, time invariant inefficiency models are somewhat restrictive, we would expect managers to learn from experience and for their technical efficiency levels to change systematically over time and would expect these changes to become more noticeable as *time* gets larger. For these reasons, we need to impose some structure on the inefficiency effects and consider time – varying technical efficiencies (incorporating '*learning – by doing*' behaviour). Consequently, the stochastic production frontier model is extended to allow data to be modeled over time with time

[81] Battese (1998) further notes that the non-neutral models have important bearing upon the estimation of the elasticity of the mean output with respect to an input variable, which is also an explanatory variable for the inefficiency effects.

– invariant technical efficiency (e.g. Pitt and Lee, 1981, Schmidt and Sickles, 1984, Kumbhakar, 1987, Battese and Coelli, 1988) or time – varying technical efficiency (e.g. Cornwell, Schmidt and Sickles, 1990, Kumbhakar, 1990, Lee and Schmidt, 1993, Battese and Coelli, 1992)[82].

The parameters of the stochastic frontier model and the inefficiency effects model are estimated using maximum likelihood estimation (MLE), which is the preferred estimation technique whenever possible (Coelli, Rao and Battese 1998, Battese and Coelli, 1993)[83]. The parameters estimated include β, λ and σ^2 where $\lambda = \left(\sigma_u / \sigma_v\right)$ and $\sigma^2 = \left(\sigma_u^2 + {}_v^2\right)$. Moreover, the model estimation results provide the joint probability density function (pdf) also known as the likelihood function. The likelihood function expresses the likelihood of observing the sample observations as a function of the unknown parameters β and σ^2. The maximum likelihood (ML) estimator of β is obtained by maximizing this function with respect to β[84]. Specifically, the maximum likelihood estimator can be shown to be consistent and asymptotically normally distributed with variances that are no larger than the variances of any other consistent and asymptotically normally distributed estimator (i.e. the ML estimator is asymptotically efficient).

3.3.1. Existence of Technical Efficiency: The parameter λ

A main instrument to measure the inefficiency component of the model is the parameterλ:

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[82] Coelli et al.(2005) classify different structures according to whether they are time – invariant or time – varying and provide a broad analysis of time – invariant inefficiency models, as well as time – varying inefficiency models.

[83] According to Battese and Coelli (1995), the explanatory variables can include intercept terms or any variables in both the frontier and the model for the inefficiency effects, provided the inefficiency effects are stochastic.

[84] Thus, in the special case of the classical linear regression model with normally distributed errors, the ML estimator for β is identical to the OLS estimator.

$$\lambda = \frac{\sigma_u^2}{\sigma_v^2} \tag{3.19}$$

The statistical significance of λ obtained from the ML estimates indicates the existence of a stochastic frontier function (Schmidt and Lin, 1984)[85]. If λ is statistically different from zero, it implies that the difference between the observed and the frontier production is dominated by technical inefficiency[86]. If λ is not statistically significant from zero, it implies that any difference in the production is attributed solely to symmetric random errors. In other words, industries operating on the frontier are accepted to be technically efficient and except for random disturbances, are receiving maximum output response for the combinations of the inputs used.

In addition to testing hypotheses concerning the variable parameters, stochastic frontier analysis is interested in testing for the absence of inefficiency effects (Coelli et al., 2005). If the model has been estimated using the method of ML, we can test such a hypothesis using a simple z – test (because unconstrained ML estimators are asymptotically normally distributed).

3.3.2. Measurement of Technical Efficiency: The parameter γ

Technical efficiency can be measured using a variance ratio parameter denoted by γ as follows (Battese and Corra, 1977):

$$\gamma = \frac{\sigma_u^2}{\sigma^2} \tag{3.20}$$

[85] If the parameter λ is significant, this indicates that the use of the frontier production function is appropriate.

[86] The parameter λ is an indication that the one sided error term u dominates the symmetric error v, so variation in actual production comes from differences in industries management practice rather than random variability.

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$ and $0 \le \gamma \le 1$.

Using the composed error terms of the stochastic frontier model, γ defines the total variation in output from the frontier level of output attributed to technical efficiency[87] indicating the ratio of the unexplained error and the total error of the regression (Aigner, Lovell, Schmidt, 1977). The variance parameter γ captures the total output effect of technical efficiency, suggesting the percentage (%) of the residual which is due to inefficiency. Considering the variance parameter γ lies on the interval [0,1], if the estimate is close to 1 and significant, this indicates that most of the total variation in output is attributable to technical efficiency. In case of γ, there are two alternative hypotheses tested:

- Under the null hypotheses the inefficiency effects are not present (H_0: $\gamma=0$) implying that industries are fully efficient. The model is equivalent to the traditional average response function without the technical inefficiency effects term, *u* (Coelli at el., 1998).
- The alternative hypothesis, (H_1: $\gamma>0$), implies that inefficiency effects are present and hence *u* is included in the estimation.

The parameters of the stochastic frontier model are mainly estimated using maximum likelihood estimation (MLE) and is the preferred estimation technique whenever possible (Coelli, Rao and Battese 1998). Using the composed error terms of the stochastic frontier model (1), the total variation in output from the frontier level of output attributed to technical efficiency is defined by:

$$\gamma = \sigma_u^2 \big/ \left(\sigma_u^2 + \sigma_v^2\right) \tag{3.21}$$

In the truncated and half-normal distribution, the ratio of industry specific variability to total variability, γ, is positive and significant, implying that industry specific

[87] The value of e.g. $\gamma = 0.12$ implies that 12% of the discrepancies between the observed and frontier values of output is due to technical inefficiencies.

technical efficiency is important in explaining the total variability of output produced. This is done with the calculation of the maximum likelihood estimates for the parameters of the stochastic frontier model.

3.3.3. Measurement of Technical Efficiency: The LR – test parameter

Before proceeding with the estimation of the SF models, it is important to ascertain statistically whether technical inefficiency effects are indeed present in the model. The model for inefficiency effects can only be estimated if the inefficiency effects are stochastic and have a particular distributional specification. Hence, there is growing interest to test the null hypotheses that the inefficiency effects are not stochastic; the inefficiency effects are not present and the coefficients of the variables in the model for the inefficiency effects are zero. These null hypotheses are tested through imposing restrictions on the model and using using the generalized likelihood ratio statistic (LR - test) to determine the significance each of the restrictions (Greene, 2003 a,b, Coelli, 1998).

A series of formal hypothesis tests are conducted to determine the distribution of the random variables associated with the existence of technical inefficiency and the residual error term. These are tested through imposing restrictions on the model and using the generalized likelihood-ratio statistic to determine the significance of the restriction.

The generalized likelihood ratio statistic (LR - test) is given by[88]:

$$LR - test = -2\{\ln[L(H_0)] - \ln[L(H_1)]\} = -2\ln\left[\frac{L(H_0)}{L(H_1)}\right] \qquad (3.22)$$

[88] Various tests of null hypotheses for the parameters in the frontier production functions and in the inefficiency models are performed using the generalised likelihood-ratio test statistic.

where $\ln[L(H_0)]$ and $\ln[L(H_1)]$ are the values of the log-likelihood function for the frontier model under the null and alternative hypotheses. The LR - test indicates the ratio of standard deviation attributable to inefficiency relative to the standard deviation due to random noise. A straightforward implication of LR - test $\rightarrow 0$ is that either σ_u^2 goes to zero or σ_v^2 goes to infinity. Hence, no inefficiency exists and all deviations are due to random noise. Likewise, for LR - test $\rightarrow \infty$ we note that either $\sigma_u^2 \rightarrow \infty$ or $\sigma_v^2 \rightarrow 0$, which implies that all deviation are explained by inefficiency. Then, inefficiency is deterministic and resembles approaches excluding random noise[89], such as DEA (Koetter, 2006).

The LR - test statistic is non-negative, and follows χ_r^2 distribution under the null hypothesis, where r denotes the number of restrictions. However, if the null hypothesis is true, the LR - test has approximately chi – square (or mixed square) distribution with degrees of freedom equal to the difference between the parameters estimated under H_1 and H_0, respectively. If the null hypothesis involves γ =0, namely the inefficiency effects are absent from the model, as specified by the null hypothesis, H_0: $\gamma=\delta_0=\delta_i=0$, then LR - test is approximately distributed according to a mixed chi-square distribution with $i+1$ degrees of freedom, the number of degrees of freedom given by the number of restrictions imposed (Coelli, 1995) because γ =0 is a value on the boundary of the parameter space for γ. Here the log-likelihood ratio of the half-normal model is that of the null hypothesis, while the log-likelihood ratio of truncated normal model is that of the alternative hypothesis. In this case, critical values for the generalized likelihood-ratio test are obtained from Table 1 of Kodde and Palm (1986).

3.4. Hypothesis Testing

To test the general hypotheses that inefficiency effects are either absent or present, or have a simpler distribution than we have assumed, we use one – sided generalized likelihood – ratio tests. Results from these tests provide evidence to reject/accept the

[89] An insignificant estimate of LR - test means that no inefficiency prevails and all of the error is due to random noise and specification of a stochastic frontier model is inappropriate.

hypotheses: that inefficiency effects are absent, that observed inefficiencies have no random component and that the efficiency explanatory (socioeconomic) characteristics of industries are not jointly significant in explaining observed patterns of inefficiency. If we reject, it means that inefficiencies are present, that these inefficiencies have a stochastic component, and that the non – stochastic component of these inefficiencies is systematically related to certain characteristics of the observed industries. We also estimate the information criteria for each estimated model, namely, the Akaike information criterion, the Bayesian Schwarz information criterion and the Hannan – Quinn criterion (model selection criteria). These criteria attempt to answer the question regrading the overall model fit. The criteria differ in how each of these aspects is measured and weighted.

The Akaike information criterion (AIC) is estimated as: $\dfrac{-2\ln \hat{L}(M_{\beta})+2k}{n}$.

The Bayesian Schwarz information criterion (BIC) is estimated as: $\dfrac{-2\ln \hat{L}(M_{\beta})+\ln(n)k}{n}$.

The Hannan – Quinn criterion (HQIC) is estimated as: $HQIC = n\ln\left(\dfrac{RSS}{n}\right)+2k\ln\ln(n)$,

where k is the number of parameters and n is the sample size[90]. Information criteria are often used as a guide in model selection (Aznar Grasa 1989). Information criteria are often used as a guide in model selection. The notion of an *information criterion* is to provide a metric that strikes a balance between goodness of fit and a small number of parameters. The most accurate models in stochastic frontier estimation present the lowest value of each of these criteria (i.e. minimize the criteria).

As far as the inefficiency effects presence, in this estimation, we use the λ - parameterization of Aigner, Lovell and Schmidt (1977), $H_0 : \lambda = 0$ and $H_1 : \lambda > 0$. The test statistic is: $z = \dfrac{\overline{\lambda}}{se(\overline{\lambda})}, N(0,1)$, where $\overline{\lambda}$ is the ML estimator of λ and $se(\overline{\lambda})$ is the estimator for its standard error.

The statistical significance of λ obtained from the ML estimates indicates the existence of a stochastic frontier function (Schmidt and Lin, 1984). If λ is statistically different from zero, it implies that the difference between the observed and the frontier production is dominated by technical inefficiency. If λ is not statistically significant from zero, this implies that any difference in the production is attributed

[90] In general, the more variables included in the regression, the smaller will be the *RSS*. But if a variable only contributes marginally to the reduction of the *RSS*, it should not be included.

solely to symmetric random errors. In other words, industries are operating on the frontier, are technically efficient and except fro random disturbances, are receiving maximum output response for the combinations of the bundle of inputs used.

The ratio of industry specific variability to total variability, γ, shows the degree in which industry specific technical efficiency is important in explaining the total variability of output produced. The value of γ estimates the percentage of the discrepancies between the observed and the maximum frontier values of output is due to the shortfall of realized output from the frontier is primarily due to factors that are within the control of the industry. In other words, γ measures total variations in output from the frontier attributable to technical efficiency[91].

One can also test whether any form of stochastic frontier production function is required at all by testing the significance of the γ parameter.[92] If the null hypothesis, that γ equals zero, is accepted, this would indicate that σ_u^2 is zero and hence that the U_{it} term should be removed from the model, leaving a specification with parameters that can be consistently estimated using ordinary least squares.

3.5. Concluding Remarks

The objective of this chapter is to estimate the Transcendental Logarithmic Production Function of manufacturing industries in selected E.U. economies, considering a panel data model for inefficiency effects in stochastic production frontiers based on the Battese and Coelli (1992, 1995) models, providing translog effects, as well as industry effects.

[91] One can also test whether any form of stochastic frontier production function is required at all by testing the significance of the γ parameter.[91] If the null hypothesis, that γ equals zero, is accepted, this would indicate that σ_u^2 is zero and hence that the U_{it} term should be removed from the model, leaving a specification with parameters that can be consistently estimated using ordinary least squares.

[92] It should be noted that any likelihood ratio test statistic involving a null hypothesis which includes the restriction that γ is zero does not have a chi-square distribution because the restriction defines a point on the boundary of the parameter space. In this case the likelihood ratio statistic has been shown to have a mixed chi-square distribution. For more on this point see Lee (1993).

More specifically, this chapter estimates stochastic parametric frontiers for which the producer effects are first an exponential function of time, followed by the estimation of producer effects as an exponential function of time and related exogenous variables (efficiency explanatory factors). The model decomposes technical efficiency into two components: technological growth (essentially, a shift of production possibility frontier, set by best-practice industries) and inefficiency changes (i.e., deviations of actual output level from the production possibility frontier). The estimated model accommodates not only heteroscedasticity but also allows the possibility that an industry may not always produce the maximum possible output, given the inputs available.

Our analysis presents different alternative models for technical efficiency estimations, as well as their empirical results. The alternative models are being compared according to their results regarding the evolution of technical change during 1980 - 2005, the estimation of technical efficiency, as well as the distribution of technical efficiency. The chapter begins with a description of the model specifications, the data set, and the definition of the variables, along with their descriptive statistics. Then the empirical model is formed with estimation results for different alternative model specifications, providing the industry -level estimates of technical efficiency using the time-varying inefficiency model within a composite error framework. Further, factors that determine variations of technical efficiency are established and a comparison of technical efficiency is made, both before and after accounting for different explanatory variables in the inefficiency term. This includes reporting the estimated technical efficiency of an industry, the discussion of causes of variations in efficiency explanatory efficiency and discussion of the conditional efficiency.

More specifically the model is extended in order to include industry specific effects (by employing industry composite dummies), so as to examine differences in efficiency level among different industries. For this reason, our model is estimated including the industry – specific composite dummies. The results include reporting the estimated technical efficiency and the related explanatory variables.

Chapter 4

Stochastic Frontier Models: Industrial Context

Abstract

In stochastic frontier model analysis it is acknowledged that the estimation of production functions must respect the fact that actual production cannot exceed maximum possible production given input quantities. Consequently, one of the main questions is to investigate the relationship between inefficiency and a number of factors which are likely to be determinants, and measure the extent to which they contribute to the presence of inefficiency. Overall, these determining factors characterize the process of technological change. Stochastic frontier models assume that producers operate under the same production technology and that the inefficiency distribution across individuals and time are homogeneous. Estimation of technical efficiency has been the subject of research in many empirical studies on industrial productivity, contributing to the theoretical development and empirical application of SFA at both the firm and industry levels, with the purpose of screening out the external effects and statistical noise from the producer's performance and achieving a more accurate efficiency measure (Wang, 2000). Following these fundamental approaches, there has been a rapid increase in the volume of research on analysis of efficiency in production, both in theoretical and empirical research. Most of the literature focused mainly on stochastic frontier model with distributional assumptions by which efficiency effects can be separated from stochastic element in the model and for this reason a distributional assumption has to be made. Unobservable individual effects also play an important role in the estimation of panel stochastic frontier models. In contrast to the conventional panel data literature, however, studies using stochastic frontier models often interpret individual effects as inefficiency (Schmidt and Sickles, 1984), such as technical inefficiency in a stochastic production frontier model.

Chapter 4 focuses on reviewing the stochastic frontier analysis literature regarding estimating inefficiency it industrial level, as well as explaining producer heterogeneity along with the relationships with productive efficiency level. The chapter begins with a general overview of the main research papers on estimating productive efficiency in different industries, both in aggregate and disaggregate level, providing the main hypotheses and results of each case. Then, the chapter continues with explaining producer heterogeneity, as well as the main determining factors towards efficiency differentiations.

Moreover, this chapter analyses the institutional context of the thesis, which lies within European industry and science and technology, where an important focus of policy and research interest has a significant role of innovation creation and diffusion and trade openness. Since all of these issues are important for the thesis, this chapter discusses the institutional context regarding the thesis research.

More specifically, this chapter also presents a discussion of the environment, institutions and policy issues, to adequately place the thesis research application within this institutional context, focusing on the institutional setting, namely European countries and industries, as well as literature relating to innovation and industrial policy and practice in European Union.

This chapter also provides an overview of the specific innovation policies that are implemented at European level, highlighting, where possible, the connections between these policies and productive efficiency. More specifically, Chapter 4 describes the main kinds of policy interventions that are implemented, providing at the same time some useful elements in order to understand the assumptions and theories which underpin them. This chapter also presents a brief survey of the choices concerning industrial and innovation policy regarding technical efficiency enhancement, describing the instruments, the actors involved in their preparation, the actions undertaken – both those explicitly identified as 'industrial' and 'innovation policy' and those that, although promoted in the context of other policies, affect the same channels or pursue similar aims.

4.1. Introduction

As analysed in the previous two chapters, in the standard stochastic frontier model it is acknowledged that the estimation of production functions must respect the fact that actual production cannot exceed maximum possible production given input quantities. The central question of the efficiency methodology is the following: first one has to fit the data to a specific frontier and from it compute the producer's efficiency measurements comparing the observed values with the optimum values defined by the estimated frontier. A question of interest is whether inefficiency occurs randomly across producers, or whether some producers have predictably higher levels of inefficiency than others. If the occurrence of inefficiency is not totally random, then it should be possible to identify factors that contribute to the existence of inefficiency (Reifschneider and Stevenson, 1991). The important task is to relate inefficiency to a number of factors that are likely to be determinants, and measure the extent to which they contribute to the presence of inefficiency.

Estimation of technical efficiency has been the subject of research in many empirical studies on industrial productivity (Hesmati and Kumbhakar, 2010). Aigner, Lovell, and Schmidt (1977), Battese and Coelli (1992, 1995), Coelli (1995), Kumbhakar and Lovell (2000), and Ahn, Lee, and Schmidt (2001) contributed to the theoretical development and empirical application of SFA at both the producer and industry levels. Moreover, Fried, Schmidt, and Yaisawarng (1999) and Fried, Lovell, Schmidt, and Yaisawarng (2002) have proposed various methods, which involve the use of SFA for the purpose of screening out the external effects and statistical noise from the producer's performance and achieving a more accurate efficiency measure (Wang, 2000). Following these foundamental approaches, there has been a rapid increase in the volume of research on analysis of efficiency in production, both in theoretical and empirical research.

Empirical attention to production functions at a disaggregated level is a literature that began to emerge in the 1960s, i.e. Hildebrand and Liu (1965) and Zellner and Revankar (1969). Since early, stochastic frontier production analysis was employed by researchers in order to estimate industry and producer efficiency and stochastic frontier models have been applied and modified in industrial research (e.g. Bagi and Huang, 1983; Battese and Corra, 1977; Kalirajan, 1981; Tyler and Lung-Fei (1979); Waldman, 1984; Färe et al., 1985; Kirkley et al., 1995; Coelli et al., 1998). Cornwell et al. (1990) and Kumbhakar (1991) were among the first to propose a stochastic production frontier model with time varying technical efficiency. Stochastic frontier approach has found wide acceptance within the industrial settings (Battese and Coelli, 1992; Coelli and Battese, 1996), because of their consistency with theory, versatility and relative ease of estimation and there have been numerous studies of the frontiers literature including Førsund et al. (1980), Greene (1993, 1997), Bauer (1990 a,b), Battese (1992), Schmidt (1985), Cornwell and Schmidt (1996), Kalirajan and Shand (1999), Murillo-Zamurano (2004), Baten et al. (2009), Kumbhakar and Lovell (2000), Coelli, Rao and Battese (1998) and Fried et al. (2008).

Most of the literature focused mainly on stochastic frontier model with distributional assumptions by which efficiency effects can be separated from stochastic element in the model and for this reason a distributional assumption has to be made (Bauer 1990 a,b), i.e.: exponential distribution (Meeusen and van den Broeck 1977); normal distribution truncated at zero (Aigner, Lovell and Schmidt 1977); a half-normal distribution truncated at zero (Jondrow et al. 1982) and two-parameter Gamma or Normal distribution (Greene 1990). However, these are computationally more complex, there are no priori reasons for choosing one distributional form over the other, and all have advantages and disadvantages (Coelli, Rao and Battese 1998).

This chapter focuses on reviewing the stochastic frontier analysis literature regarding estimating inefficiency it industrial level, as well as explaining producer heterogeneity along with the relationships with productive efficiency level. The chapter begins with a general overview of the main research papers on estimating productive efficiency in different industries, providing the main hypotheses and results of each case. Then, the chapter continues with explaining producer heterogeneity, as well as the main deterring factors.

4.2. Heterogeneity and Aggregation

The empirical methods of frontier and non-frontier production functions were primarily developed to be used for analyses of efficiency mainly across different producers, and not across industries and countires using aggregate data. Such an aggregation across industries and countries may create significant problems because of heterogeneity within the industry or the country. For example, while the production technology can perhaps be assumed to be similar witin a given industry, this is not the case when data for different regions, and particularly industries, are pooled. What it is important is to acknowledge the potential problems which it generates and attempt to address these through the empirical methiods and framework. Recent contributions include Eberhardt and Teal (2011) and Oh (2012), who demonstrate the serious implications of such aggregation for estimation both of the frontier and efficiency. Empirical estimation should take into consideration that there is likely to be some form of aggregation bias. As also becomes apparent from the analysis by Oh (2012), if SFA approach is used for the same industries and countries, but in one case aggregate industry-level data is used, and in another firm-level data is used, the results will be different. This is meant to show the impacts of aggregation bias, on the basis, that firm-level data adds up to the industry-level but smooths out firm-level heterogeneity.

Eberhardt and Teal (2011) present two general empirical frameworks for cross-country growth and productivity analysis and demonstrate that they encompass the various approaches in the growth empirics literature of the past two decades. Eberhardt and Teal (2011) argue that there are a number of important reasons why the standard cross-country growth regression framework needs to be reconsidered. Intuitively, the heterogeneity in production technology could be taken to mean that countries can choose an appropriate production technology from a menu of feasible options. Further, the cross-country heterogeneity in TFP relates to differences both in the underlying processes that make up TFP and in the impact of those processes on output.

4.3. Estimating Efficiency at industrial aggregate level

Estimation of technical efficiency has been the subject of research in many empirical studies on industrial productivity, contributing to the theoretical development and empirical application of SFA at industry levels, with the purpose of screening out the external effects and statistical noise from the producer's performance and achieving a more accurate efficiency measure. Empirical literature based on aggregate data, uses empirical models that are very similar to the work in this thesis, and are concerned with efficiency measurement for countries or regions in the European Union. Since the specific context of this thesis is on aggregate production functions and efficiency of industries/countries, relevant literature is that of western economies using aggregate rather than firm-level data, drawing reference to a recent literature that has spawned from Kumar and Russell (2002) using DEA and Kneller and Stevens (2006) using SFA. Other recent empirical contributions based on aggregate cross-country or cross-region data include: Koop (2001), Angeriz et al. (2006), Halkos and Tzeremes (2009), Ezcurra et al. (2009) and Bos et al. (2010), most of which focus on EU regions and countries. In addition, there are studies based on aggregate data focusing on specific EU countries: the UK (Driffield and Munday, 2001), Spain (Alvarez, 2007; Puig-Junoy and Pinilla, 2008) and Denmark (Bhattacharjee et al., 2009). All of these articles are based on aggregate data, use empirical models that are very similar to the work in this thesis, and are concerned with efficiency measurement for countries in the EU. This chapter, exploring the theory of Stochastic Production Frontiers, especially discusses thoroughly the literature on aggregate data and efficiency measurement for countries, drawing links to the theory used in later chapters to discuss how the results in the thesis are new or different, and thereby highlight where the contribution of the thesis truly lies.

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The process of output growth-either within countries or within industries within countries is still imperfectly understood. Standard economic models imply that the level of output by an economic entity should depend only on the inputs used. The new growth theory literature has emphasized factors such as technological spillovers, increasing returns, learning by doing, and unobserved inputs (e.g., human capital), whereas the empirical industrial organization literature (e.g., Caves and Barton 1990) has emphasized the degree of openness of countries to imports and industry structure. Another aspect of efficiency measurement literature focuses on estimating productive efficiency at aggregate data level. Since this thesis focuses on aggregate data level, this literature is rather important, both for estimations using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA).

An enormous body of research has attempted to explain why some countries or industries produce more with their inputs than do others. The empirical economic growth literature [Levine and Renelt (1992), and Persson and Tabellini (1994)] typically carried out cross-country regressions that attempt to explain economic growth using different sets of explanatory variables, both usimg DEA and SFA analysis.

The seminal paper that applied DEA to the aggregate economy was Färe et al. (1994). Fare et al. (1994) use data envelopment analysis (DEA) to examine country-specific inefficiency in a subset of the OECD countries. In this paper, the aforementioned decomposition into the two components, noted above, is used to examine productivity growth in 17 Organization of Economic Cooperation and Development (OECD) countries in the post-war period. What is more, Färe et al. (1994) first applied production-frontier methods to empirical international economic growth.

Koop, Osiewalski, and Steel (1999) carry out a similar efficiency analysis. However, neither article includes data on different industries within a country, and thus they are unable to approach the issues raised by this article. Furthermore, these articles assume a common world production frontier for real GDP. Given the large differences in the composition of GDP across countries, this assumption is at best a crude approximation. Caves and Barton (1990) use industrial data for manufacturing industries within the United States, but do not allow for ties between industries or for cross-country comparisons. Bernard and Jones (1996) use industrial data for OECD countries that are similar to those used in this thesis. The focus of Bernard and Jones (1996) article is on convergence of productivity and it is worth noting that the authors find striking differences across industries. The assumption of a common frontier is, in principle, testable (Durlauf and Johnson, 1995). But given the paucity of data and the flexible specification adopted, such tests would have little power in the present case. From an economic point of view, the frontier is deterministic. However, factors such as measurement error exist and hence add an error term to the model. The addition of this error term makes the frontier stochastic, and the latter terminology is adopted to distinguish such models from those which assume that measurement error does not exist.

Empirical contributions based on aggregate cross-country or cross-region data, most of which focus on EU regions and countries, include Koop (2001) who relates to aggregate production functions and efficiency of industries/ countries. Koop (2001) uses data from 11 countries for 19 years to investigate the forces driving output change in 6 manufacturing industries. A flexible model is adopted that allows for the decomposition of output changes into three types of change: technical, efficiency, and input. This framework allows, among other things, for the investigation of:

- the relative roles of the three components of output growth in each industry,
- the manner in which efficiency change moves over the business cycle, and
- potential technical spillovers from one industry to another.

The use of industrial data implies that Koop (2001) article has a different focus. Koop (2001) develops a modeling strategy and presents empirical evidence that sheds light on some of the points raised in both these literatures. A structural methodology is adopted that allows for the decomposition of output change into efficiency, technical, and input change using data on 6 manufacturing industries for 11 OECD countries. All these countries reasonably can be assumed to have access to the same technology in each industry, so for each industry, each country can be thought of as fac-ing the same production frontier. Koop (2001) considers a model that assumes independence across industries, but the general modeling strategy advocated allows for the possibility that production frontiers in the 6 industries move together. For the latter case, the degree to which technical change in one industry spills over to another industry can be measured. Data from 1970-1988 are available and examine patterns of efficiency change and technical change over time.

Koop (2001) aims to shed light on issues such as convergence and catch up and answer important questions such as, "What is driving output growth in an industry?" "What happens to efficiency over the business cycle?" "Is openness to trade an important factor in forcing economic efficiency?". Empirical results indicate: (1) non constant returns to scale seem to be present, (2) the marginal product of capital tends to be lower than the marginal product of labor, (3) technological change involves the marginal products of capital and labor changing over time, and (4) the various industries exhibit completely different production technologies. With regard to the decomposition, on average, positive technical change is found to play a key role in explaining output growth in all industries. Negative input change plays an important part in the stagnation of textiles and metals industries. On average, efficiency change has little role to play. However, these cross-country averages hide many interesting special cases that are discussed in detail.

Koop (2001) article begins with a stochastic production frontier model where industrial output Y is a function of capital K and labor L and then seeks to determine what insights can be gained through the use of careful statistical techniques. In statistical terms, interest in this article centers on the conditional distribution of industrial Y given K and L, and economic theory guides the construction of the distribution. In other words, Koop (2001) imposes economic regularity conditions and assume inefficiency to have a one-sided distribution. The decomposition of output growth into components due to input, technical, and efficiency growth provides a convenient way of thinking about model extensions. For any new possible explanatory variable, one can ask whether it should affect: (1) the input component and thus should enter as an input, (2) the technical change component and thus should affect the frontier parameters directly, or (3) the efficiency component, in which case it should enter the efficiency distribution. This approach is in contrast to the cross-sectional regression articles that consider a myriad of possible additional explanatory variables. Statistically, this translates into consideration of the distribution of Y conditional on K, L, and many other variables. However, the investigation of such a complicated distribution typically involves select-ing only a few out of a potentially enormous number of conditioning variables. Given the restrictiveness of such a statistical model and the lack of robustness in cross-country growth regressions (see

Levine and Renelt 1992), Koop (2001) argues that the present approach is, at the very least, a reasonable alternative. It is worth noting that the present approach can be thought of as using economic theory to move one step away from reduced-form regression approaches. The existence of a best practice technology that is non decreasing in inputs is the only economic theory used. Some theories of industrial organization (see Caves and Barton 1990), for example, imply that increased openness to imports should increase efficiency in an industry. This means that the openness variable should enter the efficiency distribution and not the production frontier itself.

However, much of the empirical economic growth literature assumes constant returns to scale. For instance, the growth accounting literature typically imposes constant returns to scale and sets the marginal products of labor and capital equal to their shares in total income (Barro and Sala-I-Martin, 1995). Econometric approaches with constant returns to scale (Romer, 1994) also exist. A rough summary of the findings of both these approaches is that they impose constant returns to scale and find the marginal product of capital to be around 0.4, at least for the OECD countries (Barro and Sala-I-Martin, 1995). Furthermore, Koop, Osiewalski, and Steel (1999, 2000), using different data sets and models, find results that are consistent with those of Koop (2001).

Koop (2001) is related to the growth accounting literature (Maddison 1987), which decomposes output growth into two parts: one explained by input changes and the other the unexplained residual, or "technical change." Growth accounting techniques have been used in a wide variety of empirical studies, and many of these articles have increased the understanding of economic growth. However, the interpretation of the unexplained residual as technical change is unreasonable unless it is assumed that all industries in all countries are producing on their frontiers. In contrast, by making some reasonable assumptions, the model of this article allows me to give a structural interpretation to the unexplained residual. Koop (200d1) interprets this residual as a combination of inefficiency and measurement error. Technical change is associated with the movement of the best-practice production frontier.

To conclude, Koop (2001) article is intended to be an empirical study of manufacturing output growth in OECD countries. However, it is also intended to develop and motivate new models and econometric techniques for working with industrial data. However, it is relevant to digress briefly to discuss more general modeling issues that might be relevant in other data sets.

Koop (2001) explores the driving forces of output growth in six manufacturing industries during the 1970s and 1980s, while Kneller and Stevens (2006) investigate the sources of inefficiency in nine industries over the same period. With the exception of Koop (2001), who estimates six frontiers for six industries, these studies all benchmark industries (countries) against a common production frontier. However, it may well be the case that not all industries share a single common frontier. Recent theoretical and empirical contributions (Basu and Weil, 1998; Los and Timmer, 2005) have stressed the 'appropriateness' of technology as industries (countries) choose the best technology available to them, given their input mix. Industries are members of the same technology club if their marginal productivity of labor and capital (the technology parameters that characterize the efficient production frontier) are the same for a given level of inputs. In other words, their input/output combinations can be described by the same production frontier (Jones, 2005). With the exception of a handful of studies that accommodate these technology clubs, therefore, allowing for parameter heterogeneity when estimating frontier or conventional production functions, the empirical (frontier) literature has largely ignored this issue.

Bos et al. (2010) investigate the forces driving output growth in a panel of manufacturing industries over the period 1980–1997. Relevant past studies typically assume that: (i) industries use resources efficiently and (ii) the underlying production technology is the same for all industries. Technical change is a crucial component for growth for industries, while input (capital, in particular) growth plays an important role. Policy makers generally agree that higher R&D spending is desirable and are willing to subsidize and/or give tax credits to industries that engage in R&D. According to results, the effects of an increased R&D effort depend on the allocation of R&D tax credits/subsidies. Bos et al. (2010) also find some evidence of a positive relationship between R&D and efficiency. Therefore, a preliminary conclusion can be that increasing the R&D effort facilitates the absorption of existing technologies. However, increases in R&D effort do not always lead to increased technical growth.

Bos et al. (2010) allow for different production technologies, differing from past attempts, which mainly relied on ex ante divisions to classify industries into different technology clubs, by endogenizing the technology club allocation, augmenting the stochastic frontier production model with a latent class structure. A logit model is used to condition group membership probabilities on technological effort as measured by R&D. As a result, technology parameters depend on the effect of the technological effort on club membership probabilities. Production function parameters differ across clubs and are estimated simultaneously with membership probabilities. Based on club-specific production parameters, Bos et al. (2010) identify technical, efficiency and input growth for endogenously determined technology clubs, introducing further flexibility to the model by permitting industries to switch between technology clubs overtime. The efficiency of industries in different technology clubs is estimated simultaneously, but relative to each club's specific frontier. Thus, the latent class stochastic frontier model avoids the imposed assumption of a common production function for all industries, while still yielding results that are comparable across industries at a given point in time.

Kumar and Russell (2002) suggest that economic growth convergence can be considered as the movements of countries toward a world production frontier. In Kumar and Russell (2002) analysis, the world production frontier is constructed using deterministic methods requiring no specification of functional form for the technology, nor any assumption about market structure or the absence of market imperfections. Then, using DEA analysis, they analyze the evolution of the cross-country distribution of labor productivity, decomposing labor-productivity growth. More specifically, Kumar and Russell (2002) used production-frontier methods to analyze the evolution of the distribution of labor productivity in terms of decomposition into three components; technological change, technological catch-up, and capital accumulation. Labour-productivity growth is decomposed into technological change, technical efficiency change and a capital accumulation effect, and then they analyse the contribution of these components to convergence.

This approach originally employed by Kumar and Russell (2002) enables decomposing the growth of labor productivity growth into some components to empirically analyze economic growth, namely into efficiency change, technological change and capital deepening (Yamamura and Inyong, 2007):

- technological catch-up (movements toward or away from the frontier): technological catch-up does not seem to have been a force for convergence as relatively rich as well as poor countries have benefited from catch-up.
- technological change (shifts in the world production frontier): Technological change has not been neutral, apparently benefiting rich countries more than poor.
- capital accumulation (movement along the frontier): It is primarily capital deepening, as opposed to technological change or catch-up, that has contributed the most to both growth and bipolar international divergence of economies.

Kumar and Russell (2002) conducted not only regression analysis but also distribution hypothesis tests for examining the relative contribution of components of productivity changes to changes in the distribution of labor productivity. Through regression analysis, they examined how the initial output per worker has an effect upon these components. By using Penn World data, Kumar and Russell (2002) decomposed labor-productivity growth into the three components to construct a cross section dataset. They conduct a very simple regression model in which independent variables are the output per worker in 1965 and the dependent variables are the percentage change between 1965 and 1990 in output per worker, technology change, efficiency index, and the capital accumulation index. In spite of their long term analysis covering over 25-year period, the analysis of Kumar and Russell (2002) conducted a very simple regression model devoid of international time specific, countries' specific, and any socioeconomic variables. Since the lack of these variables results in the omission of variable bias, they are generally included or controlled for in the micro economic analysis to reduce the bias. Kumar and Russell (2002) also recognized that there are caveats; potentially important variables (e.g., human capital and natural resources) are omitted, and long-run analysis has not taken short-run economic fluctuations into account. Kumar and Russell (2002) concluded that technological change is decidedly non neutral and that both growth and bipolar international divergence are driven primarily by capital deepening. However, the major contribution of Kumar and Russell (2002) was that they built a bridge between the two streams of literature: macroeconomic convergence and technology frontier estimation. One of the main conclusions of their study was that: It is primarily capital deepening, as opposed to technological catch-up, that has contributed the most to both growth and bipolar international divergence of economies[93].

A major drawback of the Kumar and Russell (2002) work is that the results of their estimations are biased because they omitted country specific variables such as human capital, natural resources and the year specific variables capturing international time trends. The empirical results through a fixed effects regression model show that the initial level of productivity has a negative effect on the contribution of efficiency to productivity growth, which implies that technological catch-up has done much to cause economic convergence among countries. Moreover, they ignored the unobservable individual or time effects and did not pay attention to the possibility that their estimators suffered from an omission bias. Further, Badunenkoy and Zelenyukz (2004) found that, if year dummy variables are incorporated, the relation between the initial level of productivity and the change in capital accumulation is not negative but positive. These results are contrary to the assertion of Kumar and Russell (2002).

Using data envelopment analysis, Angeriz et al. (2006) calculate indices of total factor productivity (TFP), efficiency and technological change for the manufacturing industries of 68 European NUTS1 regions over the period 1986–2002. They subsequently examine these indices using exploratory spatial data analysis techniques, before considering tendencies towards convergence in both TFP and technical efficiency levels. While the analysis reveals significant spatial autocorrelation, the convergence analysis uncovers no tendency for regions with initially lower TFP to

[93] During the period Kumar and Russell (2002) studied, between 1965 to 1990, fast growing countries (e.g. Asian Tigers) which have undergone heavy capital accumulation (Mankiw et al., 1992). Noteworthy, the effect of computers on economic growth during that time was found to be negligible, but quite considerable during the 90's (Brynjolfsson and Hitt, 2000).

catch up with regions with initially higher TFP. However, convergence is found in levels of technical efficiency, although towards a relatively lower average level.

Stochastic frontier studies often employ aggregate data to analyse the productivity and technical efficiency of regions. According to Oh (2012), a stochastic frontier model is run on plant-level data and region-level aggregate data. Comparisons of estimated coefficients and characteristics of regional production based on estimation outcomes suggest that an empirical model employing regional-level data can provide misleading results concerning the production function faced by a representative plant in a region.

Stochastic Frontier Analysis (SFA) is in most of the literature based on the micro concept of production function representing the maximum output attainable at a given quantity of inputs for a representative plant. This implies that the use of plant-level data instead of aggregate data can be adequate. However, empirical studies assessing aggregate production function often employ aggregate data to track changes in productivity and efficiency of the macro unit. SFA of the regional production function employing regional statistics of income and product accounts, aiming at analysing productivity growth at the regional level, can be examples of this (Beeson and Husted, 1989; Chandra, 2002). Researchers were concerned that employing an inadequate data set can introduce a potentially serious problem of aggregation bias. Figueiredo et al. (2009) investigated the relation between localization and establishment size in Portugal with a random utility model and reported that the estimated coefficients using aggregate data were significantly different from those using plant-level data. In an attempt to bridge the micro and macro approaches to Romanian regional output growth, Altomonte and Colantone (2008) found that aggregations across industries (e.g. within a region) were problematic. More specifically, the existence of aggregation bias has been reported in SFA. For example, Puig-Junoy (2001) empirically measured the size of the contribution of public capital to private performance and found that results varied across levels of aggregation. The existing literature provides possible explanations for how aggregation bias can occur in non micro level SFA: a production model is susceptible to aggregation bias when the estimation model is specified by a loglinear function and correlations between log-inputs are not ignorable (Lewbel, 1992), and/or marginal rates of substitution and marginal rates of transformation are inconsistent across micro unit observations within the macro unit (ten-Raa, 2005). Opposing evidence also exists. With caution concerning aggregation bias, Tyler and Lee (1979) compared the estimates of a Columbian aggregated production function with those of a plant-level one but found few differences between the two. Oh (2012) empirically examine aggregation bias in SFA on six manufacturing sectors distributed across fourteen regions in Korea and demonstrates the presence of aggregation bias associated with employing regional-level data. The empirical exercise is carried out in terms of estimating a production frontier function for the two different levels of data sets: plant-level data and regional-level data. Aggregation bias is defined as disparities in parameter estimates, input elasticity and Returns to Scale (RTS) in each manufacturing sector, using region-unit data as opposed to plant-unit data. Empirical results indicate that the estimated SFA is sensitive to the chosen unit of observation, and an estimation of SFA employing regional-level data can provide misleading results concerning the production function faced by a representative plant in a region. Oh (2012) test the existence of aggregation bias in the parameter estimates of the SFA employing regional-level data and the characteristics of production frontier within a region computed by the estimation outcomes and regional-level data. The empirical exercise is carried out in terms of estimating a production frontier function for two different level data sets: plant level versus regional levels (regional sum and regional mean). Empirical results indicate that characterizing production function faced by a representative plant in a region with regional-level data can misrepresent its actual features.

The estimation of aggregate production functions is common in regional economics. Regional production functions have been used to study different topics including, among others, the existence of agglomeration economies, the evolution of productivity, the effect of knowledge spillovers and the existence of catching-up to the technological frontier. One methodological issue that has not been widely discussed in this literature is whether it is best to estimate average production functions (where the random term has zero mean) or frontier production functions (where the random term follows a one-sided distribution). De la Fuente (1998) has questioned the use of stochastic frontiers. De la Fuente (1998) contends that by using the frontier method we are assuming that different regions use the same kind of technology in each time period. The most common alternative in the literature is to use the opposite assumption, namely that the efficiency differences are small and uncorrelated with the other explanatory variables (and can therefore be accommodated in the error term), as well as allowing for level differences between the regional production functions which are interpreted as indicators of the level of technological development of each economy.

Therefore, the point is whether there could be (separately) identified two unobservable phenomena for each region: “technical characteristics” and “productive efficiency”. Under a given set of assumptions, both effects can be identified. In particular, assuming that the technical characteristics are time invariant and hence can be modelled as a fixed effect, efficiency can be modelled, following the stochastic frontier tradition, as a one-sided error component. This model, which was first suggested by Kumbhakar and Hjalmarsson (1993), has not been applied much in the empirical literature, most likely because the estimation by generalized least squares in its original formulation was very complicated. However, Greene (2002) has developed a maximum likelihood estimator which greatly simplifies its estimation.

Alvarez (2007) implement a new model which combines the two parametric approaches most commonly used in the productivity literature: fixed effects and stochastic frontiers, discussing whether it is better to use *average* or *frontier* functions to estimate regional productivity. Alvarez (2007) estimated total factor productivity change for 17 Spanish regions between 1980 and 1995. Alvarez (2007) calculated and decomposed total factor productivity growth for the Spanish regions. The results show that TFP has increased in all regions during the sample period. The decomposition of TFP growth suggests that technical change is the most important component of productivity change. The model implemented in Alvarez (2007) incorporates time-invariant individual effects jointly with a composed error specification (fixed-effects stochastic frontier). The model allows splitting unobserved heterogeneity into two components: “technical characteristics” and “productive efficiency”. Alvarez (2007) found that both are important elements in explaining the economic performance of Spanish regions, with the higher flexibility of this model over the classical fixed-effects or the standard stochastic frontier models makes it a good candidate for empirical applications in regional economics given the considerable amount of unobserved heterogeneity that generally exists across regions.

Green and Mayes (1991) examined technical inefficiency of manufacturing industry in the United Kingdom, based on data for 19,023 establishments in 151 industries, to estimate technical inefficiency in each industry by fitting translog stochastic frontier production functions and decomposing the residuals into two components: one measuring inefficiency and the other unobservable random factors. The need for comparability among countries and the confidentiality of the data meant that cases where there were problems with the quality of explanation could not be pursued. As a result it has not been possible to estimate fully satisfactory measures of inefficiency for all 151 industries. Nevertheless, this unique access to data at the establishment level across the whole of manufacturing industry will help fill part of the gap between the aggregate analysis of Caves and Davies (1986) and Oulton and O'Mahoney (1990) on the one hand and the detailed interplant comparisons on the other.

Differences in productivity growth rates are seen solely as a function of how far a region is from its own steady state. The further productivity is below the steady-state level, the faster the growth of the capital–labour ratio and hence the faster productivity growth. But to emphasize again, this assumes that all regions have access to the same blueprint of technology and all are equally efficient (Mankiw *et al.*, 1992).

The related neoclassical growth-accounting approach explicitly includes the growth of capital and hence the growth of total factor productivity (TFP) reflects, apart from measurement errors, the rate of technological change. Thus, disparities in TFP levels can be interpreted as due to regions being on different production functions. Nevertheless, the approach still requires regions to be technically efficient (Hulten and Schwab, 1984; Melachroinos and Spence, 2001).

One advantage of this approach is that it enables a decomposition of TFP growth into changes in technical efficiency and changes in technology. A second important benefit of the method is that it allows for technical inefficiency and does not assume a specific underlying functional form for technology (Färe *et al*., 1994a). The technique has been widely used in microeconomic studies of productivity change and in estimating TFP growth in agriculture (see Coelli and Rao, 2003).

Henderson and Zelenyuk (2004), meanwhile, extend this strategy by dividing the sample into two groups (developed and developing countries) and analysing catch-up effects not only for the whole sample, but also within and between these two groups. They also analyse the consistency in the DEA or technical efficiency scores obtained both by dividing and not dividing the sample and by applying bootstrap techniques to combat the criticism that DEA methods are overly sensitive to outliers.

The same as Kumar and Russell (2002), Badunenkoy and Zelenyukz (2004) take Jones's (1997) suggestion that GDP per worker would be most appropriate definition of welfare, and hence income, once developing countries are included into analysis. Badunenkoy and Zelenyukz (2004) research is an extension to study of Kumar and Russell (2002), which they complement in two ways: they considering a more recent period (the 90's instead of 1965-90) and, as a result, they include data on transitional economies. In contrast to study by Kumar and Russell (2002), which concluded that the capital deepening was the major force of growth and of changing the world income distribution over 1965-1990, Badunenkoy and Zelenyukz (2004) analysis shows that, during the 90's, this major force was technological change, whereas capital accumulation played the minor role. Badunenkoy and Zelenyukz (2004) investigate the same sources of labor productivity growth and evolution of world distribution as in Kumar and Russell (2002), using their methodology, but now with data for 90's. More specifically, Badunenkoy and Zelenyukz (2004) investigate three sources of economic growth and evolution of world income distribution during the 90's[94]:

- technological change,
- efficiency change (the catching-up) and
- capital deepening

[94] Badunenkoy and Zelenyukz (2004) apply this estimator to sample of 73 countries over the period 1992-2000.

As in Kumar and Russell (2002), Badunenkoy and Zelenyukz (2004) identified further divergence in GDP per worker among countries in the sense that the richer the countries, the greater was the growth. Second, most importantly and opposite to period of 1965-90, Badunenkoy and Zelenyukz (2004) found that the technological change was the largest driving force of growth and of changing the distribution of income per worker in the world, causing further divergence. Both the poor and the rich countries have benefited from the technological change, but the richer the country the more was the benefit, again suggesting about the divergence, now driven by the technological change. Finally, the capital accumulation and efficiency change effects, on average, were a negligible source of change in the world distribution of income per worker.

To obtain unbiased estimators, first based on the Penn World data, Yamamura and Shin (2007) use the same method as Kumar and Russell (2002) to construct a panel dataset consisted of 57 countries from 1965 to 1990. Second, using this dataset Yamamura and Shin (2007) conduct re-estimations through a fixed effects model to reduce the omitted variable bias caused by time invariant countries' features. Yamamura and Shin (2007) also incorporate the year dummies into this model to capture the time specific effect that is individually invariant.

Kumbhakar and Wang (2005) used a stochastic production frontier approach to estimate the world production frontier. Henderson and Russell (2004) have applied similar methodology as Kumar and Russell (2002) to similar data but with human capital and found that part of the effect identified by Kumar and Russell (2002) is in fact due to human capital accumulation.

Griffith et al. (2004) find that both R&D and human capital affect the rate of convergence in a model of total factor productivity (TFP) growth, whereas Kneller (2005) also for a sample of OECD industries, finds that the effect of human capital is quantitatively more important than that of R&D on absorptive capacity, and that the latter matters only for the smaller OECD countries. Koop, Osiewalski and Steel

(1999, 2000) has previously questioned the results from the use of this two-stage modelling approach from a statistical perspective.

Using SFA, Kneller and Stevens (2006) examine the three facets of technology: its creation, dispersion and absorption[95]. They investigate whether differences in absorptive capacity help to explain cross-country differences in the level of productivity. They utilize stochastic frontier analysis to investigate two potential sources of this inefficiency – differences in human capital and R&D – for nine industries in 12 Organization for Economic Co-operation and Development (OECD) countries over the period 1973–91. Kneller and Stevens (2006) find that inefficiency in production does indeed exist and it depends upon the level of human capital of the country's workforce. Evidence that the amount of R&D an industry undertakes is also important is less robust[96].

Kneller and Stevens (2006) investigate whether absorptive capacity helps to explain cross country differences in the level of technical efficiency. These differences have been identified as key to understanding the evolution of the world income distribution (Prescott, 1998). Absorptive capacity, as discussed by Arrow (1969), captures the idea that the implementation of new technologies depends on the ability and effort applied to this task (Griffith, Redding and Van Reenen, 2003, 2004; Xu, 2000). Two factors have been suggested which determine the capacity to absorb and implement new technology: human capital (Abromovitz, 1986; Cohen and Levinthal, 1989) and domestic innovation (Fagerberg, 1994; Verspagen, 1991).

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[95] Although Koop (2001) has used SFA in the decomposition of growth rates for a similar sample, Kneller and Stevens (2006) stress the mechanism whereby technical inefficiency occurs and use a less restrictive set of efficiency determinants.

[96] Kneller and Stevens (2006) complement Griffith et al. (2004) and Kneller (2005). Griffith et al. (2004) find that both R&D and human capital affect the rate of convergence in a model of total factor productivity (TFP) growth, whereas Kneller (2005) also for a sample of OECD industries, finds that the effect of human capital is quantitatively more important than that of R&D on absorptive capacity, and that the latter matters only for the smaller OECD countries. Koop, Osiewalski and Steel (1999, 2000) has previously questioned the results from the use of this two-stage modelling approach from a statistical perspective.

A country that has a lower ability or applies less effort to absorbing new technology will produce less output than the one operating with the best available technical know-how, ceteris paribus. This deficiency, evident in the distance of the country from the production frontier, is technical inefficiency. Kneller and Stevens (2006) examine the effect of human capital and research and development (absorptive capacity) on efficiency for a panel of nine manufacturing industries in 12 Organization for Economic Co-operation and Development (OECD) countries over the period 1972–91 using stochastic frontier analysis (SFA). SFA allows the study of absorptive capacity in a framework that closely matches the idea of a technical frontier found in growth theory. In their framework, each industry faces the same production frontier – the maximum output for a given level of inputs. Kneller and Stevens (2006) consider three assumptions regarding the international transfer of technology:

- First, they remain consistent with the existing literature on absorptive capacity and follow early models of economic growth in assuming that technology is global (Solow, 1956).
- To place this in perspective, they then adopt the other extreme position of no cross-border flows of knowledge, before taking the more realistic position that technology transfer is incomplete.
- Following Keller (2001, 2002) they investigate the impact of knowledge dissemination via the effect of physical distance on productivity.

The model outlined is estimated for a sample of nine manufacturing industries in 12 countries over the period 1973–91. The total number of available observations is 1,731. The output (value added), capital stock and employment data are all taken from the OECD ISDB database. The sample countries are: Canada, Belgium, Denmark, France, Germany, Japan, Norway, Sweden, UK, US, Italy and the Netherlands. The absorptive capacity effect of R&D is measured using the flow of R&D investment made in each period from the OECD EBRD data set for the period 1973–92. Estimates of the stock of R&D in each country, necessary for the construction of the stock of frontier knowledge in each industry, are generated by accumulating R&D

expenditures. The estimated efficiency scores also provide evidence on whether national factors or industry–country factors are more important for determining efficiency scores. There is evidence for both. For some countries there is considerable variation in the ranking of countries across industries. For example, the UK has the lowest average efficiency score in the basis metals industry and other manufacturing but the highest in the food industry. Similarly, Germany is ranked as high as second (chemicals, machinery and equipment, other manufacturing) and as low as eighth (basis metals, food and textiles). There are however also some countries that suggest that national factors are important: some countries rank consistently near the top of the efficiency rankings and some consistently near the bottom. For example, France and the Netherlands never have an efficiency ranking that is lower than fourth, whereas Japan never has an efficiency ranking better than seventh. Finally, a number of countries experience steady increases in their average efficiency across industries. Most notably, Italy and Finland experience rises in efficiency from around the 70% up to almost 90%. Sweden and the UK have fairly steady levels of technical efficiency until the early 1980s when both begin a period of steadily increasing efficiency.

Kneller and Stevens (2006) have found that the notion of absorptive capacity provides a useful explanation of differences in productivity. There is strong evidence that countries differ in the efficiency with which they use frontier technology. They have investigated two mechanisms which might determine a country's absorptive capacity and hence its technical efficiency: human capital and research and development. Kneller and Stevens (2006) have found that human capital plays a significant and quantitatively important role in explaining these differences in efficiency. Moreover, there is clear evidence that human capital affects production both directly and through its indirect effect on technical efficiency. This is in direct contrast to Benhabib and Spiegel's (1994) conclusion that human capital does not enter the production function directly. R&D is found to have only an insignificant effect on inefficiency. The results in the paper also conclude that rather than as an avenue through which a country can absorb new knowledge, the effect of R&D on production is primarily through its contribution to the stock of frontier knowledge itself in each industry.

A regional application is Karadag et al. (2005), who use the technique to examine changes in manufacturing TFP in the Turkish private and public industries. In particular, using data for the period 1986–2002, Angeriz et al. (2006) analyses TFP change and its components for the manufacturing industries of 68 European NUTS1 regions. Angeriz et al. (2006) chose manufacturing because, while it now only accounts, on average, for around 20 per cent of regional output, its role is still seen as crucial in explaining regional economic growth. It remains a large component of inter-regional exports and the competitiveness (both price and nonprice) of a region’s exports is crucial to its overall prosperity (McCombie and Thirlwall, 1994). Following a description of the data, the paper then analyses the results of the DEA. Specifically, the results are tested for evidence of spatial autocorrelation at both the global and local levels, which is akin to testing for geographical clustering at both levels. Following this, the paper looks at the question of cross-regional convergence with respect to levels of TFP and technical efficiency.

The above analysis, however, does not indicate anything as regards systematic tendencies towards convergence between the NUTS1 regions. However, especially for the EU, the issue of cross-sectional convergence in income per capita and productivity levels has been one of the most widely researched in the last two decades of spatial economics.

Last decades have seen the publication of a great deal of studies on spatial disparities in the European Union (EU) using a variety of different approaches (e.g. Barro & Sala-i-Martin, 1991; Neven & Gouyette, 1995; Quah, 1996; Rodrıguez-Pose, 1999; Le Gallo, 2004; Corrado et al., 2005; Ezcurra et al., 2005a). Among them, it is worth mentioning the major advances in economic growth theory, coinciding with the introduction of endogenous growth models in the mid-1980s. The assumptions underlying these models ultimately allow for the reversal of the neo-classical prediction of convergence, and lead to the conclusion that the faster growth of rich economies causes territorial imbalances to increase over time (Barro & Sala-i-Martin, 1995). In fact, the self-sustained and spatially selective nature of economic growth has been stressed by the models of the “new economic geography” (Ottaviano & Puga, 1998). According to these theories, the increasing returns and the agglomeration economies would explain the accumulation of activity and income in the more dynamic areas, which would lead in the final instance to spatial divergence.

On the other hand, the increasing relevance of this topic in the EU has much to do with the strong emphasis placed on achieving economic and social cohesion in the context of the current economic integration process, especially since the signing of the Single Act and the Maastricht agreements. This directly raises the need to reduce the differences in terms of development across the European regions (European Commission, 2001, 2004). Thus, important contributions to the EU convergence literature have been made by, *inter alia*, Armstrong (1995), Canova and Marcet (1995), Fingleton and McCombie (1998) and Barro and Sala-i-Martin (2004). However, with the exception of Fingleton and McCombie (1998), the focus in all of these studies has been on convergence at the level of the aggregate economy rather than within the manufacturing industry. Furthermore, none of these studies has examined tendencies towards convergence in separate measures of TFP and technical efficiency. That is, none has applied convergence techniques to the results of a DEA exercise.

The literature on regional disparities within the EU has mainly focused on the possible presence of convergence in per capita gross domestic product (GDP) or labour productivity, ignoring the degree of efficiency with which the various regions use their resources in the productive process. This may be particularly relevant since, as pointed out by Grosskopf (1993) and Taskin and Zaim (1997), the omission of the phenomenon of inefficiency may cause convergence analysis to offer biased results. However, despite its potentially important implications, as far as we are aware this issue only has been examined to date in the EU case by Angeriz et al. (2006) and Enflo and Hjertstrand (2006). Thus, Angeriz et al. (2006) use the Malmquist total factor productivity change index to calculate the efficiency scores for the manufacturing industries of 68 NUTS-1 regions in the EU. Nevertheless, when assessing the findings obtained by these authors, one should not lose sight of the substantial reduction experienced by industrial activities in the EU during the last decades (Rodrıguez-Pose, 1998), to the point that manufacturing nowadays accounts only for around 23% of regional output. In turn, Enflo and Hjertstrand (2006) estimate the aggregate efficiency levels of 69 NUTS-1 and NUTS-2 regions by combining a non-parametric frontier approach with bootstrap techniques. However, the sample used in this study covers only five EU member states: Germany, Spain, France, Ireland and Italy.

The estimation of aggregate production functions is common in regional economics. Regional production functions have been used to study several different topics, such as the evolution of productivity, the role of infrastructures or human capital on income, or the existence of catching-up to the technological frontier, among many others. While initial studies used to estimate a Cobb-Douglas aggregate production function with productive capital and labor as explanatory variables, other inputs such as human capital (e.g., de la Fuente, 1995) or public capital (e.g., Aschauer, 1989; Munnell, 1990; Puig-Junoy, 2001) are commonly considered. Other variables have also been used in order to control for regional heterogeneity: Evans and Karras (1994) use the composition of public capital, García- Milà and McGuire (1992) and Munnel (1990) use the business cycle, Álvarez, Arias and Orea (2006) use a specialization index. In fact, the list of potential sources of regional heterogeneity can be fairly long, ranging from those already mentioned to differences in climate, and natural resources and even within-country differences in culture and institutions, as recently documented by Acemoglu and Dell (2009). Some of this heterogeneity embedded in regional data is unobservable for the analyst, and the failure to take it into account can lead to biased estimates, hence the importance to account for it. There are mainly two different approaches to this problem, (i) modelling heterogeneity as an individual effect or (ii) letting the model estimate different technologies in the sample (i.e., random parameters models, latent class models, nonparametric estimation).

Most empirical situations present differences across observations not reflected in the data. This information is referred to as unobserved heterogeneity. When that information is not important or is not correlated with the explanatory variables, it accommodates in the error term. However, if unobserved heterogeneity is relevant and correlated with the explanatory variables, the estimated parameters will be biased (Griliches, 1957). A frequent case occurs when the information not included in the model can be considered time-invariant, e.g., location or orography. If panel data are available, the problem is solved modeling heterogeneity as an individual effect (see Mundlak, 1961). Several papers have used the "within" or "random" effects estimators in order to estimate aggregate production functions using regional data. For instance, García-Milà, McGuire and Porter (1996), Evans and Karras (1994) or Holtz-Eakin (1994) used data from the U.S. states. Mas et al. (1996) or Moreno et al. (1997) used data from Spanish regions.

However, although traditional panel data techniques assume that individual effects are time invariant, Schmidt and Sickles (1984) suggest that this assumption is less valid as the panel becomes longer. For instance, some regional characteristics, such as its economic structure, abundance of natural resources or productive efficiency, may vary over time. In this situation, it is preferable to use models that can account for time varying unobserved heterogeneity. Cornwell, Schmidt and Sickles (1990) developed an extension to the traditional fixed effects model in which individual effects are allowed to vary over time. Wu (1996) used this model to study total factor productivity growth, technological progress and technical efficiency change in post reform China. The stochastic frontier models (Aigner, Lovell and Schmidt, 1977) are another approach capable of modelling time-varying unobserved heterogeneity. The main characteristic of these models is their composed error term. Specifically, an asymmetric error term is added to the traditional symmetric error term, the former representing technical inefficiency while the latter is supposed to engage random shocks and measurement errors. Several authors have used stochastic frontier models to estimate aggregate production functions. For instance, Puig-Junoy (2001) estimated technical efficiency indexes for the 48 contiguous U.S. states. More recently, Mastromarco and Woitek (2006) studied the link between public infrastructure investment and efficiency in the Italian regions, while Delgado and Álvarez (2004) and Arias and Rodriguez- Vález (2004) estimated this model using Spanish datasets. Recently, Greene (2005) proposed a "true fixed effects model" which is able to estimate not only individual effects but also an inefficiency term. This model was recently used by Álvarez et al. (2007) in order to decompose the productivity growth of Spanish regions.

Ezcurra et al. (2009) aim to investigate further existing disparities in technical efficiency levels, paying particular attention to the role played in this context by spatial interactions and geographical location. Ezcurra et al. (2009) use aggregate data for the whole range of economic activities corresponding to 196 NUTS-2 regions in 15 EU countries (EU-15) over the period 1986–2002. Furthermore, this is the first time that the role played by different factors is examined in explaining the changes in technical efficiency experienced by the EU regions over the sample period.

Ezcurra et al. (2009) need to estimate first the levels of technical efficiency of the European regions. To do so, as Angeriz et al. (2006), the technical efficiency indices are computed by Data Envelopment Analysis (DEA). This methodology offers major advantages in the present context, since the non-parametric nature of the technique avoids the need to specify beforehand any particular functional form for the technology. Furthermore, this approach does not require any assumption about market structure or about the absence of market imperfections. Additionally, in order to investigate the geographical dynamics of regional efficiency, this paper employs a set of methods commonly used in the literature on spatial econometrics (Haining, 1990; Anselin, 2001). These techniques provide information about the possible presence in this context of spatial autocorrelation and/or spatial heterogeneity, and allow the researcher to identify regional clusters characterized by similar efficiency levels distinguishing them from the rest of the sample.

Ezcurra et al. (2009) examine the regional distribution of technical efficiency levels within the EU, putting particular emphasis on the different patterns of spatial association observed. In turn, the econometric estimates performed inform about the impact of a set of factors on the changes in technical efficiency experienced by the EU regions throughout the study period.

Ezcurra et al. (2009) investigated the spatial distribution of technical efficiency in the EU, using data on 196 NUTS-2 regions over the period 1986–2002. To this end, the level of technical efficiency of the various regions throughout the study period has been estimated by applying DEA methods. The results reveal that inefficiency in the use of productive factors to produce regional output is clearly present in the EU, which suggests that this factor should be borne in mind when it comes to explaining the patterns of economic growth observed across the European regions. Furthermore, it needs to be said that spatial disparities in the levels of technical efficiency are relatively important in the EU. Taking into account the major advances that have taken place over the last two decades in the economic integration process currently underway in Europe, Ezcurra et al. (2009) examined the role played in this context by spatial interactions and geographical location. In this respect, the different tests performed show the presence of spatial autocorrelation and spatial heterogeneity in the distribution under consideration. This implies that technical efficiency levels are not randomly distributed across space. On the contrary, physically adjacent regions tend on the whole to register similar efficiency indices. Indeed, Ezcurra et al. (2009) detected the existence of several spatial clusters formed by regions with similar values of the study variable distinguishing them from the neighbouring zones. Specifically, the groupings of regions characterized by significantly high levels of technical efficiency are located mainly in central and northern Europe. In turn, the clusters made up by the worst-practice regions tend to be situated in the southern periphery of the Union. It is worth noting that this spatial pattern is consistent with the traditional North–South divide identified in the literature on regional disparities in the EU.

In order to complete these results, Ezcurra et al. (2009) analysed the role played by different factors in explaining regional efficiency changes throughout the study period. To this end, and taking into consideration that the presence of spatial autocorrelation affects negatively the results obtained from standard regression analysis, Ezcurra et al. (2009) have estimated an econometric model incorporating a spatial autoregressive structure in the error term. Ezcurra et al. (2009) show that the less efficient regions in 1986 have experienced greater efficiency improvements during the ensuing years. Accordingly, a process of regional convergence in terms of technical efficiency has taken place in the EU over the sample period. Additionally, Ezcurra et al. (2009) found that the initial level of capital per worker and the employment share in market services are positively correlated with efficiency growth rates. Likewise, they have detected a negative relationship between the employment share in non-market regional efficiency in the European Union 1137 services and efficiency improvements. Finally, the conclusions of Ezcurra et al. (2009) are potentially interesting from the perspective of EU regional policy. In particular, the estimates raise the possibility of improving the relative situation of the less efficient regions by means of policies aimed at increasing their capital stocks or modifying their industry mix. In any event, the relevance of spatial effects observed suggests that policy-makers should not consider the various regions as isolated units when designing any public intervention in this context.

Concluding, Ezcurra et al. (2009) examine existing disparities in technical efficiency levels across the European regions over the period 1986–2002. The results reveal that technical efficiency is not randomly distributed across space in the European setting. On the contrary, the different tests performed highlight the presence of positive spatial autocorrelation and spatial heterogeneity in the distribution under consideration. In fact, Ezcurra et al. (2009) have detected several regional clusters characterized by similar efficiency levels distinguishing them from the rest of the sample. Nevertheless, the estimates carried out show the existence of a process of regional convergence in terms of technical efficiency during the study period. Ezcurra et al. (2009) reveal that factors such as the regional stock of capital per worker or the patterns of productive specialization are relevant in explaining the changes in technical efficiency experienced by the European regions between 1986 and 2002.

Another regional aspect is that of Halkos and Tzeremes (2009) who deal with the effects of EMU enlargement (European Economic and Monetary Union) by evaluating the economic efficiency of growth policies of the 25 member countries. By using Data Envelopment Analysis, Halkos and Tzeremes (2009) measure the policies adopted initiating economic growth of the 25 EU members for the time period of 1995–2005. Different factors reflecting countries' investment policies have been used in order to measure chronically countries' economic efficiency. The results reveal that the old 15 EU members have faced problems reforming their economic policies in order to cope with the EU enlargement which in turn had an impact on their economic efficiencies. Halkos and Tzeremes (2009) examined the effects of the European Economic and Monetary Union (EMU) enlargement by evaluating the economic efficiency of growth policies of the 25 member states, for the period 1995-2005, using DEA analysis. More specifically, they incorporate a policy evaluation approach regarding European Integration, examining investment policies in order to measure country economic efficiency, putting emphasis on the economic advantages and the risks associated with the EMU enlargement. In order to measure the effect of EMU enlargement on the economic efficiency and to a larger extent to the development of the EMU member states, Halkos and Tzeremes (2009) used one output (real GDP growth rate) and five inputs (public investment, International Price Competitiveness, R&D expenditure, public expenditure on education, and total employment rate by highest level of education) which represent key economic and development investment policies (in terms of resource allocation). Halkos and Tzeremes (2009) concluded that national externalities may lead to inefficient outcomes and that a coordination of fiscal policies is needed in order to reduce countries' externalities or macroeconomic spillovers.

In addition, there are studies based on aggregate data focusing on specific European Union countries. One of the most representative studies is by Bhattacharjee et al. (2009), developing a model of labor productivity as a combination of capital-labour ratio, vintage of capital stock, regional externalities, and total factor productivity (TFP) for Denmark. Bhattacharjee et al. (2009) apply their empirical model to study regional and industrial variation in productivity in the Danish economy. The model is applied to annual data from the Danish Local Authorities Research Institute (AKF) covering the period 1979–1993. For each year, the paper considers 12 Danish regions and 9 industries. The skewness of TFP distribution is related to different growth theories. While negative skewness is consistent with the neo-Schumpeterian idea of catching up with leaders, zero skewness supports the neoclassical view that deviations from the frontier reflect only idiosyncratic productivity shocks. Bhattacharjee et al. (2009) argue that positive skewness is consistent with an economy where exogenous technology is combined with non-transferable knowledge accumulated in specific industries and regions. This argument provides the framework for an empirical model based on stochastic frontier analysis. The model is used to analyse regional and industrial inequalities in Denmark. Understanding the mechanisms underlying economic growth and the explanation of persistent geographical inequalities in levels of productivity are issues of key research interest.

Bhattacharjee et al. (2009) make three main contributions to literature. First, they propose a modeling approach based on stochastic frontier analysis, which draws on a combination of neoclassical, neo-Schumpeterian, institutionalist and evolutionary ideas and is consistent with a positively skewed cross-sectional distribution of TFP.

Second, Bhattacharjee et al. (2009) develop a model which describes an economy, with various regional units and different industries, evolving over time. The model enables decomposition of labour productivity into five components: (a) capital accumulation, (b) technology embodied in capital goods, (c) public good technology available to all industries and regions, (d) technical capabilities arising from region specific externalities, and (e) technological forge ahead through innovations in specific industries. The above five components are related to different theoretical approaches. Components (c) to (e) represent disembodied technology and are the determinants of TFP, while (a) to (d) are components of a production function describing the base level of labour productivity. The capital labour ratio (a) and vintage of capital stock (b) represent the effect of capital accumulation and technology embodied in capital goods respectively. Region specific externalities (d), stressed by institutionalist approaches, represent technical capabilities shared by all productive units located in a given region. The base level of productivity, components (a) to (d), is either the ceiling of the neo-Schumpeterian approaches or the floor implied by evolutionary theories. Component (e) corresponds to the view of technological progress as a permanent attempt to overcome the standard productivity conditions. This component can be further divided into two elements. The first is the time contingent performance of each industry. It is measured either as inefficiency in relation to the technological frontier or as the capacity of each industry to enhance productivity, moving ahead of the pattern determined by the floor, which corresponds to the evolutionary concept of industry specific technological trajectories. The second component is an idiosyncratic random element which moves each particular combination of region, industry and time, above or below the average conditions of each industry.

Third, Bhattacharjee et al. (2009) conduct an empirical analysis of productivity in the Danish economy, using panel data for 15 years (1979 to 1993), on 9 industries and the

12 regions of the country. Underlying the study are the computations of capital stock, as well as the estimation of the average age (or vintage) of capital stock. Homogeneity within Denmark enhances the validity of assuming similar production functions across different industries and regions of the country.

Bhattacharjee et al. (2009) empirical results identify several new findings. Bhattacharjee et al. (2009) find that positive skewness in the TFP distribution applies to the Danish case. Further, Bhattacharjee et al. (2009) detect an important role for vintage of capital, while the estimated region region specific externalities are consistent with previous literature. Probably, Bhattacharjee et al. (2009) most important new findings are in the patterns in technological trajectories across different industries. These findings inform substantially about the magnitude and evolution of disembodied technology in Danish industry. Further analyses of the drivers of technological trajectories and inferences for public policy is an object for future research. More explicit modeling of innovation, particularly investment in R&D, human capital, international technological spillovers and spatial diffusion are also future directions of research. Further, a key feature of Bhattacharjee et al. (2009) methodology that offers useful extensions is nonparametric modeling of technological trajectories in different industries. While Bhattacharjee et al. (2009) observe several interesting patterns in the dynamics of innovative capacity, representing these features in terms of appropriate order restrictions will be a challenging research question. Finally, developing Bayesian inference, with a priori beliefs on different theoretical positions reflected in suitable prior distributions of skewness, will be an exciting direction of further work.

The distribution of productivity implied by they estimated production function for Danish regions and industries shows evidence of positive skewness, which is consistent with the assumption of the floor. Further, the estimates of the production function reflect the importance of vintage of capital and region-specific capabilities, often omitted in empirical studies. The effect of both the capital labour ratio and vintage of capital stock show heterogeneity across the industries. The productivity enhancing component shows substantial variation over industry and time, which has important institutional explanations.

Overall, the base level of productivity, described by capital accumulation, technology embodied in capital goods and region-specific externalities, explain half of the total variation in labour productivity across industries, regions and time in Denmark. The remaining 50% is explained by industry specific technological trajectories and idiosyncratic technology shocks. The skewed error variance representing technological trajectories explains 11% of the total variation while productivity shocks account for the remaining 39%. Understanding the relative contribution of externalities affecting performance of regional economies, and industry specific effects of capital accumulation (K/L ratio) and vintage of capital, is a bit more complicated. This is because these explanatory factors are correlated with each other. However, relative importance of these factors can be approximately judged by first estimating a production function where only region-specific fixed effects are included, and then expanding the model to include the capital-labour ratio and vintage of capital. These estimates indicate that region-specific externalities explain about 11% of the variation in labour productivity, while including industry specific effects of capital accumulation into the model increased explained variation to about 48%. The estimated effects of capital accumulation show substantial variation across the industries, ranging from 0.21 and 0.25 for chemicals and food industry respectively to about 0.39 for the metals and engineering and paper and publishing industries. The effects of technology embodied in capital goods (vintage of capital) also varies widely across the industries, and is significant at 1% level in the chemicals (0.048), food (0.042) and textile (0.019) industries, as well as other manufacturing (0.012).

Bhattacharjee et al. (2009) develop a methodology for modeling alternative theoretical views on economic growth and inequality, based on the skewness of TFP. The framework is extended to include positive skewness patterns which are often observed in empirical studies. Second, based on a synthesis of neoclassical, neo-Schumpeterian, evolutionary and institutionalist ideas, Bhattacharjee et al. (2009) develop a stochastic frontier model that is consistent with both positive and negative skewness. Positive skewness was discussed by other authors (Green and Mayes 1991; Fritsch and Stephan 2004) in similar contexts, but in contrast with this paper, they did not provide any adequate explanation. The model is broadly based on the neoclassical tradition of using a Cobb- Douglas production function in intensive form. The model defines, for each spatial unit, a benchmark level of productivity generated by the stock of capital, technology embodied in capital goods and region-specific externalities, which determine different capacities to create and absorb disembodied technologies. The standard level of productivity assumed as a technological frontier ceiling or a technological floor provides the competitive basis, with each industry attempting to forge ahead through quality enhancing innovations. Finally, each individual unit is also faced with idiosyncratic movements above or below the standard.

Driffield and Munday (2001) examine how far foreign manufacturing investment in UK industries, together with the spatial agglomeration of those industries, affects technical efficiency. The paper links research on the estimation of technical efficiency, with those literatures demonstrating the economies associated with foreign direct investment and spatial agglomeration. The methodology involves estimation of a stochastic production frontier with random components associated with industry technical inefficiency, and a standard error. Driffield and Munday (2001) also explore whether the degree of foreign involvement has a greater impact on technical efficiency where the domestic industry industry is characterized by comparatively high productivity and spatial agglomeration. The policy implications of the analysis are discussed. Driffield and Munday (2001) use three digit industry data from the United Kingdom. Alvarez et al. (2007) and Puig-Junoy and Pinilla (2008) investigate production efficiency in Spain. Alvarez et al. (2007) review the different approaches the literature has used to deal with this problem and, in doing so, they address a recent puzzle in growth accounting studies for the Spanish economy, the fact that recent observed TFP growth appears to be negative.

Bos et al. (2010) empirical analysis is based on a sample that consists of manufacturing industries that are twice as disaggregated as those used in related studies (Koop, 2001; Kneller and Stevens, 2006). Bos et al. (2010) apply their modelling approach to 21 EU manufacturing industries in six countries over the period 1980–1997, with two key questions in mind: (i) do industries use different technologies? (ii) Eventually, what drives output growth? The use of a latent class structure in the specification of the stochastic frontier model results in identifying two technology clubs (regimes). One technology club appears to be technologically more advanced, as industries in that club are characterized by a high R&D spending and a high marginal productivity of labor. Bos et al. (2010) find that industries in that club exhibit constant returns to scale. In contrast, industries in the other, less technologically advanced club exhibit decreasing returns to scale. The driving forces of growth are also different across the two clubs. Technical change is a crucial component for growth for the technologically advanced club, while input (in particular capital) growth plays an important role in both technology clubs. Since Bos et al. (2010) permit switching from one club to another and condition membership on the technological effort (R&D), Bos et al. (2010) can investigate the existence of technological spillovers and catch-up behavior. Regarding the former, they find some support within the technologically advanced club. Regarding the latter, they find that the distance between the clubs has increased over time. Finally, within the advanced club, they also find some evidence of cross-country technological catch-up. Overall, Bos et al. (2010) model reveals significant heterogeneity in the growth behavior of the manufacturing industries in the sample. Many of the findings could not be obtained using traditional approaches (imposing constant returns to scale, ignoring inefficiency, assuming a common production function). Their findings are in line with other studies that have also adopted flexible modelling approaches. More specifically, some evidence of technological catch-up is also documented by Koop (2001), while the importance of input growth is also the main finding in Koop et al. (1999), Koop (2001) and Kumar and Russell (2002). Bos et al. (2010) results shed light on important policy questions, in particular for the EU (as the Lisbon Strategy sets R&D targets for the member states). For instance, does higher R&D spending result in better use of the existing best-practice technology and/or the invention of new technology? The results corroborate that it matters which industries are 'targeted' by R&D investment tax credits/subsidies. For industries in the advanced technology club, higher R&D spending can both increase the efficiency with which industries absorb the best-practice technology and lead to technological improvements. Industries in the other, less advanced, club can improve their chances of becoming a member of the more advanced club by spending more on R&D[97].

[97] To identify different technologies, many industry classifications rely on clustering industries a priori on the basis of observed R&D expenditure and estimate best-practice frontiers for each cluster

According to Bos et al. (2010), R&D can affect all parameters in the frontier production function, namely the marginal products of inputs, technical and efficiency change (Griffith et al., 2004; Kneller and Stevens, 2006). Moreover, it includes another element which may determine the parameters in the frontier production function, namely the evidence of leader–follower behaviour. Bos et al. (2010) decomposition results, and in particular the differences with respect to technical growth and efficiency, may shed some light on leader/follower models of technical growth. A body of research has examined whether technology spills over across countries, via R&D and trade. In these models, all countries have access to the same technology and the leader country, ie., the country with the highest TFP growth in an industry, develops a new technology while the rest of the countries (followers) can imitate the technology (Scarpetta and Tressel, 2002; Griffith et al., 2004; Kneller and Stevens, 2006).

Another parameter taken into consideration is the economy openness, which may also increase efficiency. It is often argued in both the international economics (Melitz, 2003) and the industrial organization literature (Caves and Barton, 1990) that increased openness to trade should be positively related with increases in productivity and/or efficiency. Higher exposure to trade facilitates the imitation of an advanced foreign technology and/or places greater pressure on the industries to adopt best-practice technologies and improve efficiency in order to cope with competition. Bos et al. (2010) and Koop (2001) state that openness does not correlate well with efficiency. Apparently, openness to trade does not wipe out inefficient industries. This result may merely corroborate findings in new international economic theory that emphasize the positive effects of openness on firm-level productivity of the very few firms that actually account for the major share of trade flows (Helpman, 2006).

Puig-Junoy and Pinilla (2008) investigated the main sources of heterogeneity in regional efficiency in developed countries with an application to the Spanish regions,

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separately (Hatzichronoglou, 1997). However, such a division is to some degree arbitrary since the appropriate cut-off levels of R&D remain unclear.

given the potential for economic growth by reducing the distance from the best practice, estimating a translog stochastic-frontier production function in the analysis of Spanish regions in the period 1964-96, to attempt to measure and explain changes in technical efficiency. Their results confirm that regional inefficiency is significantly and positively correlated with the ratio of public capital to private capital.

According to Puig-Junoy and Pinilla (2008), regional economic growth can be decomposed into two main components: increases in factor inputs (capital accumulation) and improvements in total factor productivity. The first component attributes differences among regions to differences in physical resources, physical capital, and labour. Productivity differences, the second component, may also play a determinant role in economic growth. Increases in total factor productivity may be achieved through technical change (shifts in the production frontier) and through reductions in inefficiency in production (movements toward the frontier).

In the long run, it can be hypothesized that technology transfers allow relatively homogeneous or similar regions, such as those in a developed country, to grow at a common rate. Then, not all differences in total factor productivity need to be persistent. That is, regional technology gaps may be expected among regions in developed countries to close over time as technology diffuses. If this is the case, persistent differences in total factor productivity may be attributed mainly to inefficiency in the use of input factors to produce regional output.

On the other hand, the traditional regional production-function approach omits the influence of the level and evolution of technical inefficiency on the production function, and it precludes measurement of technical inefficiencies by assuming them away. Measuring regional inefficiency in production makes it possible to distinguish between shifts in technology and movements towards the best-practice production frontier. In this context, given regional input factors, differences in economic performance could be greatly reduced by improving technical efficiency.

A frontier approach to inefficiency measurement makes it possible to separate efficiency change from technical change, rather than simply calculating the contribution of productivity as a residual, as is usually done in growth-accounting literature (Puig-Junoy and Pinilla, 2008; Murrillo-Zamorano, 2004).

Puig-Junoy and Pinilla (2008) focus on explaining cross-regional differences in output inefficiency levels and on how and why efficiency varies among regions, with a specific application to Spanish regions.

There are also a number of papers reporting inefficiency heterogeneity for decentralized regions or states in developed countries such as the United States (Domazlicky and Weber, 1997), or Italy (Percoco, 2004) and Spain (Maudos et al, 1998) in the European Union.

Despite the critical importance for regional growth of reducing the distance from the best practice, the empirical literature has paid little attention to the sources of regional differences in technical efficiency, as a disaggregated component of total factor productivity, in decentralized and developed countries.

Boisso et al (2000) used a nonparametric frontier approach and a two-step approach to explore factors that may lead to changes in the efficiency index calculated for US states, using a panel of forty-eight states over the period 1970-86.

Puig-Junoy (2001) investigated the effects of public capital level and composition on the efficiency of the forty-eight contiguous US states in the period 1970-83 using a parametric frontier approach.

4.4. Estimating Efficiency at industrial disaggregate level

Measurements of inefficiency in industry were first constructed by estimating deterministic frontiers and subsequently by using stochastic frontiers. Aigner and Chu (1968) were the first researchers to estimate a deterministic frontier using Cobb-Douglas production function through linear and quadratic programming techniques.

They argued that for a given industry producers might differ from each other in their production processes.

The distinguishing features among producers could be represented by:

1. attained values for certain technical parameters in an industry production function,
2. differences in scales of operation, and
3. various structures in their organization

As far as the efficiency analysis at industrial is concerned, the stochastic frontier model is used in a large literature of studies of production, cost, revenue, profit and other models of goal attainment. A summary of the main SFA applications are presented in the following table:

Table 4.1.Surveys implementing SFA

Application	Paper	Application	Paper
Wheat Production	Ahmad et al. (2002)	World Health Organisation	Hollingsworth and Wildman (2002)
	Kolawole and Ojo (2007)		Richardson et al. (2003)
Fishing	Chiang et al. (2004)		Greene (2004b)
	Herrero (2005)		Lauer et al. (2004)
	Martinez – Gordero and Leung (2004)	Labour markets	Sheldon (2003)
	Kompas and Che (2007)		Ibourk et al. (2004)
Forestry	Otsuki et al. (2002)		Lang (2005)
	Bi (2004)		Millimet (2005)
	Hof et al. (2004)	Macroeconomics	Cherchye et al. (2004)
	Liu and Yin (2004)		Despotis (2005)
Agricultural and Light Manufacturing	Piesse and Thirtle (2000)		Ravallion (2005)
Airports	Oum and Yu (2004)		Yoruk and Zaim (2005)
	Sarkis and Talluri (2004)	Inequality and poverty insurance	Deutsch and Silber (2005)

	Yoshiba and Fujimoto (2004)		Greene and Segal (2004)
	Yu (2004)		Cummins et al. (2005)
Air Transport	Coelli et al. (2002)		Jeng and Lai (2005)
	Sickles et al. (2002)		Tone and Sahoo (2005)
	Scheraga (2004)	Tax administration	Serra (2003)
	Duke and Torres (2005)		
Banking	Davis and Albright (2004)	Stocks, mutual funds and hedge funds	Basso and Funari (2003)
	Camanho and Dyson (2005)		Troutt et al. (2005)
	Huang and Wang (2002)		Chang (2004)
	Kumbhakar and Tsionas (2002)		Abad et al. (2004)
	Tsionas and Greene (2003)	Financial statement analysis	Chen and Zhu (2003)
	Porembski et al. (2005)		Feroz et al. (2003)
	Silva Portela and Thanassoulis (2005)	Mergers	Ferrier and Valdmanis (2004)
Bankruptcy Prediction	Wheelock and Wilson (2000)		Bogetoft and Wang (2005)
	Becchetti and Sierra (2003)	Elections	Obata and Ishii (2003)
	Cielen et al. (2004)		Foroughi et al. (2005)
Health Care	Birman et al. (2003)	Libraries	Shim (2003)
	Dervaux et al. (2003)		Kao and Lin (2004)
	Jimenez et al. (2003)	Military	
	Kirigia et al. (2004)		Brockett et al. (2004)
Credit Risk Evaluation	Emel et al. (2003)		Sun (2004)
	Paradi et al. (2004)	Sports	Haas (2003)
Electricity Distribution	Agrell et al. (2005)		Lins et al. (2003)
	Delmas and Tokat (2005)		Fried et al. (2004)
	Pollitt (2005)		Amos et al. (2005)

	Edvardsen et al. (2006)	Environment: macro applications	Jeon and Sickles (2004)
	Filippini et al. (2004)		Zaim (2004)
			Henderson and Millimet (2005)
	Giannakis et al., 2005 for UK;	Environment: micro applications	Gang and Felmingham (2004)
	Hjalmarson and Veiderpass, 1992 for Sweden;		Wagner (2005)
	Førsund and Kittelsen, 1998 for Norway		Shadbegian and Gray (2005)
Electricity Generation	Arocena and Waddams Price (2003)		Banhaf (2005)
	Korhonen and Luptacik (2004)	Internet commerce	Wen et al (2003)
	Atkinson and Halabi (2005)		Barua et al. (2004)
	Cook and Green (2005)		Chen et al. (2004)
Gas Distribution	Rossi (2001)		Serrano – Cinca et al. (2005)
	Carrington et al. (2002)	Museums	
	Hammond et al. (2002)		Bishop and Brand (2003)
	Hawdon (2003)		Basso and Funari (2005)
Oil And Gas	Managi et al. (2006)	Health	Evans et al., 2000a, 2000b
Aggregate R&D Activities	Wang (2007)		Greene, 2004b;
	Dhawan and Gerdes (1997)		Gravelle et al., 2002a, 2002b;
Rail Transport	Kennedy and Smith (2004)		Hollingsworth and Wildman, 2002).
	Loizides and Tsionas (2004)	Nursing homes	Farsi and Filippini (2003)
	Farsi et al. (2004)		Hougaard et al.

			(2004)
			Laine et al. (2005)
	Gathon and Perelman (1992)	Dentistry	Buck (2000)
Public Infrastructure	Mamtzakis (2003)		Grytten and Rongen (2000)
			Linna et al. (2003)
	Paul et al. (2004)		Widstrom et al. (2004)
	Salinas – Jiminez (2004)	Physician practices	Wagner et al. (2003)
Telecommunications	Guedes de Avellar et al. (2002)		Rosenman and Friesner (2004)
		Education	McMillan and Chan (2006)
		Education: primary and secondary	Dolton et al. (2003)
	Resende and Facanha (2004)		Mayston (2003)
Urban Transit	De Borger et al. (2002)		Ammar et al. (2004)
	Dalen and Gomez – Lobo (2003)		Dodson (2004)
	Odeck (2006)	Education: tertiary	Bonaccorsi and Daraio (2003)
Water Distribution	Corton (2003)		Mensah and Werner (2003)
	Tupper and Resende (2004)		Guan and Wang (2004)
	Aubert and Reynaud (2005)		Warning (2004)
	Cubbin (2005)	Accounting, advertising, auditing and law	Banker et al. (2005)
Refuse Collection And Recycling	Bosch et al. (2000)		Wang (2000)
	Worthington and Dolllery (2001)		Dopuch et al. (2003)
	Lozano et al. (2004)		Luo and Donthu (2005)

Ports	Clark et al. (2004)	Hospitals	Chang et al. (2004)
	Lawrence and Richards (2004)		Gao et al. (2006)
	Park and De (2004)		
	Cullinane et el. (2003)		Stanford (2004)
Real Estate Investments	Lewis et al. (2003)	Hotels	Hwang and Chang (2003)
	Anderson et al. (2004)		Chiang et al. (2004)
Fabrics	Battese, Rao, and Walujadi (2001)		Barros (2005)
			Sigala et al. (2005)
		Postal services	Pimenta et al. (2000)
			Maruyama and Nakajima (2002)
			Borenstein et al. (2004)

Source: Own elaboration, based on Fried et al. (2008), p. 16-19

As far as the research implementing technical efficiency analysis is concerned, there is a great number of papers examining technical efficiency through stochastic Frontier Approach or Data Envelopment Analysis.

Regarding primary sector, Ahmad et al. (2002) and Kolawole and Ojo (2007) examined wheat production. Most specifically, Ahmad et al. (2002) incorporated stochastic production frontier analysis in order to estimate efficiency and sustainability in wheat production in Pakistan with a production function incorporating inefficiency effects, such as: use of fertilizer nutrients, access to more reliable irrigation system, proportionate farm area devoted to crop, farm size, access to credit, closeness to markets, irrigation and agricultural extension facilities and education. The results of efficiency analysis showed that the average technical efficiency is about 68 percent and thus an average farmer is producing 32 percent less than the achievable potential output. Kolawole and Ojo (2007) examined the overall efficiency of small holder croppers in Nigeria indicating that presence of technical inefficiency and allocative inefficiency had effects in the food crop production as depicted by the significant estimated gamma coefficient, the generalized likelihood ratio test and the predicted technical and allocative efficiencies within the farmers. The mean technical, allocative and economic efficiency of 0.733, 0.872 and 0.684 respectively, indicating that the sample farmers were relatively very efficient in allocating their limited resources.

Fishing is one of the most common case studies in the efficiency estimation literature. Herrero (2005) compared data envelopment analysis, stochastic production frontiers, panel data and distance functions. These different approaches have been applied to the Spanish Trawl fishery that operated in Moroccan waters, concluding that, in most cases, the multi- versus single-output feature is determinant in producing higher differences in the efficiency estimates. Martinez-Gordero and Leung (2004) examined the shrimp industry at a global level and in Mexico based on an unbalanced panel of semi-intensive shrimp farms containing primary-source information at pond level for the period 1994, 1996–1998 in northwest Mexico, using an input distance function approach, total factor productivity (TFP) and technical efficiency (TE) using both traditional (T) and environmentally adjusted (EA) indicators. Kompas and Che (2007) investigated efficiency gains associated with cost reductions from increases in traded quota estimated with a stochastic cost frontier for the Australian South East Trawl Fishery (SETF). Estimation of this frontier also provides key information on the relative importance of input costs in the SETF, returns to scale, variations in costs as a result of trade in quota and the economic performance of each fishing vessel, year to year. Final estimations indicate that increases in the volume of quota traded have resulted in considerable efficiency gains and cost reductions in the SETF, ranging from 1.8 to 3.5 cents per kilogram for surveyed vessels for every 1% increase in the volume of quota traded, or 1-2.4% of total variable costs, with considerable gains also accruing to crew and skipper in the form of larger share payments. Mean vessel efficiency is relatively high in the SETF, estimated at over 90%, and increases further to 92% over the sample period with increased trades in quota.

In forestry, Otsuki et al. (2002) examined the effects of the Brazilian governments' title granting policies on the efficiency of agricultural and timber production in the Brazilian Amazon. A two-stage procedure is used that combines Data Envelopment Analysis (DEA) and a Tobit regression, finding that the main determinants of increasing technical efficiency seemed to be: the provision of private land titles, governmental expenditures, expenditures to secure property rights, and land-granting policies. Furthermore, Hof et al. (2004) reported the methodology and results of a data envelopment analysis (DEA) that attempts to identify areas in the country where there is maximum potential for improving the forest and rangeland condition, based on 12 indicator variables. The primary variables are measures of human activity and indicators of forest and rangeland condition in place of the traditional economic inputs (costs) and outputs. It is concluded that, based on this analysis, there are opportunities to improve the forest and rangeland condition without reducing the amount of human activity, but not over large areas, only for some indicators, and typically not for a large number of indicators in the same place. This means that large-scale improvements in environmental condition across many indicators may often not come about without a reduction in human activity.

Moreover, in agricultural and light manufacturing, Piesse and Thirtle (2000) incorporated translog stochastic frontiers with inefficiency effects to a panel of producer level data for 117 agricultural producers and 43 producers in the light manufacturing industry that technological regression dominates, giving negative productivity change. The inefficiencies are explained by overcapitalization, subsidies and excessive management costs, while producers that had established export markets were more efficient.

Stochastic frontier approach has also found wide acceptance within industrial settings (Battese and Coelli, 1992; Coelli and Battese, 1996). A number of studies examined the technical efficiency of manufacturing industries in developing countries (Nishimizu and Page, 1982; Abdulkhadiri and Pickles, 1990; and Chuang, 1996, Harris 1993, Sheehan 1997) and steel production Wu (1996). Efficiency analysis has also played a crucial role in defining regulatory policies in industries. Examples are telecommunication (Uri, 2001), energy (Jamasb and Pollitt, 2001), schooling (Mizala et al., 2002) and hospitals (Steinmann and Zweifel, 2003). Efficiency analysis is also increasingly applied to other industry-specific analysis, banking (Fare et al., 2004), or the cement industry (Tsekouras and Skuras, 2005). In the electricity industry, technical efficiency analysis has played a particularly important role in the liberalization process towards a competitive industry structure and market-orientated regulation, both in electricity transmission and electricity distribution. Many authors concentrate on scale effects, and the optimal size and relative efficiency of producers, following a benchmarking approach. Jamasb and Pollitt (2001) give an extensive comparison of international efficiency studies for the electricity industry, stressing the importance of the proper variable choice. In a subsequent paper, Jamasb and Pollitt (2003) perform an international benchmarking study of 63 utilities from six European countries comparing several SFA and DEA specifications.

Mahmood et al. (2007) examine the efficiency of the large scale manufacturing industry of Pakistan using the stochastic production frontier approach. A stochastic production frontier is estimated for two periods, 1995-96 and 2000-01, for 101 industries. The results show that there has been some improvement in the efficiency of the large scale manufacturing industry, though the magnitude of improvement remains small.

Taymaz and Saatci (1997) analyse the extent and importance of technical progress and efficiency in Turkish manufacturing industries. The rate and direction of technical change in three industries (textiles, cement, and motor vehicles) are estimated by using panel data on plants for the period 1987-92, using Cobb-Douglas, and translog stochastic frontier production functions. In addition to traditional inputs like labour, raw materials, energy and capital inputs etc., other factors like sub-contracting, advertising intensity, ownership type are also included in the analysis. The results show that there are significant inter-industrial differences in the rates of technical change and the factors influencing technical efficiency at the plant level.

Ikhsan-Modjo (2006) examines the patterns of total factor productivity growth and technical efficiency changes in Indonesia’s manufacturing industries over the period

1988-2000. The study uses the data incorporating both the liberalisation years and the crisis/post crisis years sourced from an annual panel survey of manufacturing establishments. Gross output is regressed on inputs like the cost of capital, wages, intermediate inputs and energy, and the study finds that technical progress is the most important factor in explaining TFP growth in the Indonesian manufacturing industry.

Tripathy (2006) examines efficiency gap between foreign and domestic firms in eleven manufacturing industries of India during 1990-2000. Two different techniques, i.e. stochastic frontier and data envelopment analysis are used to measure efficiency of the firms. The study assumes a Cobb-Douglas technology and estimates stochastic production and cost frontier in each industry to measure technical efficiency and cost efficiency of each firm as well as to obtain some inference on allocative efficiency.

Alvarez and Crespi (2003) explore differences in technical efficiency in Chilean manufacturing firms. The authors use plant survey data and apply nonparametric frontier Data Envelopment Analysis. A stratified random sample is employed and firms are classified according to ISIC (3-digits) classification. It is found that the average efficiency of the sample is 65 percent with a large heterogeneity among industries, and that the professional and scientific equipment industry exhibits 91 percent efficiency, while agro-industries and textiles have much lower efficiency levels at 49 percent and 34 percent respectively.

Pandya (2011) aims at estimating the Deterministic and Stochastic Production Frontiers toanalyze the Technical Efficiency of Indian Plastic Industry. The study includes estimation of Deterministic and Stochastic Production Frontiers for the Plastic Industry. The Cobb-Douglas Production Function is used for this purpose since it has been found to be the most appropriate form for Indian Industries from several research studies. Productive Capacity Realization Ratios have been obtained using the Frontier Estimates and thereby the efficiency levels in the PVC Plastic Industry are evaluated.

Njikam (2003) assesses the effects of trade reform on firm-specific technical efficiencies in Cameroon manufacturing using firm-level balanced panel data for the period from 1988-89 to 1997-98. A Cobb–Douglas stochastic production frontier is estimated for each industrial industry. Results indicate that relative average technical efficiency increased in six of eight industries and in total manufacturing. The study concludes that the trade reform provided an enabling environment for improving firm-level technical efficiency.

Parameswaran (2002) analyses the performance of the manufacturing firms in some selected industries in terms of their technical efficiency against the background of the industrial and trade policy reforms introduced in India since 1991. A stochastic frontier production function and an associated inefficiency model are used to measure time varying firm specific technical efficiency. We define technical change as the shift of the best practice production frontier and technical inefficiency change as the movement within the best practice technology. The results show that all the industries considered registered a higher rate of technical progress in the post reform period along with a decline in the level of technical efficiency. The effect of change in the policy environment on technical efficiency varies among industries. The study also found that firms' involvement in the international trade through export and import of raw materials and technology has a positive effect on technical efficiency. To measure the technical efficiency of firms over time and to test for the effect of firm's import and export activities on their technical efficiency, Parameswaran (2002) uses a stochastic frontier production function, along with an inefficiency model as proposed by Battese and Coelli (1995). Parameswaran (2002) assumes that the frontier production function is of translog form. For the analysis Parameswaran (2002) uses firm level panel data of four industries, namely electrical machinery, electronics, non-electrical machinery and transport equipment. These industries belong to the segment of capital goods industries that faced greater reduction in trade protection in 1990s along with industrial policy reform. Hence, an analysis of these four industries assumes significance. The use of panel data allows to have not only more number of observations, but also enables to look into the pattern of distribution of technical efficiency among firms and its change over time.

Regarding aviation industry, Oum and Yu (2004) investigated the effects of different forms of price regulation on airport efficiency, taking into account the interaction between concession profits and price regulations. Their results showed that while regulation may lead to over-investment in capacity, price-cap regulation is prone to under-investment, concluding that dual-till regulation would be better than the single-till regulation in terms of economic efficiency, especially for large and busy airports. Sarkis and Talluri (2004) investigated performance evaluation and process improvement of airlines and air carriers. Their study evaluated the operational efficiencies of 44 major US airports across 5 years using multi-criteria non-parametric models. These efficiency scores are treated by a clustering method in identifying benchmarks for improving poorly performing airports. Efficiency measures are based on four resource input measures including airport operational costs, number of airport employees, gates and runways, and five output measures including operational revenue, passenger flow, commercial and general aviation movement, and total cargo transportation. Yoshiba and Fujimoto (2004) examined efficient public investment, especially in the transportation infrastructure, arguing that some of the small regional airports are indeed suffering the issue of overinvestment. This paper attempted to verify the validity of such criticism by statistically measuring the efficiency of Japanese airports and conducting comparative analysis. For this objective, the paper employed two distinct methods namely data-envelopment analysis and endogenous-weight TFP methods. The results from these methods consistently indicates that the efficiency of regional airports in mainland Japan are lower than others, and that those airports constructed in the 1990s are relatively inefficient. Oum and Yu (2004) compared the performance of productivity and efficiency of airport management and operation, as well as the relationships between various performance measures and airport characteristics in order to better understand the observed differences in airport performance. This paper extracted from the benchmarking report focuses on measuring and comparing operating efficiency performance of the world’ s major airports, after removing the effects of the variables beyond managerial control. Coelli et al. (2002) also examined aviation industry, focusing on the measurement of the contribution of unused capacity, along with measures of technical inefficiency, and allocative inefficiency. The paper concludes with an empirical illustration, involving data on 28 international airline companies. The empirical results indicate that these airline companies achieve profit levels which are on average 70% below potential levels, and that gap may be attributed to unused capacity. Sickles et al. (2002)

examined the productive performance of a group of three East European carriers and compare it to thirteen of their West European competitors during the period 1977-1990 with a stochastic distance frontier using recently developed semi-parametric efficient methods. Both semi- and nonparametric methods indicate significant slack in resource utilization in the East European carriers relative to their Western counterparts, and limited convergence in efficiency or technical change between them. Scheraga (2004) examined a sample of 38 airlines from North America, Europe, Asia and the Middle East to investigate whether relative operational efficiency implied superior financial mobility. Data envelopment analysis was utilized to derive efficiency scores for individual airlines. It was found that the traditional framework developed in the literature still provided reasonable explanatory power for realized relative operational efficiency. However, the second stage of the analysis found that relative operational efficiency did not inherently imply superior financial mobility. As such, airlines that had chosen relatively efficient operational strategies found themselves in positions of vulnerability with regard to financial mobility. A similar approach has been also followed by Duke and Torres (2005), who highlighted the importance of controlling costs in the industry, and enhancing productivity.

Using a sample of 44 Indian pharmaceutical companies for the period 1992 to 2000, Saranga and Phani (2004) attempt to investigate whether internal efficiencies have any role to play in the growth of companies in a constantly changing dynamic environmental context. Companies are grouped according to three different criteria including the type of ownership, type business, and firm size. The purpose is to see how the companies in different categories fare in terms of efficiency ratings. Inputs selected are cost of production and selling, cost of material, and cost of manpower whereas outputs are profit margin, net sales, and exports. The results show that size of a company does not dictate the internal efficiency ratings; however indigenous firms, which are in the business of both bulk and formulations, have an edge over MNCs and over firms with only formulations business.

Jajri and Rahmah (2006) analyse trend of technical efficiency, technological change and TFP growth in the Malaysian manufacturing industry. The authors use Data Envelopment Analysis (DEA) to calculate output-oriented Malmquist indices of Total

Factor Productivity growth, technological change, and technical efficiency change. Technical efficiency change (catch-up) measures the change in efficiency between current (t) and next (t+1) periods, while the technological change (innovation) captures the shift in frontier technology. Seven industries are chosen viz. food, beverages and tobacco; textile, wearing apparel and leather; wood and wood products; paper and paper products; chemicals, petroleum, coal, rubber and plastic products; non-metallic mineral and iron and steel products industries. Input variables are capital and labour whereas value added is used as output. It is found that Total Factor Productivity Growth is mainly driven by technical efficiency. The industries that experienced high technical efficiency are food, wood, chemical and iron products. Analysis by industry shows that there is no positive relationship between capital intensity and efficiency, technological change and Total Factor Productivity growth.

Lee and Kim (2006) analyze the effects of research and development (R&D) on Total Factor Productivity growth in manufacturing industries, using a sample of 14 OECD (Organisation for Economic Cooperation and Development) countries for the years 1982-1993. With the assumption of constant returns to scale technology, the Malmquist Productivity Index and its components are computed using two traditional inputs i.e. labour and capital; then the exercise is repeated with the stock of R&D capital as an additional input. Inclusion of R&D capital is found to be statistically significant and the introduction of R&D capital as an additional input reduces the TFP measures on average by 10 percent. It is also found that it is technological progress rather than efficiency catch up that is driven by the accumulation of R&D capital. Spillovers of R&D capital are tested using regression analysis. Two types of spillovers are considered viz. domestic R&D spillovers across industries and international spillovers within a single industry. Domestic R&D capital stocks and foreign R&D capital stocks for different industries are used for this purpose. It is found that productivity gains in manufacturing industries depend significantly on R&D spillovers, especially for an economy that is more open to international trade.

Kim et al. (2005) examine the technical efficiency of firms in the iron and steel industry and try to identify the factors contributing to the industry's efficiency growth, using a time-varying stochastic frontier model. A firm's technical efficiency also tends to be positively related to its production level as measured by a share of the total world production of crude steel. Another important source of efficiency growth identified by our empirical findings is adoption of new technologies and equipment. Our findings clearly indicate that continued efforts to update technologies and equipment are critical to the pursuit of efficiency in the iron and steel industry. As described in Kim et al. (2005), several studies investigated the efficiency of the iron and steel industry. They include among others: Ray and Kim (1995) for the U.S. steel industry; Jefferson (1990), Kalirajan and Cao (1993), Wu (1996), and Ma et al. (2002) for Chinese iron and steel firms. In this study, they consider time-varying inefficiency, and base our analysis on the model developed by Battesse and Coelli (1995).

Camanho and Dyson (2005) eenhanced cost efficiency measurement methods to account for different scenarios relating to input price information in banking industry. These consist of situations where prices are known exactly at each decision making unit (DMU) and situations with incomplete price information. The assessments under price uncertainty are based on extensions to the Data Envelopment Analysis (DEA) model that incorporate weight restrictions of the form of input cone assurance regions. Huang and Wang (2002) estimated economic efficiency and economies of scale, using panel data of 22 Taiwanese commercial banks over the period 1982-97, employing a wide range of parametric and non–parametric cost frontiers' efficiency estimation methods to estimate economic efficiency and economies of scale, using the same panel data of 22 Taiwanese commercial banks over the period 1982–97. According to their empirical implementation, the two methodologies yield similar average efficiency estimates, yet they come to very dissimilar results pertaining to the efficiency rankings, the stability of measured efficiency over time, the consistency between frontier efficiency and conventional performance measures, and the estimates of scale economies. Thus, the choice of an estimation approach can result in very different conclusions and policy implications regarding cost efficiencies and cost economies. These findings suggest that making policy decisions and evaluations relies on multiple techniques and specifications.

Kumbhakar and Tsionas (2002), within a panel data analysis with rice farming data from Philippines, dealt with nonparametric estimation of the technology, risk and risk preferences of producers when they face uncertainty in production. Uncertainty is modeled in the context of production theory where producers' maximize expected utility of anticipated profit. Tsionas and Greene (2003), within a panel data analysis, proposed a stochastic frontier model with random coefficients to separate technical inefficiency from technological differences across firms, and free the frontier model from the restrictive assumption that all firms must share exactly the same technological possibilities.

Silva Portela and Thanassoulis (2005) using parametric and non-parametric methods, have been focusing mainly on profit efficiency and to identify the sources of any shortfall in profitability (technical and/or allocative inefficiency). The method is applied to a set of Portuguese bank branches first assuming long run and then a short run profit maximisation objective. In the long run most of the scope for profit improvement of bank branches is by becoming more allocatively efficient. In the short run most of profit gain can be realized through higher technical efficiency. Wheelock and Wilson (2000) use alternative measures of productive efficiency to proxy management quality in individual U.S. banks, and find that inefficiency increases the risk of failure while reducing the probability of a bank's being acquired. Becchetti and Sierra (2003) investigated the determinants of bankruptcy in three representative unbalanced samples of Italian firms for the periods 1989–91, 1992–94 and 1995–97. Two important results are that: (i) the degree of relative firm inefficiency measured as the distance from the efficient frontier has significant explanatory power in predicting bankruptcy (ii) qualitative regressors such as customers' concentration and strength and proximity of competitors have significant predictive power.

Country-wide research in electricity distribution is also wide, with reference to Agrell et al. (2005) in Scandinavian countries; Giannakis et al. (2005) for UK; Hjalmarson and Veiderpass (1992) for Sweden; Førsund and Kittelsen (1998) for Norway. Delmas and Tokat (2005) based on the analysis of 177 U.S. electric utilities from 1998 to

2001, our results show that the process of retail deregulation has a negative impact on firms' productive efficiency, as measured using Data Envelopment Analysis. Pollitt (2005) examined regulation effects on productive efficiency using non-parametric methods. Edvardsen et al. (2006) followed a piecewise linear frontier technology, reflecting observed best practice, accommodating the multi-output nature of distribution utilities is specified calculating shift in frontier technology and change in efficiency, for the period 1983 to 1989. Filippini et al. (2004) analyzed the efficiency of electricity distribution companies in Slovenia using SFA..

In health care industry, there are numerous papers on estimating technical efficiency, using stochastic and non-stochastic methods. To mention several representative papers, Birman et al. (2003), Dervaux et al. (2003), Kirigia et al. (2004) and Jimenez et al. (2003) examined problems associated with ageing, mental illness, learning disability or physical disability. Farsi and Filippini (2003) investigated the nursing homes operated by government administration. The results also suggest that a great majority of the nursing homes in the sample do not fully benefit from scale economies. This implies that efficiency gains can be obtained with larger capacities or joint operations.

In electricity generation, Arocena and Price (2003) introduced some novelty in modeling efficiency, including three pollutants and declared plant availability as outputs, and we test for the effect of environmental regulation in reducing pollutants. Korhonen and Luptacik (2004), Cook and Green (2005) and Atkinson and Halabi (2005) employed data envelopment analysis (DEA) to measure technical efficiency (as the relation of the desirable outputs to the inputs) in electricity plants. In gas distribution, Rossi (2001) used a stochastic frontier approach to analyze the technical change in the post-privatization period in the gas distribution industry in Argentina, finding that there is both a catching up effect and a shift in the frontier, which shows that the industry as a whole improved its efficiency not only for the average but also for every firm in the sample. Carrington et al. (2002) presented a benchmarking analysis, conducted for an Australian regulator that derives measures of efficiency for Australian gas distributors relative to U.S. counterparts. Several techniques, such as data envelopment analysis and stochastic frontier analysis, were used to ensure that their measures were robust to methodology choice. Hammond et al. (2002) attempted an investigation by using Data Envelopment Analysis to estimate the relative efficiency of a sample of undertakings under each system, finding that undertakings operating under the basic price system were found to be more efficient which suggests that incentive regulation was effective in the industry. Hawdon (2003) investigated policy developments which affect efficiency of resource use in the gas industry, and used data envelopment analysis to measure relative performance at the individual country level.

In oil and gas industries, Managi et al. (2006) examined the impact of technological change on the production frontier. To address the industry – specific feature, they also interdicted environmental variables.

In aggregate R&D activities, Wang (2007) constructed a cross-country production model for evaluating the relative efficiency of aggregate R&D activities. R&D capital stock and manpower were considered as inputs; patents and academic publications were regarded as outputs. Environmental factors that influence R&D performance were also taken into account. Dhawan and Gerdes (1997) estimated an index of technological change using producer-level data in a stochastic frontier production function model that takes into account time-varying technical inefficiency.

In rail transport, Kennedy and Smith (2004) incorporated the efficiency measurement techniques (DEA; COLS; SFA) for assessing Railtrack efficiency. Loizides and Tsionas (2004) developed a model to represent the cost structure of European railways based on a general index of technical change, which allows completely general estimation of productivity growth. The estimated model is based on a variable cost function for panel data, which allows for heterogeneity in spite of previous approaches in the railway economics and general index model literature which adopt the assumption of common technical parameters across countries. Farsi et al. (2003) examined the issue of cost-efficiency in Switzerland’s nursing homes, with a panel data of 17 public and 19 nonprofit nursing homes operating over the 9-year period from 1993 to 2001, in one of the 26 Swiss cantons, Ticino. Several specifications are used to study the robustness of the results. The results suggest that the institutional form influences the efficiency of the studied nursing homes in that non-profit foundations are likely to be more cost-efficient than the nursing homes operated by government administration. The results also suggest that a great majority of the nursing homes in the sample do not fully benefit from the scale economies. This implies that efficiency gains can be obtained with larger capacities or joint operations.

Finally, Gathon and Perelman (1992) created a stochastic frontier for European railways using a panel data approach in which technical efficiency is assumed to be endogenously determined.

In public infrastructure, Martin et al. (2004) and Paul et al. (2004) examined the effects of public infrastructure on productivity in 12 two-digit manufacturing industries, which contribute about two thirds to the total output of the manufacturing industry. A translog cost function incorporating public capital infrastructure is estimated for each industry separately using annual time-series data for 1961-1995. The cost-function approach facilitates the investigation of productive effects of public capital in terms of both cost-saving and output-augmenting measures. It also enables to examine public capital's effects on the input demand and derive the rate of return on public investment (pertaining to manufacturing). Salinas – Jiminez (2004) analyzed the effect of public infrastructure on private factor productivity and efficiency in the Spanish regions. The focus is on the role of investment in public infrastructure and on analyzing how the relative endowments of public to private capital affect productivity growth. The results obtained indicate that, although public investment contributes to enhance private productivity growth, the less productive regions are suffering from a relative deficit of private capital. Other variables that might condition productivity (i.e., human capital, asymmetries in the economic cycle, and the industry structure) are also considered.

In telecommunications industry, Guedes de Avellar et al. (2002) investigate the relative efficiency of 34 Brazilian Landline Telephone Service companies using Data Envelopment Analysis with weight constraints in the input and output variables. Uri

(2004) used several different measures of service quality, to investigate empirically whether there has been a decline in service quality between 1991 and 2000. Resende and Facanha (2005) reviewed the incentive properties of yardstick schemes with special reference to quality performance and to the economic foundations and practical applications of data envelopment analysis (DEA) for Brazilian local telephony over the period 1998–2002. The evidence indicates substantial quality underperformance, with some improvements towards the end of the period.

In urban transit efficiency estimation, De Borger et al. (2002) provided a comprehensive survey of the literature on production and cost frontiers for public transit operators, and it evaluates the contributions of frontier analysis to the performance of the public transport industry. Dalen and Gomez – Lobo (2003) estimated a cost frontier model for an eleven-year panel of Norwegian bus companies (1136 company-year observations) using the methodology by Battese and Coelli (1995), to investigate to what extent different type of regulatory contracts affect company performance. The panel model proposed by Battese and Coelli (1995) allow for year/company specific efficiency measures to be estimated. Thus, unobservable network or other time invariant characteristic of the operating environment can be controlled for by analyzing the dynamics of measured productivity across time for firms regulated under different types of contracts, rather than relying solely on variations across companies during one time period. The main and robust result of the paper is that the adoption of a more high-powered scheme based on a yardstick type of regulation significantly reduces operating costs. Odeck (2006) used Data Envelopment Analysis (DEA) to analyze efficiency differences in the industry to test for efficiency and scale differences with respect to ownership, region of operation and scope of operation. The results suggest that there is in general a potential for input saving in the whole industry of about 28 percent. Nevertheless, while no significant differences are found between urban and rural operators with respect to input saving and output increasing efficiency scores, rural operators on average have lower mean scale efficiency and a higher variance of scale efficiency.

In water distribution, Corton (2003) describes the implementation of a benchmarking scheme by the Peru water industry regulatory agency, analyzing alternative measures of efficiency and estimates an efficiency frontier from a regression model of operating costs. Management culture and political interference were detected as important issues having an impact in this industry. Tupper and Resende (2004) quantify the relative efficiencies of state water and sewage companies in Brazil during the 1996–2000 period. Relative efficiency scores obtained by Data Envelopment Analysis-DEA indicate that sub-optimal performance is salient for some utilities. In order to control for regional heterogeneities, the complementary between DEA and econometric procedures is explored as one controls for network density and water loss factors. To measure the impact of regulation on efficiency, Aubert and Reynaud (2005) use a stochastic cost frontier approach defining the unobservable efficiency of water utility in Wisconsin as a function of exogenous variables. Using a panel of 211 water utilities observed from 1998 to 2000, they show that their efficiency scores can be partly explained by the regulatory framework. Cubbin (2005) considers the use of efficiency measurement in the regulation of the water industry in England, Wales, and Scotland.

Clark et al. (2004) investigate the determinants of shipping costs to the United States with a large database of more than 300,000 observations per year on shipments of products l from different ports around the world. They find that port efficiency is an important determinant of shipping costs. Improving port efficiency from the 25th to the 75th percentile reduces shipping costs by 12%. In turn, factors explaining variations in port efficiency include excessive regulation, the prevalence of organized crime, and the general condition of the country’s infrastructure. Reductions in country inefficiencies, associated to transport costs, from the 25th to 75th percentiles imply an increase in bilateral trade ofaround 25%. Cullinane et el. (2003) investigate the efficiency of container terminals within the context of global supply chain management. The efficiency and scale properties of 104 of Europe's container terminals with annual throughput of over 10,000 TEUs[1] in 2003, distributed across 29 European countries, are derived using data envelopment analysis. The main findings are that significant inefficiency pervades most of the terminals under study and that large-scale production tends to be associated with higher efficiency.

Lewis et al. (2003) used a stochastic frontier methodology that incorporates Bayesian statistics, and analyzes the cost efficiency of real estate investment trusts (REITs) by observing the deviations of the measured costs of individual REITs from a defined efficient cost frontier, using 1995–1997 data.

Battese, Rao, and Walujadi (2001) investigate the technology gap and technical efficiencies of firms in the garment industry in different regions of Indonesia. They present a met-afrontier production function model for firms in different groups having different technologies. The meta-frontier model enables the calculation of comparable technical efficiencies for firms operating under different technologies. The model also enables the technology gaps to be estimated for firms under different technologies relative to the potential technology available to the industry as a whole.

Efficiency of accounting, advertising, auditing and law producers has been examined by Banker et al. (2005), Wang (2000), Dopuch et al. (2003) and Luo and Donthu (2005). Efficiency of hospitals is investigated by Chang et al. (2004), Gao et al. (2006) and Stanford (2004).

In education McMillan and Chan (2006) determined efficiency scores for Canadian universities using both data envelopment analysis and stochastic frontier methods. There was considerable divergence in the efficiency scores and their rankings among methods and specifications. An analysis of rankings, however, revealed that the relative positions of individual universities across sets of several efficiency rankings (e.g., all the data envelopment analysis and stochastic frontier outcomes) demonstrate an underlying consistency. Primary and secondary education efficiency is examined by Dolton et al. (2003), Mayston (2003), Ammar et al. (2004) and Dodson (2004). Tertiary education is investigated by Bonaccorsi and Daraio (2003), Mensah and Werner (2003), Guan and Wang (2004) and Warning (2004).

Internet commerce efficiency is investigated by Wen et al (2003), Barua et al. (2004), Chen et al. (2004) and Serrano – Cinca et al. (2005). Technical efficiency in museums is measured by Bishop and Brand (2003) and Basso and Funari (2005).

Panel data sets on health care attainment has been used by numerous researchers for studying different approaches to efficiency modeling (Evans et al., 2000a, 2000b; Greene, 2004b; Gravelle et al., 2002a, 2002b; Hollingsworth and Wildman, 2002). Nursing homes technical efficiency is evaluated by Farsi and Filippini (2003), Hougaard et al. (2004) and Laine et al. (2005).

Physician practices technical efficiency is measured by Rosenman and Friesner (2004). The World Health Organisation technical efficiency has also been a study case for Hollingsworth and Wildman (2002), Greene (2004) Lauer et al. (2004).

All lot of these papers suggest that technology and knowledge diffusion might help to improve production efficiency. Moreover, specific studies, as Meng and Li (2002), showed evidence of ICT industry development and diffusion but also huge gap between China and developed nations in this regards as well as digital divide among different economic regions. Gao (2004) examined regional industrial development in China with emphasis on factors representing sources of regional growth. Gao (2004) found that local competition, small size of public sector, better transport system, and exports and FDI positively effect on regional industrial growth.

In addition to traditional inputs, Heshmati and Kumbhakar (2010) incorporate several indicators of technology. One such indicator is ICT investment as an infrastructure for economic development. Other indicators are human capital and its role in acquisition and absorption of new technology, skills and management. Meng and Li (2002) is one of few studies which provided some evidence on China’s ICT industrial development and diffusion in recent years. Heshmati and Yang (2006) also investigated the relationship between TFP growth and ICT investment but at the aggregate national level, and, they provided estimation of positive returns to ICT investment in China.

4.5. Productive Efficiency and Institutional Context: Industrial and Innovation Policy in European Union

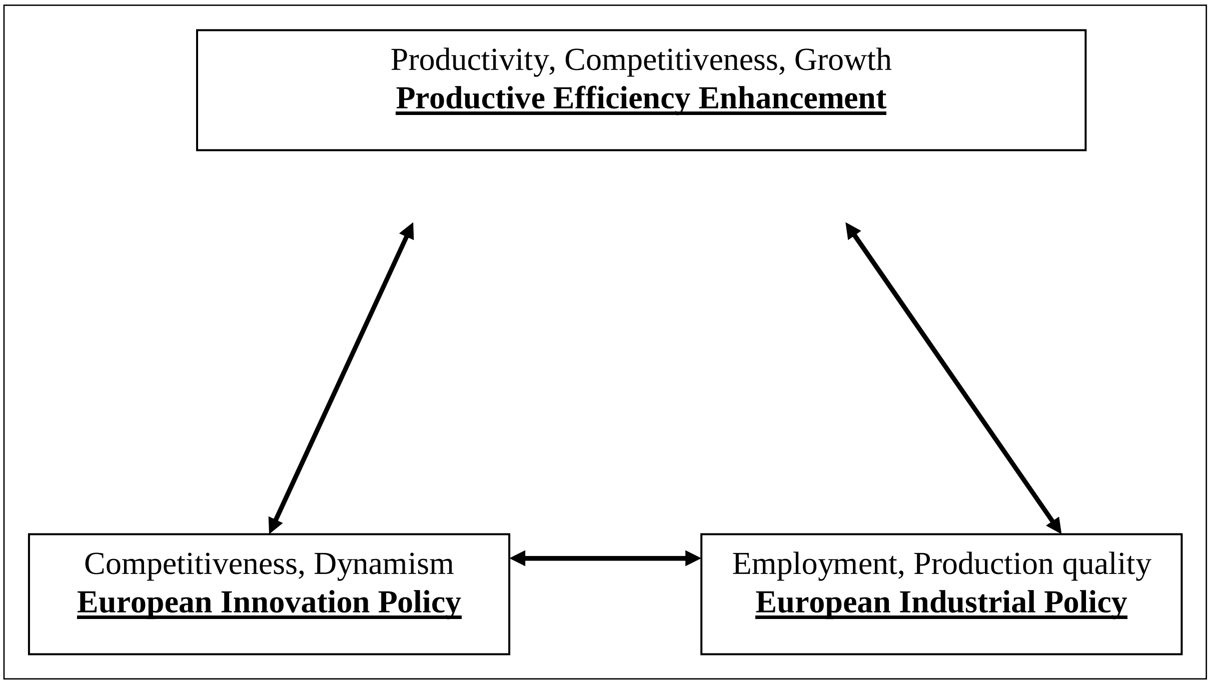
As technical efficiency enhancement becomes an increasingly important issue, production must draw on a wide range of production ideas, component technologies and complementary capabilities.

Within this framework, it is rather difficult for any single industry to incorporate and take advantage of the relevant technological advances, as well as the underlying industrial and innovation policies. This means that the actions of industries involve the targeted development of specialized knowledge assets, that are integrated from a wider range of knowledge areas (Kessler, Bierly, and Gopalakrishnan, 2000).

Growth and competitiveness become contingent on the ability of firms to compose, establish and maintain external interfaces (Nicholls-Nixon and Woo, 2003), to choose the right mode of governance (Fey and Birkinshaw, 2005) and to link these effectively to internal knowledge accumulation and capability development.

The relationship between productive efficiency and innovation and industrial policy is illustrated in the following figure (4.1):

Figure 4.1. Strategic policies flows

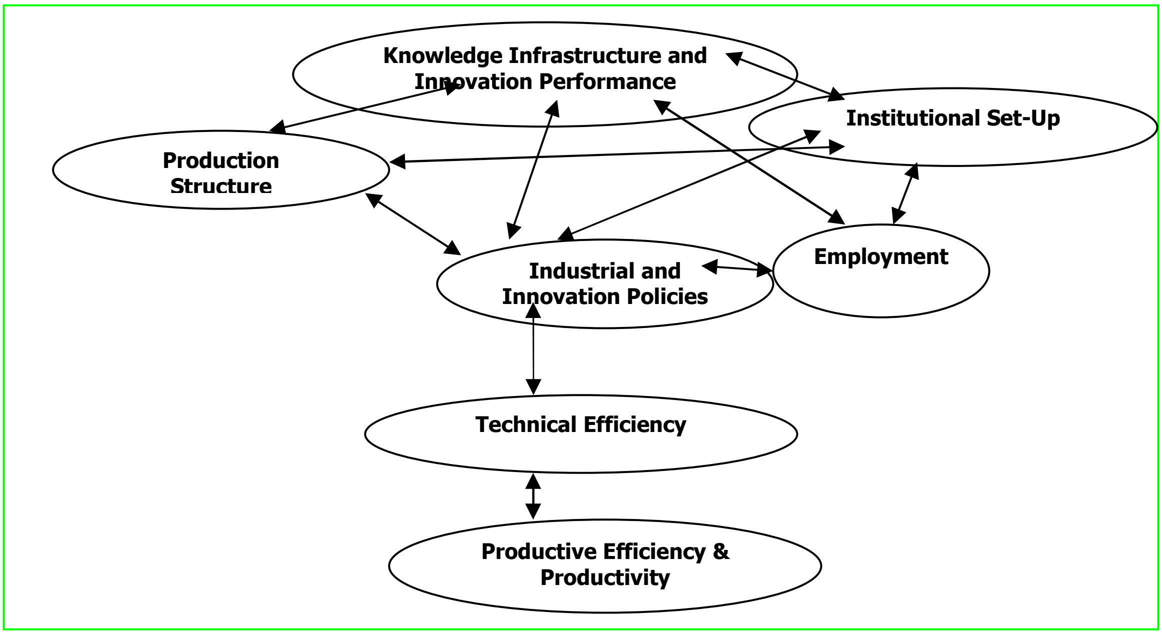


Source: Own Elaboration

European industrial, technology and innovation policies are no longer exclusively in the hands of national authorities: increasingly, national initiatives are supplemented by or even competing with regional innovation policies or transnational programmes, in particular, the activities of the European Union. At the same time, industrial innovation increasingly occurs within international networks. Research, technology and innovation policies of European countries clearly reflected the profiles of their national (and regional) 'innovation systems', understood as the various institutions, corporate actors and processes contributing to industrial and societal innovation.

The innovation policies of the European Union (Peterson and Sharp, 1998; Guzzetti, 1995) played a noticeable, but not yet a dominant role in the national contexts, at least not in the bigger member states (Kuhlmann, 2001). The following figure (4.2) highlights the interactions among the main policy elements regarding the enhancement of technical and productive efficiency.

Figure 4.2. Productive Efficiency and Institutional Framework



Source: Own elaboration

The spectrum of implemented instruments of research, technology and innovation policy is widely differentiated in the meantime, reflecting the scope of institutions and interests involved: it stretches from public funding of research institutions over various forms of financial incentives to the conducting of research and experimental development in public or industrial research labs, up to the design of an innovation-oriented infrastructure, including the institutions and mechanisms of technology transfer. In many European countries, these instruments dominated the practice or research and technology policy for the last three decades. As further instruments one could mention efforts to guide public demand, measures in education and further training and the regulatory possibilities available. In the 21st century, though, the national and (regional) innovation systems are experiencing revolutionary shockwaves: the growing pull of internationalising economic relationships has mixed up traditional regional or national divisions of work between industrial enterprises, educational and research institutions as well as administration and politics, and it debased many of their traditional strengths. Internationalisation, however, has so far not led to a uniformity of the national innovation systems, which would finally mean their abolition. The various national and regional innovation cultures and related policy arenas react very differently, which partly leads them into crises, partly stabilises, but partly also reveals unexpected, novel chances in a transformed international context. At the same time, European transnational innovation policies have been entering the stage, increasingly since 1985, nowadays covering the whole range of instruments (Kuhlmann, 2001).

4.6. Industrial Policy and Technical Efficiency

Sustainable development is a key concept within the industrial policy of the European Union. The key elements for the sustainable development policy concern the efficient use of resources encouraging the development of new productive technologies, extending the use of productivity and efficiency enhancement schemes and encouraging both innovative and productive activities. Within this context, the main role of industrial policy in the European Union is to provide the appropriate framework conditions and to make the European Union an attractive place for industrial development and employment creation.

One of the core targets of industrial policy is to influence the volume and composition of the European Union industrial output, primarily the manufacturing output, aiming to increase the volume of production and/or employment (Baldwin and Martin, 2006). More specifically, industrial policy refers to structural policies designed to strengthen the efficiency, scale and international competitiveness of industrial sectors within a country, bringing about economic growth and development (Soete, 2007).

Industrial policy has been a cornerstone of economic policy in European Union. During the 1970s and 1990s industrial policy shifted mostly towards support of high-tech industries. There is also a close relationship between the effectiveness of industrial policy and the level of development within an economy. Advanced countries have witnessed over the 1990s a major acceleration in the process of deindustrialisation with a more rapid growth in services following the diffusion of information and communication technologies (Petit and Soete, 2001).

However, the first unitary concept of an industrial policy for the European Union appeared after the European Commission‘s proposal from 1990s report ‘Industrial

Policy in an Open and Competitive Environment: Guidelines for a Community Approach', as a confirmation on the necessity of adopting industrial policy measures in a free trade economy. In 1993, the Commission published the white paper on Growth, Competitiveness and Employment, underlining the meaning of the European economy‘s competitiveness in the new conditions, and the legal frame for European Union industrial policy was settled through the Treaty of Maastricht (Nica and Cuza, 2010). The incentives for an overal approach over an industrial policy of the European Union were the differences registered as compared to the economies of the United States and Japan, regarding growth rates, investment rates, R&D and innovation, and international trade, as well as the rise of the new competitors from South-East Asia.

Within this period, the dominance of the industrial sector within European Union remains structurally very different between European member states, such as Germany or France, which are still dominated by strong industrial presence. On the other hand there are cases of small member states which have witnessed rapid deindustrialisation over the 1990s but at the same time, nevertheless witnessed rapid growth in the industrial value added, such as Austria or Finland. However, while applying certain measures at national level, the actions might become selective by aiming certain industies or industrial objectives. Certain industrial sectors are more vulnerable internationally, due either to market characteristics, or to the insufficient development of the European industry compared to the world level. As a consequence, industrial policies were defined, aiming mainly to the competitive growth of the European industry, focusing on the following objectives (Nica and Cuza, 2010):

- Accelerating the adaptive process of the industry to the structural changes;
- Developing an environment in the favour of initiative and development of enterprises;
- Encouraging the favourable environment for business cooperation;
- Favouring the industrial potential of the research, technologic development and innovation policies (Dachin, 2006).

One of the main aims of industrial policy regards the encouragement of innovation, knowledge and research. European Union industrial policy consists a framework which aims to encourage private investments in R&D, and insure an optimal use of the public resources for industrial research. Furthermore, encouraging investments in intangible assets and human capital is crucial, in order to maximize the efficiency of the current technology and its effects. Furthermore, supporting entrepreneurship and developing industrial sectors is an objective that goes beyond the limits of the industrial policy, by joining actions of the educational policies, internal market, financial services and tax policy (Nica and Cuza, 2010). Certain fields require specific intervention, in order to improve the internal market, such as the financial or services markets, where the technical barriers and the legislative differences limit the free trade, in order to improve the economic environment, with special attention in areas which present the fastest technological progress. However, the development objectives set at European level cannot be reached without a tight interconnection of the industrial policy measures with those of some complementary policies, such as the commercial policy, the single market policy, transport and energy policies, research and development policies, competition policy, regional and macroeconomic policies. While in these fields the policies are already coordinated, the sustainable development requirements, with the three development pillars: economic, social and environmental, require supplementary measures for coordinating the industrial policy with the associated policies and requirements. Thus, European Union must insure the balance between the different policies, and this balance must be followed at national level, within the limits of competency of the different member states (Nica and Cuza, 2010). On the other hand, cohesion policies amount to an efficiency-based long-run strategy of 'catch-up growth', in which the interventions aim to accelerate catch-up growth and achieve cohesion policies, rendering industrial policy aims into increased growth and employment and the improved international competitiveness of European industrial sectors

The nature and intensity of European industrial policy has drastically changed since the Rome Treaty (1957). This is due to the deepening of economic integration since the 1970s, the widening of its scope and the enlargement of the Union (Pelkmans, 2006). More specifically, the Rome Treaty (1957) did not have a clear industrial approach (apart from transport policy). Until reaching a unitary concept, the approaches on the European industrial policy passed through several stages. In a first stage, between 1958-1975, national policies prevailed. Between 1975-1985 a general tendency favouring the interventionist policies was observed. The Community measures were aiming to encourage the national efforts, and varied from subventions for the steel industry until granting funds for research and development projects and introducing commercial barriers in the trade with the countries from the rest of the world. In 2000, the Lisbon European Council set the objective of transforming the European Union in the most dynamic and competitive economy of the world. In 2004, EU‘s enlargement through the integration of the Central and Eastern European states represented a challenge for the European Union industrial policy, as the newly integrated states were to align to the industrial level of the European Union while maintaining and increasing the competitiveness of EU at a general level. After the first enlargement of the European Union, in 2004, the Commission established the main action lines of the industrial policy in the new geopolitical conditions, through the communication titled ‘Fostering structural change: an industrial policy for an enlarged Europe’ (Nica and Cuza, 2010).

Currently, competition, the efficiency of public and private services, and infrastructure are important determinants of industrial competitiveness in European member states. In many member states, increasing competition in the network industries remains a challenge. Lengthy permitting procedures and public acceptance also constitute important obstacles to the development of infrastructure. A stronger enforcement of competition rules is necessary to reduce competition distortions[98]. Moreover, today, the competitiveness of European industry crucially depends on the quality and efficiency of the energy, transport and communication infrastructure services, with the upgrading and modernisation of these networks being rather essential. Transport networks need to be improved to overcome any related obstacles

[98] The possibility of counterproductive international coordination has been extensively studied in the field of international macroeconomics (see Rogoff 1985, Canzoneri and Henderson 1991, and Canzoneri *et al.* 2006). In Canzoneri and Henderson (1991), it is also shown that if only a subset of countries (such as the EU) cooperates, then this limited cooperation may be counterproductive. The reason is again that coordination among EU members eliminates one distortion. This distortion may have actually compensated for another one with another group of countries. One could also apply this example to the issue of industrial policies (Baldwin and Martin, 2006).

and improve cross-border connections. These improvements will require massive investments and the development of innovative financing solutions. According to European Commission (2010), a new industrial innovation policy is needed to encourage the development of productive processe of goods and services, as well as the enhancement of productive efficiency.

Industrial policy of the European Union must offer solutions for industrial development. Such challenges concern globalization, the technological and organizational changes, the increasing role of innovation and entrepreneurship. Strategy framework for industrial policy must put technical efficiency and competitiveness of European industry at centre stage (European Commission, 2010):

- to adopt policies that have an impact on the cost, price and innovative competitiveness of industrial sectors, such as standardisation or innovation policies, or industrial policies targeting e.g. the innovation performance
- to speed up the adjustment of industry to structural changes
- to encourage an environment favourable to cooperation and development of firms throughout the Union
- to foster better exploitation of the industrial potential of policies of innovation, research and technological development
- to consider the competitiveness effects of all other policy initiatives such as transport, energy, environmental or social and consumer-protection policies (European Commission, 2005, Pelkmans, 2006).

European industry must also strengthen the knowledge base to remain competitive, investing in research and innovation for a sustainable and inclusive economy. Most importantly, science, technology and innovation play a significant role in increasing technical efficiency and are a driving force in international competition. Innovation policy is a broad concept that contains research and technology policy and often overlaps with industrial policy.

4.7. Innovation Policy and Technical Efficiency

Innovation policy seeks to help firms or industries to improve their capacity to innovate. This includes the provision of scientific infrastructure in research and education and direct and indirect support for research and technological development. It also includes a wide range of policies which aim to build networks, to make markets more conducive to innovation, to facilitate the transfer of technology, to help firms to acquire relevant capabilities, and to provide a supporting infrastructure in areas such as standards and intellectual property. Public innovation policy aims to strengthen the competitiveness of an economy or of selected industries, in order to increase societal welfare through economic success (Kuhlmann, 2001). Hence European Union has made innovation a top priority through several strategies, funding opportunities and assessments. The pressures of globalisation have brought innovation to the fore as a key element in increasing productivity along with technical efficiency and underpinning industrial competitiveness, taking into consideration the under-investment in business R&D and other innovative activities, strongly linked to the fragmented condition of European markets.

Innovation policy is essential for European Union productive efficiency and an important driver in enabling European Union to enhance competitiveness, increased efficiency and growth and consequently to compete on a global scale. However, policy-makers also underlined the need for interaction between innovation policy and other policy areas to improve the environment for innovative enterprises (Nilsson, 2004, Chesbrough, 2002, Georghiou, 2006). After the Second World War, and increasingly since the 1970s, with the acceleration of high technologies, the industrialised countries developed a broad spectrum of technology policy intervention measures (Roobeek, 1990, Ergas, 1987). However, neither industrial policy nor innovation policy was among the areas covered in the 1957 Treaty of Rome. By the early 1980s, however, both had found a place among the European Commission’s directorates (Guzzetti, 1995). The first research and technology development (RTD) programmes were designed and implemented in the early 1980s (Nelson and Winter, 1982; Dosi *et al.*, 1988). This included broad programmes such as the European

Strategic Programme for Research and Development on Information Technologies (ESPRIT) whose main goals were: i) to promote intra-European industrial cooperation through pre-competitive R&D; ii) to thereby furnish European industry with the basic technologies that it needed to bolster its competitiveness through the 1990s; and iii) to develop European standards (European Commission, 1987) and the Basic Research in Industrial Technologies (BRITE) programme designed to help the European manufacturing industry to become more competitive (Mytelka and Smith, 2001). Since the 1980s the Community was trying to foster the creation of strategic industries, in line with the individual member states' efforts to promote national champions. In fact, the objective was to foster cooperation, innovation and commercialization processes, where the role of Community institutions was mainly to enable and coordinate policies rather than dictate their contents (Triulzi, 1999).

Until the middle of the 1980s the Community had a research and technology policy of its own that more or less complemented national policymaking with a transnational dimension, in order to create a European Research Area (Commission 2000a). The rationale behind this approach is that European economic integration, in combination with the opportunities associated with the enlargement of the European Union and the challenges of economic and technological globalisation, functionally leads to an integrated innovation policy approach in European Union. On top of the national and regional efforts and in parallel with Europe's economic and political integration, the emergence of a European innovation policy-making system can be traced (Peterson and Sharp 1998; Grande 1996; Guzzetti 1995). Its main pillar is the Framework Program, the first of which was established in 1984 and concentrated on industrial technologies, information technology, telecommunications and biotechnology. Each subsequent FP has been broader than its predecessor in its scope of technologies and research themes, with correspondingly higher expectations of its impact on the economy and society. The Framework Programmes are the instruments through which the Commission implements its scientific and technological research policy. The system of innovation approach lays emphasis on the interactive process in which enterprises in interaction with each other and supported by institutions and organisations – such as industry associations, R&D, innovation and productivity centres, standard setting bodies, university and vocational training centres, information gathering and analysis services and banking and other financing mechanisms – play a key role in bringing new products, new processes and new forms of organisation into economic use.

Into the 1990s, Community innovation RTD programmes sought to promote technology transfer across industries and regions in Europe, aiming at achieving competitiveness and productive efficiency. A few years later enhancing innovation became a cornerstone of the strategy to meet the target agreed by the European Council in Lisbon in March 2000 of the Union becoming the most competitive and dynamic knowledge-based economy in the world by the end of the decade, drawing attention to the interfaces between industries and financial markets, R&D and training institutions, advisory services and technological markets (Nilsson, 2004). The Lisbon European Council (2000) was an important milestone for the Community's approach to innovation policy. The so-called Lisbon strategy required the Union to become, by 2010, "the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion". With the Lisbon strategy, innovation gains increasing importance in the EU policy framework; the argument that firms' competitiveness in a globalized economy is increasingly dependent on the introduction of new products and services is emphasized. Innovation policies, previously framed within the context of research policy, begin to be considered as essential components of industrial policy strategies.

In 2002, the Barcelona European Council set a twofold objective requiring the Union to reach, by 2010, a level of R&D expenditure equal to 3% of European GDP (compared with 1.9% recorded in 2000), within which the level of private funding should increase up to two thirds of community R&D investments. Today, innovation in EU is distributed right across the system in all European countries. European-level networking of key players in the innovation process links national innovation systems. On the national level the member states are expected to build national innovation strategies. Innovation system was considered to be a measure to build dynamic clusters based on technologies with large growth potential. Innovation became a new industrial policy along with research policy, industrial policy, energy policy, or labour market policy. However, policy-makers also underlined the need for interaction between innovation policy and other policy areas to improve the environment for innovation and technical efficiency (Nilsson, 2004). Nowadays, within the European Union innovation policy framework, current trends and the resultant emerging industrial innovation activities focus mainly on Information and Communication Technologies (ICT) related topics. Information and Communication Technologies (ICT) enable the development of new services and increase the efficiency of existing services. Globalisation and internationalisation of innovative industries is important, as is the convergence between the technologically intense sectors and other sectors. Maintaining and strengthening Europe's industrial base is fundamental to securing the foundation and transformation of the EU economy and ensuring employment, social progress and cohesion (European Commission, 2011b, ETEPS, 2011).

On the other hand, Europe's national innovation systems differ substantially, as well as their innovation performances. Therefore, member states have undertaken great efforts to improve their innovation support measures by investing in research and implementing new or better instruments in support of innovation. This level of financial engagement is at risk in the current global economic crisis and, as a direct impact, the innovation gap in the EU is widening again. The implication of this is that innovation policy must consider the needs of a wide set of industries – policy initiatives need not be confined to a small group of highly innovative sectors. European Union is challenged in the global arena by emerging economies when it comes to capturing and capitalising on knowledge and technology in the context of innovation. In the past few years, the budget for R&D has been increased and several initiatives have been launched to strengthen Europe's competitiveness. So far, however, these efforts have not made the EU more competitive. On the contrary, a decline can be seen and the EU is recognised as becoming less internationalised (Anvret, Granieri, and Renda, 2010). However, the innovation policy of the large European member states has not yet taken the step towards a conscious and comprehensive international integration and co-ordination of their measures. The majority of public initiatives is still mainly developed in national policy arenas, offered by national institutions, and addressed to national beneficiaries, borne by the implicit assumption that the research institutes, universities and enterprises involved carry out their innovation activities entirely or for the most part within national boundaries, or at least with a significant relation to the own economy (Kuhlmann, 2001).

The majority of public initiatives is still mainly developed in national policiess, offered by national institutions. While for the last years member states increasingly tended to compete with each other in the field of innovation policy (Porter, 1990; Roobeek, 1990), strong industrial or financial capital actors have been appearing more frequently on the scene - multinational enterprises, international strategic alliances of national enterprises- who act globally and across the national innovation systems (Meyer-Krahmer and Reger, 1999). In the member states of EU this policy initially took the form of initiatives for stimulating research, improving innovation financing and promoting technology absorption and innovation management.

Additional priorities like intensifying the cooperation between research, universities and universities, promoting ‘clustering’ and other forms of cooperation among enterprises and other organisations involved in the innovation process and encouraging the start-up of technology- based companies were added to the national innovation policy (Nilsson, 2004).

The following table (4.2.) presents the main priorities regarding the effectiveness of innovation and industrial policy implementation:

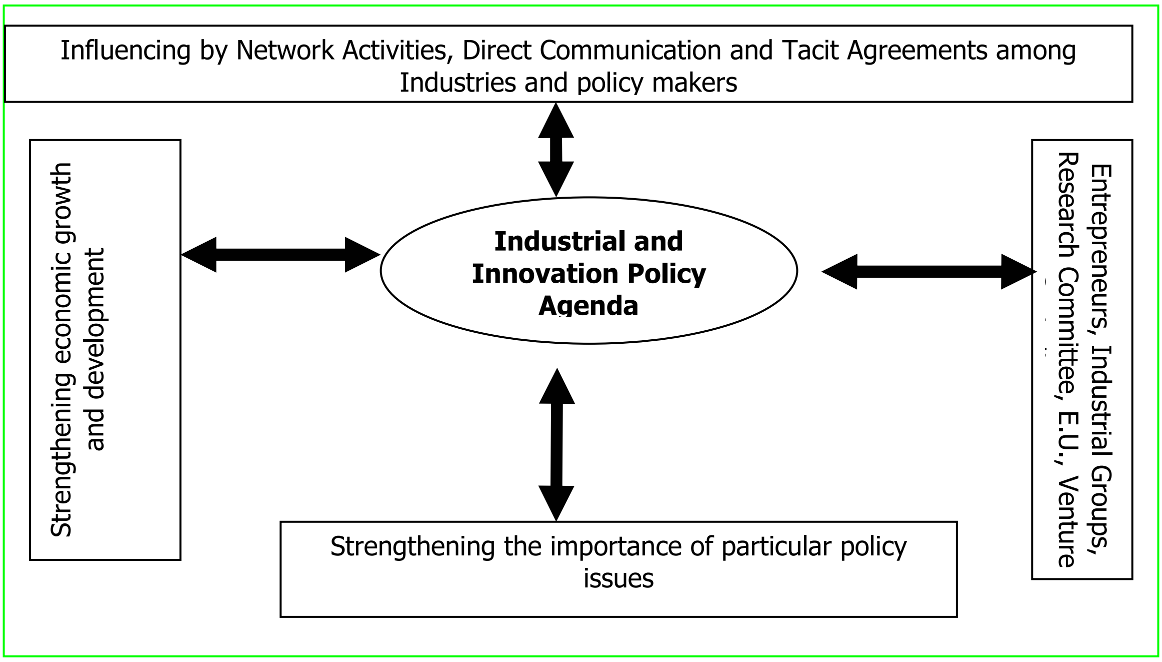
Table 4.2. Policy Effectiveness Priorities

Priority	**Means and actions**
• give priority to innovation and enterprise	• creating closer links between research institutes and industry, developing conditions favorable to R&D, improving access to finance and know-how and encouraging new business ventures;
• ensure full employment	• emphasizing the need to open up employment opportunities, to increase productivity and quality at work and to promote lifelong learning;
• ensure an inclusive labor market	• reducing unemployment and disparities in access to employment;
• connect European Union	• promoting closer integration by improving transport, telecommunications and energy networks;
• protect the environment	• stimulation of innovation, and introducing new technologies, for example, in energy and transport.

Source: Own elaboration

The evaluation of the innovation policy demonstrated that despite achieving most of the proposed actions, there are still significant obstacles to innovation in the EU. These obstacles can be overcome by taking coordinated action at both EU and national level (as illustrated in figure 4.3.:

Figure 4.3. Action framework of E.U. policies



Source: Own elaboration

As part of the Europe 2020 strategy, the Commission launched in 2010 an ambitious new industrial policy that highlighted the actions needed to strengthen the attractiveness of Europe as a place for investment and production, including the commitment to monitor Member States competitiveness policies. The changing nature and scope of global innovation activities creates very significant consequences for EU innovation policy, requiring a substantial review of the pillars of EU innovation policy, involving both the scope and the governance of innovation at the EU and national level (Anvret, Granieri, and Renda, 2010). European Union has identified the following key areas where the competitiveness of the EU economy could be further strengthened in order to make significant progress towards the Europe 2020 goals (European Commission, 2011a):

- facilitating structural changes in the economy, in order to move towards more innovative and knowledge-based sectors that have a higher productivity growth and which have suffered less from global competition;
- enabling innovation in industries, in particular by pooling scarce resources, by reducing the fragmentation of innovation support systems and by increasing the market focus of research projects;
- promoting sustainability and resource efficiency, in particular by promoting innovation and the use of cleaner technologies, by ensuring fair and undistorted pricing of energy and by upgrading and interconnecting energy distribution networks;
- improving the business environment, in particular by reducing the administrative burden on businesses and by promoting competition among service providers that use broadband, energy and transport infrastructure;
- benefiting from the single market, by supporting innovative services and by fully implementing the Single Market Regulation, in particular the Services Directive;
- supporting small and medium-sized enterprises (SMEs), in particular by favouring access to finance, by facilitating internationalisation and access to markets.

EU industry must accelerate its efforts to adopt these technologies to keep its competitive edge in the world with research and innovation driving productivity growth and industrial competitiveness.

4.8. Concluding Remarks

Stochastic frontier models assume that producers operate under the same production technology and that the inefficiency distribution across individuals and time are homogeneous.

Traditional stochastic frontier models do not distinguish between unobserved individual heterogeneity and inefficiency. They thus force all time-invariant individual heterogeneity into the estimated inefficiency. Hence, the producers only differ by the random noise term. A wide range of models are proposed that incorporate other forms of heterogeneity.

Most of the literature proposes two important categories: the first concerns the distinction between heterogeneity in the production model and heterogeneity in the inefficiency model, and the second the distinction between observable and unobservable heterogeneity (Greene, 2007a)[99].

This chapter analyses the evolution and characteristics of industrial and innovation policy as far as the enhancement of productive and technical efficiency is concerned, as well as the main effects on the European Union (EU) manufacturing industries over the period 1980-2005. Moreover, this chapter provides an assessment of the impact of these policies and the implemented programs on the productive and technical efficiency of manufacturing industries.

A transition towards a sustainable, resource efficient economy is paramount for maintaining the long-term competitiveness of European industries. Overall, European member states have made significant progress in defining and implementing consistent national legislative frameworks for stimulating efficiency. However, some lack the experience and the administrative capacity to do this and for these countries the framework legislation at the EU level can provide guidance and support.

The quality and availability of infrastructure (energy, transport, and broadband) make an important contribution to an efficiency promoting environment. Industrial sectors need a modern public administration, able to deliver efficient and high quality public services (European Commission, 2011). Coordinating clusters and networks improve industrial competitiveness and innovation by bringing together resources and expertise, and promoting cooperation among businesses, public authorities and universities. EU industrial and innovation policies should aim to overcome existing

[99] Greene (2005) proposes a true fixed-effect stochastic frontier model which, in theory, may be biased by the incidental parameters problem. The problem usually cannot be dealt with by model transformations owing to the nonlinearity of the stochastic frontier model. Regardless of the source of heterogeneity, failure to control for individual effects is likely to bias the estimation results, especially when there is correlation between the effect and other explanatory variables in the model.

market failures and funding gaps, especially to supply the bridge between technical efficiency and productivity enhancement.

European governments are in need of a more coherent, more coordinated approach towards industrial technical efficiency support. However, the pressure on public budgets adds to the urgency of this matter in different policy areas of industrial and innovation policy. The range of explicit innovation policies being applied is very much concerned with the supply side and even more with R&D support of various types, ranging from funding of science in public institutions through to fiscal incentives for firms to increase R&D spend. A comprehensive approach to industrial and innovation policy can be achieved by supporting markets for innovative goods and services and excellence in research in new technologies, including information and communication technologies (ICT), introducing a more focused strategy to facilitate the creation of areas for action, and in particular introducing a more focused strategy to facilitate the creation and marketing of new innovative products and services (European Commission, 2006). Within the domain of industrial and innovation policy, regulatory reform is seen to affect innovation indirectly through affecting the funds available for investment and market size and structure, and directly through its impact upon the promotion of technical efficiency and productivity (Lengrand, 2003).

An open, efficient and competitive business environment is a crucial catalyst for growth in a global context. Improving the business environment covers policies in areas ranging from improving infrastructure to shortening the time needed to obtain a building license. In many cases, better institutional mechanisms need to be functioning as a single research area, business environment and innovation system. There need to be strategic approaches, which not only promote closer interaction among sectors but also among policy-makers (from different policy fields and different levels of government). European innovation and industrial policy is therefore recommended to develop strategic approaches which integrate R&D, innovation and industrial policy along with a more coherent EU strategy for innovative competitiveness, giving special attention to ICT in innovation and industrial policy (ETEPS, 2011).

At the national level, governments could set up agencies funded by public bonds with the mission to provide venture capital, investment credits and R&D support to new activities in the above fields. Productive efficiency and competitiveness would be strengthened by:

- Pooling scarce resources to help to achieve critical mass in bringing innovation to the market; and by increasing cooperation in innovation to create large scale demonstration projects and pilot test facilities
- Reducing the fragmentation of innovation support systems, facilitating bringing innovative solutions to the market, and increasing the market focus of research projects.
- Developing support for innovative services based on measureable outcomes
- Facilitating the growth of manufacturing industries by ensuring that regulations do not pose obstacles to expansion; by favouring access to appropriate finance; and by providing support services for accessing new markets, and publicising these.

A new generation of policies have to overcome the limitations and failures of past experiences, such as collusive practices between political and economic power, heavy bureaucracy, lack of accountability and entrepreneurship. They have to be creative and selective, with decision-making mechanisms that are more democratic and inclusive of different social interests. These new approaches to industrial and innovation policies could play a key role in pulling Europe out of the current crisis. The politics behind such a new departure has to be based on a wide social consensus over the distribution of the productivity and efficiency gains deriving from new technologies and economic activities (Pianta, 2010).

Industrial and innovation policy programmes and projects claim to contribute to technical efficiency. This implies that policies should concentrate on areas in which there is expansion and therefore good prospects for growth, community businesses are supposed to become more competitive, and scientific and technological progress is expected to offer a medium- or long-term potential for dissemination and exploitation (Kuhlmann, 2001). An open, efficient and competitive business environment is a crucial catalyst for growth in a global context. Rising to these challenges can improve the competitiveness of European manufacturing industries, and the Commission aims to help the member states to use their limited resources efficiently in order to increase the global competitiveness of their industries. Addressing these challenges will improve the growth prospects of industries. A competitive industry can lower costs and prices, create new products and improve quality, contributing thus decisively to wealth creation and productivity growth throughout the economy.

A greater coordination of policies at national level can leverage scarce funds to foster innovation and growth in times of budgetary austerity. Towards this direction, the main measures suggested include (Rossi, 2007):

- Set up an open process of co-ordination on actions in science and technology,
- Encourage diffusion of “good practice” and transnational cooperation among regions regarding research and innovation policies
- Improve the effectiveness of public actions to promote research and innovation by designing policy mixes using in a coherent way various policy instruments
- Pursue or initiate necessary regulatory and administrative reforms, and support measures, to enable public research institutions to develop more effective links with industry
- Promote public research and technology transfer
- Pursue efforts to create a legal, fiscal and financial environment favourable to the creation and development of start-ups
- Support EU-level initiatives, such as networking and pilot experiments, to facilitate transnational technology partnerships, by encouraging clustering or integration of resources

The difficult fiscal environment sets limits to policy action, but robust growth will reduce the burden of public deficit and debt, in line with the goals of the Stability and Growth Pact. For this an environment that favours new ideas and new businesses is required. Innovation is the primary driver of a successful and sustainable industrial policy. A strong lead in R&D and innovation is Europe’s key competitive advantage and of central importance in finding solutions to economic challenges (European Commission, 2011b). With increased globalisation, one can only hope that industry will be an engine for the spreading of social progress, environmentally friendly technologies and innovations world wide (Soete, 2007). To achieve a truly sustainable, positive effect for manufacturing industry and the workforce it employs, the EU and its Members States should aim to avoid the relocation of manufacturing activities and related services (e.g. R&D, ICT) and support the permanent upgrading of European manufacturing industries.

Taking into consideration the underlying industrial and innovation policy framework in European Union manufacturing industries, this thesis aims to estimate the level and evolution of technical efficiency in selected European Union manufacturing industries, providing the links between the policy framework and technical efficiency level. Concluding, a framework reliant upon efficiency has become an important policy objective in all European countries to promote productive efficiency.

Chapter 5

Stochastic Frontier Model: Empirical Results

Abstract

The objective of this chapter is to estimate the Transcendental Logarithmic Production Function of manufacturing industries in selected E.U. economies, considering a panel data model for inefficiency effects in stochastic production frontiers based on the Battese and Coelli (1992, 1995) models, providing translog effects, as well as industry effects. More specifically, this chapter estimates stochastic parametric frontiers for which the producer effects are first an exponential function of time, followed by the estimation of producer effects as an exponential function of time and related exogenous variables (efficiency explanatory factors). The model decomposes technical efficiency into two components: technological growth (essentially, a shift of production possibility frontier, set by best-practice industries) and inefficiency changes (i.e., deviations of actual output level from the production possibility frontier). The estimated model accommodates not only heteroscedasticity but also allows the possibility that an industry may not always produce the maximum possible output, given the inputs available. Our analysis presents different alternative models for technical efficiency estimations, as well as their empirical results. The alternative models are being compared according to their results regarding the evolution of technical change during 1980 - 2005, the estimation of technical efficiency, as well as the distribution of technical efficiency. The chapter begins with a description of the model specifications, the data set, and the definition of the variables, along with their descriptive statistics. Then the empirical model is formed with estimation results for different alternative model specifications, providing the industry -level estimates of technical efficiency using the time-varying inefficiency model within a composite error framework. Further, factors that determine variations of technical efficiency are established and a comparison of technical efficiency is made, both before and after accounting for different explanatory variables in the inefficiency term. This includes reporting the estimated technical efficiency of an industry, the discussion of causes of variations in efficiency explanatory efficiency and discussion of the conditional efficiency. More specifically the model is extended in order to include industry specific effects (by employing industry composite dummies), so as to examine differences in efficiency level among different industries. For this reason, our model is estimated including the industry – specific composite dummies. The results include reporting the estimated technical efficiency and the related explanatory variables. This chapter is organized as follows: the first section presents the theoretical framework; the second section develops the model estimation and in the third section presents the econometric estimation and the related results. Then, Chapter 5 estimates and compares the two main alternative Battese and Coelli specifications, also comparing the estimation results of time invariant versus time varying technical efficiency.

5.1. Introduction

Efficiency frontier analysis in theory of industrial production does not assume that every industry is fully efficient. Within growth process, therefore, efficiency of production resources becomes a critical element in growth, through utilizing the available, yet scarce, resources more productively. Combining the production functions in order to create and disseminate innovations leads to improvements in productivity and efficiency. However, at a given moment of time, when technology and production environment are essentially the same, producers may exhibit different productivity levels due to differences in their production efficiency. Within this framework, efficiency estimation represents how well a producer uses the available resources to produce outputs from inputs.

Consequently, one of the main goals of frontier analysis is the estimation of inefficiency, with a major question being whether inefficiency occurs randomly across industries, or whether some industries have predictably higher levels of inefficiency than others. If the occurrence of inefficiency is not totally random, then it should be possible to identify factors that contribute to the existence of inefficiency (Reifschneider and Stevenson, 1991). As a result, in order to account for these inefficiencies, alternative methods make explicit assumptions of inefficiencies between different industries [see for example, DEA (Data Envelopment Analysis; see Coelli, Rao, Battese, 1997, Chap. 6 & 7) and frontier approach (ibid. Chap. 8 & 9).

The objective of this chapter is to estimate the Transcendental Logarithmic Production Function of manufacturing industries in selected E.U. economies, considering a panel data model for inefficiency effects in stochastic production frontiers based on the Battese and Coelli (1992, 1995) models, providing translog effects, as well as industry effects. More specifically, this chapter estimates stochastic parametric frontiers for which the producer effects are first an exponential function of time, followed by the estimation of producer effects as an exponential function of time and related exogenous variables (efficiency explanatory factors). The model decomposes technical efficiency into two components: technological growth (essentially, a shift of production possibility frontier, set by best-practice industries) and inefficiency changes (i.e., deviations of actual output level from the production possibility frontier). The estimated model accommodates not only heteroscedasticity but also allows the possibility that an industry may not always produce the maximum possible output, given the inputs available.

The model used in this chapter follows the Battese and Coelli (1992 and 1995) approach of modelling both the stochastic and the technical inefficiency effects in the frontier, in terms of observable variables, and estimating all parameters by the method of maximum likelihood, in a one - step analysis[100], in conjunction with the parameters of the variables included to explain efficiency, allowing for balanced panel data, which is the only model allowing for one – step analysis[101]. The translog production frontier used in this study follows Battese and Coelli (1992, 1995) stochastic production frontier model by including a time variable in the deterministic kernel of the stochastic production frontier to capture the effect of technical progress. Maximum likelihood techniques are used to estimate the frontier and the inefficiency parameters.

The chapter is organized as follows: the first section presents the theoretical framework; the second section develops the model estimation and in the third section presents the econometric estimation and the related results.

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[100] Battese and Coelli (1995) suggested that under the assumption of truncated normal one-sided error term, the mean of the truncated normal distribution could be expressed as a function of certain covariates, a closed form likelihood function can be derived, and the method of maximum likelihood may be used to obtain parameter estimates, and provide inefficiency measures.

[101] Bhattacharyya et al. (1997) pointed out that when employing regression analysis in the second step to explain the variation of the efficiency scores, it is likely that the included explanatory variables fail to explain the entire variation in the calculated efficiencies and the unexplained variation mixes with the regression residuals, adversely affecting statistical inference. They propose the use of a stochastic frontier regression model, which allows for the decomposition of the variation of the calculated efficiencies into a systematic component and a random component.

More specifically, the chapter begins with a description of the model specifications, the data set, and the definition of the variables, along with their descriptive statistics. Then the empirical model is formed with estimation results for different alternative model specifications, providing the industry -level estimates of technical efficiency using the time-varying inefficiency model within a composite error framework. Further, factors that determine variations of technical efficiency are established and a comparison of technical efficiency is made, both before and after accounting for different explanatory variables in the inefficiency term. This includes reporting the estimated technical efficiency of an industry, the discussion of causes of variations in efficiency explanatory efficiency and discussion of the conditional efficiency. More specifically the model is extended in order to include industry specific effects (by employing industry composite dummies), so as to examine differences in efficiency level among different industries.

5.2. Empirical Model Data

The empirical analysis is based on estimating efficiencies as industry - specific fixed - effects at industry level of selected member – states within European Union, during 1980 – 2005[102]. The European Union member – states selected to be included in the model are: United Kingdom, Germany[103], the Netherlands, Denmark, Finland, Italy, Spain and France. This sample creates a data set including both countries with strong industrial productive base, such as United Kingdom, Germany and France, as well as countries with low industrial productive base, such as Spain[104].

[102] The choice of European Union member – states and the time period is determined by the availability of the data.

[103] The data for Germany prior to 1991 refer to former Western Germany.

[104] This topic has been broadly examined in: Kokkinou A. (2010a) Estimating Technical Inefficiency: An Empirical Approach to E.U. Industries, *Regional Science Inquiry Journal*, Vol. II (2), 2010, pp 95-104.

The data used is extracted from the EU KLEMS data base of industrial accounts for productivity analysis (Timmer et al., 2008), NACE 2 – digit level of industry disaggregating, comprising 13 manufacturing industries[105]. The EU KLEMS Growth and Productivity Accounts is the result of a research project, financed by the European Commission, to analyze productivity in the European Union at the industry level. This database is meant to support empirical and theoretical research in the area of economic growth, such as study of the relationship between skill formation, investment, technological progress and innovation on the one hand, and productivity, on the other.

EU KLEMS Accounts include measures of output growth, employment and skill creation, capital formation and multi-factor productivity (MFP) at the industry level for European Union member states from 1970 onwards. The input measures include various categories of capital (K), labour (L), energy (E), material (M) and service inputs (S). A major advantage of growth accounts is that it is embedded in a clear analytical framework rooted in production functions and the theory of economic growth and that it examines the productivity performance of individual industries and their contribution to aggregate growth (EU KLEMS, 2008).

EU KLEMS database provides data on a detailed industry level. In general, data for 1970-2005 are available for the “old” EU-15 countries and for the US. Series from 1995 onwards are available for the new EU member states which joined the EU on 1 May 2004 (EU-10). The variables covered can be split into three main groups: (1) basic variables; (2) growth accounting variables and (3) additional variables.

The basic series contain all the data needed to construct single productivity measures, such as labour productivity (output per hour worked). These series include nominal, volume and price series of output and intermediate inputs, and volumes and prices of employment. Finally, additional series are given which have been used in generating the growth accounts and are informative by themselves. These include, for example,

[105] EU KLEMS stands for EU level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs.

various measures of the relative importance of ICT-capital and non-ICT capital, and of the various labour types within the EU KLEMS classification.

Importantly, EU KLEMS makes a distinction between three ICT assets (office and computing equipment, communication equipment and software) and four non-ICT assets (transport equipment, other machinery and equipment, residential buildings and non residential structures).

The real investment series are used to derive capital stocks through the accumulation of investment into stock estimates using the Perpetual Inventory Method (PIM) and the application of geometric depreciation rates. Then capital service flows are derived by weighting the growth of stocks by the share of each asset's compensation in total capital compensation. In this way, aggregation takes into account the widely different marginal products from the heterogeneous stock of assets. The weights are related to the user cost of each asset (EU KLEMS, 2008). The industries included in the model are presented in the following table:

Table 5.1. EU KLEMS industries

EU KLEMS industries
Electrical and optical equipment
Food products, beverages and tobacco
Textiles, textile products, leather and footwear
Manufacturing nec; Recycling
Wood and products of wood and cork
Pulp, paper, paper products, printing and publishing
Coke, refined petroleum products and nuclear fuel
Chemicals and chemical products
Rubber and plastics products
Other non-metallic mineral products
Basic metals and fabricated metal products
Machinery, nec
Transport equipment

Source: EU KLEMS (2008) database

The industries included in the model sample account for a large percentage of each economy's value added. The following table illustrates output of each one of the sample manufacturing industries within each country, in terms of value added,, as well as the evolution between the first and the last year of the analysis period (1980 – 2005), respectively:

Table 5.2. Value Added per industry and country (actual values)

		Country							
Industry	Year	Denmark	Finland	France	Germany	Italy	Netherlands	Spain	United Kingdom
1	1980	5.374	458	10.310	33.420	5.433	2.888	1.303	6.368
	2005	21.511	7.531	21.684	70.692	23.504	3.612	7.134	13.911
2	1980	14.656	857	11.610	21.649	23.504	4.933	3.392	7.693
	2005	30.011	2.334	28.883	40.806	23.486	11.827	16.960	21.202
3	1980	3.838	694	6.134	12.655	8.581	1.073	3.126	4.249
	2005	3.469	529	7.683	9.049	25.546	1.159	6.492	3.989
4	1980	3.270	299	3.892	7.454	3.182	2.046	1.179	1.151
	2005	10.048	720	7.573	11.860	11.519	4.674	6.451	6.281
5	1980	1.635	734	1.271	4.248	1.533	357	741	892
	2005	5.355	1.351	3.318	7.660	5.809	973	2.784	4.269
6	1980	7.142	1.797	6.254	15.411	2.840	3.011	1.534	5.270
	2005	17.039	5.403	16.573	32.613	14.332	7.328	11.347	19.566
7	1980	1.441	274	2.758	7.249	772	913	698	1.963
	2005	112	653	5.101	4.974	5.144	3.611	2.750	2.175
8	1980	7.164	442	7.122	21.649	3.716	3.717	2.503	4.883
	2005	34.390	1.984	20.040	47.598	16.695	9.579	11.598	16.465
9	1980	2.227	240	5.549	8.303	2.058	574	712	2.049
	2005	9.886	1.048	10.303	22.770	9.652	1.889	5.564	7.655
10	1980	3.559	336	2.978	10.357	3.595	1.217	1.736	2.266
	2005	7.576	1.122	8.224	14.546	13.753	1.989	10.159	5.042
11	1980	5.298	759	11.882	32.322	8.141	3.696	5.211	7.461
	2005	19.206	3.919	30.945	60.775	39.345	7.418	21.566	14.509
12	1980	9.044	890	10.237	31.827	6.572	1.696	1.604	5.989
	2005	25.454	3.797	18.352	70.200	32.439	5.890	9.312	12.006
13	1980	3.053	400	7.408	25.146	3.996	1.158	2.421	5.782
	2005	4.369	1.054	21.727	76.407	11.533	2.609	13.477	16.729

Notes:

1. Industry 1 = Electrical and optical equipment, Industry 2 = Food products, beverages and tobacco, Industry 3 = Textiles, textile products, leather and footwear, Industry 4 = Manufacturing nec; Recycling, Industry 5 = Wood and products of wood and cork, Industry 6 = Pulp, paper, paper products, printing and publishing, Industry 7 = Coke, refined petroleum products and nuclear fuel, Industry 8 = Chemicals and chemical products, Industry 9 = Rubber and plastics products, Industry 10 = Other non-metallic mineral products, Industry 11 = Basic metals and fabricated metal products, Industry 12 = Machinery, nec, Industry 13 = Transport equipment.
2. For Finland, France, Germany, Italy, Netherlands, and Spain, Gross value added is expressed at current basic prices (in millions of Euros).
3. For Denmark, Gross value added is expressed at current basic prices (in millions of Danish Kroner).
4. For United Kingdom, Gross value added is expressed at current basic prices (in millions of British Pounds).

Source: EU KLEMS data base

As it is illustrated in the table (5.2), Denmark moved its specialisation from paper and textiles in 1980, making a major shift into high technology and high value – added industries in 2005, presenting a high specialisation in Electrical and Optical, as well as in Chemicals industries. Finland also moved its specialisation from textiles industry in 1980, making a major shift into high technology and high value – added Electrical and Optical industry in 2005.

The rest of the manufacturing industries present similar specialisation rate. France presents a rather intense enhancement of specialisation in Electrical and Optical and Rubber and Plastic industries between 1980 - 2005, making also a major shift into high technology and high value – added industries in 2005.

The opposite happened in Metals and Textiles industries which lowered their value added share. Germany presents an enhancement of specialisation in almost all the industries apart from Food and beverages, Textiles and Manufacturing nec industries between 1980 - 2005, making also a rather important shift into high technology and high value – added industries in 2005.

The highest value added industries are Electrical and Optical, Chemicals and Transport equipment. Italy presents a more balanced picture as far as the manufacturing industries specialisation is concerned both in 1980 and 2005.

Italy had an increase in valued added in the majority of the industries, mostly in Chemicals, Rubber and Plastic and Food and Beverages.

Netherlands presents a significant specialisation shift into manufacturing industries between 1980 and 2005, with the most specialized industries being Chemicals and Transport equipment.

Spain presents also a relatively balanced picture as far as the manufacturing industries specialisation is concerned both in 1980 and 2005. Italy had an increase in valued added in the majority of the industries, mostly in Machinery industry.

In addition, United Kingdom presents also a balanced picture as far as the manufacturing industries specialisation is concerned both in 1980 and 2005, with the most specialised industries being Chemicals and Transport equipment industries.

The same picture becomes apparent if we compare the value added per industry and country in relative values considering 1995 as base year (1995=100):

Table 5.3. Value Added per industry and country (1995=100)

		Country							
Industry	Year	Denmark	Finland	France	Germany	Italy	Netherlands	Spain	United Kingdom
1	1980	51.5	20	53.8	74.1	58.7	66.9	41.7	50.6
	2005	166.2	538.9	211.5	137.4	103	99.8	107.2	113.6
2	1980	76.3	79.8	91.3	113.4	71.5	70.6	70	89.4
	2005	91.7	148.3	104.3	101.2	90.8	109	103.9	106.3
3	1980	131.3	214.9	130.8	160.8	82.5	108.3	114.3	118.2
	2005	56.9	87.7	77.9	80.3	70.2	94	86.6	55.7
4	1980	80.7	97.9	64.5	130.7	85.8	90.2	79.1	111.8
	2005	86.4	129.1	117.9	77	97.5	127.1	141.2	105.9
5	1980	77.6	90.2	43.3	81.6	80.2	71.3	95.7	91.2
	2005	99.9	154.3	159.9	97.1	106.1	119.7	122.4	92.7
6	1980	122.6	64.8	100.5	86.1	67.1	68.4	63	72.6
	2005	107.1	115.7	105.7	97.6	100.5	105.2	145	91.7
7	1980	338.2	51.5	1.1	1,532.5	136.1	158.8	146.2	77.5
	2005	22.0	159.6	158.9	51.0	10.8	91.2	90.9	81.6
8	1980	42.3	61.8	46.5	68.8	48.5	55	55.5	58.4
	2005	197.7	139.2	110.5	131.6	103.3	145.1	118.3	112.9
9	1980	70.5	56.3	34.3	59.8	66.1	44.6	56.5	57.4
	2005	130.3	133.2	249.6	123.1	107.8	124	145.2	89.7
10	1980	120.4	98.2	114.2	86	84	91.3	62.6	98.7
	2005	97.4	171.9	113.4	92.8	114.5	92	143	108.5
11	1980	65.8	52.7	217.5	91.4	69.6	79.9	87.3	94.6
	2005	99	158.8	104.6	112.6	112.9	114.1	134.7	99.8
12	1980	85.7	63.8	42.4	100.2	90	64.4	68.1	108.3
	2005	88.2	147.4	127.4	106.3	104.5	136.5	154	96.2
13	1980	81.5	92.9	85.9	80.2	96.4	66.8	74.8	92.1
	2005	74.5	103.3	124.5	136.2	83.9	141.3	127.8	120.2

Notes:

1. Industry 1 = Electrical and optical equipment, Industry 2 = Food products, beverages and tobacco, Industry 3 = Textiles, textile products, leather and footwear, Industry 4 = Manufacturing nec; Recycling, Industry 5 = Wood and products of wood and cork, Industry 6 = Pulp, paper, paper products, printing and publishing, Industry 7 = Coke, refined petroleum products and nuclear fuel, Industry 8 = Chemicals and chemical products, Industry 9 = Rubber and plastics products, Industry 10 = Other non-metallic mineral products, Industry 11 = Basic metals and fabricated metal products, Industry 12 = Machinery, nec, Industry 13 = Transport equipment.

Source: EU KLEMS data base

Denmark moved its specialisation from paper and textiles in 1980, presenting a high specialisation in Electrical and Optical, as well as in Chemicals industries. Finland also moved its specialisation from textiles industry in 1980, making a major shift into high technology and high value – added Electrical and Optical industry in 2005. France presents a rather intense enhancement of specialisation in Electrical and Optical and Rubber and Plastic industries between 1980 - 2005. Germany presents an enhancement of specialisation in almost all the industries apart from Food and beverages, Textiles and Manufacturing nec industries between 1980 - 2005. Italy presents a more balanced picture as far as the manufacturing industries specialisation is concerned both in 1980 and 2005. Netherlands presents a significant specialisation shift into manufacturing industries between 1980 and 2005, with the most specialized industries being Chemicals and Transport equipment. Spain presents also a relatively balanced picture as far as the manufacturing industries specialisation is concerned both in 1980 and 2005. Italy had an increase in valued added in the majority of the industries, mostly in Machinery industry. In addition, United Kingdom presents also a balanced picture as far as the manufacturing industries specialisation is concerned both in 1980 and 2005, with the most specialised industries being Chemicals and Transport equipment industries.

5.3. Empirical Model Determining Factors

As Kumbhakar and Lovell (2000) indicated, the main advantage of stochastic production frontier models is that the impact on output of shocks due to variation in labour, machinery performance, vagaries of the weather, and just plain luck can at least in principle be separated from the contribution of variation in technical efficiency. However, at a given moment of time, when technology and production environment are essentially the same, producers may exhibit different productivity levels due to differences in their production efficiency. Therefore, efficiency of production resources becomes a critical element in productivity and growth, through utilizing the available, yet scarce, resources more productively.

Specifically, in line with this empirical framework, based on stochastic frontier analyses (SFA) and data envelopment analyses (DEA), productivity is decomposed into the production possibility frontier and technical (in) efficiency. For this reason, there should be a distinction on what should determine the frontier and what affects efficiency. On the other hand, technical efficiency relates to neo-Schumpeterian ideas of catching-up with the leaders (technology diffusion and absorption) and forge-ahead through investments in R&D (innovation creation). However, this cannot be satisfactorily achieved by drawing only on theories of exogenous and endogenous growth, both of which relate to production technology, which lies in the domain of the frontier. Also, efficiency depends on the effectiveness of the institutional environment, which is closely related to evolutionary and institutional approaches. Recent contributions to the literature clearly emphasize the connection with theory of empirical models for the production possibility frontier (or production function) and efficiency. More specifically, contributions to the literature (Kneller and Stevens, 2006, Bhattacharjee et al., 2009, and Eberhardt and Teal, 2011) clearly emphasize the connection with theory, of empirical models for the production possibility frontier (production function) and efficiency.

Consequently, one of the main questions is to investigate the relationship between inefficiency and a number of factors which are likely to be determinants, and measure the extent to which they contribute to the presence of inefficiency. These factors are neither inputs to the production process nor outputs of it but nonetheless exert an influence on producer performance. Such factors are widely referred to as efficiency explanatory variables[106].

In this context, the term ‘efficiency explanatory variables’ is used to describe factors that could influence the efficiency of a producer, where such factors are not traditional inputs and are not under the control of the producer (Fried et al., 1999). However, they may influence productive efficiency. In particular, in order to investigate the determinants of the productive efficiency we distinguish between producers or

[106] In many cases, the distinction between decision-maker controlled and efficiency explanatory variables is not always distinct. As in McMillan and Chan (2006), efficiency explanatory variables include purely exogenous variables as well as producer-specific variables representing production methods and output characteristics.

industry -specific and efficiency explanatory factors (Caves and Barton, 1990) [107]. Efficiency explanatory factors are not under direct control of the producer, at least in the short-run, and they may be industry-affiliated, such as producer location characteristics, managerial restrictions, slow adoption to changes of the market environment and/or to technological developments, or asymmetric information in the labour market, social aspects, geographical or climatic conditions, as well as regulatory and institutional constraints, ownership differences (public/private), and government regulations (Coelli et al, 1998, Stephan et al. 2008). Producer-specific factors, on the other hand, refer to characteristics that can be influenced by the producer in the short-run, as producer size, R&D intensity and degree of outsourcing. Regarding productive efficiency, theory literature has mainly emphasized on efficiency determining factors such as technological spillovers, increasing returns, learning by doing, und unobserved inputs (e.g. human capital quality), whereas the empirical industrial organization literature has emphasized the degree of openness of countries to imports and industry structure (Koop, 2001).

Underlying our analysis, innovation creation and dissemination are among the main factors which determine the production efficiency level [Fagerberg et al. (1997), Freeman & Soete (1997)] and technological variables are able to explain a significant part of the diverging trends in the economic growth [Fagerberg & Verspagen (1996)] and productivity [Abramovitz (1986), Fagerberg (1988 a,b, 1994)]. Industry growth rate depends on the amount of technological activity within the economy and on the ability to exploit external technological achievements (Martin and Ottaviano, 1999, Grossman and Helpman, 1994, Coe and Helpman, 1995). Increasing returns and technical change are incorporated within the production function as determinants of the endogenous growth rate (Romer 1986, Lucas 1988, Grossman and Helpman 1994,

[107] Caves and Barton (1990) and Caves (1992) suggested that several studies have developed a strategy for identifying the determinants of efficiency, which can be grouped into three categories (Stephan et al. 2008):

4. factors external to the industry ;
5. factors internal to the industry; and
6. Ownership structures (e.g. public versus private).

Barro and Sala-i-Martin, 1997) and economic growth is sustained because of the continuous creation and diffusion of technological advances.

As in Consoli (2008), research agrees that: first, strong emphasis is placed on the sources and the effects of technological change; second, great attention is paid to the dynamics generated by the interaction between business firms and their environment, including other firms and key institutional players (Malerba and Orsenigo, 1996; Antonelli, 2003; Metcalfe, 2001).

In the same analysis framework, Bos et al. (2010) investigate the sources of output growth for a panel of manufacturing industries. They propose a flexible model beyond the division of output growth applied in the conventional growth accounting and cross-country growth regression literature, as well as the strong assumptions they typically rely upon (efficient use of resources, constant returns to scale). Bos et al. (2010) focus on the use of technology, the sources of output growth, technology spillovers and catch-up, as well as policy implications. To decrease the aggregation bias that may occur when these issues are considered at the country-level (Bernard and Jones, 1996 a,b), Bos et al. (2010) focus on manufacturing industries. Traditionally, the growth accounting literature has referred to the unexplained part of output growth as the 'productivity residual' or 'technical change' (Solow, 1957). This interpretation, however, depends, among other things, on the strong assumption that economic units (countries or industries) are always efficient. In reality, however, economic units may well use the best-practice (frontier) technology with varying degrees of efficiency. If this is the case, part of what is measured as technical change is in fact an improved use of the best-practice technology. Put differently, inefficient industries increase output by becoming more efficient in the use of the best-practice technology, whereas efficient industries increase output through technical change. In addition, not controlling for possible inefficient use of inputs may also result in underestimating the productivity of outputs for the best-practice technology. Bos et al. (2010) account for inefficiency and estimate a stochastic production frontier, which is the empirical analog of the theoretical production possibility frontier. This modelling strategy adds structure to the unexplained residual. Under reasonable assumptions, it disentangles the residual into inefficiency and measurement error. Technical change is modelled as a shift of the stochastic frontier, whereas efficiency change is a movement towards or away from the frontier. This framework decomposes output changes into three types of change: technical, efficiency and input change. Empirical literature carries out efficiency analyses along lines similar to Bos et al. (2010), although using different modelling approaches, considering that output change is also decomposed into technical, efficiency, and input change. Even though the attention has largely been at decomposing aggregate (country-level) output, a number of studies have investigated the role of efficiency in explaining growth differentials for a panel of manufacturing industries in the OECD countries (Bos et al., 2010).

5.4. Empirical Model Specification

Our empirical model is based both on frontier parametric analysis (involving Stochastic Frontier Analysis) and non-frontier nonparametric analysis, which employs mathematical programming methods (regarding Data Envelopment Analysis) as a robustness test for the model results. The level of optimal industry performance is determined by constructing an efficiency frontier, which consists of the best performing producers.

The type of efficiency we estimate using the production frontier is technical efficiency, characterized by the relationship between observed production and some ideal or potential production, based upon deviations of observed output from the best production or efficient production frontier. We also consider that technological progress is assumed to push the frontier of potential production upwards, while efficiency change will change the capability of productive units to improve production with available inputs and technology (Batesse and Coelli, 1992, 1995).

The stochastic frontier typically permits assessment of maximal output subject to input levels; as such, it appears to be an output-oriented measure. The stochastic frontier is, in fact, a base or non-orienting measure. That is, the assessment of efficiency is not conditional on holding all inputs or all outputs constant. Utilizing the one-stage routine of Battese and Coelli (1993), however, facilitates an assessment of maximal output from an input-based perspective. With this approach, the inefficiency error term, and subsequently the maximal output, is specified as a function of inputs.

Thus, it is possible to consider the input reduction coinciding with a fixed maximum or frontier output. Another attractive feature of the stochastic frontier model is the separation of the impact of exogenous shocks on output from the contribution of variation in technical efficiency. The component (v) is a symmetric normally distributed error term that represents factors that cannot be controlled by production units, measurement errors, and left-out explanatory variables. On the other hand, the component (u) is a one-sided non-negative error term representing the stochastic shortfall of producer i's output from the production frontier due to technical inefficiency. In this context, technical efficiency is defined in an output-expanding manner and reveals the maximum amount by which output can be increased using the same level of inputs and technological conditions (Giannakas, et al., 2003). In addition, it is generally regarded as a disadvantage that the distribution of the technical inefficiency has to be specified (i.e., half-normal, normal, exponential, log-normal, etc.).

Under these assumptions and underlying hypotheses, first, we employ LIMDEP 9.0 software program to estimate technical efficiency using the Batesse and Coelli (1992, 1995) model specifications. As in Bhattacharjee et al. (2009), we employed the SFA methodology, since it has emerged as the most popular methodology to study TFP at the firm level, for analysis of efficiency dynamics using panel data (Tsionas, 2006).

As far as the production function variables are concerned, following a value added approach, our analysis comprises:

1. Output (in Gross value added, volume indices, 1995 = 100)
2. Labour input (in Labour services, volume indices, 1995 = 100)
3. Capital input (in Capital services, volume indices, 1995 = 100)
4. Moreover, the model includes a time variable to capture the effect of technical progress.

The efficiency determining variables comprise:

1. Information and communication technologies (ICT) Capital services[108], as the proportion of industry ICT capital services to total industry capital services (in ICT capital services / Total capital services, volume indices, 1995 = 100)
2. Trade openness, as sum of exports and imports over GDP, in constant 1995 prices (PENN tables).

The core depended variable of our empirical analysis is the natural logarithm of gross value added. The core independent variables are set to be the labour and capital services, along with time, denoting technical progress. The variables are used in the model in the logarirthmic form (ln):

1. Output = *lnva*
2. Labour = *lnlab*
3. Capital = *lncap*
4. Information and communication technologies (ICT) Capital services = *lnitc*
5. Trade openness = *lnopen*

The following table presents the model variables, providing a short description of each one of the variables, the source from which come the statistical data, as well as the symbol used in the model for each one of the variables:

[108] The ICT specification in EU KLEMS (2008) data base, makes a distinction between three ICT assets (office and computing equipment, communication equipment and software) and four non-ICT assets (transport equipment, other machinery and equipment, residential buildings and nonresidential structures). ICT assets are deflated using a quality-adjusted investment deflator.

Table 5.4. Model Variables

	Core input variables	Symbol	Source
1.	Output (in Gross value added, volume indices, 1995 = 100)	lnva	EU KLEMS
2.	Labour input (in Labour services, volume indices, 1995 = 100	lnlab	EU KLEMS
3.	Capital input (in Capital services, volume indices, 1995 = 100)	lncap	EU KLEMS
4.	Time, to capture the effect of technical progress across countries in 1980 – 2005	time	

	Optional variables (efficiency determining variables)	Symbol	Source
1.	Information and Communication technologies (ICT) capital services (volume indices, 1995 = 100)	lnict	EU KLEMS
2.	Trade openness, as sum of exports and imports over GDP (Exports plus Imports divided by Real GDP per capita (Constant Prices: Laspeyres), Share of total trade (imports plus exports) in GDP, in constant 1995 prices	lnopen	PENN

Source: EU KLEMS, PENN tables

The following table presents the summary descriptive statistics for both the core and efficiency determining variables included in the analysis, as described in chapter (3.3). They involve the mean value and the standard deviation, together with the minimum and maximum values:

Table 5.5. Descriptive statistics of the core variables

Variable	Mean	Std.Dev.	Minimum	Maximum
LNVA	4.55	0.23	3.43	5.52
LNCAP	4.54	0.26	3.19	5.28
LNLAB	4.65	0.16	3.68	5.64
LNICT	4.41	0.90	1.27	6.46
LNOPEN	3.81	0.40	2.95	4.88

Source: EU KLEMS, own calculations

Provided the inefficiency effects are stochastic, the model permits the estimation of both technical change and time-varying technical inefficiencies[109].

The variable 'Trade openness', as sum of exports and imports over GDP, in constant 1995 prices is extracted form the PENN tables data base. All the other variables come from EU KLEMS database. The sample has 1872 observations in a balanced data set (12 industries *x* 6 countries *x* 26 years).

The capital data are derived form the EU KLEMS (2008) data base. According to the data base specification, the real investment series are used to derive capital stocks through the accumulation of investment into stock estimates using the Perpetual Inventory Method (PIM) and the application of geometric depreciation rates. Then capital service flows are derived by weighting the growth of stocks by the share of each asset's compensation in total capital compensation as follows: $\Delta \ln K_t = \sum_k \bar{v}_{k,t} \Delta \ln S_{k,t}$ where $\Delta \ln S_{k,t}$ indicates the growth of the stock of asset *k* and weights are given by the average shares of each asset in the value of total capital compensation.

In this way, aggregation takes into account the widely different marginal products from the heterogeneous stock of assets. The weights are related to the user cost of each asset.

As far as the labor variable is concerned, according to the EU KLEMS (2008) data base specification, it is assumed that the flow of labour services for each labour type is proportional to hours worked, and workers are paid their marginal productivities. Then the corresponding index of labour services input L is given by: $\Delta \ln L_t = \sum_l \bar{v}_{l,t} \Delta \ln H_{l,t}$ where $\Delta \ln H_{l,t}$ indicates the growth of hours worked by labour type *l* and weights are given by the average shares of each type in the value of labour compensation.

Labour input measures in EU KLEMS (2008) take account of changes in the composition of the labour force. Capital input measures include the effects of the

[109] A relevant topic has been broadly examined in: Kokkinou A. (2009d) Public spending efficiency: assessment through stochastic frontier analysis, 49th Annual Congress of the European Regional Science Association, Lodz, Poland.

rapid shift in investment towards Information and Communications Technology (ICT) goods in recent years. The productivity of various types of labour input, such as low- versus high-skilled, will also differ. Standard measures of labour input, such as numbers employed or hours worked, will not account for such differences. Hence one needs measures of labour input which take the heterogeneity of the labour force into account in analysing productivity and the contribution of labour to output growth. These measures are called labour services, as they allow for differences in the amount of services delivered per unit of labour in the growth accounting approach. It is assumed that the flow of labour services for each labour type is proportional to hours worked, and workers are paid their marginal productivities. Labour service input has been measured in a standardised way by distinguishing labour types in terms of gender, age and educational attainment. Capital service input has been measured using harmonised depreciation rates and common rules to deal with a variety of practical problems, such as weighting and rental rates. Importantly, capital input is measured as capital services, rather than stocks.

As analytically described in chapter 3.2 - 3.3, our analysis estimates different model specifications, starting from a model with no inefficiency effects (a time-invariant efficiency model is also estimated, i.e. a model in which technical efficiency is not determined by any other variables, including time), estimating a Batesse and Coelli (1992) model (technical efficiency is assumed to be a function of time), and finally, estimating alternative models for the Batesse and Coelli (1995) model (technical efficiency is assumed to be a function of efficiency determining optional variables, including time). More specifically, we estimate the following model variations:

Table 5.6. Models with alternative variables in inefficiency effects

Model	Efficiency determinants	Model
a. Time invariant		
b. Battese and Coelli (1992)	none	[1]
c. Battese and Coelli (1995)	*time*	[2]
d. Battese and Coelli (1995)	*ICT capital*	[3]
e. Battese and Coelli (1995)	*Economy Openness*	[4]
f. Battese and Coelli (1995)	*Time, ICT capital, Economy Openness*	[5]

Source: Own elaboration

These are the model variations in which our empirical analysis is based, regarding alternative model specifications, bearing different results. As it is also explained in parts 2.6.1. and 2.6.2., one of the main features which characterize Batesse and Coelli models is that, by definition, Batesse and Coelli approach incorporates fixed effects. For that reason the underlying hypothesis on our model is for fixed effects. Moreover, we use translog function with industry dummies, both with and without explanatory terms in the inefficiency residuals. Following Battese and Coelli (1992, 1995), technical efficiency assumed to be a function of time, hence time-varying. For comparison purposes, following Schmidt and Sickles (1984), a time-invariant efficiency model is also estimated, i.e. a model in which technical efficiency is not determined by any other variables, including time. We use translog function with industry dummies, with explanatory terms in the inefficiency residuals. There also should be a distinction on what should determine the frontier and what affects efficiency. The following table presents the determining variables included in production function and inefficiency term of each model:

Table 5.7. Empirical Models Determining Factors

SF Model	What determines Output	What determines Inefficiency
[1]	*Labour, Capital, Time*	none
[2]	*Labour, Capital, Time*	*time*
[3]	*Labour, Capital, Time*	*lnict*
[4]	*Labour, Capital, Time*	*lnopenk*
[5]	*Labour, Capital, Time*	*time, lnict, lnopenk*

Source: Own elaboration

Under the inclusion of the above production function and inefficiency term determining factors, we form the above defined five empirical models [(models (1) – (5] according to Battese and Coelli (1992 and 1995).

The data set used in the empirical model estimation is panel data. Unlike time series data, in which one individual is observed over time, or cross – section data, in which multiple individuals are observed for one point in time, panel data models can control for both variation across time periods and individuals, or cross – sections, simultaneously (Frees, 2004, Hsiao, 2003). An important advantage of using panel data in an empirical study is that effects of differences across individuals (individual effects) can be distinguished from effects changing over time within individuals. Although time-invariant and individual-specific effects are often unobservable, they frequently account for an important share of the heterogeneity in data. We will focus on static panel data models, in which the dependent variable does not exhibit temporal autocorrelation. The translog stochastic frontier function is estimated with the maximum likelihood estimation (MLE) technique, which is the preferred estimation technique whenever possible (Coelli, Rao and Battese 1998)[110]. The model estimates time – varying technical efficiencies, (incorporating 'learning – by doing' behaviour), considering industry-specific fixed effects. According to Coelli et al. (2005) it is convenient for estimation purposes, a problem with assuming uit are independently distributed. However, for many industries the independence assumption is unrealistic – all other things being equal, it is expected that efficient firms to remain reasonably efficient from period to period and it is suggested that inefficient firms improve their efficiency levels over time.

On the other hand, time invariant inefficiency models are somewhat restrictive, we would expect managers to learn from experience and for their technical efficiency levels to change systematically over time and would expect these changes to become more noticeable as time gets larger.

[110] According to Battese and Coelli (1995), the explanatory variables can include intercept terms or any variables in both the frontier and the model for the inefficiency effects, provided the inefficiency effects are stochastic.

For these reasons, we need to impose some structure on the inefficiency effects and consider time – varying technical efficiencies. Consequently, the stochastic production frontier model is extended to allow data to be modeled over time with time – invariant technical efficiency (e.g. Pitt and Lee, 1981, Schmidt and Sickles, 1984, Kumbhakar, 1987, Battese and Coelli, 1988) or time – varying technical efficiency (e.g. Cornwell, Schmidt and Sickles, 1990, Kumbhakar, 1990, Lee and Schmidt, 1993, Battese and Coelli, 1992)[111].

Kumbhakar (1991), Polachek and Yoon (1996) and Greene (2005b) have suggested to extend the original stochastic frontier model by adding an individual time-invariant random or fixed effect. These models are called "true" models because they include two stochastic terms for unobserved heterogeneity: one for the time-variant factors and one for the producer-specific constant characteristics (Farsi et al., 2003). The basic assumption is the existence of producer-specific and time-invariant factors that cannot be captured by efficiency explanatory variables due to the variation of the latter over time and/or omitted variables.

Time-invariant inefficiency assumption has been relaxed, as in Kumbhakar (1990) and Battese and Coelli (1992). These studies specify inefficiency (u_{it}) as a product of two components. One of the components is a function of time and the other is an individual specific effect so that $u_{it} = f(t)u_i$. In these models, however, the time-varying pattern of inefficiency is the same for all individuals, so the problem of inseparable inefficiency and individual heterogeneity remains. In all these models, the inability to separate inefficiency and individual heterogeneity is likely to limit their applicability in empirical studies (Greene, 2005), who argues that the (in)efficiency effect and the time-invariant country-specific effect are different and should be accounted for separately in the estimation. If, for example, the country-specific heterogeneity is not adequately controlled for, then the estimated inefficiency may be picking up country-specific heterogeneity in addition to or even instead of

[111] Coelli et al. (2005) classify different structures according to whether they are time – invariant or time – varying and provide a broad analysis of time – invariant inefficiency models, as well as time – varying inefficiency models.

inefficiency. In this way, the inability of a model to estimate individual effects in addition to the inefficiency effect poses a problem for empirical research (Wang and Ho, 2010).

The heterogeneity in the inefficiency model can be expressed by a shift in the underlying mean of u_i or heteroscedasticity. Battese and Coelli (1995) established a model where producer-specific attributes are incorporated in the inefficiency distribution. Heterogeneity is expressed in the location parameter, the mean, of the underlying distribution of inefficiency u_i. This model specification became popular to explain efficiency differences across producers. Reifschneider and Stevenson (1991) and Simar et al. (1994) established a SFA model incorporating heterogeneity in the variance of u_i or v_i, allowing for heteroscedasticity. Applications of the heteroscedastic SFA model can be found in Hadri (1999), Hadri et al. (2003 a,b) and Caudill et al. (1995).

Unobserved heterogeneity means that heterogeneity is not reflected in measured variables but expressed in the form of effects (Greene, 2007a). Several models attempt to separate unobserved heterogeneity from inefficiency and it became more important to model both heterogeneity in the stochastic part and producer-specific heterogeneity in the production or cost function of the underlying production process. Unobservable individual effects also play an important role in the estimation of panel stochastic frontier models. In contrast to the conventional panel data literature, however, studies using stochastic frontier models often interpret individual effects as inefficiency (Schmidt and Sickles, 1984), such as technical inefficiency in a stochastic production frontier model.

5.5. Empirical Results

The econometric software programs used in our empirical analysis are LIMDEP 9.0 and STATA 10.0. The two packages, Limdep 9.0 (Greene, 2007) and Stata 10.0 (StataCorp, 2007), even though they differ slightly in their computations details, however, they yield, in most of the cases, almost similar or even marginally different results. LIMDEP program has first developed by Greene (1980), initially to provide an easy to use tobit estimator - hence the name, '*LIM*ited *DEP*endent variable models[112]. LIMDEP 9.0 is an integrated program for estimation and analysis of linear and nonlinear models, with cross section, time series and panel data. LIMDEP has provided innovations including cutting edge techniques in panel data analysis, frontier and efficiency estimation and discrete choice modelling. LIMDEP 9.0 has also been recognized for years as the standard software for the estimation and manipulation of discrete and limited dependent variable models. STATA 10.0 is a general-purpose statistical software package created in 1985 by StataCorp[113]. Stata's capabilities include data management, statistical analysis, graphics, simulations, and custom programming, integrating statistics with graphics and data management. In this analysis, STATA 10.0 is used in order to estimate technical efficiency in a non-stochastic context, so to be able to compare results regarding stochastic context, respectively.

First, we proceed in estimating the input elasticities in each one of these alternative models. Apart from the information provided by the elasticity estimation (as explained in chapter 3.3), elasticities are also a tool in order to check whether our model works properly, as well as a tool in order to estimate technical change and economies to scale.

[112] Greene, W. H. (2007), Limdep 9.0, Econometric Software, Inc., Plainview, NY. and Greene, W. H. (2007) LIMDEP 9.0 User's Guide, Student version, Econometric Software, Inc., 1986 – 2007, Plainview, NY.

[113] Statacorp (2007) Stata Statistical Software: Release 10, College Station, TX: StataCorp LP.

In order to implement the input elasticities estimation, a flexible (translog) production function is used to represent the underlying production technology. The coefficients β_{it} are transformed into output elasticities with respect to inputs and the sum of them $k = \sum_i \varepsilon_i(x,t)$ provides the elasticity of scale, which indicates the returns to scale, i.e. the presence of increasing or decreasing returns to scale.

As far as the time variable is concerned, output elasticity with respect to time indicates technical progress. The input elasticities estimation is presented in the following table:

Table 5.8. Estimation of input elasticities for standard models

SF Model	Inefficiency Determinants	$\partial \ln va / \partial \ln cap$	$\partial \ln va / \partial \ln lab$	$\partial \ln va / \partial \ln time$	TC	RTS
[1]	none	0.148	0.395	0.017	1.71%	0.544
[2]	*time*	0.150	0.479	0.001	0.10%	0.629
[3]	*lnict*	0.031	0.459	0.013	1.30%	0.490
[4]	*lnopenk*	0.142	0.375	0.015	1.50%	0.516
[4]	*time,lnict,lnopenk*	0,217	0,348	0,023	2.30%	0,588

Notes:

1. SF: Stochastic Frontier
2. TC: Technical change
3. The elasticity $\partial \ln va / \partial \ln time$ shows technical change
4. RTS: Returns to Scale
5. Returns to scale = sum of output elasticities

Source: Own estimation

As illustrated in the above table, capital and labour elasticities are both positive in every one of the different model specifications. In Model [1], with no inefficiency effects, capital elasticity is approximately 0.15, labor elasticity is 0.40, whereas, technical change is 1.71%. In Model [2], with time as inefficiency determining variable, capital elasticity is approximately 0.15, labor elasticity is 0.48, whereas, technical change is 0.10%. In Model [3], with ICT investment as inefficiency determining variable, capital elasticity is approximately 0.031, labor elasticity is 0.46, whereas, technical change is 1.30%. In Model [4], iwith economy openness as inefficiency determining variable, capital elasticity is approximately 0.42, labor elasticity is 0.37, whereas, technical change is 1.50%. In Model [5], with all the three inefficiency determining variables, capital elasticity is approximately 0.21, labor elasticity is 0.35, whereas, technical change is 2.30%. All the five models seem to work properly, as far as the estimated input elasticities are concerned, presenting the expected signs and results. On the other hand, it becomes apparent the significance of the time dimension, denoting the effect of technical change, onto the production output.

A second model fitness control in order to predict whether the model specifications fit to the data set is the estimation of log likelihood and AIC information criterion (as described in chapter 3.4):

Table 5.9. Diagnostic Tests – standard models

SF Model	Inefficiency Determinants	Log Likelihood Diagnostic	AIC
[1]	none	4350.433	-4.19875
[2]	*time*	4272.647	-4.51565
[3]	*lnict*	4122.787	-4.35554
[4]	*lnopenk*	4062.332	-4.29095
[5]	*time, lnict, lnopenk*	4272.585	-4.51345

Source: Own estimation

AIC criterion and Log Likelihood are both ways of assessing the relative goodness of fit of our alternative model specifications. Regarding the model relative fit criteria, we report only the AIC criterion, because the other two alternative tests (BIC, HQIC), also referred and described in chapter (3.4.), are both consistent and give the same results with the AIC criterion (as explained in chapter 3.4.). Reference to the diagnostic test is estimated in order to reinforce which model we adopt. The smaller the AIC criterion is, the better the relative goodness of fit of the model is. Comparing our models, both regarding log likelihood and AIC criterion, we conclude that all the models are relatively fitted well, respectively. This issue provides a first hint that the production function and efficiency determining variables seem to work well with our model specifications, implying that it has significant effect on technical efficiency estimation.

In conclusion, comparing the different AIC criterion values for each one of the alternative models, it becomes apparent that the two best working models are those with the lowest AIC criterion values. In this case the two best working models are: Model [2], with the variable '*time*' in the inefficiency term, implying that technical efficiency is attributed to technical change, and Model [5] with the variables '*time, ICT and economy openness*' in the inefficiency term, implying that technical efficiency is attributed to technical change, ICT investment level, as well as the degree to which an economy is open to imports and exports. To sum up, the models which include only time (as a proxy for technical change), as well as time, ICT investment and economy openness as inefficiency effects determining variables, present the best criteria, considering that they provide a good fit.

Next, we estimate the technical efficiency determining variables within the five different model forms.

Table 5.10. Estimation of Inefficiency Effects

SF Model	Inefficiency Determinants	*time*	*lnict*	*lnopenk*
[1]	none	-	-	-
[2]	*time*	-0.157 (0.008)		
[3]	*lnict*	-	-0.782 (0.077)	-
[4]	*lnopenk*	-	-	0.587 (0.131)
[5]	*time,lnict,lnopenk*	-0.176 (0.023)	0.108 (0.142)	0.131 (0.366)

Notes:

1. Standard errors in parentheses

Source: Own estimation

It is apparent that in each one of the different model specifications (Models [2] – [5]), which include specific efficiency determining variables, these variables are statistically significant, having a statistically significant effect on efficiency. The variables with negative sign denote the negative relationship with inefficiency, e.g. inefficiency is decreasing, as the variable input is increasing. This effect is present when the time dimension variable and ICT investment variable are concerned, exercising a negative effect on inefficiency.

For each one of the models, we also estimate the efficiency variance parameters for each one of the models, as described in chapter 3.3. The parameters of the stochastic frontier model and the inefficiency effects model are estimated using maximum likelihood estimation (MLE). The statistical significance of λ obtained from the MLE estimates indicates the existence of a stochastic frontier function (Schmidt and Lin, 1984). If λ is statistically different from zero, it implies that the difference between the observed and the frontier production is dominated by technical inefficiency. If λ is not statistically significant from zero, it implies that any difference in the production is attributed solely to symmetric random errors. Lamda is the ratio of variance of *u* (σ_u) over variance of *v* (σ_v) and is an indication that the one sided error term *u* dominates the symmetric error *v*, so variation in actual production comes from differences in industries production practice rather than random variability.

Table 5.11. Estimation of Efficiency Variance Parameters for standard models

SF Model	Inefficiency Determinants	$\lambda = \sigma_u^2 / \sigma_v^2$	σ_u	$\gamma = \sigma_u^2 / \sigma^2$
[1]	none	4.584 (.032)	.102 (.000)	0.006
[2]	*time*	4.837 (.069)	.112 (.000)	0.979
[3]	*lnict*	15.390 (.011)	.395 (.010)	0.999
[4]	*lnopenk*	.0757 (.052)	.002 (.000)	0.997
[5]	*time,lnict,lnopenk*	2.234 (.533)	.051 (.000)	0,834

Note:

1. Standard errors in parentheses

Source: Own estimation

Technical efficiency is measured using the variance ratio parameter γ. Using the composed error terms of the stochastic frontier model, γ defines the total variation in output from the frontier level of output attributed to technical efficiency indicating the ratio of the unexplained error and the total error of the regression (Aigner, Lovell, Schmidt, 1977), in other words, the variance parameter γ captures the total output effect of technical efficiency, suggesting the percentage (%) of the residual which is due to inefficiency.

Large value of parameter γ highlights the importance of inefficiency effects in explaining the total variance in the model. Considering the variance parameter γ lies on the interval [0,1], if the estimate is close to 1 and significant, this indicates that most of the total variation in output is attributable to technical efficiency.

In Model [1], with no efficiency explanatory variables, the variation which is attributable to inefficiency effects is practically zero. In Models [2] – [4], which include efficiency determining variables, total variation in output from the frontier level of output attributed to technical efficiency is 97.9%, 99.9%, or 99.7% respectively, indicating the total output effect of technical efficiency, suggesting the percentage (%) of the residual which is due to inefficiency, in the models in which time, ICT, or economy openness variables are included. In Model [5], total variation in output from the frontier level of output attributed to technical efficiency is 83.4%,

As in Coelli et al. (2005), in addition to testing hypotheses concerning the variance parameters, stochastic frontier analysis is interested in testing for the absence of inefficiency effects. Lamda is the ratio of variance of u (σ_u) over variance of v (σ_v) and is an indication that the one sided error term u dominates the symmetric error v, so variation in actual production comes from differences in industries production practice rather than random variability. Finally, the large value of parameter γ highlights the importance of inefficiency effects in explaining the total variance in the model.

The following tables present the estimation results calculated according to each one of the alternative estimated stochastic frontier models.

For each one of the two best working models, we also estimate the related efficiency effects determining variables and the efficiency variance parameters for each one of the models, as described in chapter 3.3.

The parameters of the stochastic frontier model and the inefficiency effects model are estimated using maximum likelihood estimation (MLE):

Table 5.12. Empirical Model [2]: Efficiency Estimation

Model		Variances	
Log likelihood function	4272.647	Sigma-squared(v)	.00054
Info. Criterion: AIC	-4.51565	Sigma-squared(u)	.01273
Finite Sample: AIC	-4.51438	Sigma(v)	.02332
Info. Criterion: BIC	-4.37964	Sigma(u)	.11281
Info. Criterion:HQIC	-4.46554	Sigma = Sqr[(σ^2(u)+σ^2(v)]	.11519
Stochastic Production Frontier, e=v-u.			
Time varying u(i,t)=exp[eta*z(i,t)]*|U(i)|			

Source: Own estimation

As becomes apparent from the estimation results, the statistical significance of λ obtained from the MLE estimates indicates the existence of a stochastic frontier function (Schmidt and Lin, 1984), since λ is statistically different from zero.

The time dimension variable, as a determinant of the inefficiency effect, is statistically significant with a negative sign, implying that it has a negative effect on inefficiency level, by 15.75%.

Table 5.13. Empirical Model [2]: Coefficient Estimation

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Primary Index Equation for Model					
Constant	4.29675191	.97032174	4.428	.0000	
LNCAP	.52266804	.32995187	1.584	.1132	4.53813827
LNLAB	-.94672093	.18290314	-5.176	.0000	4.64818191
TIME	-.00974744	.01263264	-.772	.4403	13.5000000
LAB2	.53520349	.05878035	9.105	.0000	10.8158946
CAP2	.31500076	.07110208	4.430	.0000	10.3307444
TIME2	.00045271	.00020044	2.259	.0239	119.250000
LABCAP	-.32426713	.08318463	-3.898	.0001	21.0930324
LABTIME	.01990003	.00354828	5.608	.0000	62.3692144
CAPTIME	-.01638246	.00300150	-5.458	.0000	62.8256562
LNCAPD1	-.40088057	.04688821	-8.550	.0000	.37753423
LNLABD1	.27745558	.03852795	7.201	.0000	.38837574
TIMED1	.03077261	.00226402	13.592	.0000	1.12500000
LNCAPD2	.18624047	.03679873	5.061	.0000	.37617450
LNLABD2	-.13011486	.03220976	-4.040	.0001	.38535840
TIMED2	-.01845507	.00173244	-10.653	.0000	1.12500000
LNCAPD3	-.15924141	.05037117	-3.161	.0016	.38133607
LNLABD3	.19167868	.04250873	4.509	.0000	.38972613
TIMED3	-.01317418	.00231969	-5.679	.0000	1.12500000
LNCAPD4	-.82724007	.03591286	-23.035	.0000	.37960654
LNLABD4	.81331706	.02948446	27.585	.0000	.38383682
TIMED4	.00525235	.00167908	3.128	.0018	1.12500000
LNCAPD5	-.04904778	.06658107	-.737	.4613	.38112430
LNLABD5	.02690744	.05852509	.460	.6457	.38450072
TIMED5	.00256154	.00282981	.905	.3654	1.12500000
LNCAPD6	-.15564014	.03719988	-4.184	.0000	.37286709
LNLABD6	.16122972	.03084875	5.226	.0000	.38400415
TIMED6	-.00211754	.00181209	-1.169	.2426	1.12500000
LNCAPD8	.29927706	.06131773	4.881	.0000	.38079571
LNLABD8	-.34022610	.05168456	-6.583	.0000	.39087342
TIMED8	.00539822	.00262452	2.057	.0397	1.12500000
LNCAPD9	.17637302	.04272857	4.128	.0000	.37480414
LNLABD9	-.21729386	.03073691	-7.069	.0000	.38228242
TIMED9	.00791660	.00296996	2.666	.0077	1.12500000
LNCAPD10	-.30706039	.06975794	-4.402	.0000	.37896495
LNLABD10	.28619911	.06079022	4.708	.0000	.38765447
TIMED10	.00254864	.00352055	.724	.4691	1.12500000
LNCAPD11	-.32802639	.04965664	-6.606	.0000	.38435061
LNLABD11	.34046247	.04595183	7.409	.0000	.38898708
TIMED11	-.00679019	.00168480	-4.030	.0001	1.12500000
LNCAPD12	.26778303	.07324738	3.656	.0003	.38044290
LNLABD12	-.24516886	.06841212	-3.584	.0003	.38900706
TIMED12	-.00963988	.00258669	-3.727	.0002	1.12500000
Variance parameters for compound error					
Lambda	4.83756520	.06991360	69.193	.0000	
Sigma(u)	.11280724	.00051277	219.997	.0000	
---------+Coefficients in u(i,t)=[exp{eta*z(i,t)}]*|U(i)|					
TIME	-.15753435	.00894748	-17.607	.0000	

Source: Own estimation

Regarding the second best working model, it is Model [5] with time, ICT investment and economy openness as inefficiency determining variables.

Table 5.14. Empirical Model [5]: Efficiency Estimation

Model		Variances	
Log likelihood function	4272.585	Sigma-squared(v)	.00054
Info. Criterion: AIC	-4.51345	Sigma-squared(u)	.00269
Finite Sample: AIC	-4.51207	Sigma(v)	.02322
Info. Criterion: BIC	-4.37153	Sigma(u)	.05188
Info. Criterion:HQIC	-4.46116	Sigma = Sqr[(σ^2(u)+σ^2(v)]	.05683

Stochastic Production Frontier, e=v-u.

Time varying u(i,t)=exp[eta*z(i,t)]*|U(i)|

Source: Own estimation

Model [5] presents time variant inefficiency. As becomes apparent from the estimation results, the statistical significance of λ obtained from the MLE estimates indicates the existence of a stochastic frontier function (Schmidt and Lin, 1984), since λ is statistically different from zero, so variation in actual production comes from differences in industries production practice rather than random variability. Technical change is statistically significant and negatively associated with technical inefficiency levels (as expected by the literature, with coefficient 0.1762). However, ICT investment and economy openness variable are not statistical significant, in this model specification even though this is not that case when they are estimated in models as sole inefficiency determining variables.

Table 5.15. Empirical Model [5]: Coefficient Estimation

Variable	Coefficient	Standard Error	b/St.Er.	P[|Z|>z]	Mean of X
Primary Index Equation for Model					
Constant	4.22338155	1.04570858	4.039	.0001	
LNCAP	.57458818	.33663804	1.707	.0879	4.53813827
LNLAB	-.96246364	.20778210	-4.632	.0000	4.64818191
TIME	-.01101349	.01209198	-.911	.3624	13.5000000
LAB2	.54231036	.05944439	9.123	.0000	10.8158946
CAP2	.30787795	.07541348	4.083	.0000	10.3307444
TIME2	.00046059	.00022503	2.047	.0407	119.250000
LABCAP	-.32863457	.08851120	-3.713	.0002	21.0930324
LABTIME	.02015502	.00362739	5.556	.0000	62.3692144
CAPTIME	-.01638387	.00334272	-4.901	.0000	62.8256562
LNCAPD1	-.39886408	.05156847	-7.735	.0000	.37753423
LNLABD1	.27540973	.04293267	6.415	.0000	.38837574
TIMED1	.03076592	.00239183	12.863	.0000	1.12500000
LNCAPD2	.19029024	.03698026	5.146	.0000	.37617450
LNLABD2	-.13380496	.03219683	-4.156	.0000	.38535840
TIMED2	-.01855293	.00178089	-10.418	.0000	1.12500000
LNCAPD3	-.15657938	.05003347	-3.129	.0018	.38133607
LNLABD3	.18929632	.04168132	4.542	.0000	.38972613
TIMED3	-.01326200	.00238188	-5.568	.0000	1.12500000
LNCAPD4	-.83434550	.03954290	-21.100	.0000	.37960654
LNLABD4	.81930851	.03274724	25.019	.0000	.38383682
TIMED4	.00550838	.00179628	3.067	.0022	1.12500000
LNCAPD5	-.05044662	.07098990	-.711	.4773	.38112430
LNLABD5	.02811536	.06331817	.444	.6570	.38450072
TIMED5	.00261260	.00269061	.971	.3315	1.12500000
LNCAPD6	-.15162061	.04041641	-3.751	.0002	.37286709
LNLABD6	.15771536	.03399381	4.640	.0000	.38400415
TIMED6	-.00225326	.00191245	-1.178	.2387	1.12500000
LNCAPD8	.30156467	.06375379	4.730	.0000	.38079571
LNLABD8	-.34228923	.05327100	-6.425	.0000	.39087342
TIMED8	.00533496	.00277888	1.920	.0549	1.12500000
LNCAPD9	.18188197	.04724075	3.850	.0001	.37480414
LNLABD9	-.22219146	.03459398	-6.423	.0000	.38228242
TIMED9	.00776839	.00302413	2.569	.0102	1.12500000
LNCAPD10	-.30447447	.06560259	-4.641	.0000	.37896495
LNLABD10	.28376994	.05907700	4.803	.0000	.38765447
TIMED10	.00249030	.00326177	.763	.4452	1.12500000
LNCAPD11	-.32488532	.05209067	-6.237	.0000	.38435061
LNLABD11	.33765525	.04860678	6.947	.0000	.38898708
TIMED11	-.00688089	.00176665	-3.895	.0001	1.12500000
LNCAPD12	.27007461	.07298551	3.700	.0002	.38044290
LNLABD12	-.24718002	.06682091	-3.699	.0002	.38900706
TIMED12	-.00971771	.00272355	-3.568	.0004	1.12500000
Variance parameters for compound error					
Lambda	2.23449218	.53331910	4.190	.0000	
Sigma(u)	.05187668	.00023930	216.787	.0000	
Coefficients in u(i,t)=[exp{eta*z(i,t)}]*|U(i)|					
TIME	-.17624961	.02369534	-7.438	.0000	
LNICT	.10812426	.14275688	.757	.4488	
LNOPENK	.13190578	.36600687	.360	.7186	

Source: Own estimation

5.6. Estimation of Technical Efficiency

Førsund, Lovell and Schmidt (1980) asserted that the main weakness of the stochastic frontier model is that it is not possible to decompose individual residuals into their two components, and so it is not possible to estimate technical efficiency by observation. The best that one can do is to obtain an estimate of mean inefficiency over the sample. However, Jondrow et al (1982) proposed either the mean or the mode of the conditional distribution $[u_i \mid v_i\text{-}u_i]$ to provide estimates of the technical inefficiency of each producer in the sample. The possibility of obtaining producer – specific estimates of efficiency has greatly enhanced the appeal of stochastic frontier analysis. Within this framework, several models for estimating technical efficiency have been developed, extending the stochastic frontier methodology to account for different theoretical and empirical issues (Coelli et al (1998), Greene (1999), Kubhakar and Lovell (2000)). However, another possible weakness with the approach is that in order to distinguish the two error components it is also necessary to make some strong distributional assumptions. In stochastic frontier models the symmetric error v has been assumed to be iid normal but a variety of different assumptions have been made about the distribution of technical inefficiency. However, different distributional assumptions can lead to different results in terms of estimated efficiencies.

In order to define the inefficiency determinants variables effects, we compare the inefficiency effects in best working Model [5] with the inefficiency estimation when no inefficiency determinants are included in the model function.

To begin with, within this framework, Model [1] has no inefficiency effects and since technical efficiency is considered to be time-invariant in this model specification, it remains the same for the whole period 1980-2005[114].

[114] The inefficiency levels ($E[u|e]$) per industry and country for the period covering 1980-2005 are presented in the Appendix.

Table 5.16. Inefficiency Analysis per Industry and country – Without inefficiency determinants

	France	Germany	Italy	Netherlands	Spain	United Kingdom	Average
Electrical - Optical	0.018	0.025	0.161	0.119	0.232	0.192	0,1245
Food - Beverages	0.081	0.016	0.138	0.148	0.122	0.096	0,1002
Textiles	0.032	0.073	0.225	0.021	0.075	0.087	0,0855
Manufacturing nec	0.123	0.060	0.126	0.016	0.172	0.125	0,1037
Wood	0.157	0.277	0.111	0.208	0.012	0.153	0,1530
Paper	0.017	0.074	0.141	0.079	0.115	0.111	0,0895
Chemicals	0.066	0.026	0.094	0.030	0.076	0.100	0,0653
Rubber - Plastics	0.186	0.051	0.141	0.021	0.030	0.104	0,0888
Non-metallic	0.027	0.045	0.057	0.039	0.083	0.065	0,0527
Metals	0.012	0.172	0.273	0.204	0.154	0.163	0,163
Machinery	0.175	0.019	0.119	0.077	0.081	0.043	0,0857
Transport	0.109	0.016	0.066	0.085	0.170	0.168	0,1023
Average	0.084	0.071	0.137	0.087	0.110	0.117	0,1010

Source: Own estimation

Model [1] presents time invariant inefficiency, which is the same inefficiency level for each one of the years in analysis. The table above presents the inefficiency levels estimation for each one of the industries and countries included in our estimation. On average, Germany, France, and Netherlands are the best performer countries, since they have the lowest average inefficiency levels, whereas Italy, Spain and United Kingdom seem to be the worst performer countries, since they have the highest levels of inefficiency. As far as the industry inefficiency is concerned, the best performing industries, on average, are the non- metallic, the chemicals and textiles industries, whereas, the worst performing industries are those of wood, electrical/optical and metals.

Among the best performing industries are the industries of paper in France, Metals in France and Transport Equipment in Germany. On the other hand, the worst performing industries are those of wood in Germany and Netherlands, as well as metals industry in Italy and Netherlands.

The detailed inefficiency analysis per industry and country for the rest of the time variant inefficiency models ([2]-[4]) is illustrated in the Appendix. It is apparent that the inefficiency level decreases over time in the vast majority of the industries and countries[115]. Even though there is a general trend that inefficiency decreases over time, however, there are significant differences, both in inter-industry and inter-country level.

[115] Model [3] presents time variant inefficiency. The inefficiency level decreases over time in all the industries and countries, even though certain industries and countries have mixed increases and decreases in inefficiency levels, such as the wood industry, or the non – metallic industry in Spain or the machinery industry in France. However, the general trend of the inefficiency shows that inefficiency levels decrease over time. Model [4] presents also time variant inefficiency. Even though the inefficiency level decreases over time in all the industries and countries, the decrease rate is rather small. The countries which present the highest levels of inefficiency are Italy, Spain and France.

Table 5.17. Inefficiency Analysis per Industry and country – With inefficiency determinants

	France	Germany	Italy	Netherlands	Spain	United Kingdom	Average
Electrical - Optical	0.0221	0.0157	0.0220	0.0159	0.0430	0.0140	0.0221
Food - Beverages	0.0060	0.0203	0.0031	0.0190	0.0098	0.0225	0.0135
Textiles	0.0138	0.0369	0.0052	0.0119	0.0024	0.0200	0.0150
Manufacturing nec	0.0722	0.0548	0.0369	0.0372	0.0178	0.0006	0.0366
Wood	0.0190	0.0064	0.0226	0.0082	0.0046	0.0050	0.0110
Paper	0.0220	0.0180	0.0208	0.0227	0.0351	0.0212	0.0233
Chemicals	0.0101	0.0127	0.0137	0.0074	0.0065	0.0207	0.0119
Rubber - Plastics	0.0021	0.0271	0.0054	0.0774	0.0304	0.0065	0.0248
Non-metallic	0.0154	0.0142	0.0135	0.0061	0.0135	0.0233	0.0143
Metals	0.0138	0.0199	0.0089	0.0088	0.0019	0.0872	0.0234
Machinery	0.0140	0.0139	0.0106	0.0067	0.0072	0.0148	0.0112
Transport	0.0067	0.0188	0.0090	0.0180	0.0174	0.0026	0.0121
Average	0.0181	0.0216	0.0143	0.0200	0.0158	0.0200	0.0183

Source: Own estimation

Model [5] presents time variant inefficiency included inefficiency term with determining variables. Regarding the inefficiency gap variations by country and industry, the table above presents the inefficiency levels estimation for each one of the industries and countries included in our estimation. On average, Italy, Spain are the best performing countries, since they have the lowest average inefficiency levels, whereas Germany seems to be the worst performer country, since it has the highest levels of inefficiency. As far as the industry inefficiency is concerned, the best performing industries, on average, are the non- metallic and chemicals industries, whereas, the worst performing industries are those of manufacturing nec and rubber/plastics. In more detail, the industries with the lowest inefficiency levels are rubber/plastics in France and Italy, as well as the manufacturing nec industry in United Kingdom. As far as the industries with the highest inefficiency levels are concerned, these are the metals industry in United Kingdom and manufacturing nec in France.

However, the inefficiency gap does not seem to follow a rather constant pattern as far as country-wise and industry-wise, meaning that different countries present best and worst performances in different sectors and there is no a single country with best performance in every industry, or a single industry with best or worst performance in every country.

On the other hand, the following table (5.15) presents the parameters of the distribution of productive efficiency scores calculated according to each one of the alternative estimated stochastic frontier models.

Table 5.18. Estimated varying production efficiencies $Exp[(-\hat{u}_{it})]$

SF Model	Inefficiency Determinants	Mean	Standard Deviation	Min.	Max.
[1]	none	0. 983	0. 289509E-01	0.758	0.999
[2]	*time*	0. 982	0. 285662E-01	0. 716	0.999
[3]	*lnict*	0. 990	0. 171634E-01	0. 711	0.999
[4]	*lnopenk*	0. 984	0. 124007E-01	0. 920	0.998
[5]	*time,lnict,lnopenk*	0.982	0. 283101E-01	0. 721	0.999

Source: Own estimation

It is apparent that efficiency levels are rather high in all model specifications. In the first model specification, in which there are no inefficiency effects, the efficiency levels range from 0.758 to 0.999. In the second model specification, in which inefficiency effects are attributed solely to time, efficiency levels range from 0.758 to 0.999. On model [5] with time, ICT investment and economy openness as inefficiency term determinants, efficiency levels range from 0.716 to 0.999.

On the other hand, apart from the discussion on inefficiency levels by industry and country, it is also important to estimate the effect of each one of the inefficiency term determining variables in the model. The following table presents the estimated coefficients in efficiency determining variables. In model [1] with no inefficiency effects, the variable *eta*, which is statistically significant, presents the inefficiency level (18.44%).

Table 5.19. Estimated coefficients in efficiency determining variables

Model	Variable	Coefficient	St. Error	b/St.Er.	P[|Z|>z]|
[1]	Eta	-.1844	.0122	-15.092	.0000
[2]	*time*	-.1575	.0089	-17.607	.0000
[3]	*lnict*	-.7821	.0778	-10.041	.0000
[4]	*lnopenk*	.5870	.1310	4.480	.0000
[5]	*time*	-.1762	.0236	-7.438	.0000
	lnict	.1081	.1427	.757	.4488
	lnopenk	.1319	.3660	.360	.7186

Notes:

1. For Model [1], Eta parameter for time varying inefficiency
2. For Models [2] – [5], coefficients in u(i,t)=[exp{eta*z(i,t)}]*|U(i)|

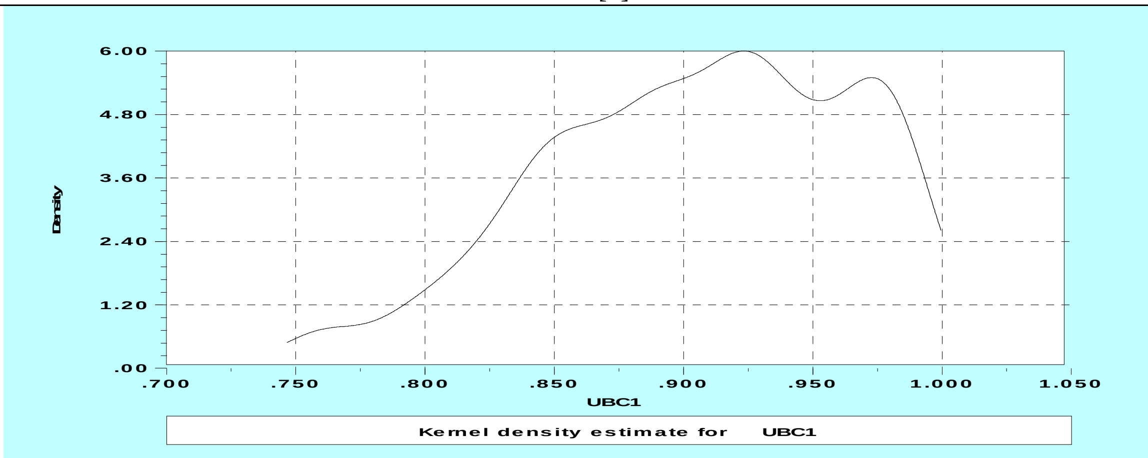
Source: Own Estimation

The models [2] – [4] all have statistical significant efficiency determining variables (time, ICT investment and economy openness). From the models estimation, it becomes apparent that the variables time, ICT investment and economy openness have a significant impact on technical efficiency in the model in which they are included. All the three variables are statistically significant, bearing the negative sign, as expected by the theory, meaning that an increase in those variables decreases the inefficiency level. However, in model [5], in which all the three efficiency determining variables are included, it is only time variable which is statistically significant.

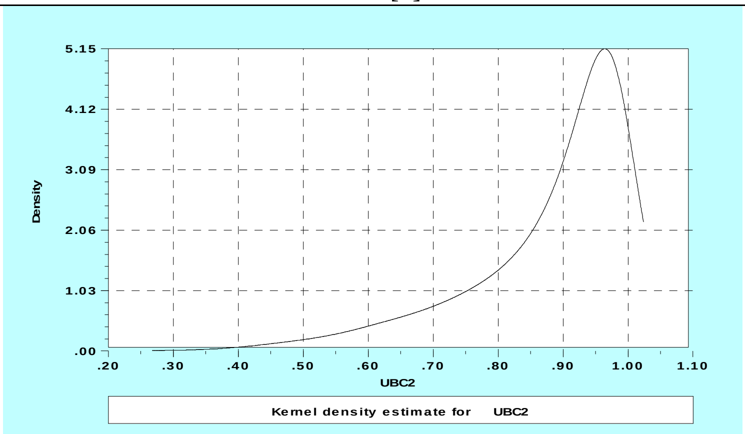
As far as Kernel Density Estimates are concerned, they present the estimated mean inefficiencies for each one of the estimated models, illustrating the form of the distribution of the estimated efficiency:

Figure 5.1. Kernel Estimators

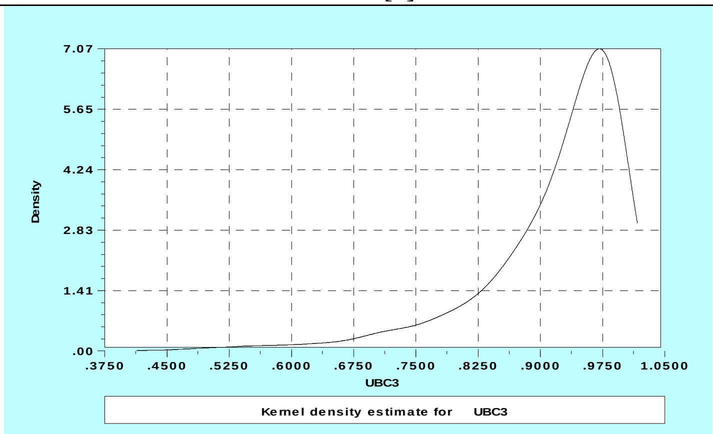
Model [1]



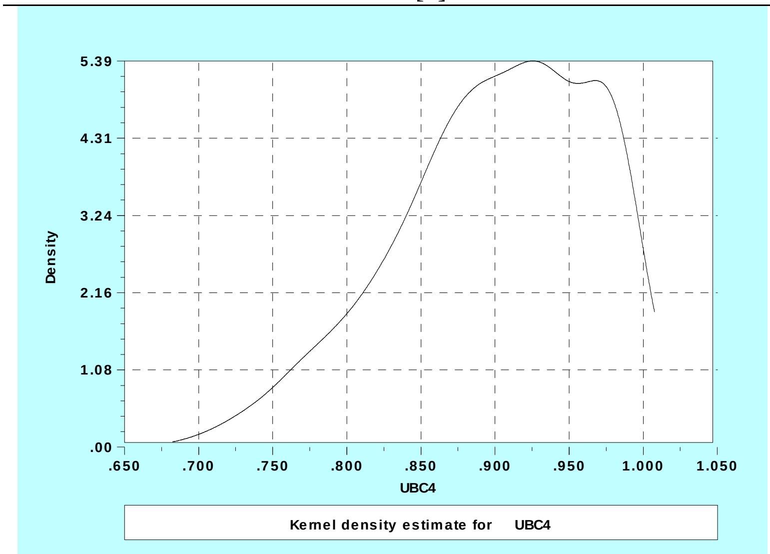
Model [2]



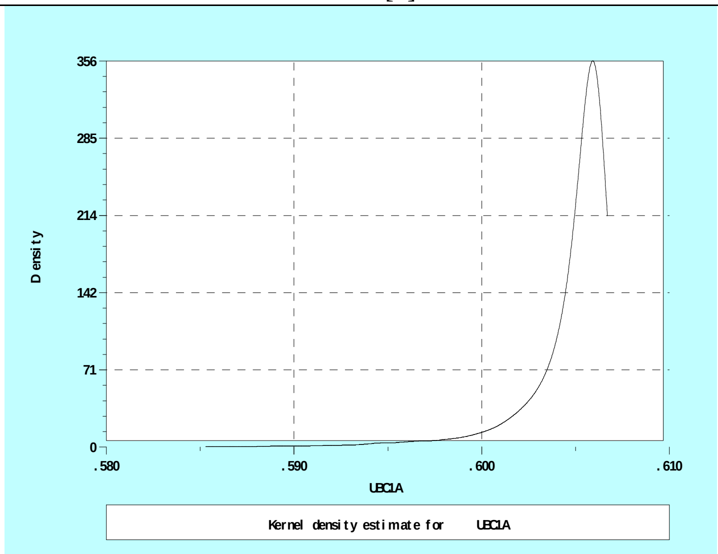
Model [3]



Model [4]



Model [5]



Source: Own estimation

As it is illustrated in the Kernel density estimates (Figure 5.1), the distribution of productive efficiency is centered implying that most industries are clustered close to the mean. The reason for the peak in the distribution at the maximum level is from the hypothesis that at least one producer in each industry is fully efficient.

The following part refers to the underlying policy implications, presents what measures and initiatives are suggested in order to close the inefficiency gap across counties and industries, and what are the relative policy implications.

5.7. Policy Implications

There is a huge literature on factors influencing productive efficiency and productivity growth. In this literature, it is widely accepted that decision making units are not homogeneous producing units and, therefore, not all units are operating at the same level of efficiency (Caves, 1989). Within this framework, productivity represents the estimation of how well a producer uses the available resources to produce outputs from inputs. However, the productivity theory literature has emphasized factors such as productive efficiency, mainly through technological spillovers, increasing returns, learning by doing, und unobserved inputs (e.g. human capital quality), whereas the empirical industrial organization literature has emphasized the degree of openness of countries to imports and industry structure (Koop, 2001). Currently, output and employment are expanding fast in high-technology industries such as computers and electronics, as well as in knowledge-based services such as financial and other business services and more resources are spent on the production and development of new technologies, in particular on information and communication technology.

The developments in the theory of productive efficiency have renewed the interest for the role that the innovation plays in the development process, underlining the interaction between the investment in innovative activities, the technological change and productive efficiency growth. Innovation and technology is an important source of industry competitiveness through facilitating productive efficiency. In particular, they can improve collective processes of learning and the creation, transfer and diffusion of knowledge, critical for innovation. Such cooperation and the networks that are formed help to translate knowledge into economic opportunity, while at the same time building the relationships between organizations which can act as a catalyst for innovation.

The productive processes that create and diffuse the new knowledge are critical in production and there are powerful contacts between the investment in the human capital, the technological change and finally, technical efficiency. As a motive force, it prompts the enterprises to long-term development objectives and the advancement of productive structures, so that they maintain the elements of efficiency and competitiveness. From an economic analysis point of view, the theoretical framework of the effects of innovation on the economic efficiency, productivity and growth is based on endogenous growth theory, claiming that not only the accumulation of capital, but mainly the development and accumulation of knowledge and technological change leads to increased and sustainable growth. Investments in new technologies aim to the modernisation of productive process and the qualitative upgrade of products. The reason is that the new technologies lead to increase of productivity of factors of production, contributing in the long-term improvement of competitiveness.

Furthermore, innovation process requires cooperation and collaboration of a great number of different actors, which, to a large extent, incorporates high transaction cost and high uncertainty level. According to this view, economic success and competitiveness result from the combination of favorable entrepreneurial environment, network systems and innovative behavior and the establishment of new combinations of factors of production is a process that will become the engine that drives economic development. On the other hand, as mentioned before, due to information asymmetries, uncertainty and high cost features of innovation, entrepreneurship becomes more important in a modern economy, since it may provide one of the mechanisms by which new economic knowledge is disseminated into different networks. Entrepreneurship generates growth because it serves as a link between innovation and change. Thus, by serving as a vehicle for knowledge transmission and spillover, entrepreneurship plays a key role in the link between knowledge and growth.

Within this framework, measuring efficiency is a quite important task in economic analysis. First only by measuring efficiency and by separating their effects from those of the general economic environment, can we explore hypotheses concerning the sources of efficiency or productivity differentials, as well as effectiveness of private practices and public policies designed to improve productive performance.

Following the empirical results of our model, the significance of the time dimension (which denotes technical change) regarding inefficiency estimation, and technical change, facilitated by a favourable institutional framework become more of an issue in technical efficiency analysis. Innovative actions are considered to be rather important to technical efficiency enhancement. Firstly, they stimulate investments which introduce new commodities and processes, which improve the living standards of the society. Moreover, they lead to new developments, which increase the comparative advantage of an economy and affect positively the trade performance and competitiveness of a country worldwide. These effects result in a greater level of economic growth.

Discussion in more specific terms vis-à-vis our empirical results, suggests that there are specific underlying policy implications, measures and initiatives in order to close the inefficiency gap across counties and industries.

Since, nowadays, competition has shifted the comparative advantage of countries and industries towards the factor of knowledge and innovation, where productivity based on endogenous development capabilities plays a rather important role, as far as efficiency and competitiveness enhancement are concerned. Within this framework, technical change as a productive efficiency determinant consist two of the core subjects both in economic analyses. Respectively, there is an increasing interest in the contribution of knowledge in productive efficiency, taking into consideration the need of enterprises to import technological innovations that increase productivity and competitiveness.

What does this mean for productivity and competitiveness? Regarding productivity enhancement, economies increase their efficiency in two ways—micro and macro. Microeconomic gains take place within an enterprise as it invests, trains workers, innovate and compete. Macroeconomic gains occur when the overall economy reorganizes and shifts resources so they produce more than before. Within this micro and macro framework, technical efficiency has a leading role in using productive resources efficiently.

On macro-level, two complimentary sets of conditions need to be satisfied. The first is the existence of suitable endowment of both basic infrastructure (in the form of efficient transport, telecommunications and energy networks and environmental facilities and so on) and a labor force with appropriate levels of skills and training, strengthening of both physical and human capital, together with improvements in institutional support facilities and the administrative framework in place. The second set of conditions, which directly relates to the factors of competitiveness which are important in the knowledge-based economy, is that innovation should be accorded high priority, that information and communication technologies (ICT) should be widely accessible and used effectively and that development should be sustainable in environmental terms.; a business culture which encourages entrepreneurship; and the existence of cooperation networks and clusters of particular activities. European cohesion policy makes a major contribution to these objectives, especially in those countries where there is unused economic and employment potential which can be realized through targeted cohesion policy measures. From a policy perspective, for national development to be sustained requires favorable conditions being established at the national level, in particular a macroeconomic environment conducive to growth, employment and stability and a tax and regulatory system which encourages business and job creation.

In European Union there is an increasing interest in the contribution of productive efficiency in the sustainable long-term economic growth, taking into consideration the need that competition forces technological innovations, that increase productivity, renewed the interest for the role of innovation in the development process, underlining the interaction between investment in innovative activities, technological change and sustainable economic growth.

European Union industrial and innovation policy is aimed at strengthening the competitiveness of European Union producers by promoting competition, ensuring access to markets and establishing an environment which is conducive to R&D across the Union. Knowledge and access to it has become the driving force for growth in advanced economies like the European Union known-how and intellectual capital, much more than natural resources or the ability to exploit abundant low-cost labor, have become the major determinants of economic competitiveness since it is through these that economies can not only increase their productive efficiency but also develop new products. Productive efficiency, therefore, holds the key to maintaining and strengthening competitiveness which in turn inessential for achieving sustained economic development. To achieve both sets of conditions requires an effective institutional and administrative framework to support development. The cost of not pursuing a vigorous cohesion policy to tackle disparities is, therefore, measured in economic terms, as a loss of the potential real income and higher living standards. Given the interdependencies inherent in an integrated economy, these losses are not confined to the less competitive states but affect every state in the Union.

By securing a more balanced spread of economic activity across the European Union, it will reduce the risk of imbalances and divergence, making it easier to sustain the European model of economic growth and cohesion. In policy terms, the objective is to help achieve a more balanced development by reducing existing disparities, avoiding regional imbalances, by making policies more coherent, improving integration and encouraging cooperation between states and regions. Among other development factors, countries or industries facing lags in productive efficiency face also a lag in growth. Lagging countries or industries in European Union has been one of the main objectives of the European strategy. Development problems are more intense in lagging regions or industries which present major differences in level of economic performance, output, productivity and employment. These disparities arise due to structural deficiencies in factors, which restrain economic activities and overall development.

These disparities cannot be ignored, since they affect the overall competitiveness of the European Union economy. Covering costs of congestion or treating the consequences of disparities implies a sub-optimal allocation of resources, as well as a lower level of efficiency and economic competitiveness than could potentially be attained. To combat disparities and achieve a more balanced pattern requires some coordination of innovation and industrial policies if they are to be coherent and consistent with each other[116].

However, the answer to closing the inefficiency gap is also micro-related, suggesting perhaps cutting off the rail of more inefficient plants, or moving the distribution for all the plants in a specific industry. As companies become more efficient, the economy reallocates resources to more productive uses, either in existing companies or new ones. On the other hand, efficiency may be improved primarily through innovation and technological progress, better developed in a collaborative environment.

On micro-level, a firm which undertakes R&D programmes in order to enhance technical efficiency levels, acquires new information and knowledge to embody in the new commodities, as well as new production and marketing processes, ready to be employed in

[116] This issue has been broadly reviewed in Kokkinou A. (2011) Innovation Policy, Competitiveness, and Growth: Towards Convergence or Divergence? *in* Patricia Ordonez de Pablos, W.B. Lee and Jingyuan Zhao (editors) *Regional Innovation Systems and Sustainable Development: Emerging Technologies*, Information Science Reference, Hershey, New York, pp. 187 – 201.

product and process innovation. As a result, through innovation, a company is able to develop directly new products and processes and bring them to the market acquiring an advantage over its competitors. Furthermore, it can enhance the ability of the firm to develop and maintain capabilities to absorb and expand technology information available by external sources, and identify, assimilate and exploit new knowledge and technology.

However, productive efficiency enhancement depends extensively on the presence or the formation of a network and environment favourable to innovation, which is based on the endogenous development capabilities. Even though the firm specific factors are important determinants of innovation activity, technological opportunities and favourable entrepreneurial environment have a positive effect on innovation activity, as well. This could also be related to country-level institutional reform or restructuring, or it could be mainly focused on measures and initiative actions in order to increase overall Research and Development expenditure and innovation investments, and/or promoting exporting activities. These actions should also be linked not only to different country-level programs, in order to tackle any inefficiency features found in different countries and industries, but also linked to European Union structural plans for innovation and growth.

It is also useful, in order to enhance technical efficiency that firms cooperate in order to bring technological advances and access, create and diffuse technological knowledge, trying to exploit the benefits from cooperative manufacturing and commercialising of research, to gain large-scale operation benefits and to take advantages of sharing the associated risks. These alliances are characterised ‘strategic’ because they aim to provide a competitive advantage to participating firms against their competitors by making them able to respond more effectively and dynamically to technological competition, organizing innovation in such a way that can successfully act in response to market conditions, by generating, coordinating, and controlling technology, since they are able to achieve a more efficient outcome, avoiding spillovers and unnecessary duplication of effort problems, and permitting the smooth dissemination of technology and information, beneficial for industries and countries. Co-operation and exchange of technology among firms and/or other research organisations can take place at a given point of R&D and/or commercialisation process, or cover the process as a whole and it may refer to the creation or just acquisition and use of knowledge.

Synergies may increase the rate of innovation, decrease the costs of knowledge diffusion and enhance the efficiency of the investment, due to effective pooling of resources and exploitation of research results having positive effects on costs. This development establishes favourable incentives to participants to combine their expertise and assets and engage in collaborative research activities.

Moreover, in Europe 2020 strategy, European Union has identified the following key areas in order to promote productivity and competitiveness of the European Union economy (European Commission, 2011a):

- facilitating structural changes, to move towards more innovative and knowledge-based sectors;
- enabling innovation in industries, in particular by pooling scarce resources, by reducing the fragmentation of innovation support systems and by increasing the market focus of research projects;
- promoting sustainability and resource efficiency, in particular by promoting innovation;
- improving the business environment;
- benefiting from the single market, by supporting innovative services.

Through these five core pillars, industrial and technological policy should move towards a new path to build economic effectiveness and stimulate economic growth, supporting both basic science and strategically oriented research. In addition to the creation of new technologies, particular consideration should be dedicated to the diffusion of existing knowledge and innovations focusing on the ability of the firms to locate, access, adapt, and use new technologies. This development could be of collective nature, incorporating industries, government authorities, universities, and research institutes, through interactive relationships, to assist the authorities to engage in the needed technology policy goals.

To conclude, efficiency enhancement, mainly through innovation creation and dissemination, is a complex phenomenon that involves not only technological, economic, and social activity, but also research and development investment, production, and application, with the relationship between innovation and efficiency being a core analysis point.

Economies and industries should directly point towards the new challenges and focus on the newly raised prospects, recognising that government can play a major role in developing and reaping the benefits of productive efficiency promotion. There is excess need for active policies directed on science and technology crucial to today's business economy, which would be able to create a secure business environment in which innovation investments may have the expected results.

Concluding, it is believed that such an approach will result in more efficient production levels, and can be rather beneficial for the business units and the overall economy. The suggestion made could be summarised in the view that cooperation activities should be treated as a core mechanism, accompanied by special policy considerations concerning any problems and drawbacks which may arise in their application.

5.8. Concluding remarks

This chapter analyses and discusses the empirical findings of the technical efficiency of European Union industries in selected member-states. More specifically, this main research aim is twofold: first to estimate and analyze technical efficiency in European Union manufacturing industries, and second to compare the results of parametric and non – parametric methods of technical efficiency estimation.

This chapter proposes a model for technical inefficiency effects in a stochastic frontier production function for panel data. Provided the inefficiency effects are stochastic, the model permits the estimation of both technical change in the stochastic frontier and time-varying technical inefficiencies (Battese and Coelli, 1992, 1995). As has been already broadly described into previous chapters, this original specification has been extended to include a wide array of assumptions and specifications, including panel data analysis[117]

[117] Stochastic frontier approach has found wide acceptance within the agricultural economics literature and industrial settings (Battese and Coelli, 1992; Coelli and Battese, 1995), because of their consistency with theory, versatility and relative ease of estimation.

Some literature focused on stochastic frontier model with distributional assumptions by which efficiency effects can be separated from stochastic element in the model and for this reason a distributional assumption has to be made. Among others, an exponential distribution (Meeusen and van den Broeck 1977); a normal distribution truncated at zero (Aigner, Lovell and Schmidt 1977); a half-normal distribution truncated at zero (Jondrow *et al.* 1982) and a two-parameter Gamma or Normal distribution (Greene 1990).

first by Schmidt and Sickles (1984) who modeled technical inefficiency as time-invariant, then by Battese & Coelli (1992) who modeled the technical inefficiency as time variant. Battese and Coelli (1995) followed, using a stochastic frontier production function for panel data concluding that a model of technical inefficiency effects is a significant component of the stochastic frontier production function.

The analysis and estimation in this chapter investigates whether there is evidence of technical inefficiency in manufacturing industries in European Union selected member – states, and whether factors such as ICT investment (as a proxy of knowledge creation) and economy openness (as a proxy for knowledge transfer and dissemination) exert any influence on to technical efficiency growth. The chapter begins with a description of the model used, the data set used in the analysis and the definition of the variables, along with their descriptive statistics. Then the empirical model is formed with estimation results for different alternative model specifications.

This chapter presents a range of different stochastic model approaches based on alternative hypotheses, discussing and comparing them in detail. First, this chapter applies a stochastic translog production function to examine the underlying causes of technical inefficiency for 13 manufacturing industries in European Union over the period 1980 – 2005. The results indicate that inefficiency was present in production and the relevant technical efficiency determining variables contribute to it. From our model analysis, it is evident that the manufacturing industries in our research sample are not fully efficient. The inefficiency observed is endogenous to the firm since the technical inefficiency is largely associated with the firms' choice of ICT investments and openness achievement. Even though there is a notable improvement in technical efficiency after accounting for variations, technical inefficiency remains significant which calls for further investigation of the variations regarding to the alternative explanatory variables. Conclusions and policy implications may be drawn from this model analysis.

Specifically, in line with the empirical framework, based on stochastic frontier analyses (SFA), we decomposed productivity into the production possibility frontier and technical (in) efficiency, investigating the role of efficiency in explaining growth differentials for a

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However, there are no priori reasons for choosing one distributional form over the other, and all have advantages and disadvantages (Coelli, Rao and Battese 1998).

panel of manufacturing industries in selected European Union countries (Bos et al., 2010). We also accept that decision making units are not homogeneous producing units and, therefore, not all units are operating at the same level of efficiency (Caves, 1989), with one of the main questions being to investigate the relationship between inefficiency and a number of factors which are likely to be efficiency explanatory variables.

As in Bos et al. (2010), we accounted for inefficiency and estimate a stochastic production frontier, which is the empirical analog of the theoretical production possibility frontier. This modelling strategy adds structure to the unexplained residual. Under reasonable assumptions, it disentangles the residual into inefficiency and measurement error. Technical change is modelled as a shift of the stochastic frontier, whereas efficiency change is a movement towards or away from the frontier. As in Bos et al. (2010), our models focus on the use of technology, the sources of output growth, technology spillovers and catch-up. To decrease the aggregation bias that may occur when these issues are considered at the country-level (as in Bernard and Jones, 1996 a,b), Bos et al. (2010) focus on manufacturing industries. Even though the producer-specific factors are important determinants of innovation activity, technological opportunities have a positive effect on efficiency enhancement. Technological change, innovation and technology creation and diffusion are an important factor to economic progress (Koop, 2001). In order to investigate the determinants of the productive efficiency we distinguish between producers or industry -specific and efficiency explanatory factors (as the methodology followed by Caves and Barton, 1990).

Our analysis followed the methodology by Kneller and Stevens (2006), who used panel data on manufacturing industries of OECD countries, estimating the distance to the technological frontier, as a function of the levels of investment in R&D and human capital, which in turn are related to the absorptive capacity of the economic system. Of great influence is also the methodology by Bhattacharjee et al. (2009) who explored the idea that the productivity enhancing positive component captures innovative activity raising certain industries above common productivity standards at specific times. Moreover, according to Bhattacharjee et al. (2009), more explicit modeling of innovation, particularly investment in R&D, human capital, international technological spillovers and spatial diffusion are also to be considered

As in Kumbhakar (1991), Polachek and Yoon (1996) and Greene (2005b) we extended the original stochastic frontier model by adding an individual time-invariant fixed effect. In our modelling, heterogeneity is not reflected in measured variables but expressed in the form of effects (Greene, 2007a). As in Consoli (2008), we placed strong emphasis on the sources and the effects of technological change, namely technology creation and technology dissemination.

Last, the results included reporting the estimated technical efficiency and the related explanatory variables. This chapter provided the industry-level estimates of technical efficiency using alternative model specifications under time-invariant and time-varying efficiency assumption. Further, factors that determine variations technical efficiency were estimated and a comparison of technical efficiency is made, both before and after accounting for different explanatory variables in the inefficiency term.

Chapter 6

Data Envelopment Model: Empirical Results

Abstract

The objective of this chapter is to estimate the Transcendental Logarithmic Production Function of manufacturing industries in selected E.U. economies, considering a panel data model for inefficiency effects in production frontiers, providing translog effects, as well as industry effects. In addition, this chapter also applies the deterministic nonparametric approach Data Envelopment Analysis (DEA), in order to compare the two approaches and investigate whether, despite the different underlined assumptions and specifications, they produce comparable (similar or not) results regarding technical efficiency estimation.

Contrary to the Stochastic Frontier Analysis approach (SFA), which requires a functional form to estimate the frontier production function and is based on the idea that the data is contaminated with measurement errors and noise (Bauer. 1990), Data Envelopment Analysis (DEA) approach uses linear programming techniques and cannot discriminate between inefficiency and noise. Thus, it tends to produce overestimated inefficiency measures, a fact which is the most important disadvantage of DEA in comparison to SFA (Bauer. 1990). This chapter proposes a slack-based DEA which allows a full evaluation of inefficiency in an industry's performance. The model estimated in this chapter is a DEA variant called slack-based measure, which is able to deal directly with the input excesses and the output shortfalls of the industry under evaluation (Tone, 2001). Estimated slacks are invariant to the units of measurement and are monotone decreasing with respect to each input and output slack. By using slack-based efficiency measure, we obtain different frontier levels and more appropriate performance benchmarks for inefficient industries. The production assumptions in DEA are that all actual observed inputs and outputs of any industries are feasible for all industries, as are linear combinations of observed inputs and outputs.

Comparing the outcomes of the two different approaches (between parametric and non-parametric method) for the period 1980-2005, regarding the efficiency progress, within an output-oriented stochastic function, there are different outcomes regarding the estimation of the technical efficiency values. On the other hand, the common results produced are that technical efficiency changes over time (time-varying technical efficiency) and that the estimated parameter γ is close to (1), and it is statistical significant, showing the existence of technical efficiency. However, similar results are produced regarding scale efficiency and returns to scale.

6.1. Introduction

Data Envelopment Analysis involve the use of linear programming methods to construct a piecewise linear surface or frontier over the data and measures the efficiency for a given unit relative to the boundary of the convex hull of the input-output vectors. The individual efficiencies of the firms relative to this production frontier are then calculated by means of distance functions and they can be interpreted as the proportional reduction of the inputs to become technically efficient by a projection onto the efficient boundary, the production frontier. The efficiency score is the point on the frontier characterized by the level of inputs that should be reached to be efficient (Simar and Wilson, 1998).

The main merit of these approaches is that it can deal with the case of multiple input and outputs as well as factors outside the control of individual managements, treating them as fixed inputs (Levitt and Joyce, 1987). There is also no need to make restrictive assumptions about either the technology representing the production process or the distribution of the component of the residuals which represent inefficiency, since they place no restrictions on the functional form of the production relationship and makes no a priori distinction between the relative importance of any combination of outputs or inputs.

As in Kalirajan and Shand (1999), the data envelopment analysis does not require imposition of any distributional assumption of producer – specific effects ui's. Supplementary, DEA can accommodate multiple inputs and multiple outputs simultaneously. One of the principal disadvantages is that DEA can be extremely sensitive to variable selection and data errors. Another limitation is that DEA efficiency measures in small samples are sensitive to the difference between the number of firms and the sum of inputs and outputs (Seiford, 1996).

DEA permits the use of multiple inputs and outputs, but does not impose any functional form on the data, nor does it make distributional assumptions for the inefficiency term DEA overcomes some of the specific weaknesses of the other methods, such as a particular functional form for technology, particular assumptions on market structure, and the hypothesis that markets are perfect. DEA is usually handled with linear programming techniques. The analysis assumes that there is a frontier technology (in the same spirit as the stochastic frontier production model) that can be described by a piecewise linear hull that envelopes the observed outcomes. Some (efficient) observations will be on the frontier while other (inefficient) individuals will be inside. The technique produces a deterministic frontier that is generated by the observed data, so by construction, some individuals are efficient. Many studies have further developed the DEA methodology, including those by Färe, Grosskopf and Lovell (1985).

Data Envelopment Analysis (DEA) is, in fact, a mathematical programming approach for the construction of production frontiers and the measurement of efficiency relative to the constructed frontiers. The basic idea of this approach consists of enveloping the data (the observed input-output combinations) in order to obtain an approximation of the production frontier (best-practice frontier) and using this to identify the contribution of technological change, technological catch-up, and inputs accumulation to productivity growth.

However, the DEA approach, by being non-stochastic, does not distinguish data noise and inefficiency (Lovell, 1993; Coelli, 1995). It should be noted here that stochastic DEA models, which eliminate such problems, have been developed in the literature (e.g. Desai and Schinnar, 1987 and Sengupta, 1987). However, empirical applications of those models are extremely difficult due to strict data requirements. In addition to the inputs and outputs data, they demand information about the expected values of all variables, variance-covariance matrices for all variables, and probability levels at which feasibility constraints are to be satisfied (Lovell, 1993). Another problem that might occur in DEA models refers to the dimensionality of the input/output space relative to the number of observations in the cross-section.

The dimensionality problem arises when the number of observations is relatively small compared with the number of inputs and outputs used. A negative consequence of this problem is that many of the analyzed producers will be rated as "efficient" and therefore lie on the production frontier (Leibenstein and Maital, 1992).

Fernandez-Cornejo (1994) argued that the ratio between the number of observations and number of inputs and outputs that will enable the DEA model to discriminate efficient producers from inefficient should exceed five. Smith (1997), after conducting a simulation study, found that even in cases when the number of observations exceeded the number of factors by more than thirteen times, DEA can still overestimate true efficiency by 27 percent. Due to this limitation, many producers may be seen to be efficient, even though they are not.

6.2. DEA results analysis

Following our analysis under stochastic frontier model specification, as in Kuah, et al. (2010), this chapter aims to develop a model to assess efficiency of industries by using Data Envelopment Analysis (DEA), since DEA provides an opportunity to evaluate and cross-check the results obtained by the stochastic frontier analysis.

Towards this method, there have been several studies that have analyzed data with both DEA and parametric, deterministic frontier estimators. Coelli (1995) presented a review of both parametric and non-parametric techniques used in efficiency measurement, including their limitations, strengths, and applications in agricultural production. Although his review indicated that parametric approaches were used more frequently than DEA, neither model appears to have dominant advantages above the other.

However, Bjurek, Hjalmarsson and Førsund (1990) used the stochastic frontier analysis and data envelopment analysis techniques to study the Swedish social insurance system. Førsund (1992) also did a similar analysis of Swedish ferries. In both studies, the authors do not observe radical differences in the results across the various procedures. On the same path, Ray and Mukherjee (1995) using data on U.S. electricity generation found a good agreement between DEA and stochastic frontier based estimates. Likewise, Murillo-Zamorano and Vega-Cervera (2001) found similar results for a sample of U.S. electricity generators. Cummins and Zi (1998) also found concordance in their analysis of the U.S. insurance industry. Finally, Chakraborty, Biswas and Lewis (2001) analyzed public education in Utah in which the empirical results using the various techniques were largely similar.

However, these studies do stand in contrast to Ferrier and Lovell (1990) who found major differences between DEA and stochastic frontier based inefficiency estimates in a large sample of American banks. Bauer et al. (1998) likewise found substantial differences between parametric and nonparametric efficiency estimates for a sample of U.S. banks.

Sharma et al (1999) studied swine producers in Hawaii and their study the Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis were used to estimate technical efficiencies. They found that, on average, the estimated technical efficiencies were significantly higher in the SFA compared to the DEA under the assumption of constant returns to scale (CRS). Under the assumption of variable returns to scale (VRS) however, the measures were quite similar. The efficiency ranking of the producers following both approaches was positively correlated,indicating that the two approaches assess relative efficiency to the same producers.

Wadud and White (2000) compared DEA (both VRS and CRS) and stochastic frontier methods while estimating producer household efficiency of rice producers in two villages in Bangladesh. Mean technical efficiency obtained from the stochastic frontier was 0.79 and from CRS and VRS DEA, 0.79 and 0.86. respectively. The efficiency rankings were highly positively correlated under a Spearman rank correlation test. Similar to the results of Sharma et al. (1999), the variability of technical efficiency scores obtained by DEA models was greater than that obtained by the stochastic frontier model. Hjalmarsson et al. (1996) provided results obtained from the stochastic frontier model and DEA models. Similarity and dissimilarity depended upon the inclusion of the control variables in the stochastic frontier and sequential or intertemporal specification in the DEA frontier. Lovell (1996) attempted to evaluate DEA SFA and DFA (Deterministic Frontier Approach), relative to their abilities to exploit the panel nature of the data in order to provide evidence about the sources of productivity change among producers. Despite its flexibility, DFA approach appeared to be heavily burdened by being both deterministic and parametric.

The SFA approach has the great advantage of being the only stochastic approach among the three, but its parameterization has been a major problem, and it has not yet oriented itself toward productivity measurement. Johansson (2005) estimated technical, allocative, and economic input efficiency scores for an unbalanced panel of Swedish dairy producers, using data envelopment analysis (DEA) and the stochastic frontier approach (SFA). By comparing the results it was concluded that DEA measures for technical and economic efficiency were significantly higher than the corresponding SFA measures. Serrao (2003) examined the differences in agricultural productivity growth among eighteen countries and five regions in the European Union from 1980 to 1998. Findings indicate that the mean TFP scores are higher under DEA than under SFA because DEA fits a tighter (i.e. more flexible) frontier. Hence, Serrao (2003) warned against the subjective choice of a particular approach and suggested the use and comparisons of more than one approach. DEA reports all deviations from the frontier as inefficiency, and thus should report lower efficiency scores compared to SFA. However, misspecification of the functional form by the SFA method would possibly cause lower efficiency scores relative to DEA methods.

In conclusion, in summary, the evidence is mixed, but it does appear that quite frequently, the overall picture drawn by DEA and stochastic frontier based techniques are similar. For this reason, we also employ the DEA analysis in our model in order to check whether they produce similar and comparable or quite different results and incomparable results.

We employed the variable returns model of Data Envelopment Analysis (DEA), proposing a slack-based DEA. As described in chapter (2.3), the model chosen for this approach is the DEA variant called slack-based measure, which is able to deal directly with the input excesses and the output shortfalls of the industry under evaluation (Tone, 2001).

Slack-based measure is invariant to the units of measurement and is monotone decreasing with respect to each input and output slack. By using slack-based efficiency measure, we obtain different frontier levels and more appropriate performance benchmarks for inefficient industries[118].

First, we estimate the technical efficiency levels by country and industry under two different assumptions regarding the returns to scale. that is why we estimate technical efficiency under constant returns to scale and variable returns to scale.

As far as the comparability of the results is concerned, DEA analysis evaluates the industries as having increasing returns to scale, whereas in the stochastic frontier analysis, the results showed decreasing returns to scale. The production assumptions in DEA are that all actual observed inputs and outputs of any industries are feasible for all industries. as are linear combinations of observed inputs and outputs.

The estimation is input-oriented, meaning that efficiency is relative to the amount of input needed. as opposed to being output-oriented, meaning that efficiency is relative to the amount of output that could be produced. Each industry is evaluated by itself.

[118] This topic has been broadly examined in: Kokkinou A. (2010c) A study in theory and models of Data Envelopment Analysis, *The Journal of World Economic Review*, Vol. 5, No. 1, pp. 1 -12.

Table 6.1. DEA technical efficiency estimation by country

	CRS_TE	VRS_TE	SCALE	RTS
	France			
Electrical - Optical	0.729	0.916	0.797	irs
Food - Beverages	0.721	0.913	0.790	irs
Textiles	0.740	0.918	0.807	irs
Manufacturing nec	0.738	0.924	0.799	irs
Wood	0.739	0.929	0.797	irs
Paper	0.759	0.927	0.820	irs
Chemicals	0.721	0.925	0.781	irs
Rubber - Plastics	0.744	0.922	0.807	irs
Non-metallic	0.727	0.912	0.798	irs
Metals	0.728	0.912	0.799	irs
Machinery	0.739	0.917	0.807	irs
Transport	0.710	0.907	0.784	irs
	Germany			
Electrical - Optical	0.739	0.915	0.808	irs
Food - Beverages	0.725	0.918	0.791	irs
Textiles	0.722	0.919	0.786	irs
Manufacturing nec	0.723	0.930	0.778	irs
Wood	0.712	0.939	0.760	irs
Paper	0.729	0.912	0.799	irs
Chemicals	0.732	0.897	0.817	irs
Rubber - Plastics	0.723	0.900	0.803	irs
Non-metallic	0.730	0.923	0.791	irs
Metals	0.710	0.905	0.785	irs
Machinery	0.730	0.921	0.793	irs
Transport	0.726	0.909	0.799	irs
	Italy			
Electrical - Optical	0.727	0.907	0.801	irs
Food - Beverages	0.717	0.909	0.789	irs
Textiles	0.738	0.918	0.802	irs
Manufacturing nec	0.723	0.918	0.791	irs
Wood	0.709	0.899	0.790	irs
Paper	0.724	0.898	0.807	irs
Chemicals	0.706	0.897	0.788	irs
Rubber - Plastics	0.714	0.908	0.787	irs
Non-metallic	0.722	0.916	0.790	irs
Metals	0.670	0.902	0.741	irs
Machinery	0.704	0.904	0.779	irs
Transport	0.731	0.926	0.791	irs
	Netherlands			
Electrical - Optical	0.720	0.905	0.797	irs
Food - Beverages	0.735	0.916	0.801	irs
Textiles	0.732	0.924	0.793	irs
Manufacturing nec	0.743	0.920	0.808	irs

Wood	0.728	0.914	0.797	irs
Paper	0.721	0.914	0.789	irs
Chemicals	0.744	0.928	0.803	irs
Rubber - Plastics	0.558	0.897	0.610	irs
Non-metallic	0.725	0.911	0.796	irs
Metals	0.709	0.902	0.787	irs
Machinery	0.715	0.908	0.788	irs
Transport	0.733	0.920	0.797	irs
		Spain		
Electrical - Optical	0.712	0.908	0.784	irs
Food - Beverages	0.701	0.915	0.766	irs
Textiles	0.738	0.914	0.808	irs
Manufacturing nec	0.759	0.924	0.821	irs
Wood	0.709	0.906	0.782	irs
Paper	0.723	0.910	0.795	irs
Chemicals	0.734	0.916	0.801	irs
Rubber - Plastics	0.742	0.925	0.802	irs
Non-metallic	0.730	0.910	0.802	irs
Metals	0.723	0.916	0.790	irs
Machinery	0.754	0.928	0.812	irs
Transport	0.750	0.927	0.810	irs
		United Kingdom		
Electrical - Optical	0.729	0.904	0.807	irs
Food - Beverages	0.745	0.924	0.807	irs
Textiles	0.733	0.932	0.787	irs
Manufacturing nec	0.729	0.919	0.794	irs
Wood	0.856	0.959	0.889	irs
Paper	0.719	0.908	0.791	irs
Chemicals	0.728	0.927	0.787	irs
Rubber - Plastics	0.724	0.924	0.783	irs
Non-metallic	0.720	0.913	0.789	irs
Metals	0.733	0.926	0.793	irs
Machinery	0.725	0.914	0.792	irs
Transport	0.719	0.911	0.790	irs

Source: Own estimation

Technical efficiency estimation is higher under variable returns to scale assumption, compared to industry efficiency under constant returns to scale assumption. United Kingdom, Netherlands and France present the higher levels of technical efficiency across industries. As far as the technical efficiency per industry is concerned, Manufacturing nec and transport equipment present the higher levels of technical efficiency compared to the rest of the industries in our model.

Table 6.2. DEA technical efficiency estimation by industry

	CRS_TE	VRS_TE	SCALE	RTS
	Electrical - Optical			
France	0.729	0.916	0.797	irs
Germany	0.739	0.915	0.808	irs
Italy	0.727	0.907	0.801	irs
Netherlands	0.720	0.905	0.797	irs
Spain	0.712	0.908	0.784	irs
United Kingdom	0.729	0.904	0.807	irs
	Food - Beverages			
France	0.721	0.913	0.790	irs
Germany	0.725	0.918	0.791	irs
Italy	0.717	0.909	0.789	irs
Netherlands	0.735	0.916	0.801	irs
Spain	0.701	0.915	0.766	irs
United Kingdom	0.745	0.924	0.807	irs
	Textiles			
France	0.740	0.918	0.807	irs
Germany	0.722	0.919	0.786	irs
Italy	0.738	0.918	0.802	irs
Netherlands	0.732	0.924	0.793	irs
Spain	0.738	0.914	0.808	irs
United Kingdom	0.733	0.932	0.787	irs
	Manufacturing nec			
France	0.738	0.924	0.799	irs
Germany	0.723	0.930	0.778	irs
Italy	0.725	0.918	0.791	irs
Netherlands	0.743	0.920	0.808	irs
Spain	0.759	0.924	0.821	irs
United Kingdom	0.729	0.919	0.794	irs
	Wood			
France	0.739	0.929	0.797	irs
Germany	0.712	0.939	0.760	irs
Italy	0.709	0.899	0.790	irs
Netherlands	0.728	0.914	0.797	irs
Spain	0.709	0.906	0.782	irs
United Kingdom	0.856	0.959	0.889	irs
	Paper			
France	0.759	0.927	0.820	irs
Germany	0.729	0.912	0.799	irs
Italy	0.724	0.898	0.807	irs
Netherlands	0.721	0.914	0.789	irs
Spain	0.723	0.910	0.795	irs
United Kingdom	0.719	0.908	0.791	irs
	Chemicals			

France	0.721	0.925	0.781	irs
Germany	0.732	0.897	0.817	irs
Italy	0.706	0.897	0.788	irs
Netherlands	0.744	0.928	0.803	irs
Spain	0.734	0.916	0.801	irs
United Kingdom	0.728	0.927	0.787	irs
	Rubber - Plastics			
France	0.744	0.922	0.807	irs
Germany	0.723	0.900	0.803	irs
Italy	0.714	0.908	0.787	irs
Netherlands	0.558	0.897	0.610	irs
Spain	0.742	0.925	0.802	irs
United Kingdom	0.724	0.924	0.783	irs
	Non-metallic			
France	0.727	0.912	0.798	irs
Germany	0.730	0.923	0.791	irs
Italy	0.722	0.916	0.790	irs
Netherlands	0.725	0.911	0.796	irs
Spain	0.730	0.910	0.802	irs
United Kingdom	0.720	0.913	0.789	irs
	Metals			
France	0.728	0.912	0.799	irs
Germany	0.710	0.905	0.785	irs
Italy	0.670	0.902	0.741	irs
Netherlands	0.709	0.902	0.787	irs
Spain	0.723	0.916	0.790	irs
United Kingdom	0.733	0.926	0.793	irs
	Machinery			
France	0.739	0.917	0.807	irs
Germany	0.730	0.921	0.793	irs
Italy	0.704	0.904	0.779	irs
Netherlands	0.715	0.908	0.788	irs
Spain	0.754	0.928	0.812	irs
United Kingdom	0.725	0.914	0.792	irs
	Transport			
France	0.710	0.907	0.784	irs
Germany	0.726	0.909	0.799	irs
Italy	0.731	0.926	0.791	irs
Netherlands	0.733	0.920	0.797	irs
Spain	0.750	0.927	0.810	irs
United Kingdom	0.719	0.911	0.790	irs

Source: Own estimation

Estimating also technical efficiency by industry, under both assumptions of constant and variable returns to scale, it is evident that ‘variable returns to scale’ assumption bears higher efficiency levels. Industries present, also in this case, increasing returns to scale. As far as the relative efficiency per industry and country is concerned, the results are reported in the following table:

Table 6.3. Relative Analysis per Industry and country

Country / Industry	France	Germany	Italy	Netherlands	Spain	United Kingdom
1	0.956	0.962	0.929	0.935	0.935	0.927
2	0.974	0.981	0.965	0.954	0.967	0.967
3	0.980	0.978	0.939	0.986	0.979	0.974
4	0.940	0.987	0.936	0.969	0.952	0.964
5						
6	0.990	0.972	0.958	0.980	0.976	0.968
8	0.965	0.979	0.963	0.977	0.969	0.953
9	0.901	0.942	0.935	0.946	0.944	0.922
10	0.979	0.970	0.974	0.973	0.967	0.970
11	0.944	0.904	0.879	0.901	0.907	0.914
12	0.934	0.969	0.954	0.975	0.976	0.965
13	0.949	0.970	0.959	0.958	0.948	0.953

Notes:

1. Industry 1 = Electrical and optical equipment. Industry 2 = Food products. beverages and tobacco. Industry 3 = Textiles. textile products. leather and footwear. Industry 4 = Manufacturing nec; Recycling. Industry 5 = Wood and products of wood and cork. Industry 6 = Pulp. paper. paper products. printing and publishing. Industry 7 = Coke. refined petroleum products and nuclear fuel. Industry 8 = Chemicals and chemical products. Industry 9 = Rubber and plastics products. Industry 10 = Other non-metallic mineral products. Industry 11 = Basic metals and fabricated metal products. Industry 12 = Machinery. nec. Industry 13 = Transport equipment.

Source: Own Estimation

As far as the relative efficiency per industry is concerned, it is apparent that industries such as Food – Beverages, Textiles, Paper, Chemicals and non metallic products experience the highest efficiency levels among the manufacturing industries in our sample. Even though the pricture changes for each industry, however, Germany is experiencing the highest level of technical efficiency among the other countries, followed by the Netherlands.

In addition, the following table presents the output-oriented DEA estimates of the production function under constant returns to scale (CRS) and variable returns to scale (VRS).

The value indicates whether the DMU is operating in an area of increasing or decreasing RTS. This may be determined by running an additional DEA problem with non- increasing returns to scale (NIRS) imposed.

The nature of the scale inefficiencies (i.e. due to increasing or decreasing returns to scale) for a particular DMU can be determined by seeing whether the NIRS TE score is equal to the VRS TE score. If they are unequal, then increasing returns to scale exist for that DMU. If they are equal. then decreasing RTS apply.

Table 6.4. DEA VRS frontier per Industry and country

Electrical - Optical					
Frontier	(-1:drs)	(0:crs)	(1:irs)		
	CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France	0.951	0.955	0.971	0.995	0.846
Germany	0.953	0.961	0.964	0.992	0.923
Italy	0.923	0.929	0.939	0.993	1.000
Netherlands	0.930	0.934	0.962	0.996	0.884
Spain	0.918	0.934	0.954	0.982	1.000
United Kingdom	0.917	0.927	0.941	0.989	0.884
Food - Beverages					
Frontier	(-1:drs)	(0:crs)	(1:irs)		
	CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France	0.965	0.973	0.981	0.991761	-0.69231
Germany	0.977	0.980	0.987	0.997149	-0.76923
Italy	0.958	0.965	0.974	0.992824	-0.61538
Netherlands	0.949	0.953	0.962	0.995598	-0.61538
Spain	0.955	0.966	0.985	0.987814	-0.53846
United Kingdom	0.956	0.966	0.982	0.989826	-0.65385
Manufacturing nec					
Frontier	(-1:drs)	(0:crs)	(1:irs)		
	CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France	0.931	0.938	0.952	0.993	0.538
Germany	0.953	0.972	0.978	0.980	0.423
Italy	0.932	0.935	0.955	0.996	1.000
Netherlands	0.958	0.968	0.981	0.990	0.462
Spain	0.932	0.951	0.955	0.981	0.269
United Kingdom	0.954	0.964	0.967	0.990	0.962

Paper					
Frontier	(-1:drs)	(0:crs)	(1:irs)		
	CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France	0.982	0.986	0.989	0.996	0.462

Germany		0.963	0.972	0.978	0.991	0.654
Italy		0.953	0.958	0.967	0.995	1.000
Netherlands		0.967	0.970	0.975	0.997	0.615
Spain		0.961	0.976	0.976	0.985	0.192
United Kingdom		0.963	0.968	0.980	0.995	1.000

Chemicals

	Frontier	(-1:drs)	(0:crs)	(1:irs)		
		CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France		0.963	0.965	0.971	0.998	0.731
Germany		0.978	0.979	0.986	0.999	0.885
Italy		0.961	0.963	0.968	0.998	0.846
Netherlands		0.973	0.976	0.979	0.997	0.731
Spain		0.956	0.969	0.980	0.987	0.923
United Kingdom		0.948	0.953	0.966	0.994	0.962

Rubber - Plastics

	Frontier	(-1:drs)	(0:crs)	(1:irs)		
		CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France		0.895	0.901	0.906	0.993	0.846
Germany		0.938	0.941	0.949	0.997	0.962
Italy		0.933	0.935	0.943	0.998	0.808
Netherlands		0.943	0.946	0.962	0.997	0.962
Spain		0.936	0.944	0.970	0.992	0.692
United Kingdom		0.915	0.921	0.933	0.993	0.654

Non-metallic

	Frontier	(-1:drs)	(0:crs)	(1:irs)		
		CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France		0.974	0.978	0.979	0.996	-0.038
Germany		0.966	0.970	0.969	0.995	0.423
Italy		0.965	0.973	0.974	0.991	0.000
Netherlands		0.968	0.973	0.975	0.995	0.462
Spain		0.958	0.967	0.965	0.991	0.385
United Kingdom		0.963	0.970	0.972	0.993	-0.231

Metals

	Frontier	(-1:drs)	(0:crs)	(1:irs)		
		CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France		0.974	0.978	0.979	0.996	-0.038
Germany		0.966	0.970	0.969	0.995	0.423
Italy		0.965	0.973	0.974	0.991	0.000
Netherlands		0.968	0.973	0.975	0.995	0.462
Spain		0.958	0.967	0.965	0.991	0.385
United Kingdom		0.963	0.970	0.972	0.993	-0.231

Machinery

	Frontier	(-1:drs)	(0:crs)	(1:irs)		
		CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France		0.933	0.934	0.937	0.999	0.769

Germany	0.965	0.969	0.972	0.997	0.808
Italy	0.949	0.954	0.957	0.995	0.962
Netherlands	0.961	0.974	0.976	0.986	0.846
Spain	0.957	0.975	0.970	0.982	0.462
United Kingdom	0.962	0.964	0.968	0.998	0.462
Transport equipment					
Frontier	(-1:drs)	(0:crs)	(1:irs)		
	CRS_TE	VRS_TE	NIRS_TE	SCALE	RTS
France	0.944	0.948	0.964	0.995	0.731
Germany	0.965	0.969	0.986	0.995	0.923
Italy	0.956	0.959	0.969	0.996	0.615
Netherlands	0.953	0.957	0.963	0.996	0.885
Spain	0.933	0.948	0.960	0.985	0.962
United Kingdom	0.938	0.952	0.971	0.985	0.962

Source: Own estimation

It is clear that all the manufacturing industries operate in increasing returns to scale with the electrical – optical industry presenting the higher increasing returns to scale rate. However, the causes for the technical inefficiency levels can be identified and estimated by the slack variables obtained, presenting also potential improvement in capital and labour production functions.

Consequently, according to the analysis of DEA slacks in chapter 2.3, the following table (6.5) illustrates the input slacks for each industry in each country, as well as the input slacks evolution over time. The slack variables of inefficient industries are not equal to zero, so the result of slack analysis can be adopted to improve the input or output items. In DEA. non-zero input and output slacks are very likely to present after the radial efficiency score improvement.

Often, these non-zero slack values represent a substantial amount of inefficiency. Therefore, in order to fully measure the inefficiency in industry's performance. it is very important to also consider the inefficiency represented by the non-zero slacks in the context-dependent DEA (Hiroshi Morita. Koichiro Hirokawa and Joe Zhu. 2005).

The number of resources reduced is the value of slack variable in the input construct. suggesting aspects in which efficiency of a producer can be improved in terms of resource input[119].

Table: 6.5. Average slacks

Industry	Slacks	France	Germany	Italy	Netherlands	Spain	United Kingdom
Electrical - Optical	Capital	0.133	0.059	0.057	0.155	0.073	0.058
	Labour	0.008	0.032	0.019	0.018	0.064	0.055
Food - Beverages	Capital	0.122	0.042	0.134	0.087	0.186	0.155
	Labour	0.000	0.000	0.000	0.000	0.009	0.012
Textiles	Capital	0.045	0.016	0.072	0.073	0.067	0.129
	Labour	0.000	0.000	0.000	0.000	0.000	0.000
Manufacturing nec	Capital	0.136	0.050	0.173	0.172	0.143	0.056
	Labour	0.000	0.000	0.000	0.025	0.077	0.024
Wood	Capital	0.098	0.030	0.125	0.031	0.160	0.088
	Labour	0.000	0.000	0.000	0.000	0.000	0.000
Paper	Capital	0.037	0.026	0.089	0.049	0.037	0.091
	Labour	0.000	0.010	0.000	0.000	0.001	0.000
Chemicals	Capital	0.031	0.014	0.007	0.010	0.080	0.045
	Labour	0.001	0.031	0.026	0.004	0.038	0.057
Rubber - Plastics	Capital	0.009	0.000	0.001	0.000	0.022	0.001
	Labour	0.073	0.024	0.029	0.039	0.119	0.089
Non-metallic	Capital	0.006	0.002	0.012	0.000	0.001	0.011
	Labour	0.000	0.000	0.000	0.000	0.000	0.000
Metals	Capital	0.034	0.040	0.084	0.096	0.114	0.121
	Labour	0.000	0.000	0.004	0.000	0.018	0.021
Machinery	Capital	0.065	0.007	0.042	0.089	0.011	0.054
	Labour	0.000	0.004	0.018	0.000	0.010	0.000
Transport	Capital	0.138	0.189	0.094	0.063	0.164	0.156
	Labour	0.002	0.004	0.002	0.002	0.048	0.064

Source: Own estimation

The slack estimation results show that electrical and Optical industry presents significantly high capital and labor slacks, showing that there are major technical efficiency improvement prospects. Food – Beverages industry presents also significantly high capital slacks; whereas the labor slacks are more limited. Slacks are also present in technical progress, showing that there are major technical efficiency improvement prospects. Manufacturing nec industry presents also significantly high capital slacks; whereas the labor slacks are more limited. Slacks are also present in technical progress, showing that there are major technical efficiency improvement prospects.

[119] For inefficient DMUs, specific suggestions can be provided, so that the composition of input and output items can be properly adjusted to achieve higher efficiency.

Textiles industry presents also significantly high capital slacks; whereas the labor slacks are limited. Slacks are also present in technical progress, showing also an increasing trend. Similarly, wood industry presents also significantly high capital slacks; whereas the labor slacks are limited. Slacks are also present in technical progress, showing also an increasing trend. Paper industry presents also significantly high capital slacks; whereas the labor and technical progress slacks are limited.

Chemicals industry presents also significantly high capital and labor slacks; whereas the technical progress slacks are more limited. increasing only to the last years in analysis, 2000 – 2004. Rubber – Plastics industry presents also significantly high labor slacks; whereas it also experienced an increase in capital and technical change slacks. Non-metallic industry presents also significantly high capital and technical progress slacks; whereas the labor slacks are more limited. Slacks present in capital and technical progress show that there are major technical efficiency improvement prospects.

As in non-metallic industry, metals industry presents also significantly high capital and technical progress slacks; whereas the labor slacks are more limited. Slacks present in capital and technical progress show that there are major technical efficiency improvement prospects. Machinery industry presents also significantly high capital slacks. Labor and technical progress slacks were limited; however, they increased in the last years in analysis, 2000 – 2004, showing that there are major technical efficiency improvement prospects. Transport equipment industry presents high slacks in capital, labor and technical progress, showing that there are major technical efficiency improvement prospects.

As far as the relative efficiency per industry is concerned, we concluded that industries such as Food – Beverages, Textiles, Paper, Chemicals and non metallic products experience the highest efficiency levels among the manufacturing industries in our sample. Even though the picture changes for each industry, however, Germany is experiencing the highest level of technical efficiency among the other countries, followed by the Netherlands. We also found that all the manufacturing industries operate in increasing returns to scale with the electrical – optical industry presenting the higher increasing returns to scale rate. Manufacturing nec industry presents also significantly high capital slacks; whereas the labor slacks are more limited.

Regarding frontier and data envelopment data methods, in summary, it does appear that the overall picture drawn by DEA and stochastic frontier techniques are quite different[120]. The results derived from DEA application are different with those regarding stochastic frontier analysis. Taking into consideration that we followed the same approach for both methods, namely we estimated technical inefficiency levels per industry and per country, incorporating the same data set, with the same assumptions and hypotheses, our results are considered comparable. Even though the results are different, the comparison between the results derived from Stochastic Frontier Approach and Data Envelopment Analysis is quite important since it provides a cross-check of our model and our empirical application and it also creates a safety span for the robustness of our obtained results.

Comparing the outcomes of the two different approaches (between parametric and non-parametric method) for the period 1980 – 2005, regarding the efficiency progress, within an output-oriented stochastic function, there are different outcomes regarding the estimation of the technical efficiency values.

To begin with, as far as the DEA results are concerned, regarding relative efficiency per industry, we concluded that industries such as Food – Beverages, Textiles, Paper, Chemicals and non metallic products experience the highest efficiency levels among the manufacturing industries in our sample. Even though the picture changes for each industry, however, Germany is experiencing the highest level of technical efficiency among the other countries, followed by the Netherlands. We also found that all the manufacturing industries operate in increasing returns to scale with the electrical – optical industry presenting the higher increasing returns to scale rate. Manufacturing nec industry presents also significantly high capital slacks; whereas the labor slacks are more limited.

The slack estimation results show that electrical and Optical industry presents significantly high capital and labor slacks, showing that there are major technical efficiency improvement prospects. Food – Beverages industry presents also significantly high capital slacks; whereas the labor slacks are more limited. Slacks are also present in technical progress, showing that there are major technical efficiency improvement prospects.

[120] This topic has been broadly examined in: Kokkinou A. (2011b) *Technical Efficiency through Stochastic Frontiers: an Analysis of Manufacturing Sector in E.U.*, 5th Biennial Hellenic Observatory PhD Symposium, LSE, London.

Manufacturing nec industry presents also significantly high capital slacks; whereas the labor slacks are more limited. Slacks are also present in technical progress, showing that there are major technical efficiency improvement prospects.

Textiles industry presents also significantly high capital slacks; whereas the labor slacks are limited. Slacks are also present in technical progress, showing also an increasing trend. Similarly, wood industry presents also significantly high capital slacks; whereas the labor slacks are limited. Slacks are also present in technical progress, showing also an increasing trend. Paper industry presents also significantly high capital slacks; whereas the labor and technical progress slacks are limited.

Chemicals industry presents also significantly high capital and labor slacks; whereas the technical progress slacks are more limited. increasing only to the last years in analysis, 2000 – 2004. Rubber – Plastics industry presents also significantly high labor slacks; whereas it also experienced an increase in capital and technical change slacks. Non-metallic industry presents also significantly high capital and technical progress slacks; whereas the labor slacks are more limited. Slacks present in capital and technical progress show that there are major technical efficiency improvement prospects.

As in non-metallic industry, metals industry presents also significantly high capital and technical progress slacks; whereas the labor slacks are more limited. Slacks present in capital and technical progress show that there are major technical efficiency improvement prospects. Machinery industry presents also significantly high capital slacks. Labor and technical progress slacks were limited; however, they increased in the last years in analysis, 2000 – 2004, showing that there are major technical efficiency improvement prospects. Transport equipment industry presents high slacks in capital, labor and technical progress, showing that there are major technical efficiency improvement prospects.

As far as the SFA results are concerned, it is apparent that in every one of the different model specifications (Models [2] – [4]), which include specific efficiency determining variables, these variables are statistically significant and have a statistically significant effect on efficiency with the expected sign, e.g. inefficiency is decreasing, as the variable input is increasing.

However, as far as the two best working models in SFA are concerned, in Model [1], on average, Germany, France, and Netherlands are the best performer countries, since they have the lowest average inefficiency levels, whereas Italy, Spain and United Kingdom seem to be the worst performer countries, since they have the highest levels of inefficiency. As far as the industry inefficiency is concerned, the best performing industries, on average, are the non- metallic, the chemicals and textiles industries, whereas, the worst performing industries are those of wood, electrical/optical and metals. Among the best performing industries are the industries of paper in France, Metals in France and Transport Equipment in Germany. On the other hand, the worst performing industries are those of wood in Germany and Netherlands, as well as metals industry in Italy and Netherlands.

In Model [5], on average, Italy, Spain are the best performing countries, since they have the lowest average inefficiency levels, whereas Germany seems to be the worst performer country, since it has the highest levels of inefficiency. As far as the industry inefficiency is concerned, the best performing industries, on average, are the non- metallic and chemicals industries, whereas, the worst performing industries are those of manufacturing nec and rubber/plastics. In more detail, the industries with the lowest inefficiency levels are rubber/plastics in France and Italy, as well as the manufacturing nec industry in United Kingdom. As far as the industries with the highest inefficiency levels are concerned, these are the metals industry in United Kingdom and manufacturing nec in France.

From the models analysis, it becomes apparent that ICT investment variable has a significant impact on technical efficiency in the model specification in which it is included. This becomes rather apparent, for example in model (3), in which ICT is introduced as the only technical efficiency determining factor. Economy openness has also an important impact on technical efficiency in the models in which it is included as a technical efficiency certain industries and certain countries. The results indicate that inefficiency was present in production and the relevant technical efficiency determining variables contribute to it. From our model analysis, it is evident that the manufacturing industries in our research sample are not fully efficient. The inefficiency observed is endogenous to the firm since the technical inefficiency is largely associated with the firms' choice of ICT investments and openness achievement. ICT investment and economy openness have been modelled as productive inputs and as variables which affect efficiency. This research found that the ICT investment and economy openness are both positively associated with technical efficiency in European Union manufacturing.

On the other hand, the common results produced are that technical efficiency changes over time (time-varying technical efficiency) and that the estimated parameter γ is close to (1), and it is statistical significant, showing the existence of technical efficiency. However, similar results are produced regarding scale efficiency and returns to scale.

However, both sets of results have common conclusions regarding policy implications and institutional context towards the technical efficiency obtained results. As it has been asserted above, globalization and worldwide competition has shifted the comparative advantage of corporations and economies towards the factor of knowledge and innovation, where entrepreneurship based on the endogenous development capabilities plays a rather important role, as far as the growth, productivity and competitiveness enhancement are concerned.

In order to promote innovation activities and technological opportunities entrepreneurship enhancement seems to have a significant importance not only to business success, but also to the long run performance of the economy as a whole. Under this perspective, growth policies should focus on creating favorable environment for the co-operation between firms and institutions that support the development and exploitation of knowledge and innovation.

Furthermore, policies should promote the entrepreneurial relations between firms and institutions, fostering the development and dissemination of the expertise, the mobility of human and physical capital and the enhancement of the relationships between business and research entities. Specifically, they should encourage actions such as, promoting innovation, technology transfer and interactions between firms and higher education and research institutes, networking and industrial co-operation and support for research and technology supply infrastructure.

As it has already been mentioned, innovation and technology is an important source of regional competitiveness through facilitating cooperation between the various parties involved in both the public and private sectors. In particular, they can improve collective processes of learning and the creation, transfer and diffusion of knowledge and transfer, which are critical for innovation. Such cooperation and the networks that are formed help to translate knowledge into economic opportunity, while at the same time building the relationships between people and organizations which can act as a catalyst for innovation. Such actions should extend to all the policy areas relevant for economic, scientific and social development and should ideally establish a long-term policy horizon. This, however, needs to happen not just in central parts where productivity and employment are highest and innovative capacity most developed but throughout the Union. Countries and regions need assistance in overcoming their structural deficiencies and in developing their comparative advantages. This means, among others, that encouraging the development of knowledge-based economic activities and innovation and that particular attention needs to be given to:

1. developing new innovation promotion policies which focus much more on the provision of collective business and technology services to groups of firms which can affect their innovative behaviour, rather than direct grants to individual firms which tend only to reduce costs temporarily.

2. developing new policies to strengthen the capacity of SMEs to innovate through business networks and clusters and improving their links with the knowledge base, including with universities and research centres.

3. encouraging the development of the indigenous R&D potential of weaker regions and their capacity to adapt technological advances made elsewhere to local circumstances and needs.

4. facilitating access of researchers, businesses and others in less favoured regions to international networks of excellence, sources of new technology and potential R&D partners.

These conditions are largely related to economic competitiveness and include, among others, the capacity of a regional economy to generate, diffuse and utilize knowledge and so maintain an effective regional innovation system. Furthermore, policies should promote the entrepreneurial relations between firms and institutions, fostering the development and dissemination of the expertise, the mobility of human and physical capital and the enhancement of the relationships between business and research entities. Specifically, they should encourage actions such as, promoting innovation, technology transfer and interactions between firms and higher education and research institutes, networking and industrial co-operation and support for research and technology supply infrastructure. Such cooperation and the networks that are formed help to translate knowledge into economic opportunity, while at the same time building the relationships between people and organizations which can act as a catalyst for innovation. Such actions should extend to all the policy areas relevant for economic, scientific and social development and should ideally establish a long-term policy horizon.

Under this perspective, growth policies should focus on creating favorable environment for the co-operation between firms and institutions that support the development and exploitation of knowledge and innovation. Furthermore, policies should promote the entrepreneurial relations between firms and institutions, fostering the development and dissemination of the expertise, the mobility of human and physical capital and the enhancement of the relationships between business and research entities. Specifically, they should encourage actions such as, promoting innovation, technology transfer and interactions between firms and higher education and research institutes, networking and industrial co-operation and support for research and technology supply infrastructure. These conditions are largely related to economic competitiveness and include, among others, the capacity of a regional economy to generate, diffuse and utilize knowledge and so maintain an effective regional innovation system, contributing into a sustainable economic growth path.

However, the main concern of an industry or country in its innovation policy should be to have the optimal combination of business activities in various stages of the innovation cycle. Countries, industries, or firms concerned primarily with activities of the innovation takeoff stage may find themselves lacking sufficient economic resources to exploit these activities through improvement-related innovations. Countries, industries, or firms dominated by activities of the maturation stage, such as limitation and improvement of given technologies, incremental innovation, diversification of products, exploitation of scale economy, extension of vertical integration, and automation of production processes, will lose their advantage with respect to dynamic efficiency and experience stagnation (Haustein, et al., 1981). Without knowing the needs of and possibilities offered by the economic environment, one cannot understand the mechanism of technological change towards productivity enhancement. A crucial task to improve innovation policy at the national and industrial levels is to provide information about fields of innovation, which are dependent on factors which fall into three categories:

1. Urgency of demand for the innovation
2. Existence of scientific and technological advancements
3. Existence of a socio-economic environment which allows productive efficiency enhancement through scientific and technological feasibilities

Successful producers will probably be those able to respond effectively in these fields. Once the right direction is chosen, success depends on managing the factors that influence innovative activities towards efficiency enhancement.

6.3. Concluding remarks

Contrary to the Stochastic Frontier Analysis approach (SFA), which requires a functional form to estimate the frontier production function and is based on the idea that the data is contaminated with measurement errors and noise (Bauer. 1990), Data Envelopment Analysis (DEA) approach uses linear programming techniques and cannot discriminate between inefficiency and noise. Thus, it tends to produce overestimated inefficiency measures, a fact which is the most important disadvantage of DEA in comparison to SFA (Bauer. 1990). This chapter proposes a slack-based DEA which allows a full evaluation of inefficiency in an industry's performance. The model estimated in this chapter is a DEA variant called slack-based measure, which is able to deal directly with the input excesses and the output shortfalls of the industry under evaluation (Tone, 2001). Estimated slacks are invariant to the units of measurement and are monotone decreasing with respect to each input and output slack. By using slack-based efficiency measure, we obtain different frontier levels and more appropriate performance benchmarks for inefficient industries. The production assumptions in DEA are that all actual observed inputs and outputs of any industries are feasible for all industries, as are linear combinations of observed inputs and outputs.

The nonparametric approach relies on a production frontier which is defined as the geometrical locus of optimal production plans (Simar and Wilson, 1998). The individual efficiencies of the firms relative to this production frontier are calculated by means of distance functions employing DEA and involving the use of linear programming methods to construct a piecewise linear surface or frontier over the data and measures the efficiency for a given unit relative to the boundary of the convex hull of the input-output vectors.

Comparing the outcomes of the two different approaches (between parametric and non-parametric method) for the period 1980 – 2005, regarding the efficiency progress, within an output-oriented stochastic function, there are different outcomes regarding the estimation of the technical efficiency values. On the other hand, the common results produced are that technical efficiency changes over time (time-varying technical efficiency) and that the estimated parameter γ is close to (1), and it is statistical significant, showing the existence of technical efficiency. However, similar results are produced regarding scale efficiency and returns to scale.

However, there is an on-going debate among researchers about the applicability and usefulness of the DEA approach vs. the stochastic frontier approach. Data Envelopment Analysis (DEA) methodology offers major advantages, since the non-parametric nature of the technique avoids the need to specify beforehand any particular functional form for the technology. Furthermore, this approach does not require any assumption about market structure or about the absence of market imperfections. Unlike stochastic production frontier, however, it does not require imposing any particular functional form of the production frontier on the data, and it is able to analyse both single and multiple outputs.

The data required for a DEA analysis are the same types of data required for SFA. With DEA, however, multiple output technologies may be examined more easily. There is no need to aggregate outputs, and producer-specific capacity measures are possible. Like the SPF approach, multiple inputs can also be incorporated in the analysis if available (Färe, Grosskopf and Kirkley, 2000).

A recognized limitation of using the DEA to assess technical efficiency is that recommendations for decreasing input usage or expanding output levels are in terms of scalar valued ratios which are held constant (i.e., recommendations are in terms of fixed proportions). This limitation, however, is partially mitigated by considering changes in terms of slack variables. In this case, it is possible to determine decreases in inputs or increases in outputs relative to the slack variables; changes are not restricted to constancy of the input or output mixes. Another option to avoid the problem of constant mix ratios is to consider either an economic cost approach or an economic revenue approach. With the economic DEA approaches, prices on inputs or on outputs are all that are required. Changes to achieve technically and allocatively efficient levels are determined and are not restricted to constant input or output mixes.

Chapter 7

Conclusions and Policy Implications

Abstract

The issue of estimating technical efficiency in industrial and national level is thought to be of particular research interest because empirical evidence shows that even though European Union industries are widely analyzed with respect to performance, yet little attention has been paid to the estimation of technical efficiency. The basic aim of this thesis is the estimation of industrial technical efficiency and benchmark industries regarding technical efficiency attainment levels. Our research is focused on manufacturing industries in selected European Union countries, since they constitute one of the major productive units in European economy,. in terms of value added. The methods employed are the Stochastic Frontier Analysis and the Data Envelopment Analysis, in order to compare the estimated results under alternative theoretical hypotheses and conclude to safe results as well as the estimation of technical efficiency and the allocation of technical efficiency in national and industrial level is concerned.

Our analysis considered a European Union perspective efficiency analysis to derive broader conclusions about European Union productive performance within selected countries. Our analysis is based on estimating efficiencies as industry - specific fixed - effects at industry level of selected member – states within European Union. during 1980 – 2005, employing the econometric software program LIMDEP 9.0 and STATA 10.0. The European member – states selected to be included in the model are Germany, France, United Kingdom, Denmark, Finland, Netherlands, Italy and Spain), in order to create a data set including both countries with strong industrial productive base, such as United Kingdom, Germany and France, as well as countries with low industrial productive base, such as Spain. Based on the obtained results, the concluding chapter 7 introduces comparative results, leading to improvements in efficiency estimation. The chapter assesses the significance of the obtained results and the possible channels of impact and it concludes the thesis, highlighting the main findings and stating their academic significance and their policy implications. Finally, chapter 7 addresses implications and contributions for academics, practitioners and public policy. A presentation of the study's limitations and suggestions for further research closes the chapter.

This thesis tried to fill a gap in the economic literature by exploring and studying various dimensions of the interaction between technical change and innovation and links to efficiency growth. In particular, this thesis explored whether the interactions between these factors have any implications for efficiency growth, and whether there are any complementarities between them and fostering technical efficiency growth, providing the industry -level estimates of technical efficiency using the time-varying inefficiency translog model. Further, factors that determine variations technical efficiency are established and a comparison of technical efficiency is made, both before and after accounting for different explanatory variables in the inefficiency term, presenting a range of different stochastic model approaches based on alternative hypotheses. discussing and comparing them in detail.

7.1. Concluding remarks

Explaining the course of technical efficiency and determining factors which might affect it, have been for a long time, and continue to be, one of the most important topics of economic literature. The work of Farell (1957) first attempted to answer questions about the sources of differences in technical efficiency across producers and after six decades, this enquiry into the sources of differences in efficiency levels across industries. or over time within the same industry, is still as important as used to be. In response to this most important question, and with the increase in data availability, economic literature has shown a resurgence of interest in testing and quantifying various theories of economic growth and explaining technical efficiency growth.

This dissertation considers a European perspective within efficiency analysis to increase the information base and derive broader conclusions about European performances. A framework more reliant upon efficiency has become an important policy objective in all European countries to promote efficiency. effectiveness and competitiveness[121]. We have shown that upon this background efficiency analysis plays an important role for the determination of technical efficiency. The aim is to investigate various aspects of the relationship between ICT investment. innovation activities and economy openness in an attempt to reach a better understanding of the contribution of these determining factors to technical efficiency growth. empirically examining the implication of the interrelationship and the complementarities between them and their contribution to technical efficiency.

The basic aim of this thesis is the estimation of industrial technical efficiency and benchmark industries regarding technical efficiency attainment levels. The related challenge is to define robust and reliable models for empirical implementation. confronting with the academic diversity of approaches and definimg the most adequate and reliable methods to put into practice. Within this framework, we summarized and applied

[121] The topic of regional innovation and productivity differences has been broadly examined in: Kokkinou A. (2010d) Innovation Convergence And Regional Development: Goal Or Reality?, *The Cyprus Journal of Sciences*, Vol. 8, 2010/pp. 89 – 104 and in: Kokkinou, A. and Korres, G. (2010) *Innovation and Convergence Process: An empirical benchmarking analysis of European regions*, European Network on Industrial Policy International Conference (EUNIP), 2010, Spain.

deterministic nonparametric approach like the Data Envelopment Analysis (DEA), as well as stochastic frontier methods (SFA).

Our research is focused on manufacturing industries in selected European Union countries. since they constitute one of the major productive units in European economy, in terms of value added. The methods employed are the Stochastic Frontier Analysis and the Data Envelopment Analysis, in order to compare the estimated results under alternative theoretical hypotheses and conclude to safe results as well as the estimation of technical efficiency and the allocation of technical efficiency in national and industrial level is concerned.

This thesis analyzes the technical efficiency performance of manufacturing industries in a selected sample of European Union countries. The purpose is to study these countries' and these industries' technical efficiency evolution in an effort to determine the potential determinants, in order to increase the technical efficiency information base and derive broader conclusions about European Union manufacturing industries performance. This thesis attempts to answer questions about the sources of differences in technical efficiency across the selected countries and industries, as well as the sources of differences in efficiency levels over time. The aim of this thesis is to investigate various aspects of the relationship between technical efficiency determining factors in an attempt to reach an understanding of the contribution of these factors to technical efficiency growth. In particular, this thesis empirically examines the implication of the interrelationship and the complementarities between these factors and estimates their contribution to technical efficiency. This thesis aimed to show that efficiency analysis plays an important role for the determination of technical efficiency and productivity and that a framework more reliant upon efficiency has become an important policy objective in all European countries to promote efficiency, effectiveness and competitiveness.

This issue is of particular importance because empirical evidence shows mainly that European Union countries are widely analyzed with respect to productivity. yet little focus has been put on efficiency analysis. Explaining the course of technical efficiency and determining factors which might affect it, have been for a long time, and continue to be, one of the most important topics of economic literature. However, this thesis does not claim to identify any single "best practice" for academic benchmarking. Mainly, the challenge is to define a robust and reliable model for empirical implementation. Within this framework, this thesis summarizes and applies alternative deterministic nonparametric approaches like the Data Envelopment Analysis (DEA), as well as stochastic approaches, like the Stochastic Frontier Analysis (SFA).

More specifically, our analysis considered a European Union perspective efficiency analysis to derive broader conclusions about European Union productive performance within selected countries. Our analysis is based on estimating efficiencies as industry - specific fixed - effects at industry level of selected member- states within European Union, during 1980 – 2005, employing the econometric software program LIMDEP 9.0 and STATA 10.0. The European member-states selected to be included in the model are Germany, France, United Kingdom, Denmark, Finland, Netherlands, Italy and Spain. in order to create a data set including both countries with strong industrial productive base, such as United Kingdom, Germany and France, as well as countries with low industrial productive base, such as Spain.

Our main research hypothesis is that stochastic frontier analysis assumes that industries operate under the same production technology and that the inefficiency distribution across individuals and time are homogeneous. For that reason, there is no distinction between unobserved individual heterogeneity and inefficiency, which therefore forces time-invariant individual heterogeneity into the estimated inefficiency. Hence, the industries only differ by the random noise term. However, modern stochastic frontier models (Batesse and Coelli. 1992, 1995) incorporate heterogeneity proposing the distinction between heterogeneity in the production model and heterogeneity in the inefficiency model. Provided the inefficiency effects are stochastic, our model permitted the estimation of both technical change in the stochastic frontier and time-varying technical inefficiencies (Battese and Coelli. 1992, 1995). We also extended the original specification of the models by Batesse and Coelli (1992, 1995) to include a wide array of assumptions and specifications, including panel data analysis and modeling technical inefficiency as time variant. We attempted to identify and examine the application of stochastic frontier models in obtaining measures of efficiency that enable a comparison of performance across manufacturing industries in European Union member states, explaining the determining factors due to which, in the same country, some industries achieve superior efficiency performance. Then, the main task was to relate efficiency to a number of determining factors and measure the extent to which they contribute to efficiency level.

This thesis also examined and applied Data Envelopment Analysis (DEA) as a nonparametric approach and Stochastic Frontier Analysis (SFA) as a parametric framework. The nonparametric method of Data Envelopment Analysis has been included mostly as a robustness check, determining the reference technology by means of linear programming methods whereas the parametric method of Stochastic Frontier Analysis assumes a functional relationship for the production process and determines the reference technology based on econometric methods.

The thesis empirically examined the implication of the interrelationship and the complementarities between value added. Capital, labour and technical change and the contribution of additional determining factors to technical efficiency and attempted to highlight the characteristics of alternative models specification and suggested a concrete method to estimate technical efficiency in national and industrial level.

Within this framework, the theoretical part of the study dealt with stochastic parametric frontier methodology and the applied part of the study focused on examining the impact of the efficiency in different industries and industries. More specifically, this thesis examined whether the interactions between technical progress. ICT investment and economy openness, namely the process of the integration into the world economy, had any implications for technical efficiency, reviewing two of the main heterogeneity determining factors. namely innovation investments (as a proxy of knowledge creation) and economy openness (as a proxy of knowledge dissemination).

7.2. Results

In empirical application, this thesis contributed with an inter – industry and inter – country approach to estimate production inefficiency using the Battese and Coelli (1992, 1995) model, which allows technical inefficiency to vary over time, and allows inefficiency to depend on a set of covariates and explore the effects of innovation – related investment on production, allowing for simultaneous estimation of the parameters of the stochastic frontier and the inefficiency model using the one – step, maximum – likelihood estimation method. More specifically, the empirical application of the thesis estimated the Transcendental Logarithmic Production Function of manufacturing industries in these selected European Union member – states, considering a panel data model for inefficiency effects in stochastic production frontiers based on the Battese and Coelli (1992, 1995) models, providing translog effects. as well as industry effects.

The depended variable of our empirical analysis is the natural logarithm of the product (*lnva*), namely, value added. The independent variables are set to be the labour and capital services, along with time, denoting technical progress.

To confirm the presence of inefficiencies or inefficiency component in the model, we also report the results of γ. The results indicate that the vast majority of the residual variation is due to inefficiency effect (u_i) and that the random error, v_i. is approximately zero. That is the estimated γ is significantly different from zero, suggesting that the technical inefficiency equation plays an important role in the estimation of the production frontier.

The results show that based on the likelihood – ratio (LR) test, the stochastic frontier is statistically different from the OLS estimation. That is the estimated γ is significantly different from zero, suggesting that the auxiliary equation (the technical inefficiency equation) plays an important role in the estimation of the production frontier. Moreover, Kernel Density Estimates present the estimated mean inefficiencies for each one of the estimated models, illustrating the form of the distribution of the estimated efficiency of the models. The distribution of productive efficiency is centered implying that most industries are clustered close to the mean. The reason for the peak in the distribution at the maximum level is from the hypothesis that at least one producer in each industry is fully efficient. Symmetry, as well as skeweness of the distribution of productive efficiency largely coincides with the normal distribution.

First, it is specified the technical efficiency in terms of purely exogenous factor (time trend) and exogenous economic technology shifter factors. Second, we use panel data methodology and flexible functional form in which we control for effects on technical efficiency. In addition, technical efficiency is modeled via exogenous factors and the production function specification is enriched by the introduction of non-traditional production factor inputs. These determining factors are investment in information and communication technology. economic openness, Research and Development stock and capital intensity.

This chapter provides the industry-level estimates of technical efficiency using alternative model specifications under time-invariant and time-varying efficiency assumption. Further, factors that determine variations technical efficiency are established and a comparison of technical efficiency is made, both before and after accounting for different explanatory variables in the inefficiency term.

The empirical analysis presents a range of different stochastic model approaches based on alternative hypotheses, discussing and comparing them in detail. First, this chapter applies a stochastic translog production function to examine the underlying causes of technical inefficiency for 13 manufacturing industries in European Union over the period 1980 – 2005. The results indicate that inefficiency was present in production and the relevant technical efficiency determining variables contribute to it. From our model analysis, it is evident that the manufacturing industries in our research sample are not fully efficient. The inefficiency observed is endogenous to the firm since the technical inefficiency is largely associated with the firms' choice of ICT investments and openness achievement. Even though there is a notable improvement in technical efficiency after accounting for variations, technical inefficiency remains significant which calls for further investigation of the variations regarding to the alternative explanatory variables.

Apart from the stochastic frontier analysis, the empirical analysis also employed Data Envelopment Analysis (DEA) and the slack variable analysis to evaluate the operating efficiency. The SFA approach requires a functional form to estimate the frontier production function and is based on the idea that the data is contaminated with measurement errors and noise (Bauer, 1990). The DEA approach uses linear programming techniques and cannot discriminate between inefficiency and noise. Thus, it tends to produce overestimated inefficiency measures. a fact which is the most important disadvantage of DEA in comparison to SFA (Bauer, 1990). This section proposes a slack-based DEA which allows a full evaluation of inefficiency in an industry's performance. The model chosen for this study is a DEA variant called slack-based measure, which is able to deal directly with the input excesses and the output shortfalls of the industry under evaluation (Tone, 2001).

Conclusions and policy implications may be drawn from this model analysis. First, ICT investment and economy openness have been modelled as productive inputs and as variables which affect efficiency. This research found that the ICT investment, capital intensity and economy openness are both positively associated with technical efficiency in European Union manufacturing. The analysis and evidence in this chapter investigates whether there is evidence of technical inefficiency in manufacturing industries in European Union selected member – states. and whether factors such as ICT investment (as a proxy of knowledge creation) and economy openness (as a proxy for knowledge transfer and dissemination) exert any influence on to technical efficiency growth.

While usually used to measure technical efficiency (i.e. maximum output from available inputs), both the SF and the DEA methods can be used to derive allocative efficiency (the least-cost input combination yielding the output) and, thus, overall efficiency measures. The efficiency scores from both econometric and programming approaches are often subject to second-stage regression analysis to help determine the impact upon efficiency of efficiency explanatory factors beyond decision maker control. The success of both approaches relies on some common factors, including that all inputs and outputs are homogeneous across productive units, are measurable, are measured accurately, are included, and that productive units are relatively alike and employ a common technology.

Comparing the outcomes of the two different approaches (between parametric and non-parametric method) for the period 1980 – 2005, regarding the efficiency progress, within an output-oriented stochastic function. there are different outcomes regarding the estimation of the technical efficiency values. The two approaches also give different results as far as the industries or countries technical efficiency benchmarking is concerned. In addition, the common results produced are that technical efficiency changes over time (time-varying technical efficiency) and that the estimated parameter γ is close to (1) and it is statistical significant, showing the existence of technical efficiency. However, similar results are produced regarding scale efficiency and returns to scale.

In our results. the inefficiency level decreases over time in all the industries and countries, even though certain industries and countries have mixed increases and decreases in inefficiency levels, such as the wood industry, or the non – metallic industry in Spain or the machinery industry in France. However, the general trend of the inefficiency shows that inefficiency levels decrease over time, with Italy and France presenting the higher efficiency improvement. Technical inefficiency has significantly increased in all countries and industries. converging into low levels of inefficiency.

The inefficiency observed is endogenous to the industries, since technical inefficiency is largely associated with the industries choice of ICT investments, economic openness. Research and Development stock, and capital intensity. Industries could improve their technical efficiency by enhancing their investments in ICT, providing incentives in facilitating exports activities, as well as increasing the Research and Development stock and capital intensity. Even though there is a notable improvement in technical efficiency after accounting for variations in technical efficiency, technical inefficiency remains significant, which calls for further investigation of the variations by including other technological determining variables.

Central to this view is the appreciation of the ways in which organizations, industries and industries change and adapt in the presence of new opportunities and constraints. Accordingly, our research studies how changing configurations of the knowledge base combined with the emergence and adaptation of institutional structures stirred a paradigm of service innovation in an information-intensive industry like manufacturing industries in our sample. In particular, the case study presented here discloses a dual evolutionary process: the growth in ICT investment in the industry and the emergence of knowledge communication across countries. In doing so it highlights the coordinating role of ICT technologies investment,, economy openness, R&D stock and capital intensity in enabling the technical efficiency enhancement (Nelson and Sampat, 2001; Nelson, 2002, 2005).

Following our main research questions on what are the reasons for diverging efficiency in a production industry, which factors contribute to production industries efficiency differences; and how the efficiency of a production industry evolves over time, with respect to technical progress and other related determining factors. the thesis main findings suggest the great importance of the interaction between the different determining factors and estimate any implication for productive efficiency. The results indicate that inefficiency was present in production and several relevant explanatory variables vastly contribute to it, such as ICT investment and economy openness. This research found that the ICT investment and economy openness are both positively associated with technical efficiency in European Union manufacturing. The empirical evidence reported in this thesis supports the hypothesis and shows that technical change, ICT investment and economy openness have a positive impact on technical efficiency in the examined industries, playing a significant role in determining the contribution of innovation in efficiency, productivity and, consequently, economic growth. Even though there is a notable improvement in technical efficiency after accounting for variations, technical inefficiency remains significant which calls for further investigation of the variations regarding to the alternative explanatory variables.

7.3. Policy implications

Nowadays, the role of manufacturing industries to the economy is even more important taking into consideration the slowdown in the world economy, and the effects on the business environment created by the financial crisis. Thus, manufacturing industries have a very important role in creating opportunities making an important contribution to economic growth and development. However, due to their nature, manufacturing industries are characterized by being very heterogeneous since they differ in their endowments of resources as well as on the risks involved in their productive activities. For this reason, it is of great importance, on the one hand to analyze their efficiency level and potential, and in addition, to analyze the factors which determine their efficiency potential. Thus, this thesis provided insights into the level of industry-specific technical efficiency along with factors affecting inefficiency, focusing on manufacturing industries and seeks to obtain the empirical results by specifying the translog functional form and the model for the technical inefficiency effects in the stochastic frontiers.

The key factors influencing the competitiveness of the EU manufacturing industry are access to innovation, R&D and international trade. The main recommendations revolve around three key areas innovation and research and strengthening networks and clusters; responsible use of natural resources; and the need for open world markets with fair competition. Clustering, collaboration and the formation of strategic alliances are becoming increasingly important. Continuous R&D and innovation efforts are essential elements into guaranteeing the long-term competitiveness of Europe's manufacturing industries. European research, technical development and innovation policies should focus on developing the framework conditions that stimulate innovation. entrepreneurship and, thus, growth and employment. Innovation for sustainable manufacturing requires paying attention to the interfaces between R&D policies with other critical policy fields. Strong emphasis needs to be placed upon the management of the interfaces between R&D policy and other policy realms competition policy, intellectual property rights, standardization, education and training, environmental policy, labour market, employment and social policy, to facilitate the creation of a sustainable European manufacturing industry environment, along with fiscal instruments and incentives. Understanding future challenges and issues is important on future developments in manufacturing. Industrial change driven by new technological opportunities will impact on the manufacturing structures in European Union. contribute to sustainable growth and improve technical efficiency[122].

Finally, technical progress is another major determinant as new technologies allow the automation of production processes that have led to many new and improved products. allow for better and closer links between firms. and can help improve information flows and organization of production. At the same time, technical progress can be embodied in new equipment and trained workers can only be fully productive if they have the appropriate equipment with which to work. Increases in physical capital are clearly necessary as there are spillovers from capital investment to productivity growth. Thus it is not appropriate to consider physical capital, human capital and technology as separate factors since their contributions are closely linked. It is the combination of these three factors and the way in which they are organized and managed within the industry that will determine the extent of productivity growth. For sustained output growth, it is also important that a balance between the three main factors be maintained[123].

The potential for technical efficiency enhancement is considered to a large extent to depend on the EU's capability to transform the economy towards one that makes more productive use of its resources. Much will depend on the capacity of markets to facilitate the reallocation of resources to industries that show rapid productivity growth. However, it is difficult to predict which industries will be the most productive in the future, as technology and innovation trends are inherently difficult to forecast. For now, a productive use of a larger input from skilled employment and the exploitation of ICT investments in manufacturing industries appear the most successful policy avenues for a European productivity revival[124].

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[122] This topic has been broadly examined in: Alexiadis, S., Kokkinou, A. and Ladias C. (2011) *Sustainable Growth and Adoption of Innovation,* International Conference on Integrated Information - IC-ININFO, 2011, Kos Island, Greece.

[123] This issue has been investigated in Korres, G. M., Tsobanoglou, G. O. and Kokkinou, A. (2011) Innovation Geography and Regional Growth in European Union, *SAGE Open* published online 17 June 2011, DOI: 10.1177/2158244011413142, the online version of this article can be found at: http://sgo.sagepub.com/content/early/2011/06/15/2158244011413142

[124] This topic of regional divergence and convergence has been broadly examined in: Kokkinou A. (2006b) *Innovation and Productivity: A story of convergence and divergence process in E.U. countries*, 46th European Congress of the Regional Science Association, Volos, Greece, in: Korres, G.M., Tsobanoglou,

Promoting technical and productive efficiency into the European Union has resulted in a growing challenge for policymakers. Productive and regional disparities and inequalities are an increasing issue for the European Union to consolidate, as a result policy makers have to adapt the policy agenda considering industrial and innovation policy in order to enhance technical and productive efficiency capabilities.

Moreover, efficiency and policy planning is a major matter which due to the wide interpretations and implications should have a clear mix of principles and priorities, mainly focusing on the effectiveness of the related EU policies. EU industrial and innovation policy should aim to bridging the technical efficiency gaps, both in industrial and country level, benefiting for economic cohesion, allowing members states with a backwards economy or backwards industries to modernise and thus compete in European and international markets, promoting convergence, competitiveness and cooperation. Infrastructure, innovation and investments should be among the main goals.

As it has been asserted above, globalization and worldwide competition has shifted the comparative advantage of corporations and economies towards the factor of knowledge and innovation, where entrepreneurship based on the technical efficiency enhancement plays a rather important role, as far as the growth, productivity and competitiveness enhancement are concerned. In order to promote innovation activities and technological opportunities entrepreneurship enhancement seems to have a significant importance not only to business success, but also to the long run performance of the economy as a whole. Under this perspective, growth policies should focus on creating favorable environment for the co-operation between firms and institutions that support the development and exploitation of knowledge and innovation and technical efficiency. Furthermore, policies should promote the entrepreneurial relations between firms and institutions, fostering the development and dissemination of the expertise, the mobility of human and physical capital and the enhancement of the relationships between business and research entities. Specifically, they should encourage actions such as, promoting innovation, technology

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G.O. and Kokkinou A. (2006) *Technological and Industrial Policies in Europe. Lessons for Asia in Measuring the Effects on Growth and Sustainability*, Congress on Social, Political and Economic Transition of the Turkic Republics of Caucasus and Central Asia in the 21st Century, Kocaeli University, Turkey., and Kokkinou A. (2006a) *Productivity, Innovation and Regional Growth*, 10th International Conference of the Economic Society of Thessaloniki "The Challenges of a Wider European Union", Thessaloniki, Greece.

transfer and interactions between firms and higher education and research institutes, networking and industrial co-operation and support for research and technology supply infrastructure.

As it has already been mentioned, innovation and technology is an important source of regional competitiveness through facilitating cooperation between the various parties involved in both the public and private sectors. In particular, they can improve collective processes of learning and the creation, transfer and diffusion of knowledge and transfer, which are critical for innovation. Such cooperation and the networks that are formed help to translate knowledge into efficiency opportunities. Such actions should extend to all the policy areas relevant for economic, scientific and social development and should ideally establish a long-term policy horizon.

This, however, needs to happen not just in central parts where productivity and employment are highest and innovative capacity most developed but throughout the Union. Countries and regions need assistance in overcoming their structural deficiencies and in developing their comparative advantages. This means, among others, that encouraging the development of knowledge-based economic activities and innovation and that particular attention needs to be given to:

- developing new innovation promotion policies which focus much more on the provision of collective business and technology services to groups of firms which can affect their innovative behaviour, rather than direct grants to individual firms which tend only to reduce costs temporarily.
- developing new policies to strengthen the capacity of SMEs to innovate through business networks and clusters and improving their links with the knowledge base, including with universities and research centres.
- encouraging the development of the indigenous R&D potential of weaker regions and industries and their capacity to adapt technological advances made elsewhere to local circumstances and needs.
- facilitating access of researchers, businesses and others in less favoured regions to international networks of excellence, sources of new technology and potential R&D partners.

These conditions are largely related to productive and technical efficiency and include, among others, the capacity of a regional economy to generate, diffuse and utilize knowledge and so maintain an effective production system.

Towards this direction, our expected contribution is considered providing a better understanding of the contribution of technical change; ICT investment, innovation activities and economy openness to technical efficiency taking into account the interrelationships and the complementarities between innovation and efficiency. This thesis investigated various aspects of the relationship between productive efficiency and determining factors in an attempt to reach a better understanding of the contribution of alternative factors to technical efficiency growth. Industries should investigate and act towards identifying, developing and deploying their resources that may influence their technical efficiency, competitiveness and consequently their productivity performance, with better identification and understanding of the key resources, mainly increased knowledge about the impacts of different determining factors on technical efficiency.

7.4. Further research

The issue of estimating technical efficiency in industrial and national level is thought to be of particular research interest because empirical evidence shows that even though European Union industries are widely analyzed with respect to performance, yet little attention has been paid to the estimation of technical efficiency.

This thesis tried to fill a gap in the economic literature by exploring and studying various dimensions of the interaction between technical change and innovation and links to efficiency growth. In particular, this thesis explored whether the interactions between these factors have any implications for efficiency growth and whether there are any complementarities between them and fostering technical efficiency growth, providing the industry -level estimates of technical efficiency using the time-varying inefficiency translog model. Further, factors that determine variations technical efficiency are established and a comparison of technical efficiency is made, both before and after accounting for different explanatory variables in the inefficiency term. presenting a range of different stochastic model approaches based on alternative hypotheses, discussing and comparing them in detail.

Regarding further research. special focus should be put on the appreciation of the ways in which organizations, industries and industries change and adapt in the presence of new opportunities and constraints. Accordingly, future research could study how changing configurations of the knowledge based economy combined with the emergence and adaptation of institutional structures in an technology - intensive industry like manufacturing industries, especially these of high technology and high value added. In particular, a dual evolutionary research could be undertaken regarding the growth in ICT investment in the industry and the emergence of knowledge communication across countries. In doing so, it highlights the coordinating role of ICT technologies and economy openness in enabling the innovative potential opened up by new technologies and innovation activities.

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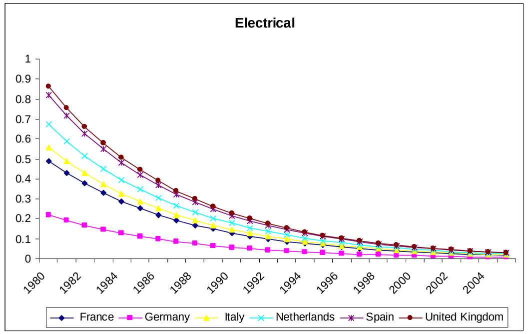
Appendix

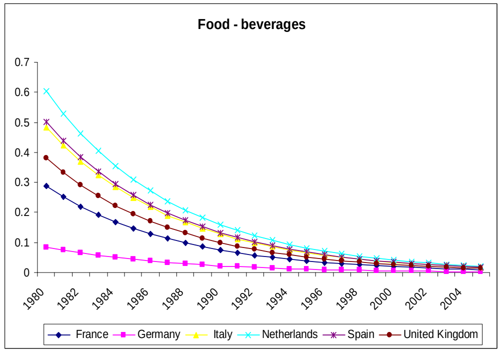
The appendix includes the graph presenting the results regarding the inefficiency analysis (estimation and trends) per industry and country for each one of the alternative estimated models.

Figure A1. Inefficiency Analysis per Industry and country – Model 2

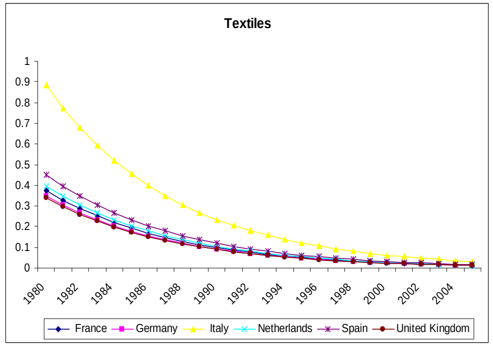
Electrical - Optical



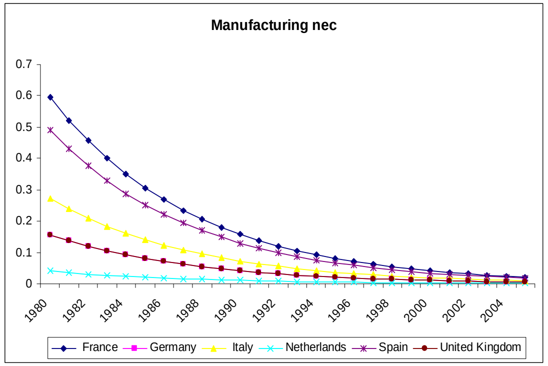
Food - Beverages



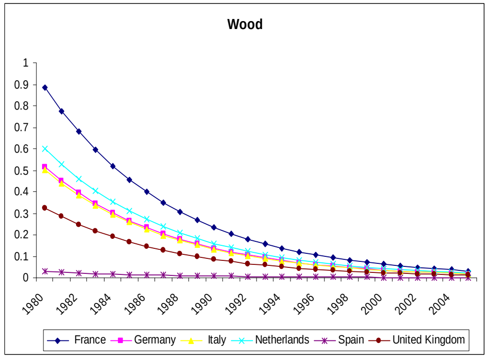
Textiles



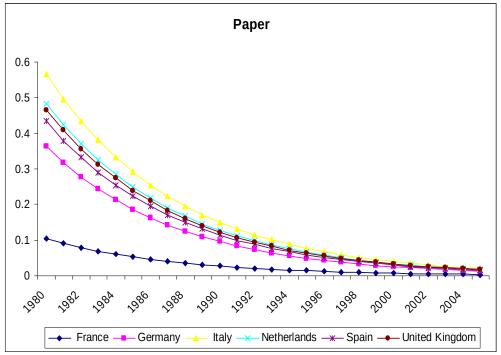
Manufacturing nec



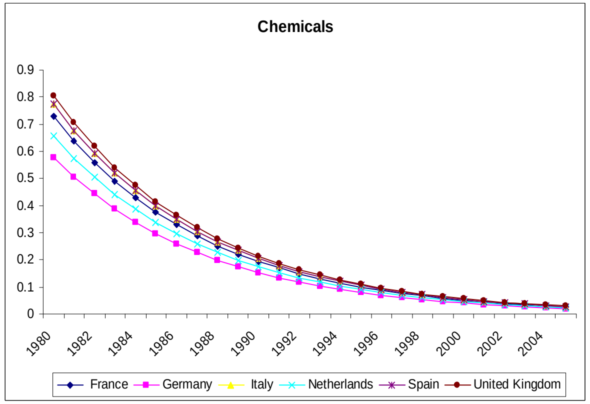
Wood



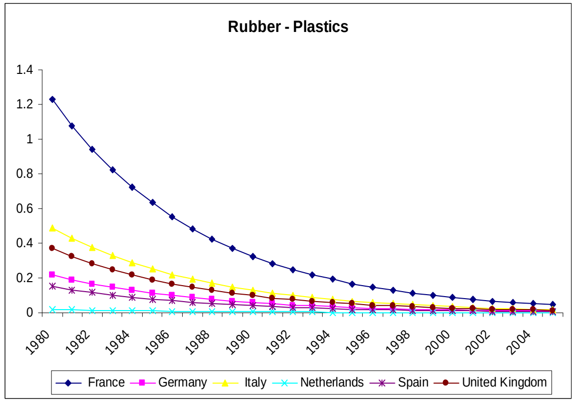
Paper



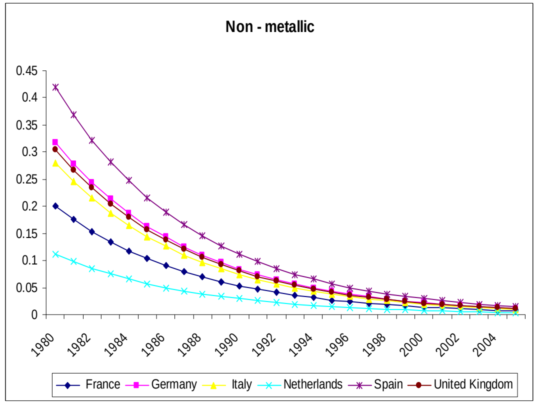
Chemicals



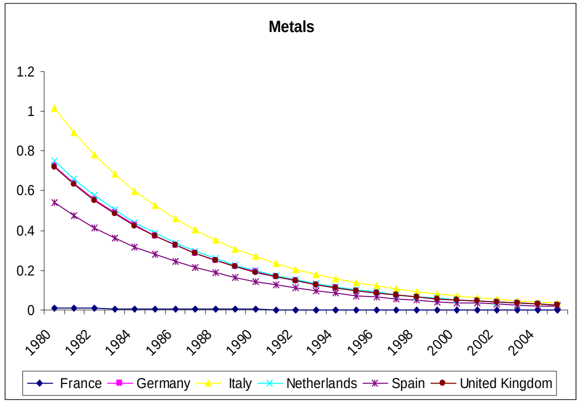
Rubber - Plastics



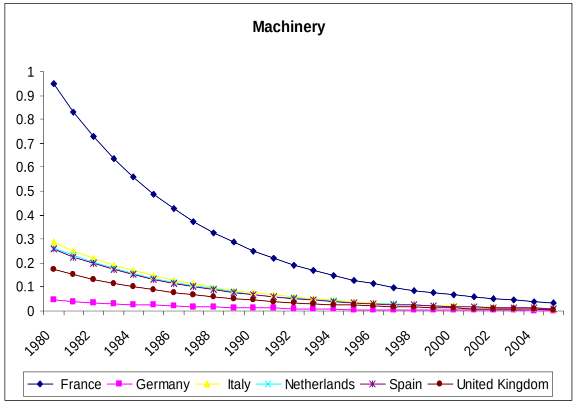
Metals



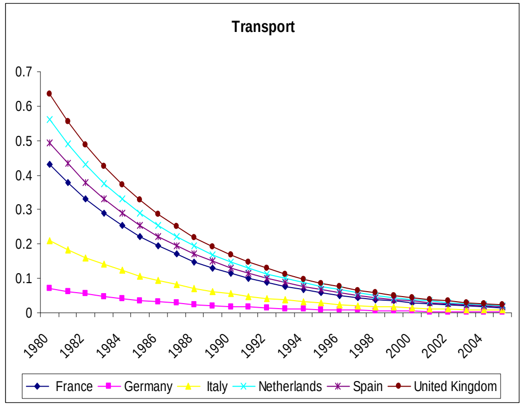
Metals



Machinery



Transport equipment

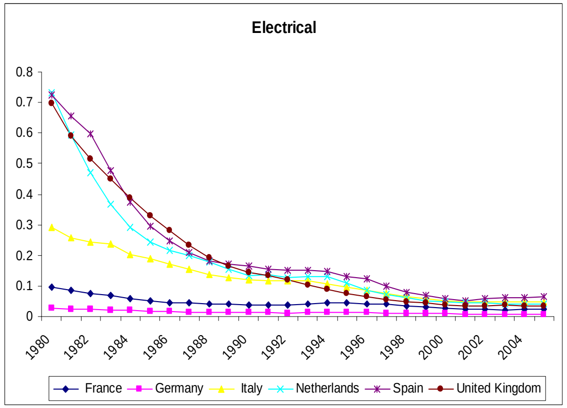


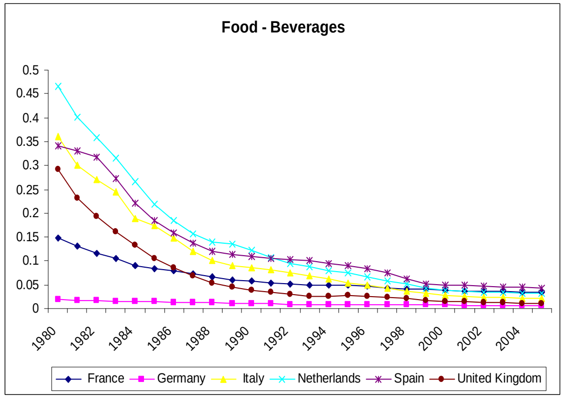
Source: Own estimation

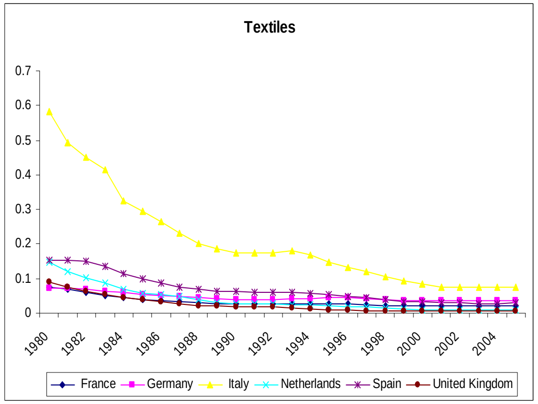
Model (2) presents time variant inefficiency. The inefficiency level decreases over time in all the industries and countries. with Italy and France presenting the higher efficiency improvement.

Figure A2. Inefficiency Analysis per Industry and country – Model 3

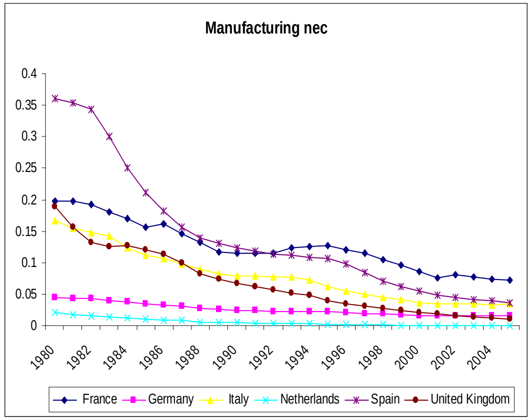
Electrical - Optical	Food - Beverages	Textiles

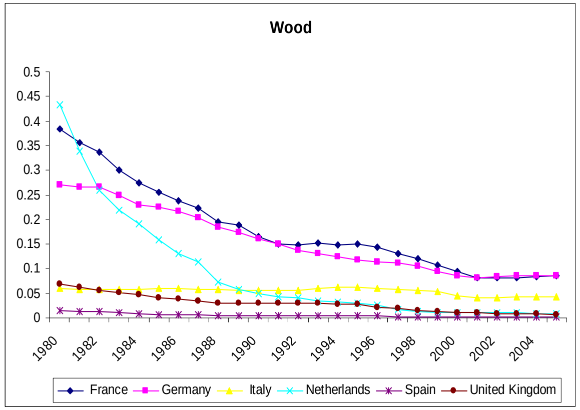


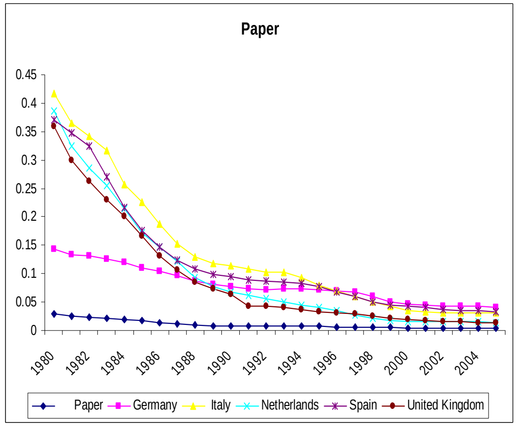




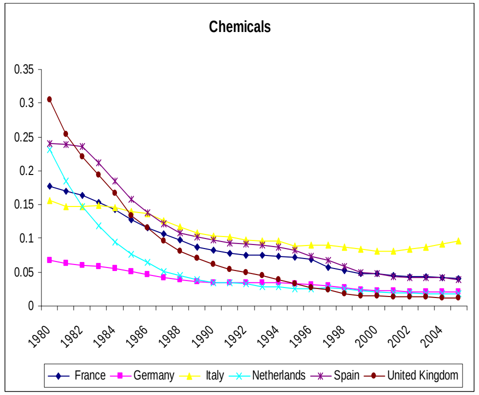
Manufacturing nec	Wood	Paper



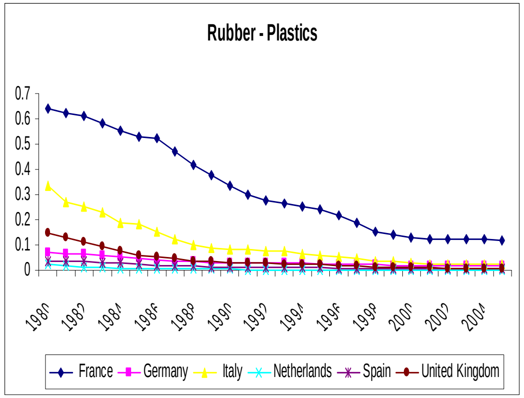




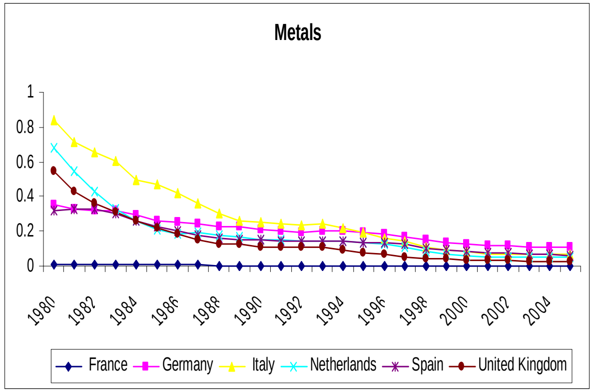
Chemicals



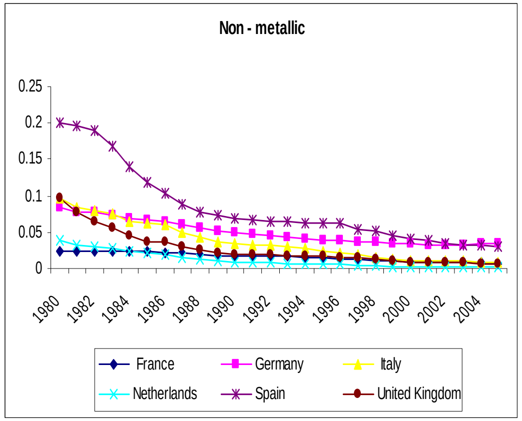
Rubber - Plastics



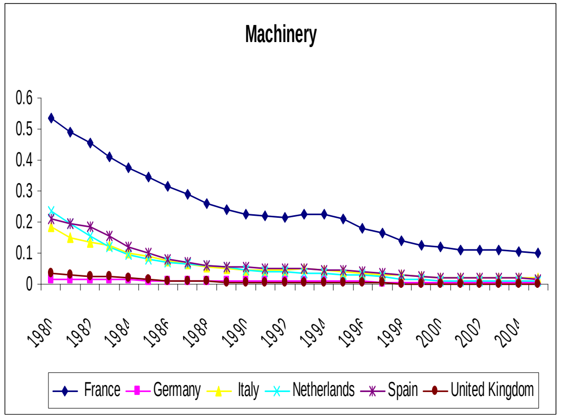
Metals



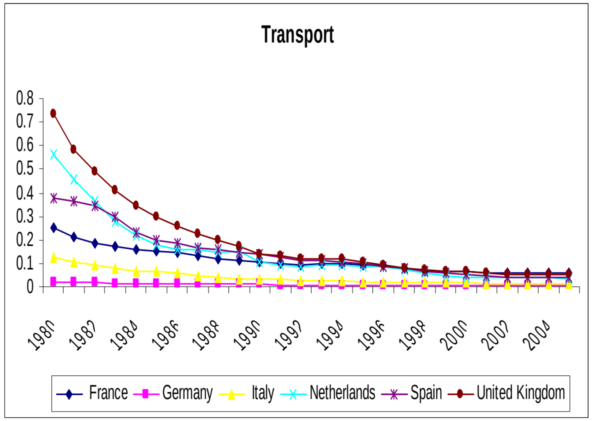
Non-metallic



Machinery



Transport equipment

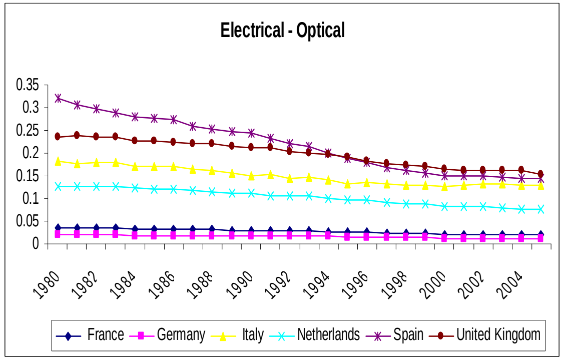


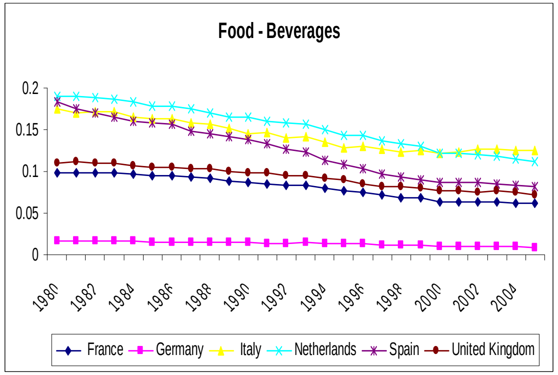
Source: Own estimation

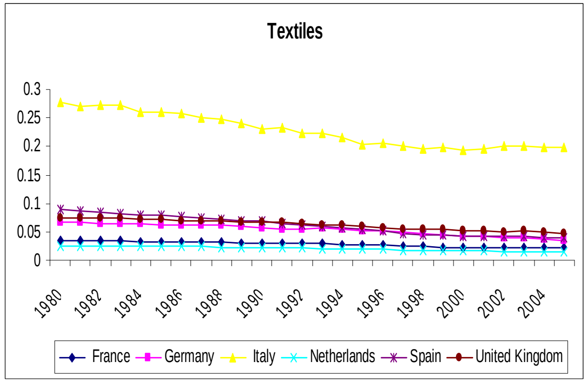
Model (3) presents time variant inefficiency. The inefficiency level decreases over time in all the industries and countries. even though certain industries and countries have mixed increases and decreases in inefficiency levels. such as the wood industry. or the non – metallic industry in Spain or the machinery industry in France. However. the general trend of the inefficiency shows that inefficiency levels decrease over time.

Figure A3. Inefficiency Analysis per Industry and country – Model 4

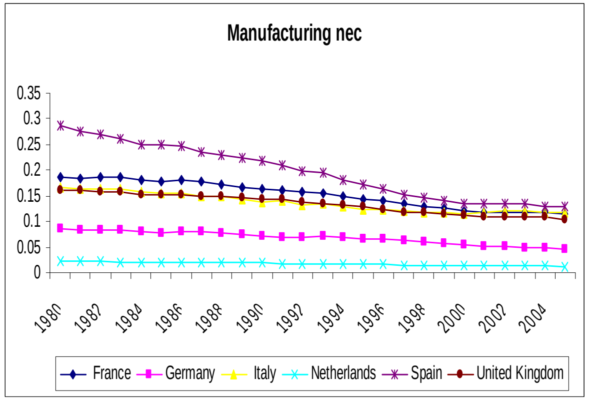
Electrical - Optical	Food - Beverages	Textiles



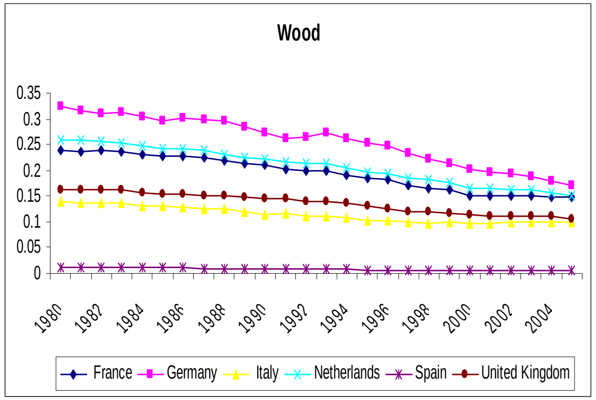




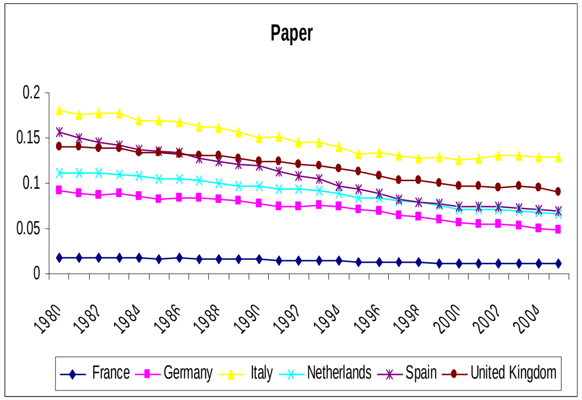
Manufacturing nec



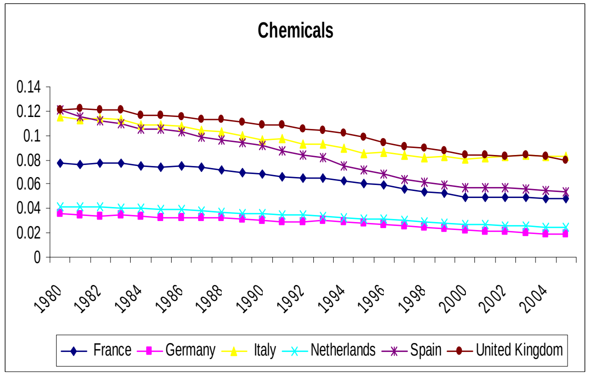
Wood



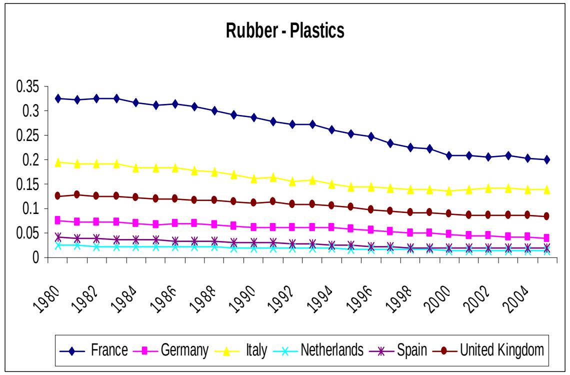
Paper



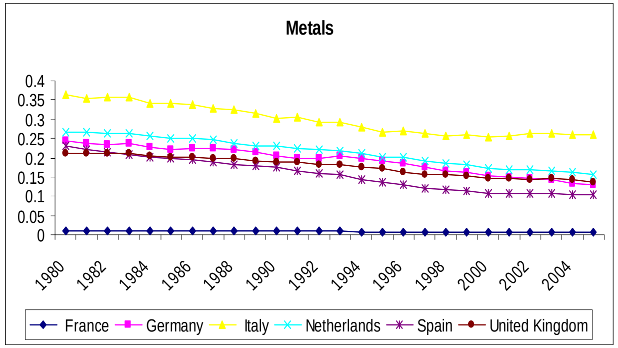
Chemicals



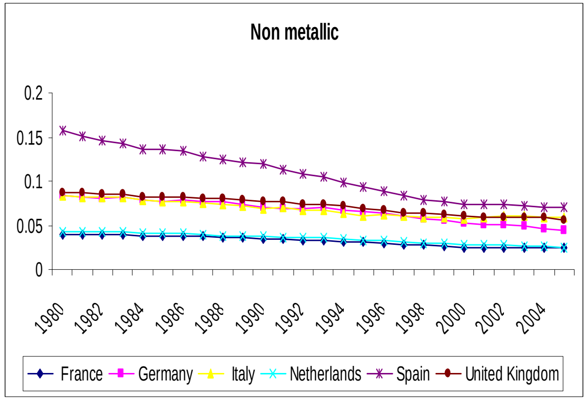
Rubber - Plastics



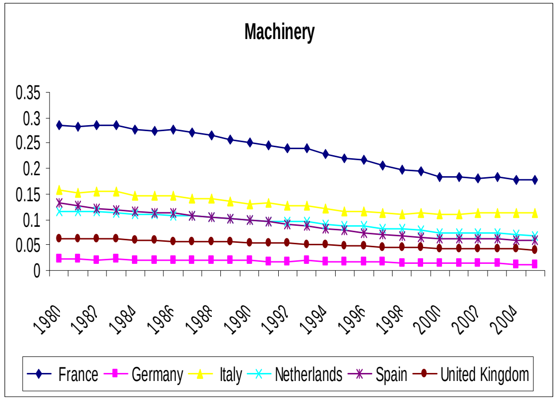
Metals



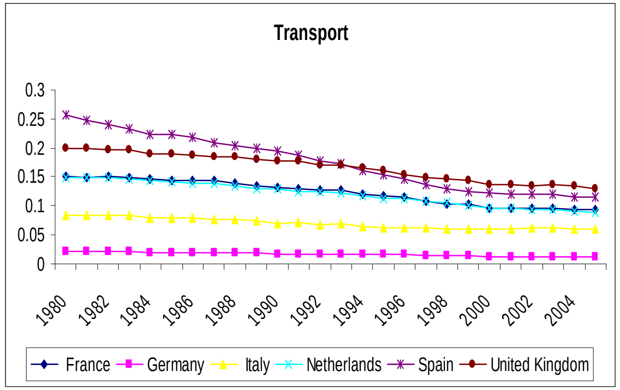
Non-metallic



Machinery



Transport equipment

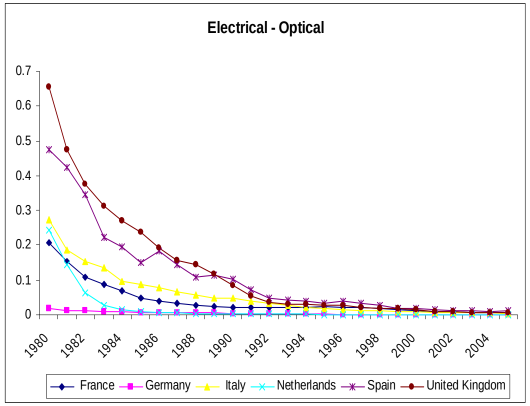


Source: Own estimation

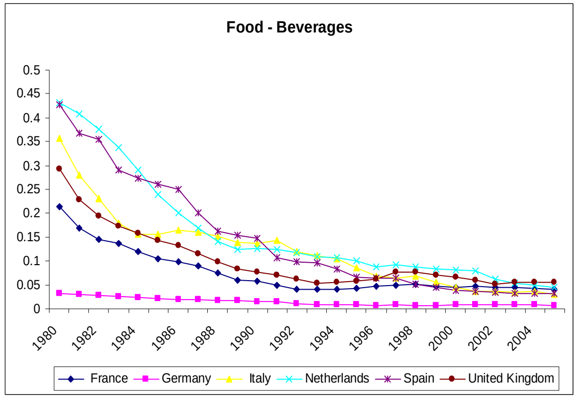
Model (4) presents also time variant inefficiency. Even though the inefficiency level decreases over time in all the industries and countries. the decrease rate is rather small. The countries which present the highest levels of inefficiency are Italy. Spain and France.

Figure A4. Inefficiency Analysis per Industry and country – Model 5

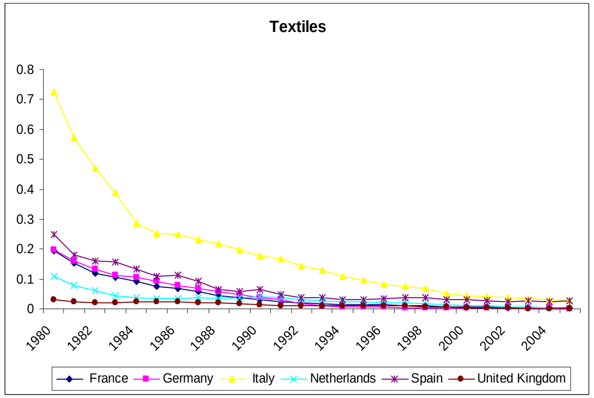
Electrical - Optical



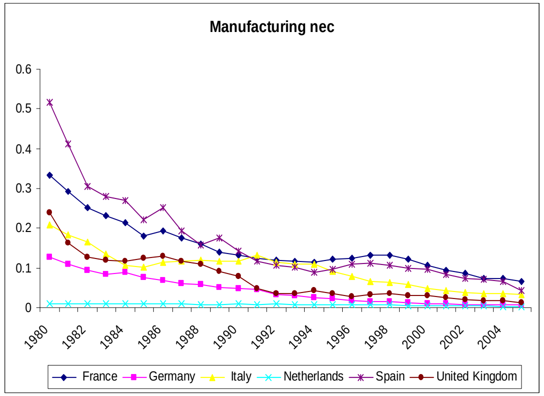
Food - Beverages



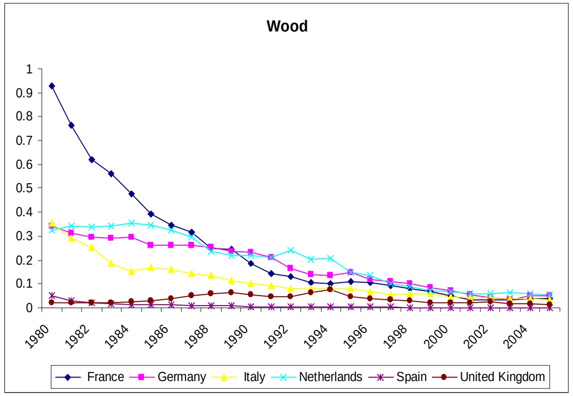
Textiles



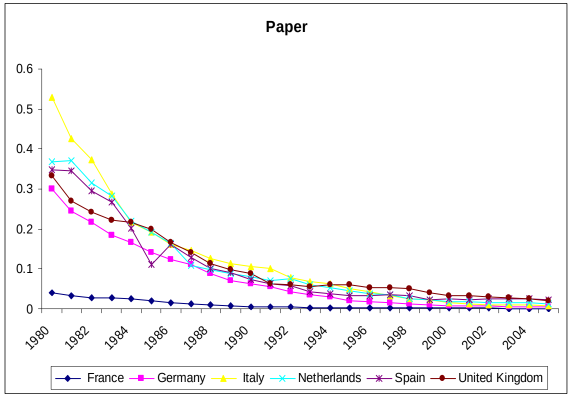
Manufacturing nec



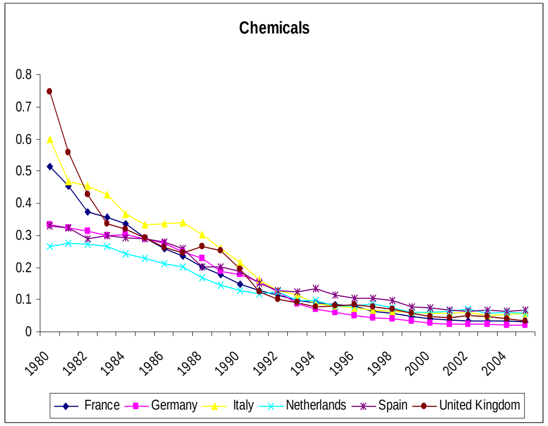
Wood



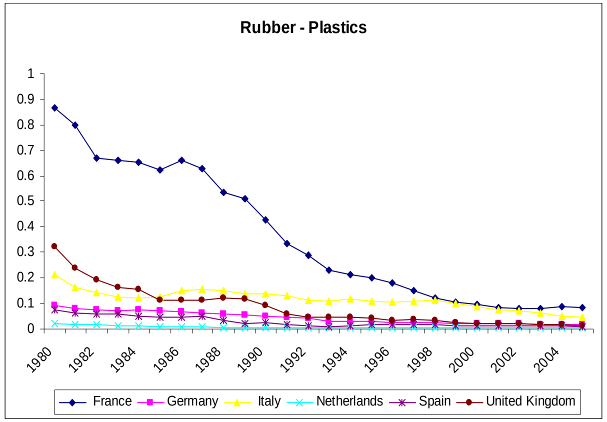
Paper



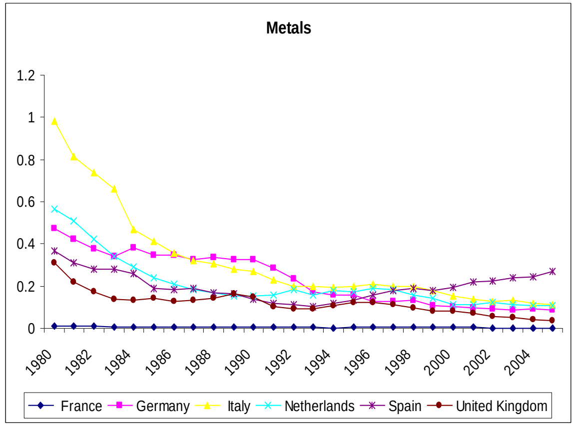
Chemicals



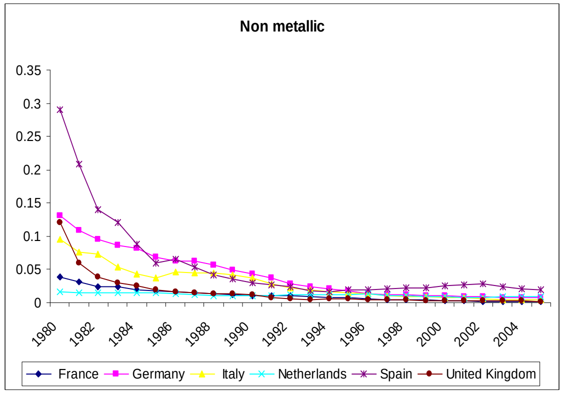
Rubber - Plastics



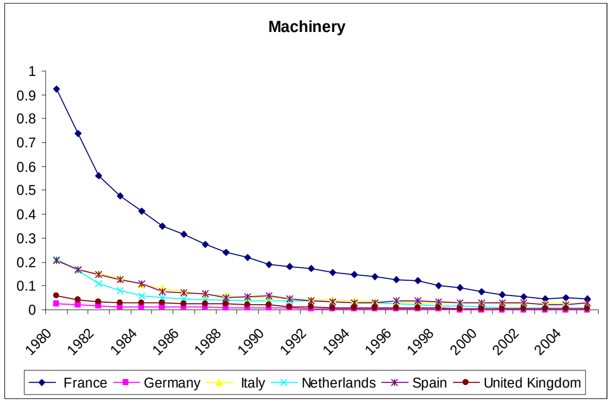
Metals



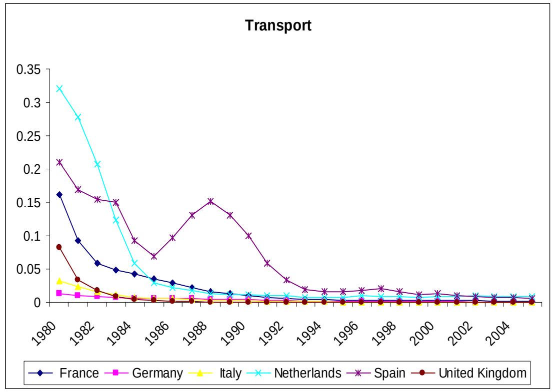
Non-metallic



Machinery



Transport equipment

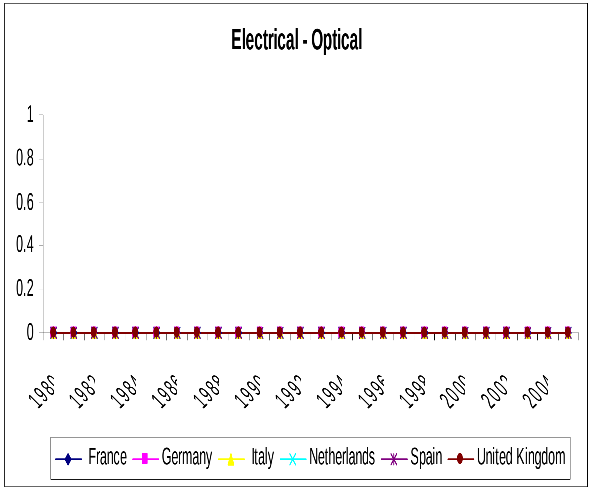


Source: Own estimation

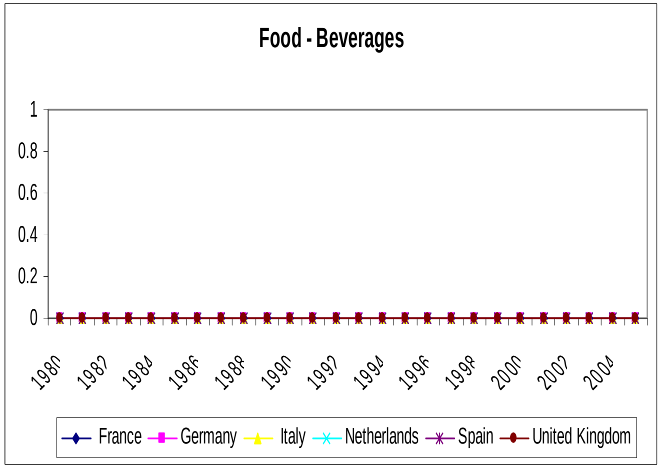
Model (5) presents time variant inefficiency. The inefficiency level decreases over time in all the industries and countries. with Spain. Italy and France presenting the higher efficiency improvement. starting also from the highest inefficiency level.

Figure A5. Inefficiency Analysis per Industry and country – Model 6

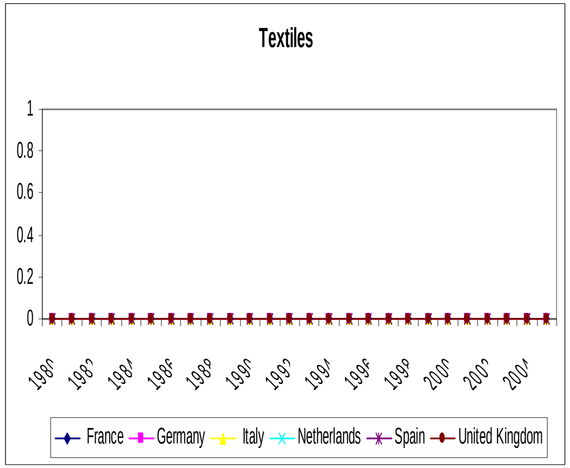
Electrical - Optical



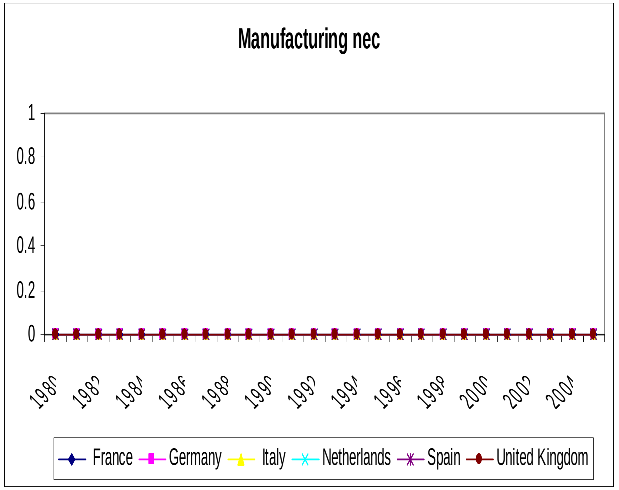
Food - Beverages



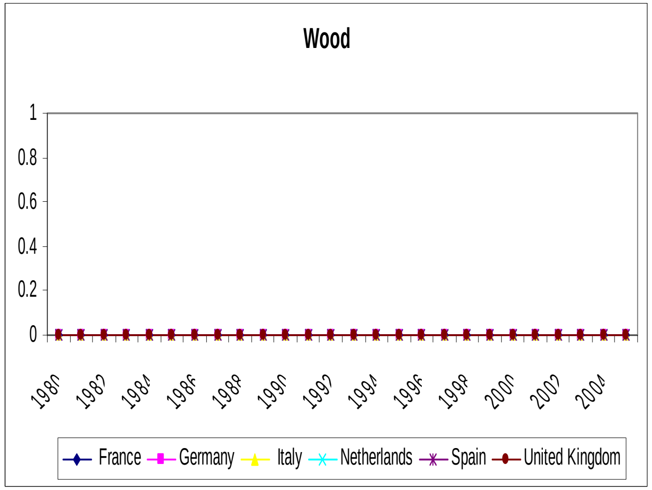
Textiles



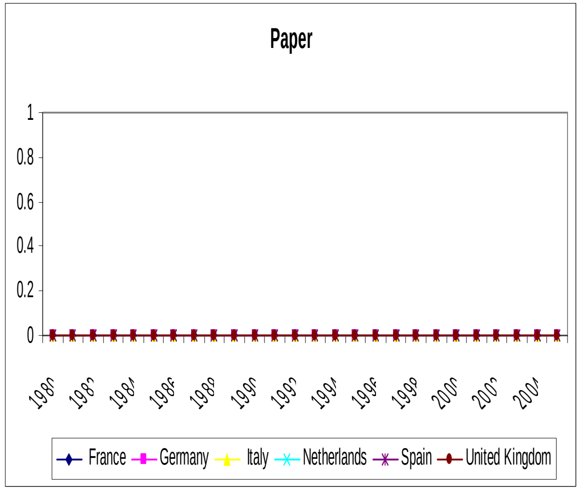
Manufacturing nec



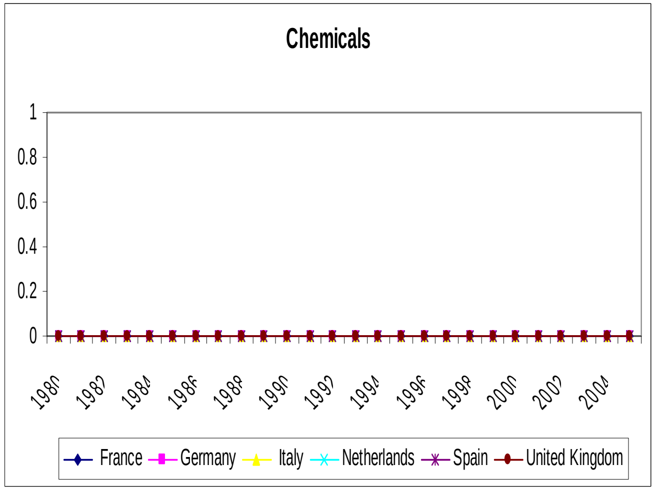
Wood



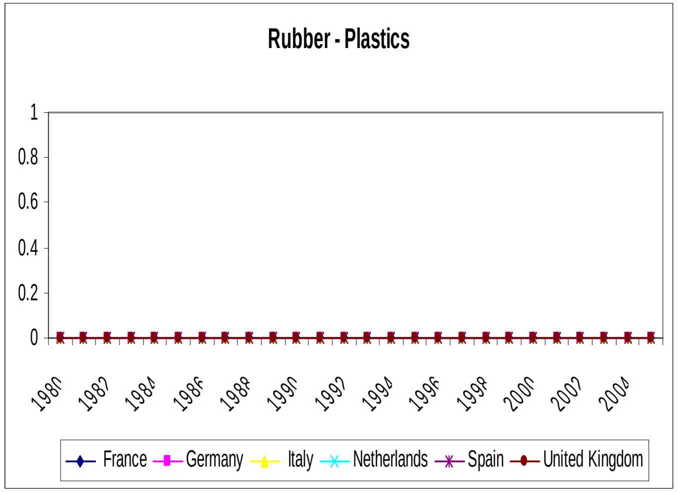
Paper



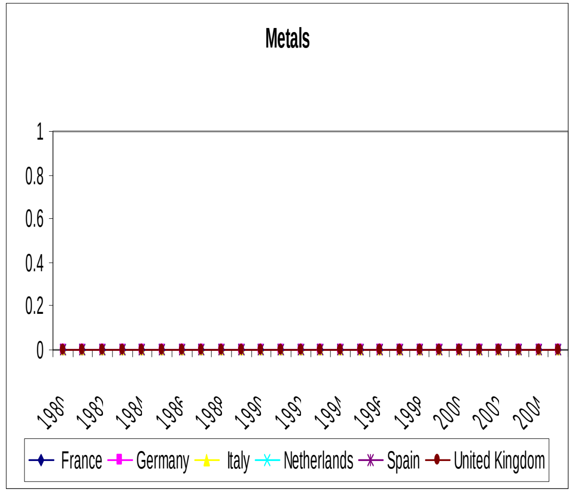
Chemicals



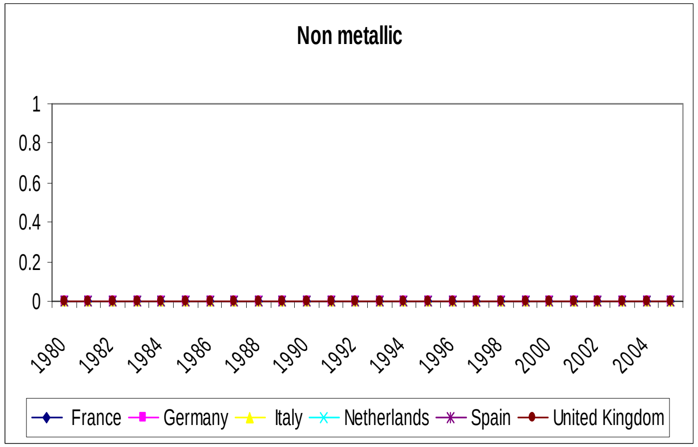
Rubber - Plastics



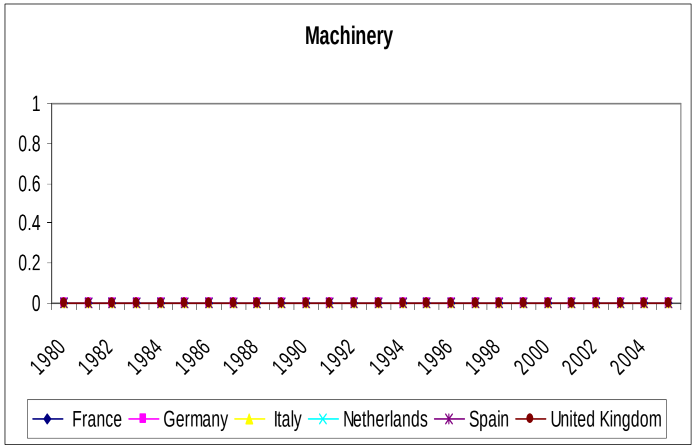
Metals



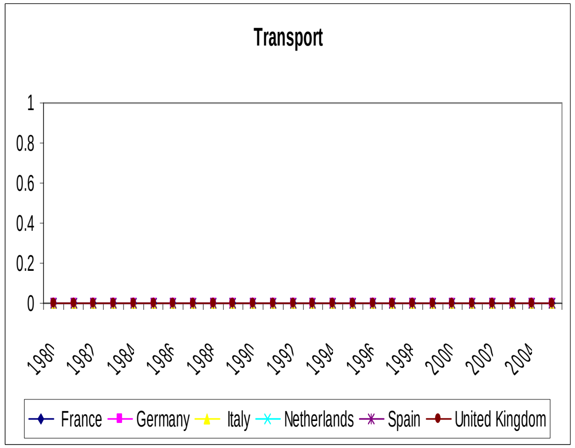
Non-metallic



Machinery



Transport equipment

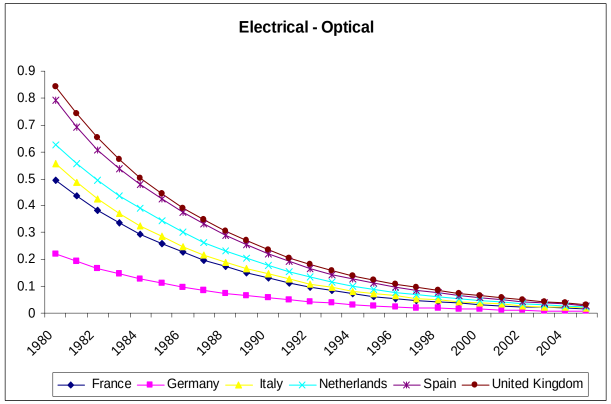


Source: Own estimation

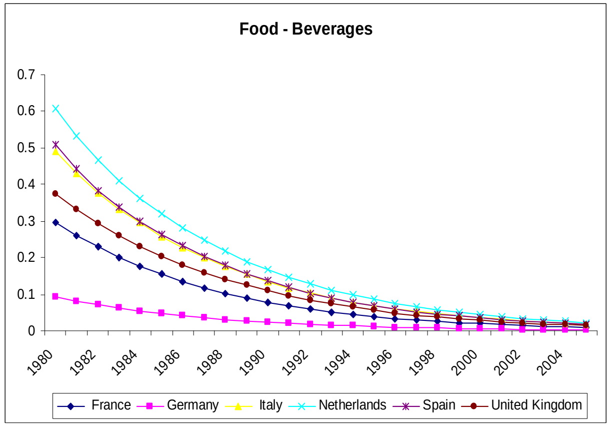
Model (6) does not produce any reliable results.

Figure A6. Inefficiency Analysis per Industry and country 7

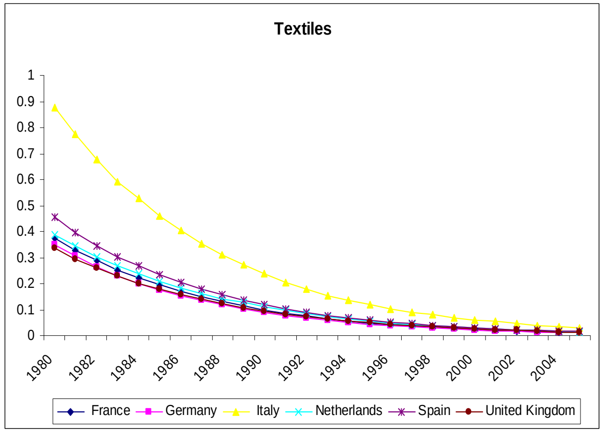
Electrical - Optical



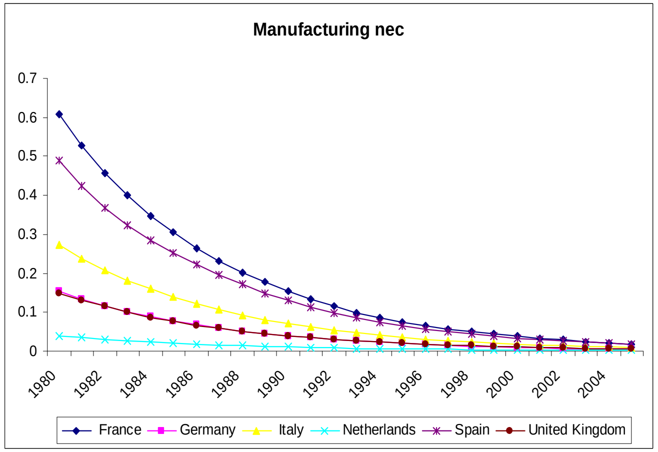
Food - Beverages



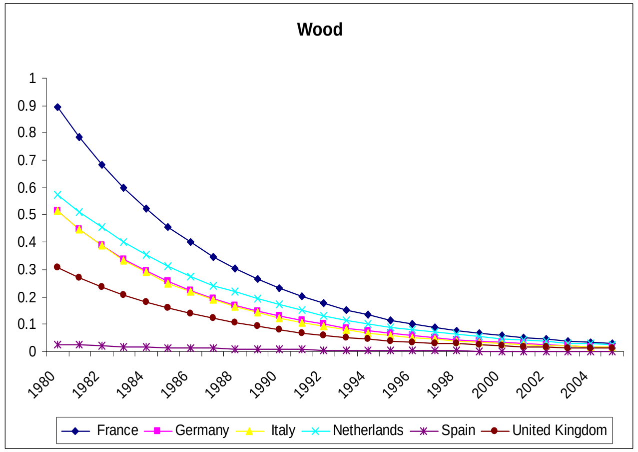
Textiles



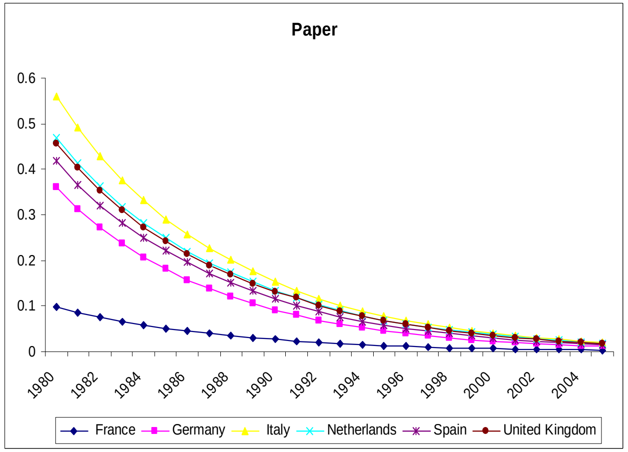
Manufacturing nec



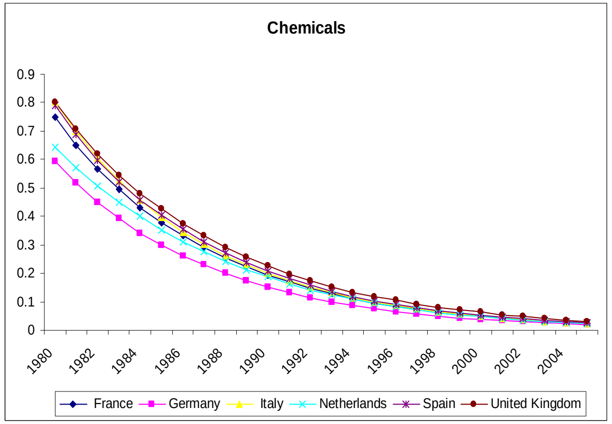
Wood



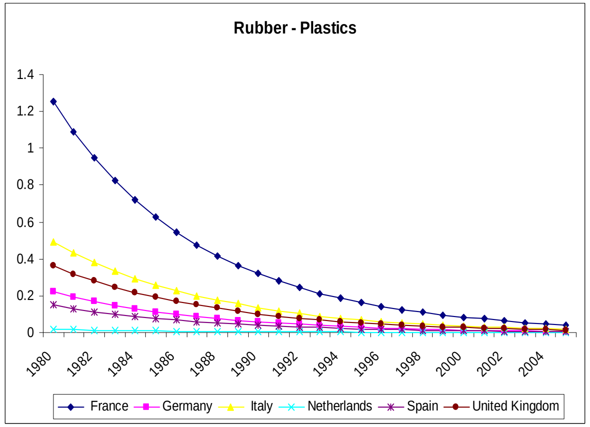
Paper



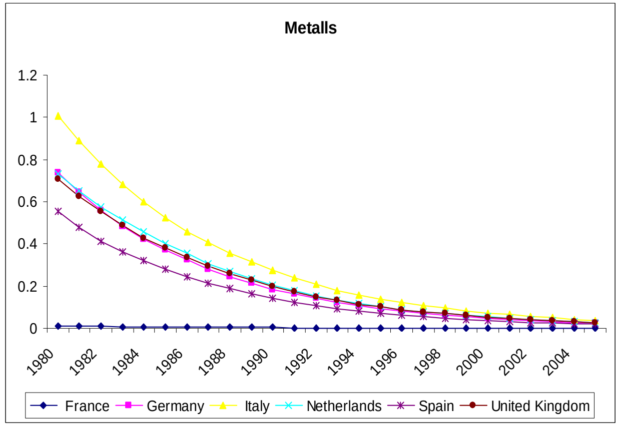
Chemicals



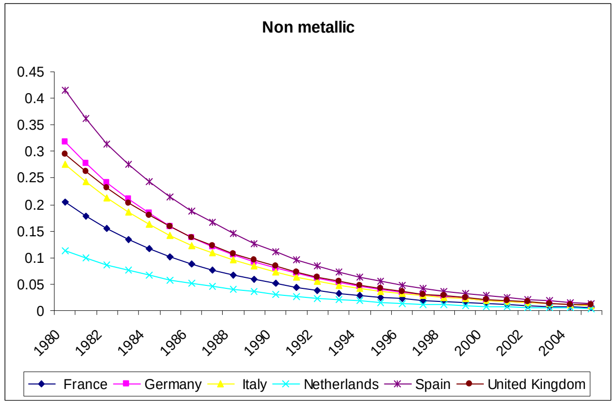
Rubber - Plastics



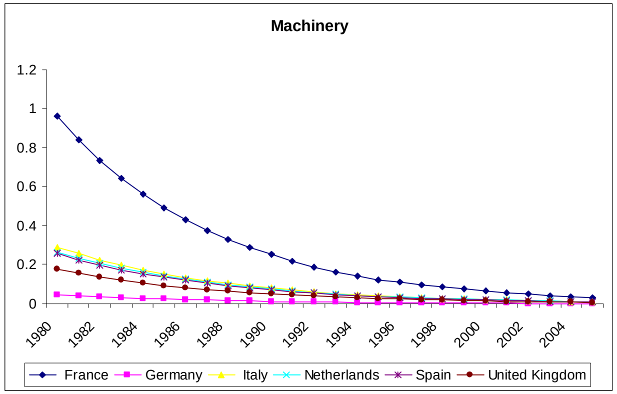
Metals



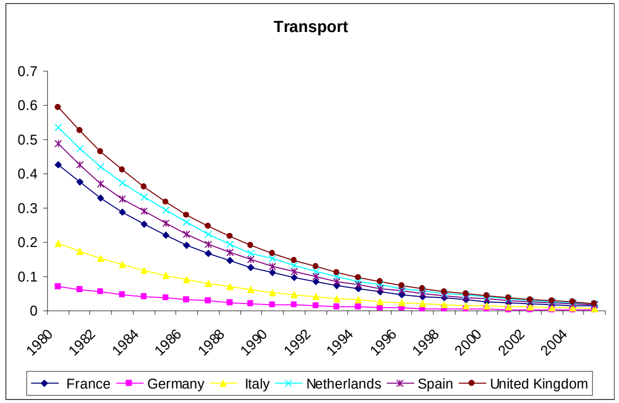
Non-metallic



Machinery



Transport equipment

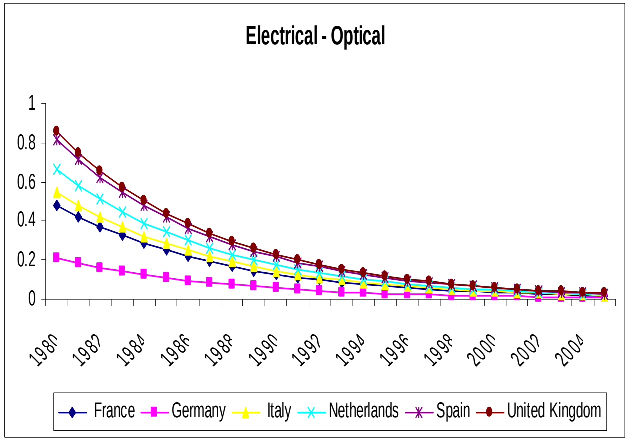


Source: Own estimation

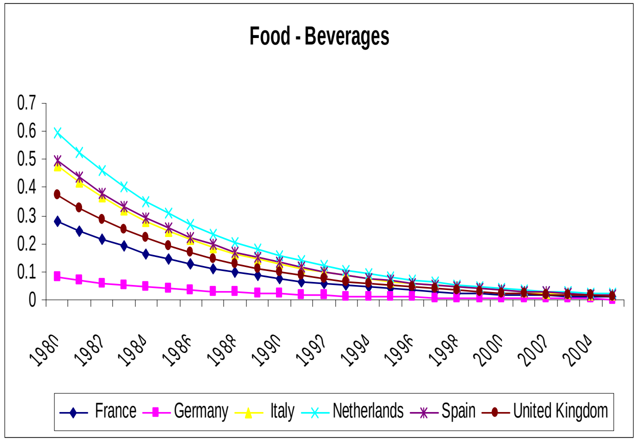
Model (7) presents also time variant inefficiency. The inefficiency level decreases over time in all the industries and countries. with Italy and France presenting the higher efficiency improvement.

Figure A7. Inefficiency Analysis per Industry and country – Model 8

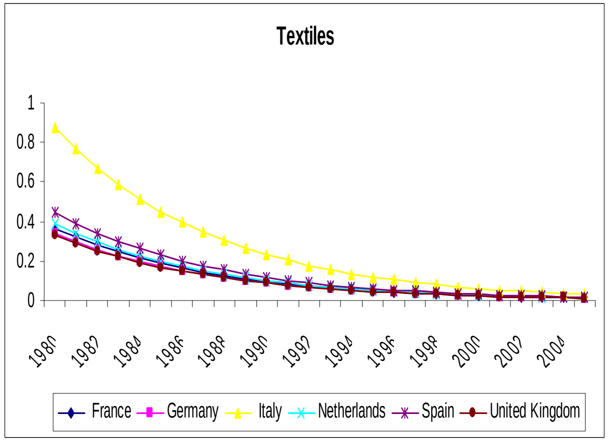
Electrical - Optical



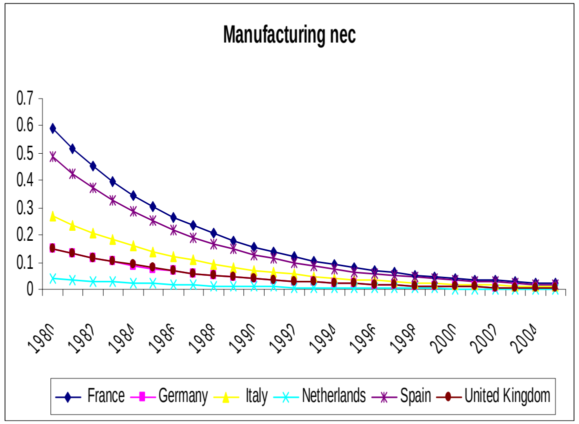
Food - Beverages



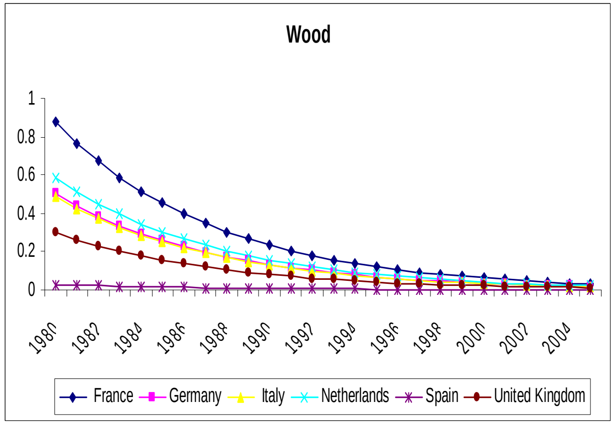
Textiles



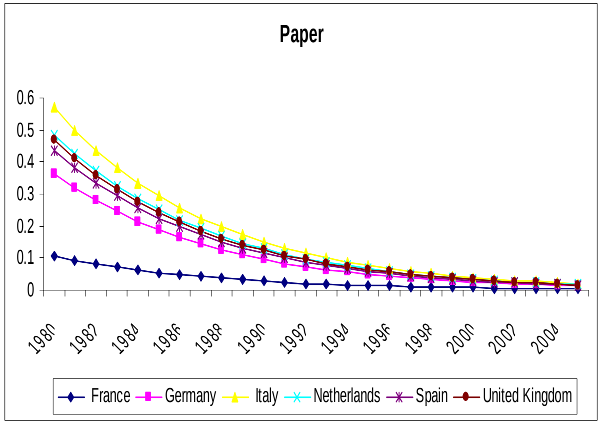
Manufacturing nec



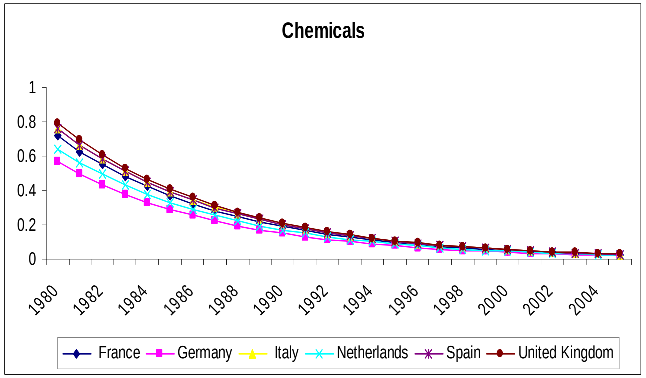
Wood



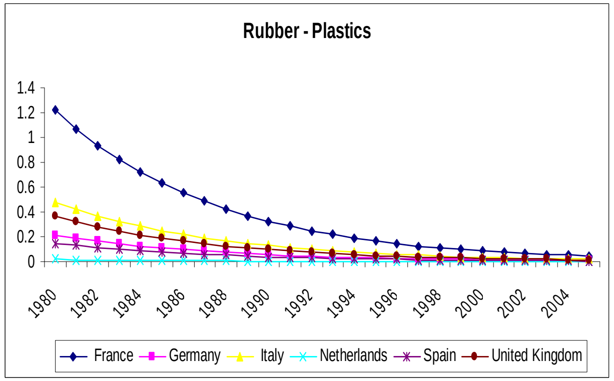
Paper



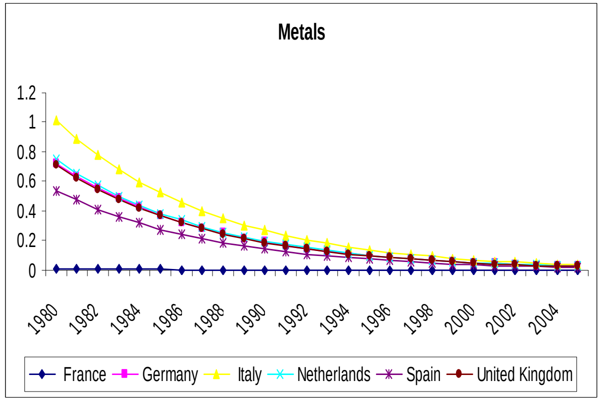
Chemicals



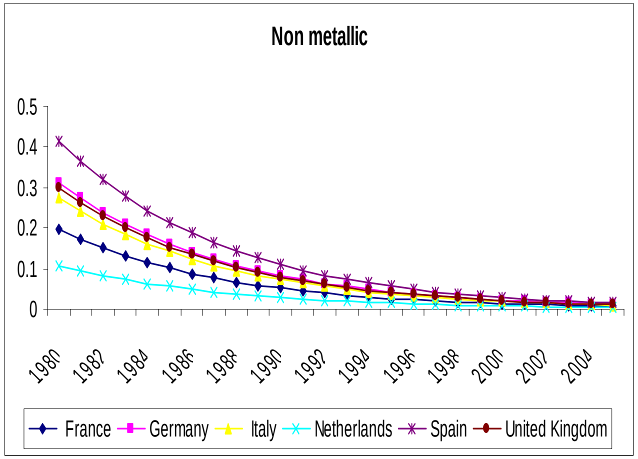
Rubber - Plastics



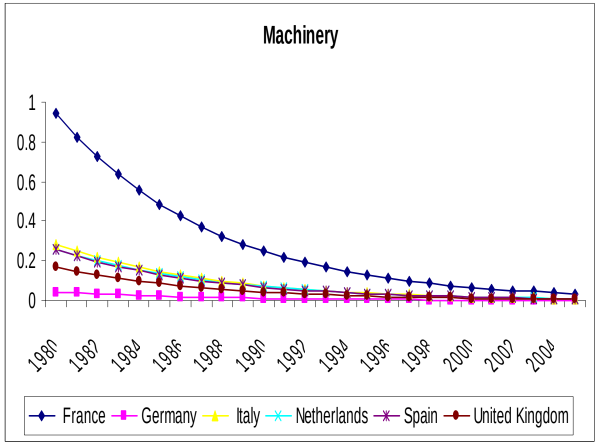
Metals



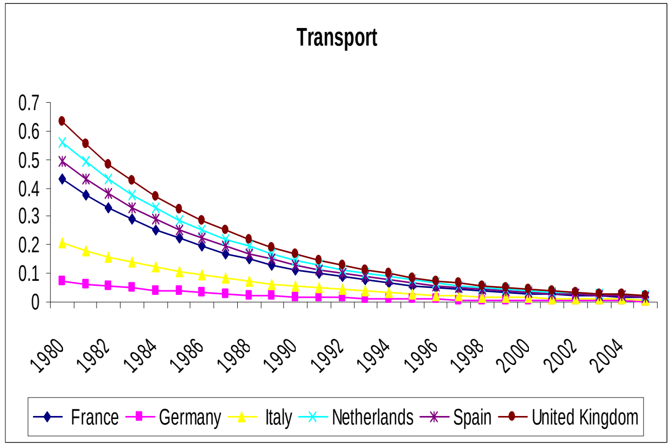
Non-metallic



Machinery



Transport equipment

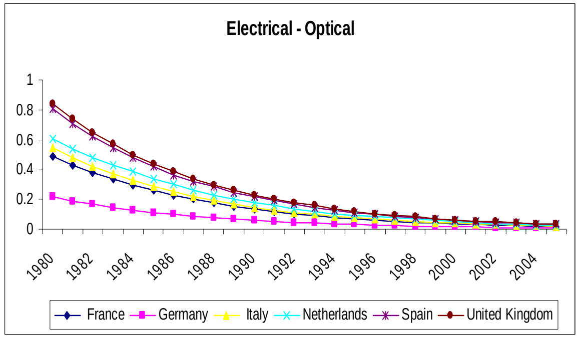


Source: Own estimation

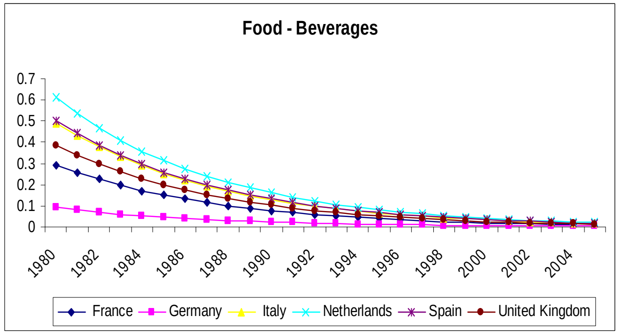
Model (8) presents also similar picture with time variant inefficiency and the inefficiency level decreasing over time in all the industries and countries.

Figure A8. Inefficiency Analysis per Industry and country – Model 9

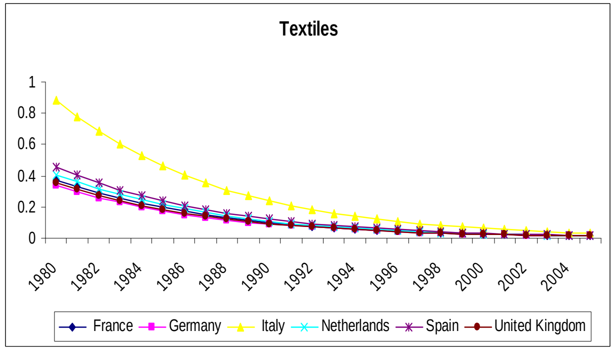
Electrical - Optical



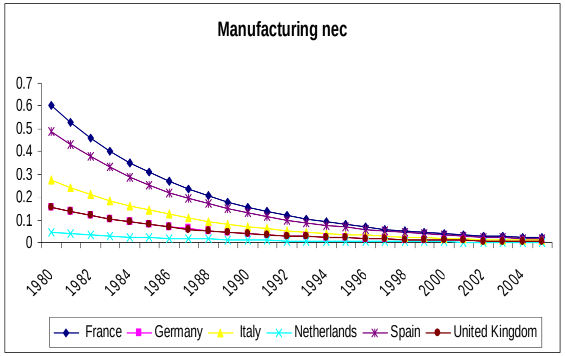
Food - Beverages



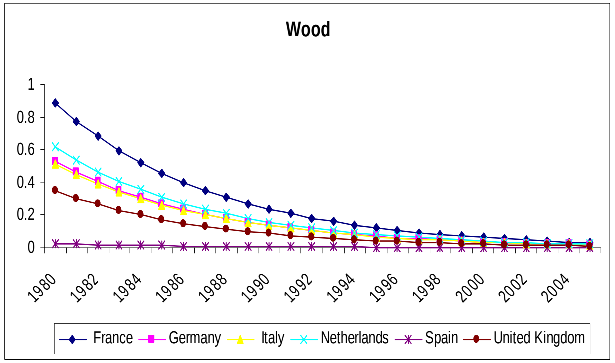
Textiles



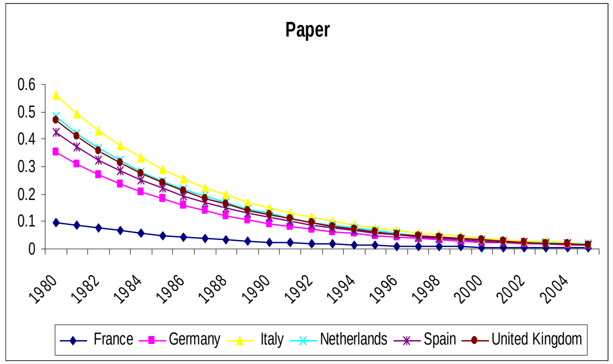
Manufacturing nec



Wood



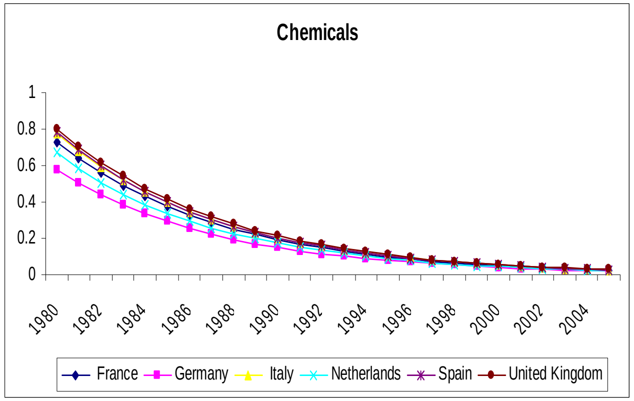
Paper

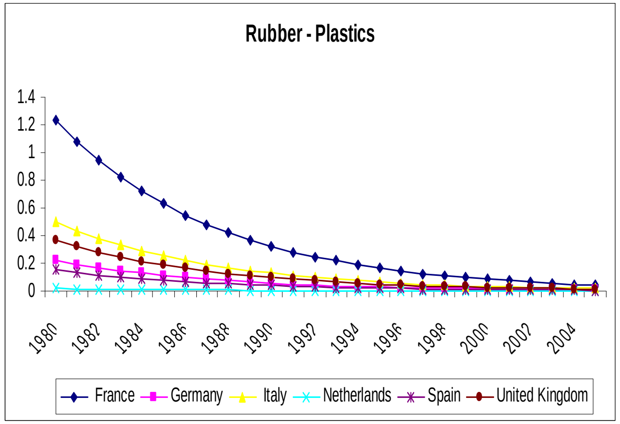


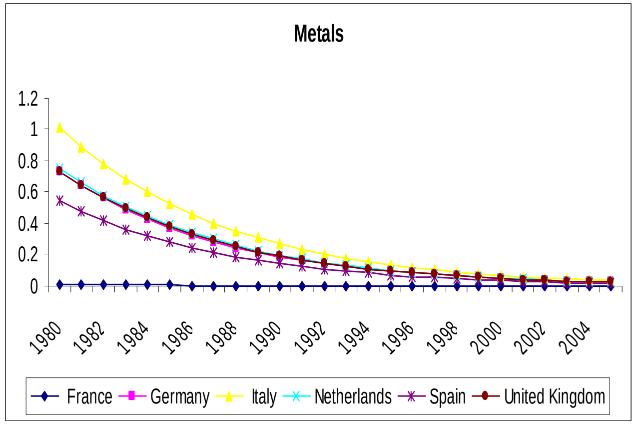
Chemicals

Rubber - Plastics

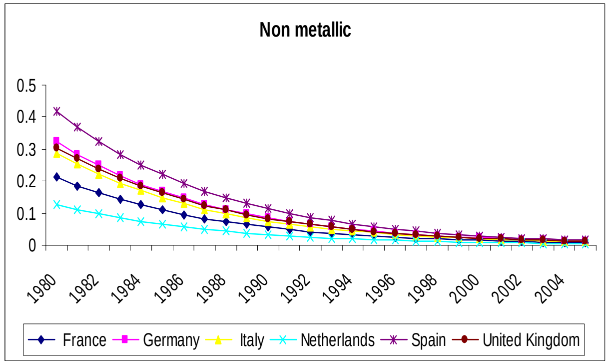
Metals



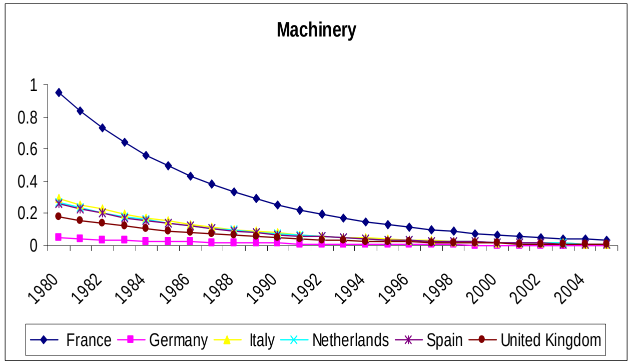




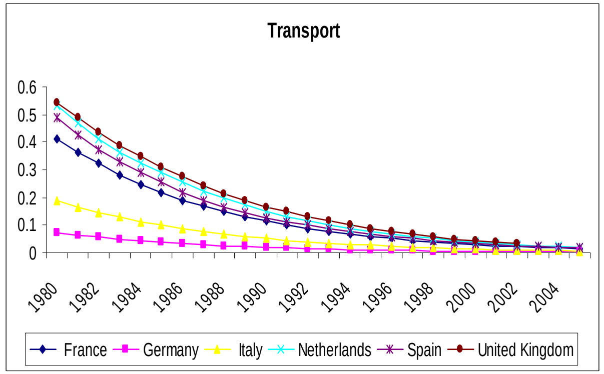
Non-metallic



Machinery



Transport equipment

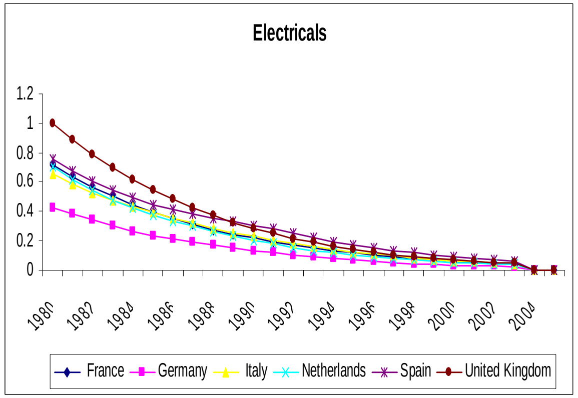


Source: Own estimation

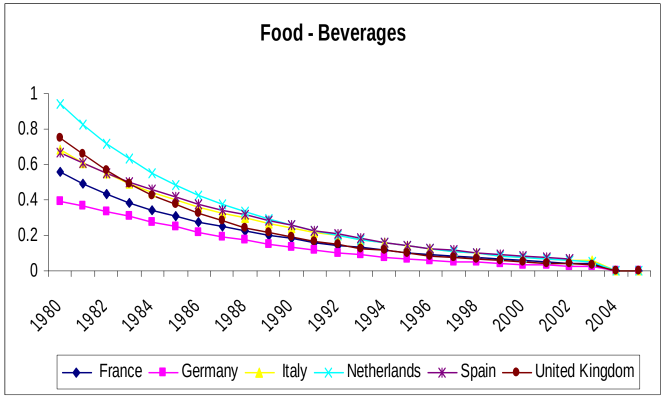
Model (9) presents also similar picture with time variant inefficiency and the inefficiency level decreasing over time in all the industries and countries with Italy. France and Spain presenting the higher efficiency improvement.

Figure A9. Inefficiency Analysis per Industry and country – Model 10

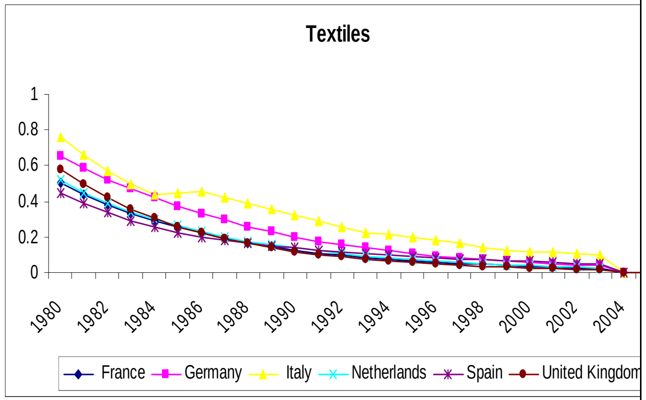
Electrical - Optical



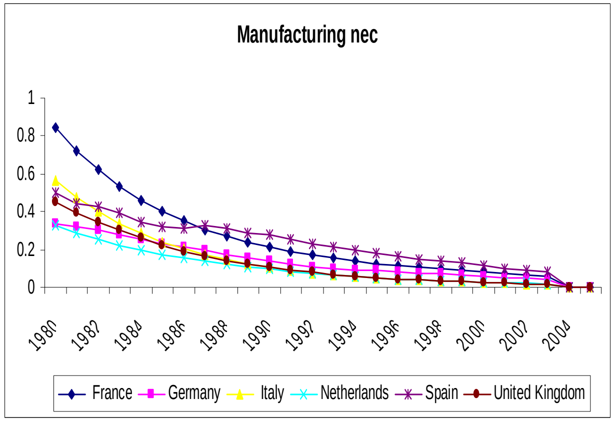
Food - Beverages



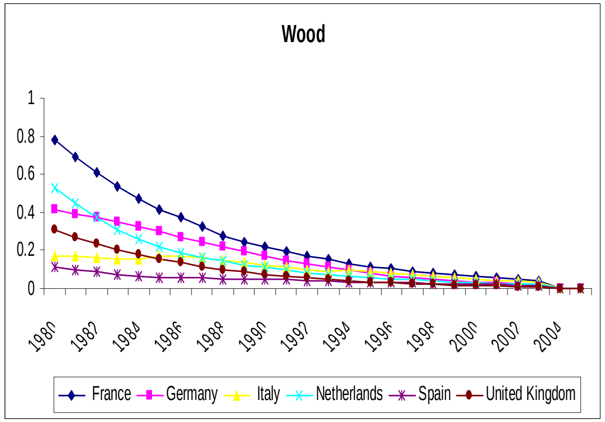
Textiles



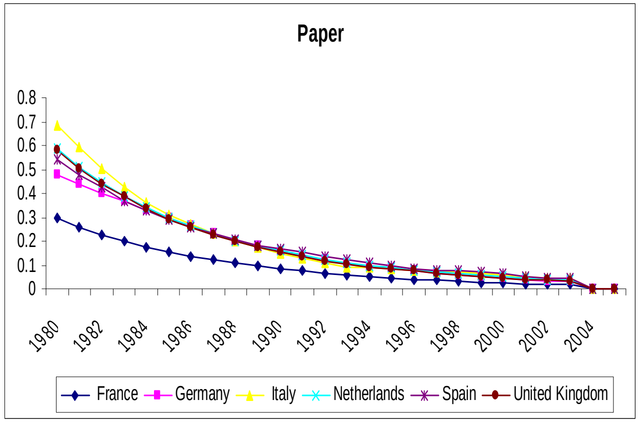
Manufacturing nec



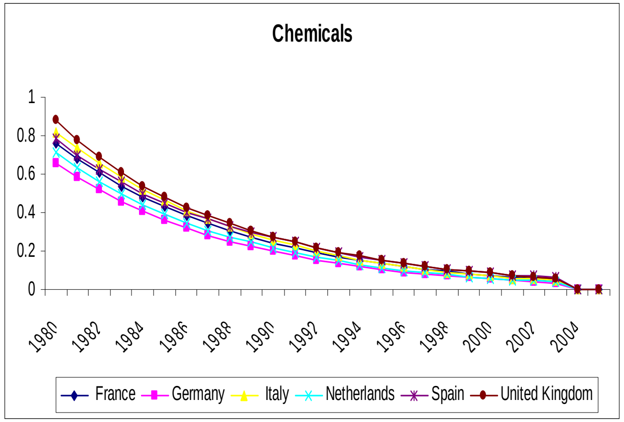
Wood

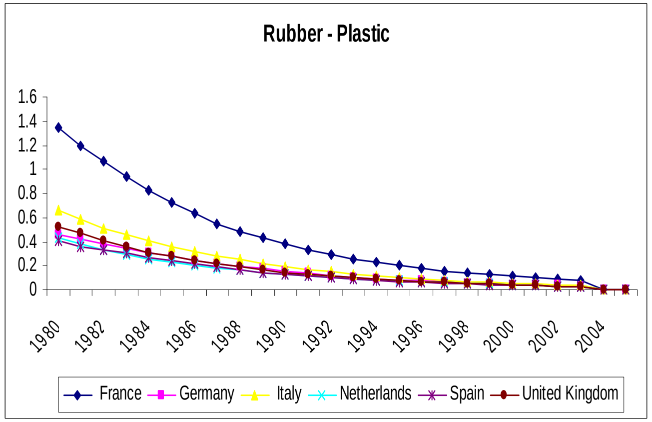


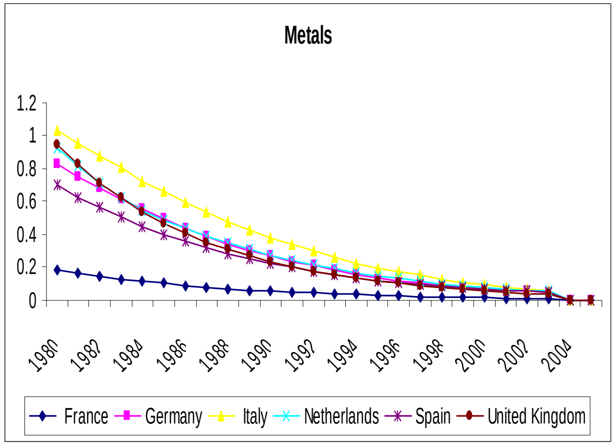
Paper



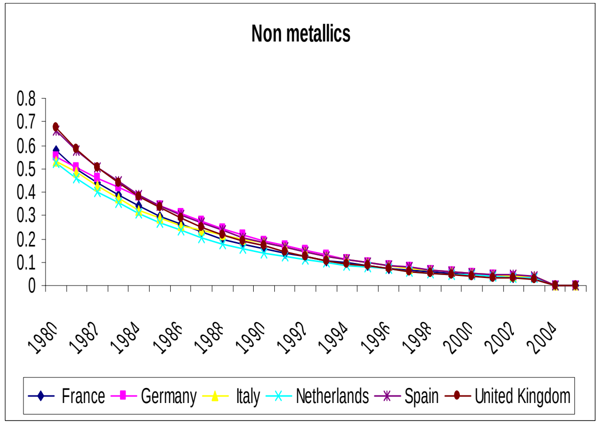
Chemicals	Rubber - Plastics	Metals

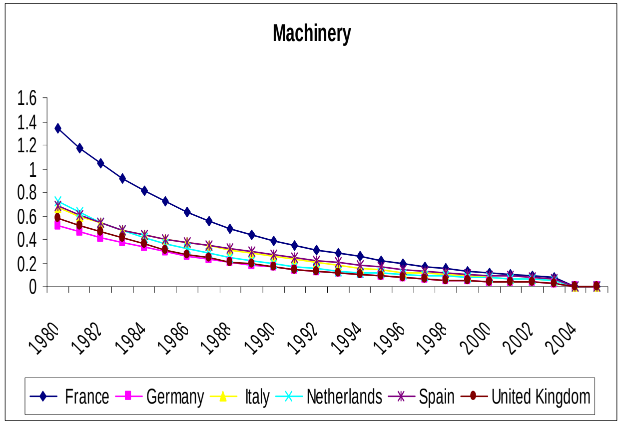


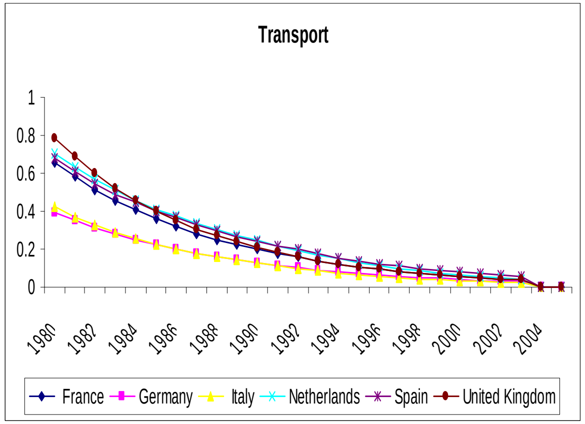




Non-metallic	Machinery	Transport equipment



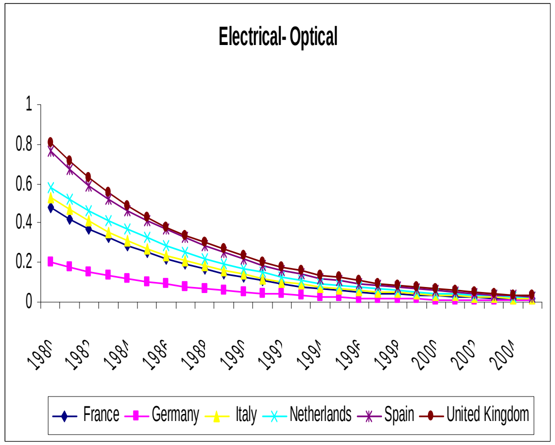
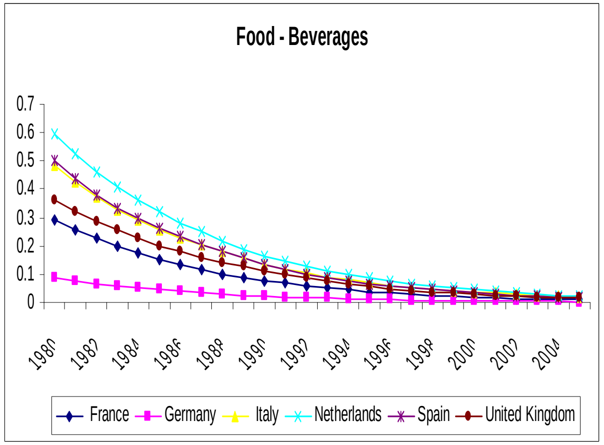
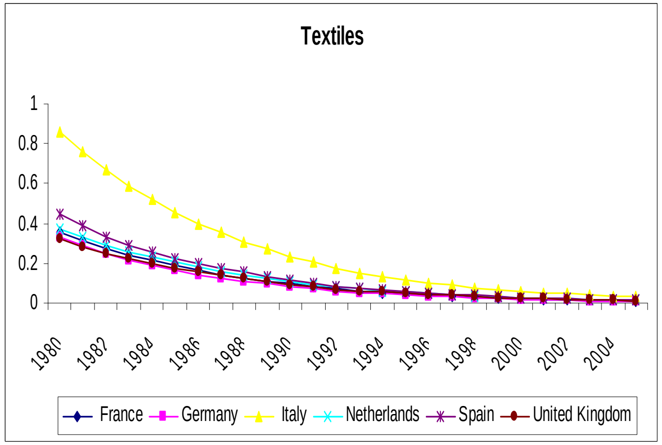


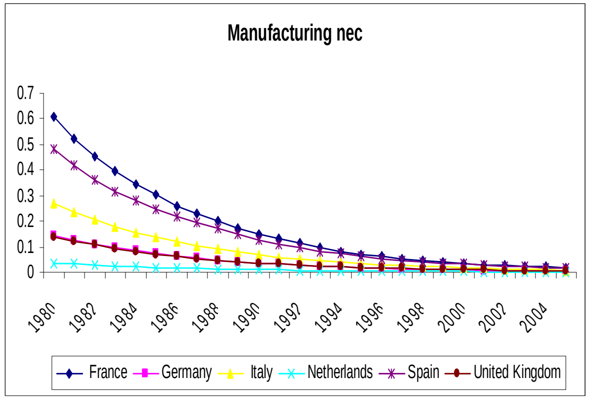
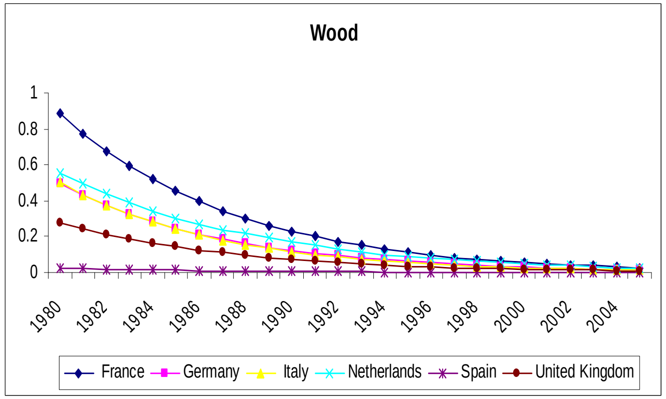
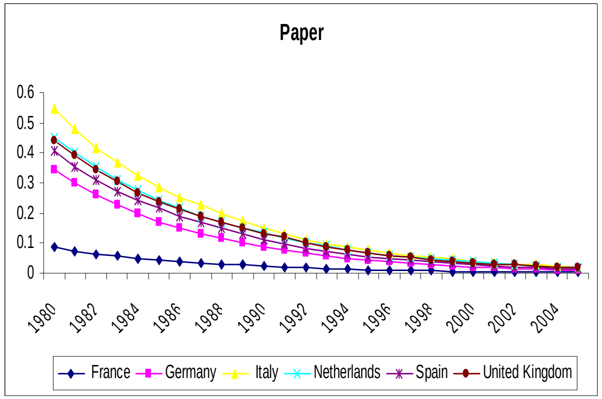


Source: Own estimation

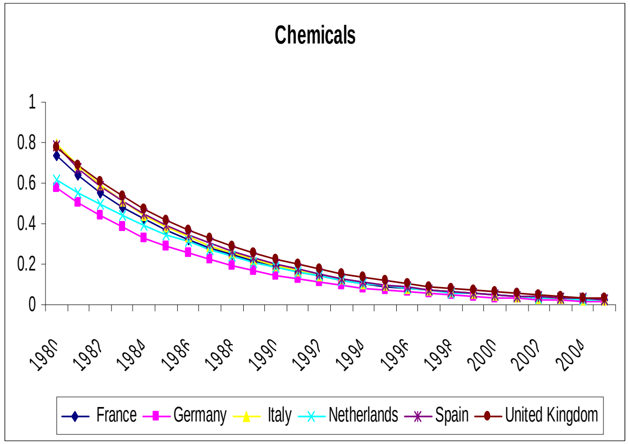
Model (10) presents time variant inefficiency. The inefficiency level decreases over time in all the industries and countries. with almost all the countries and industries experience inefficiency decreasing progress.

Figure A10. Inefficiency Analysis per Industry and country – Model 11

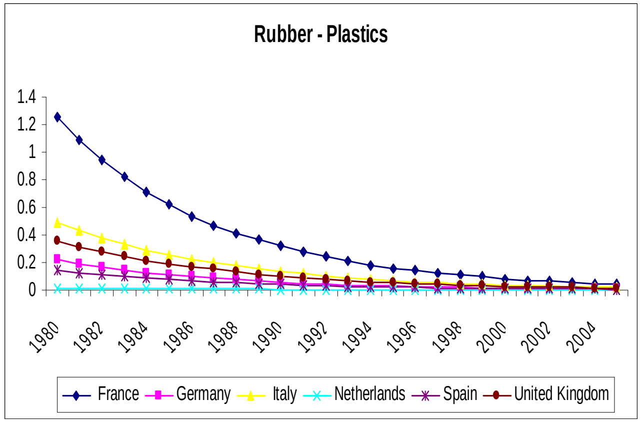
Electrical - Optical	Food - Beverages	Textiles
		

Manufacturing nec	Wood	Paper
		

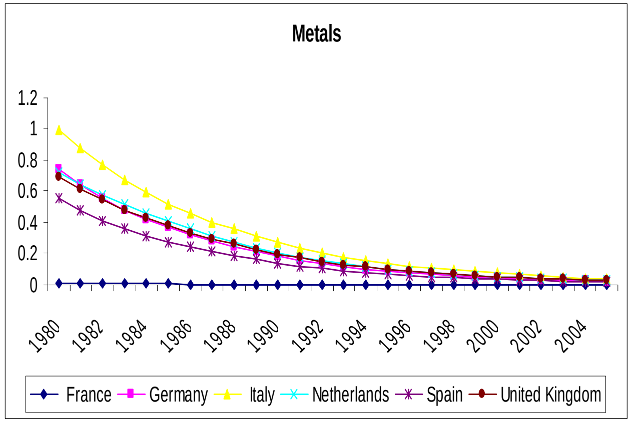
Chemicals



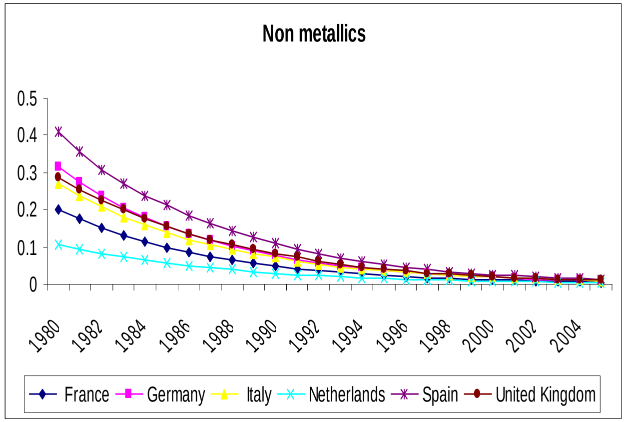
Rubber - Plastics



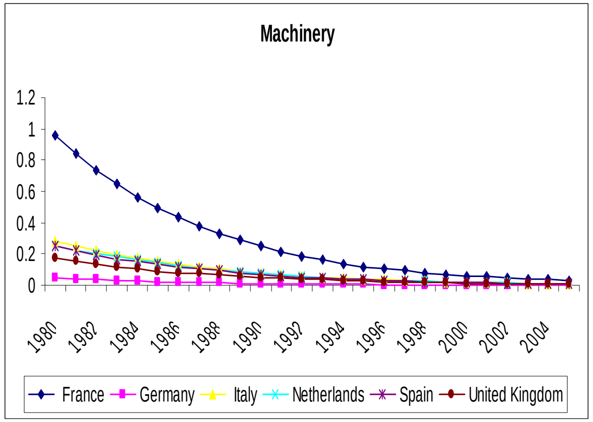
Metals



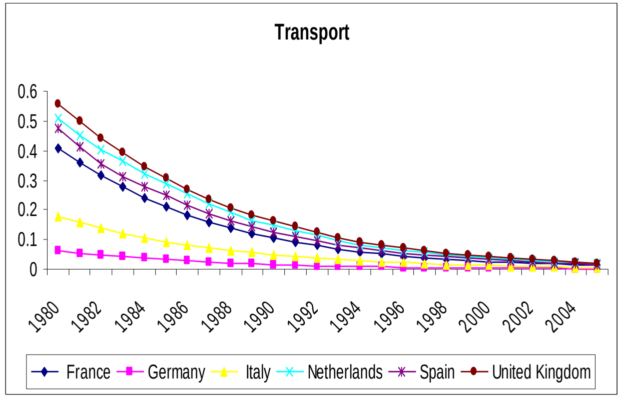
Non-metallic



Machinery



Transport equipment

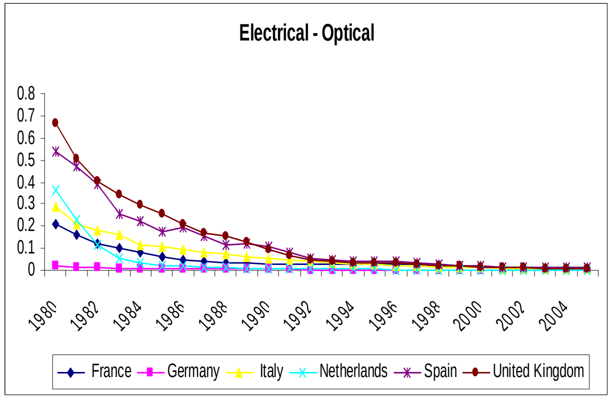


Source: Own estimation

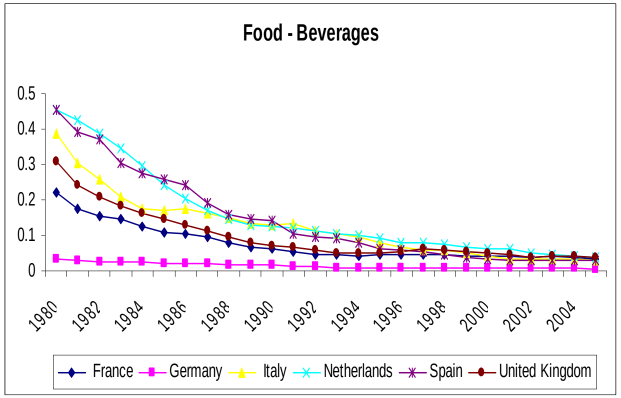
Model (11) presents time variant inefficiency. The inefficiency level decreases over time in all the industries and countries. with United Kingdom. Italy and France presenting the higher efficiency improvement.

Figure A11. Inefficiency Analysis per Industry and country – Model 12

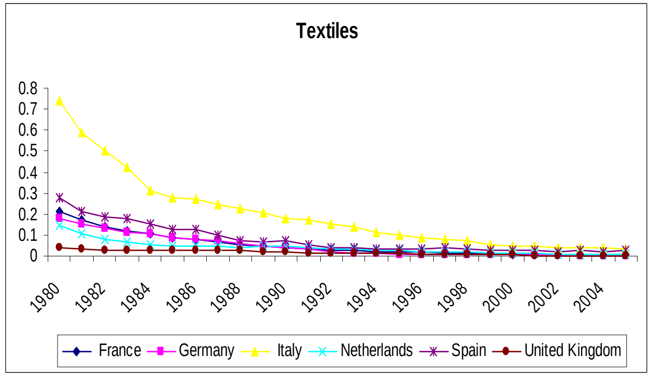
Electrical - Optical



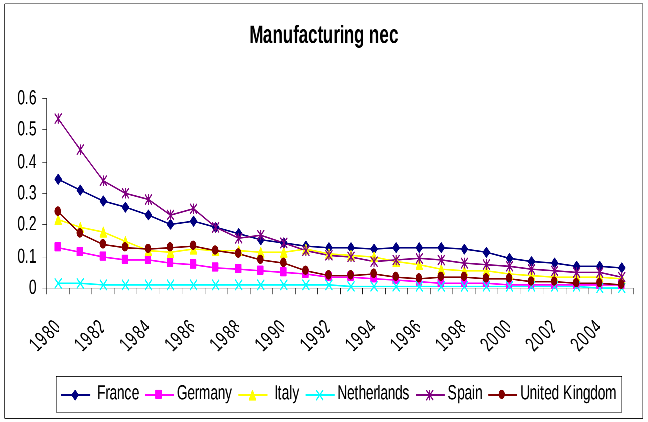
Food - Beverages



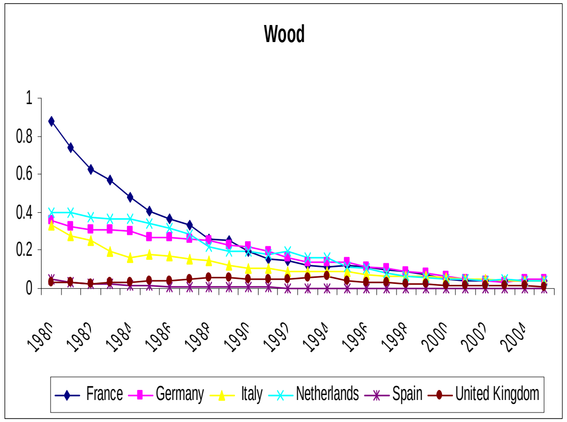
Textiles



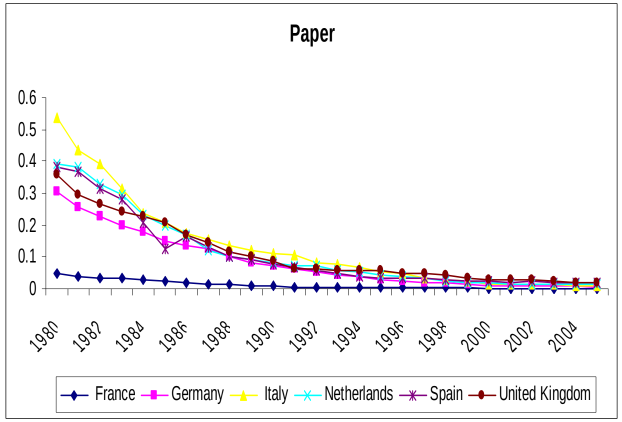
Manufacturing nec



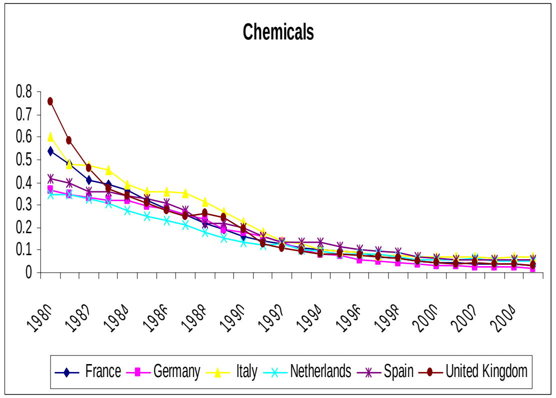
Wood



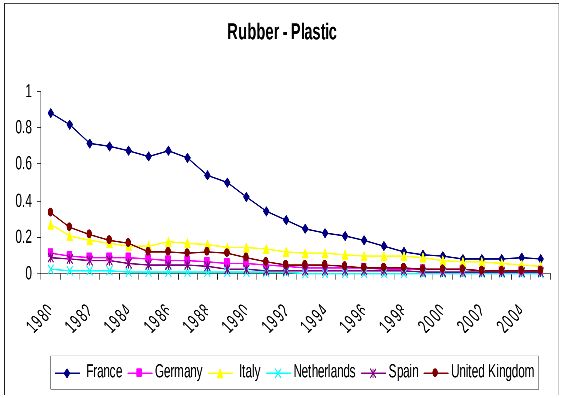
Paper



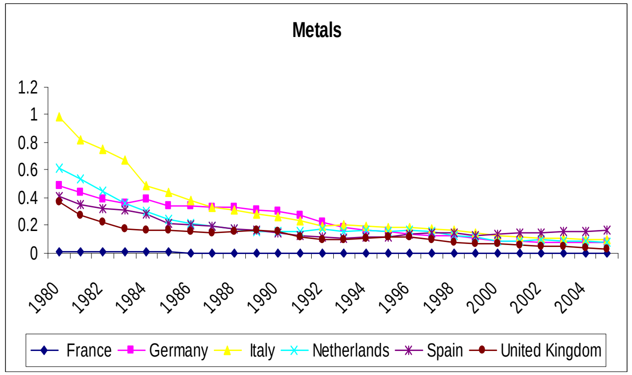
Chemicals



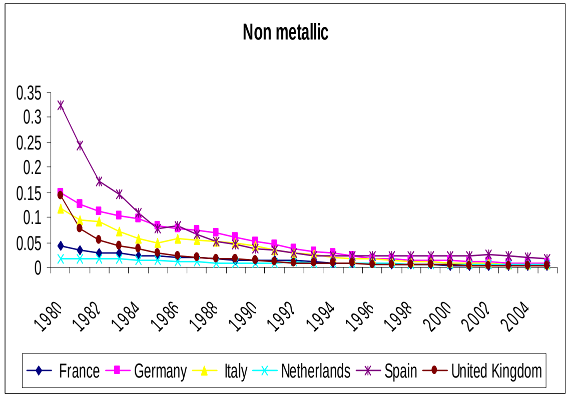
Rubber - Plastics



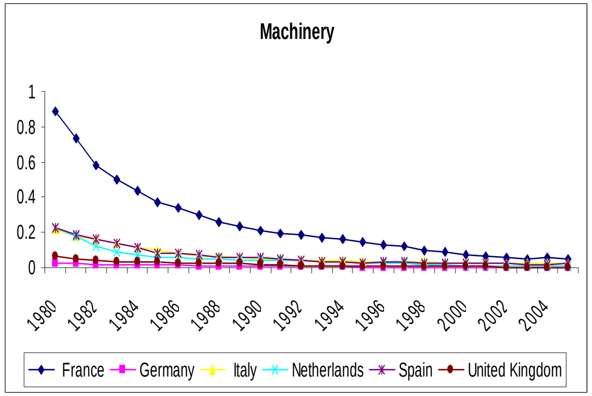
Metals



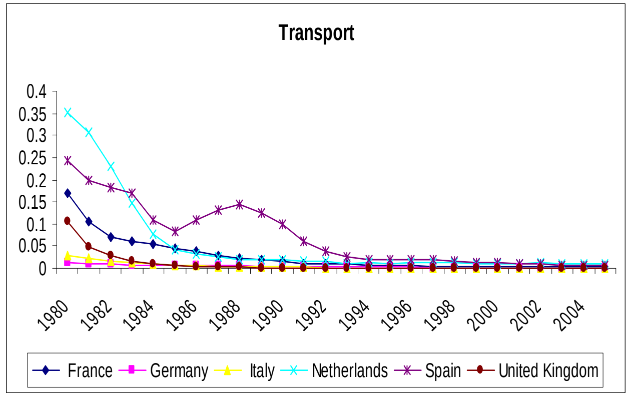
Non-metallic



Machinery



Transport equipment

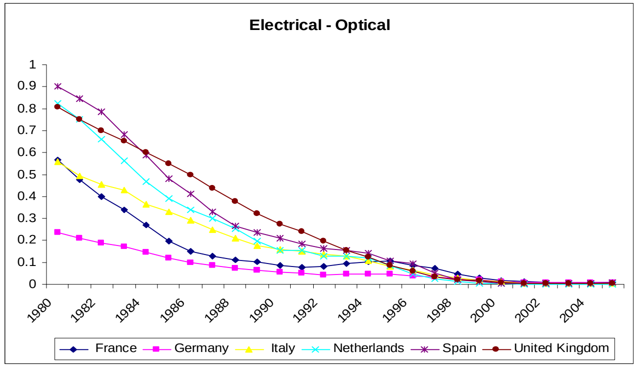


Source: Own estimation

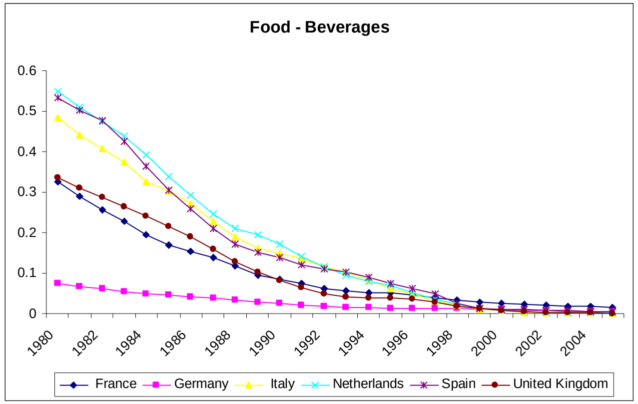
Model (12) presents time variant inefficiency. Even though not rather smooth. the inefficiency level decreases over time in all the industries and countries.

Figure A12. Inefficiency Analysis per Industry and country – Model 13

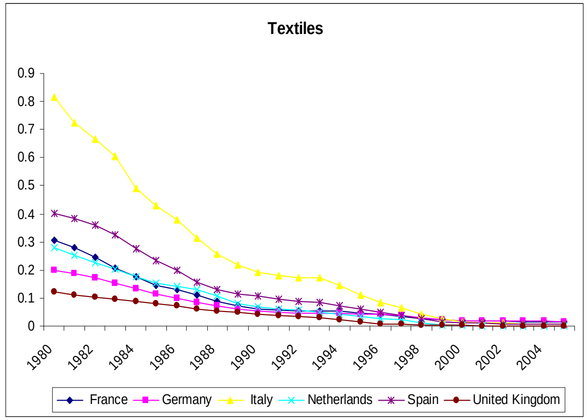
Electrical - Optical



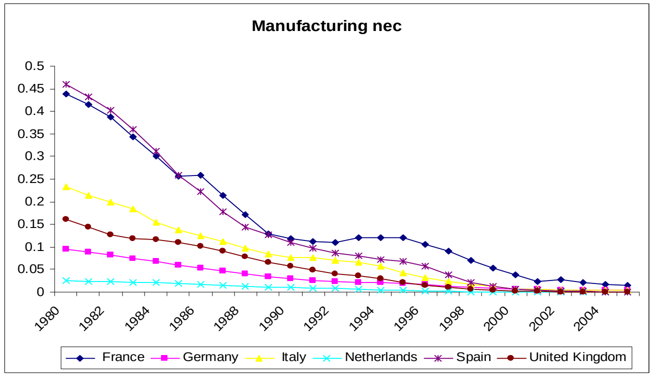
Food - Beverages



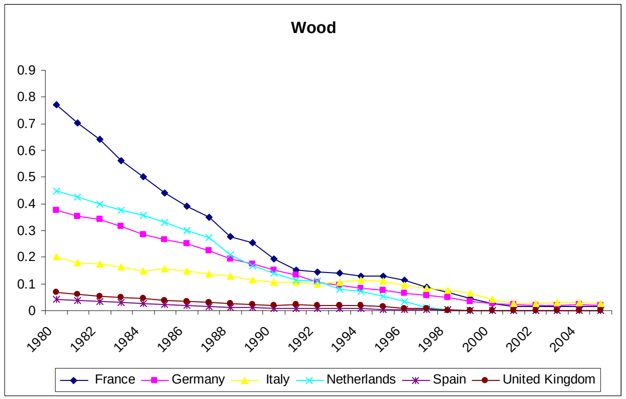
Textiles



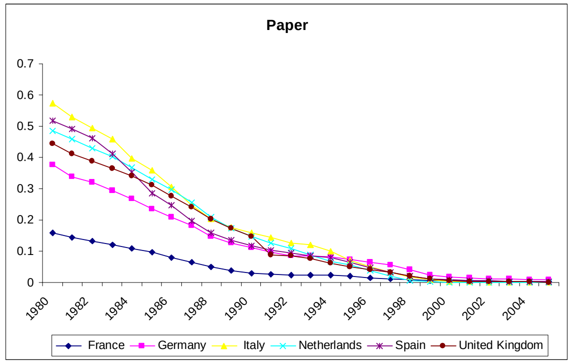
Manufacturing nec



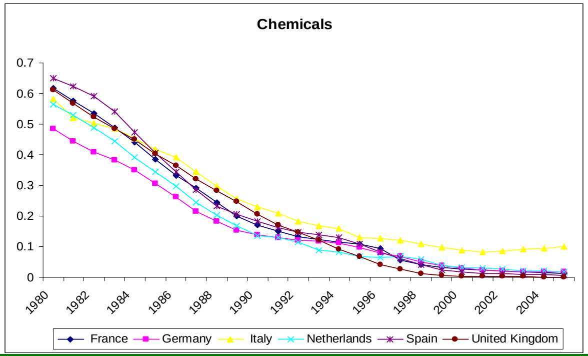
Wood

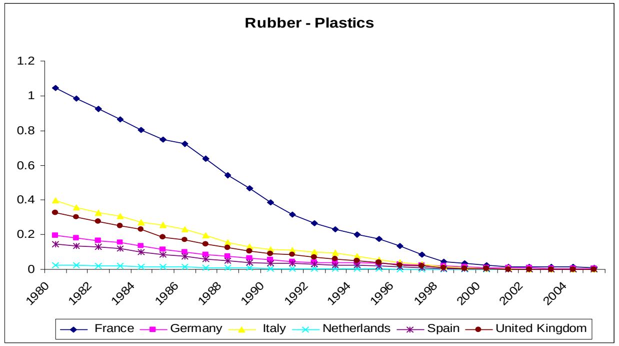


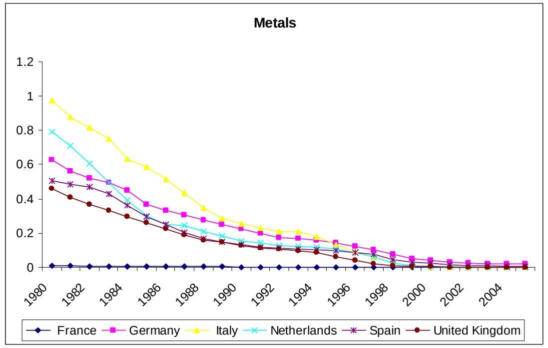
Paper



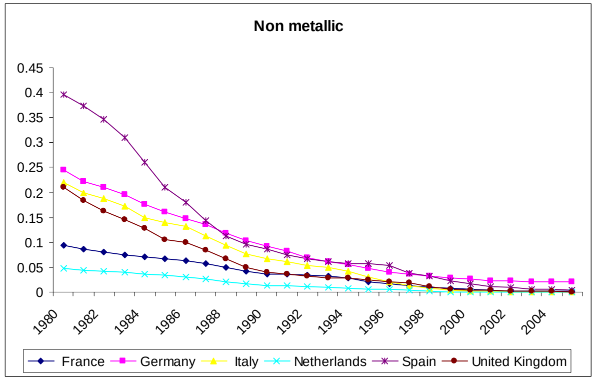
Chemicals	Rubber - Plastics	Metals

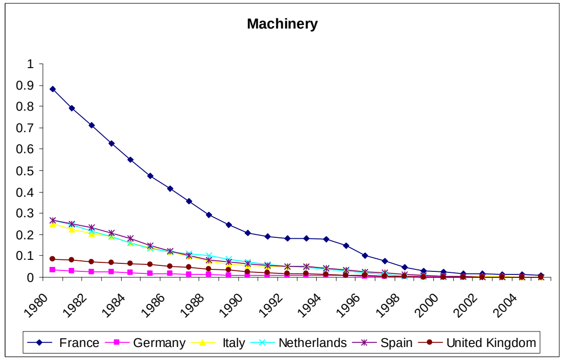


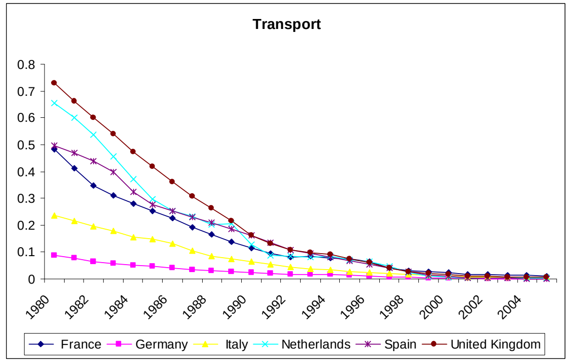




Non-metallic	**Machinery**	**Transport equipment**





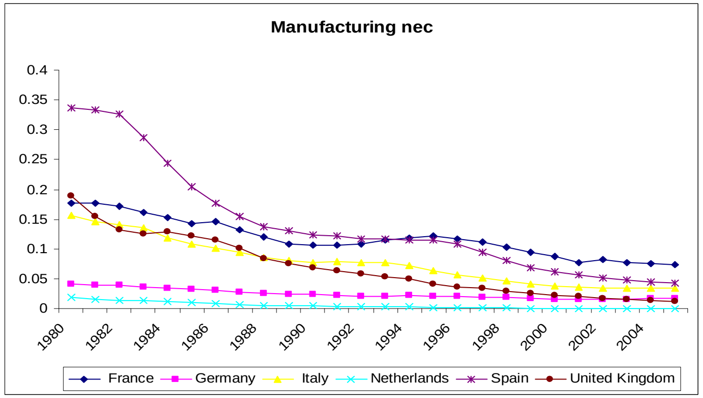


Source: Own estimation

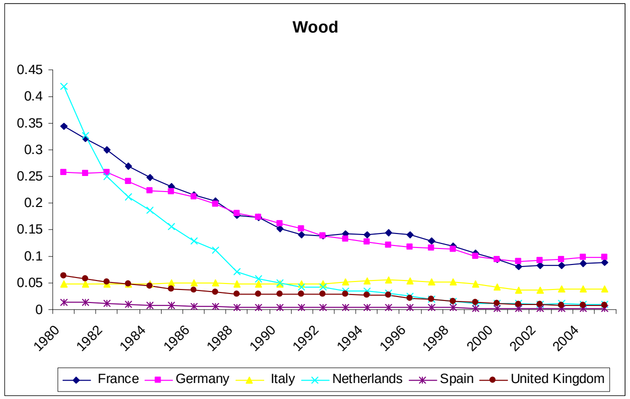
Model (13) presents time variant inefficiency. The inefficiency level decreases over time in all the industries and countries. with Italy and France presenting the higher efficiency improvement.

Figure A13. Inefficiency Analysis per Industry and country – Model 14

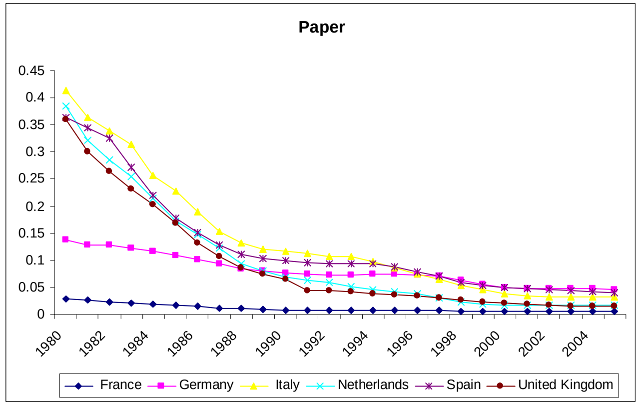
Manufacturing nec



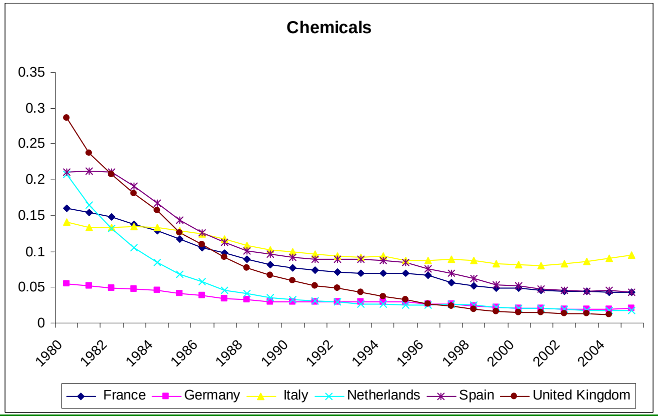
Wood



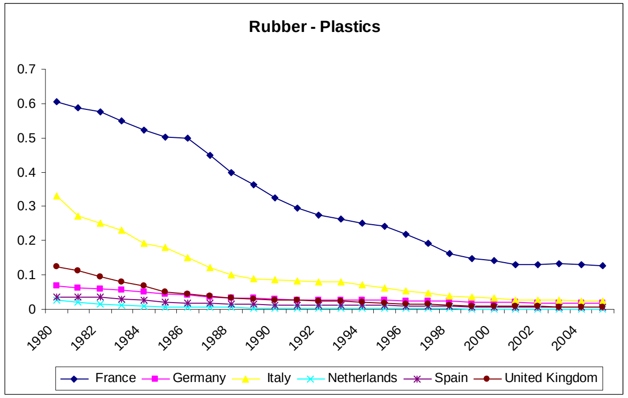
Paper



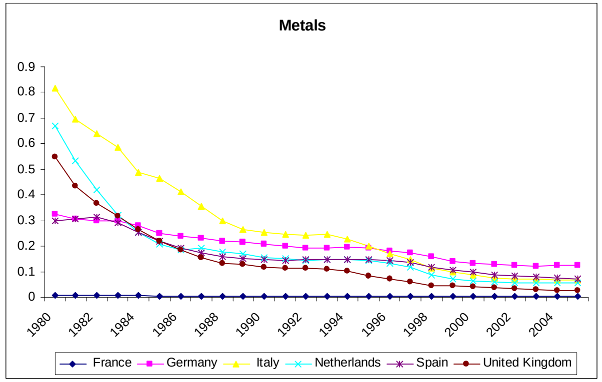
Chemicals

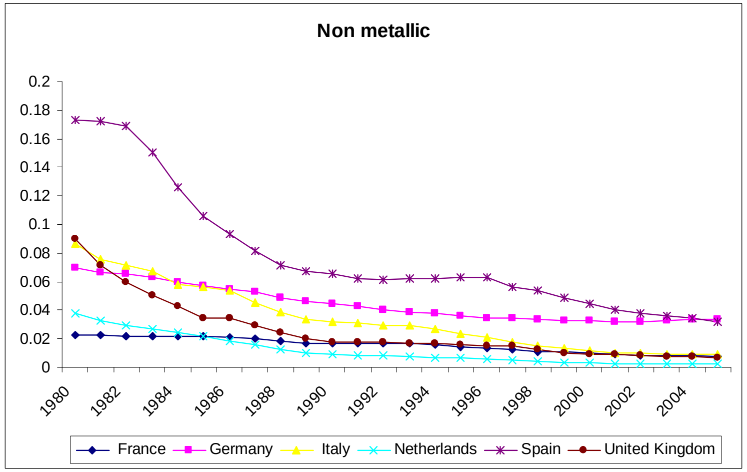
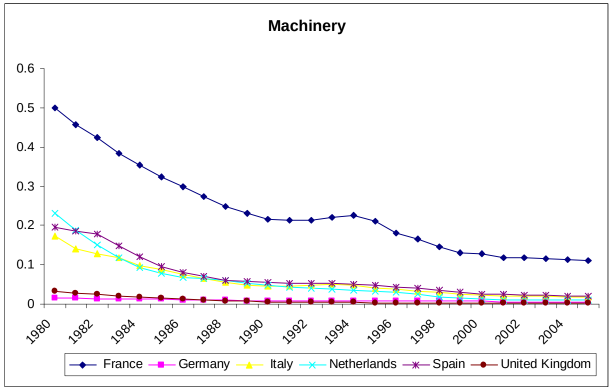
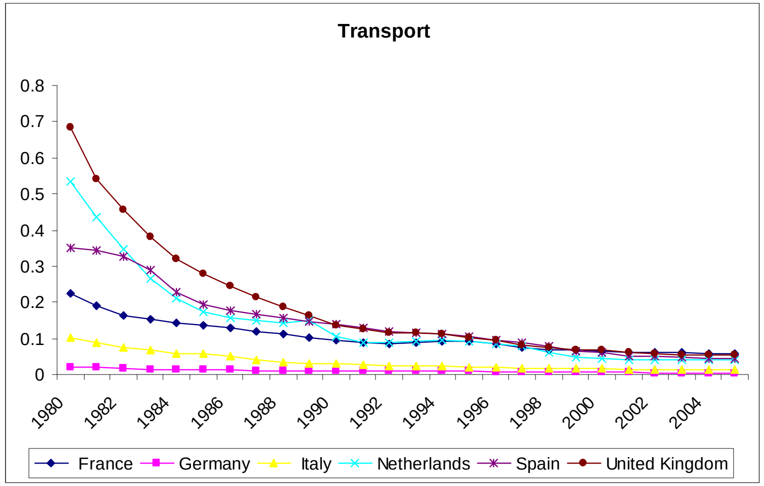


Rubber - Plastics



Metals



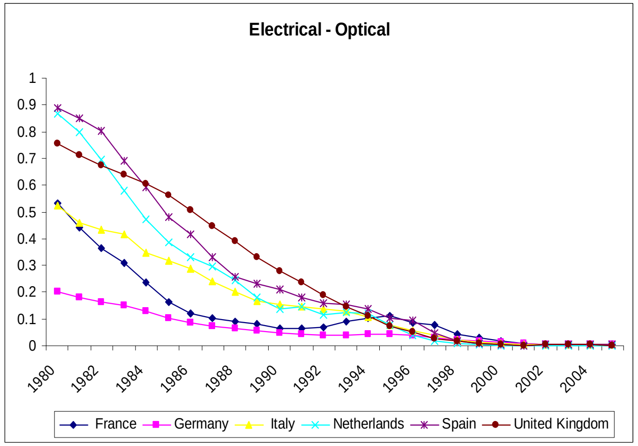
Non-metallic	Machinery	Transport equipment
		

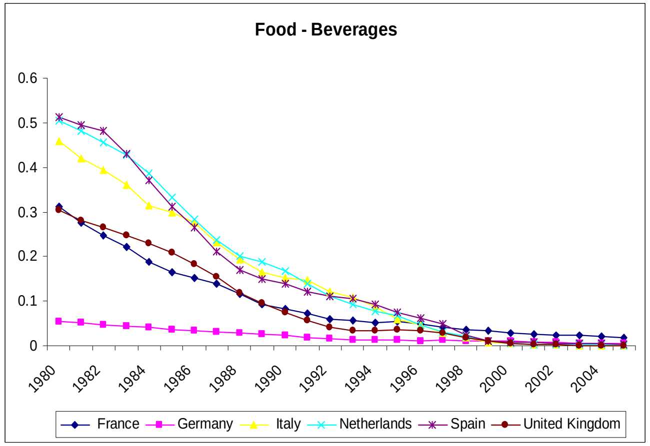
Source: Own estimation

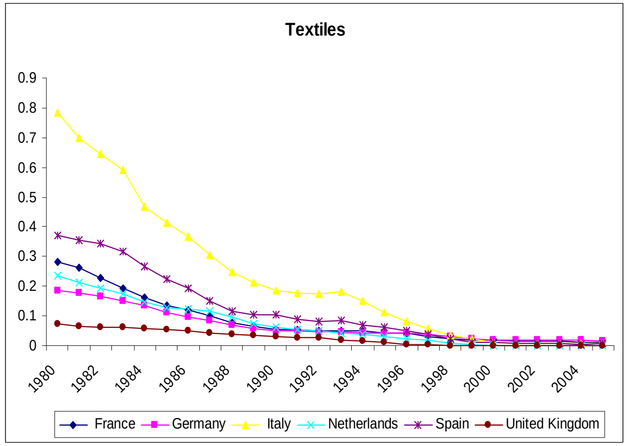
Model (14) presents time variant inefficiency. Even though with some inefficiency increases present in certain year and industries. the inefficiency level decreases over time in all the industries and countries. presenting overall higher efficiency improvement.

Figure A14. Inefficiency Analysis per Industry and country – Model 15

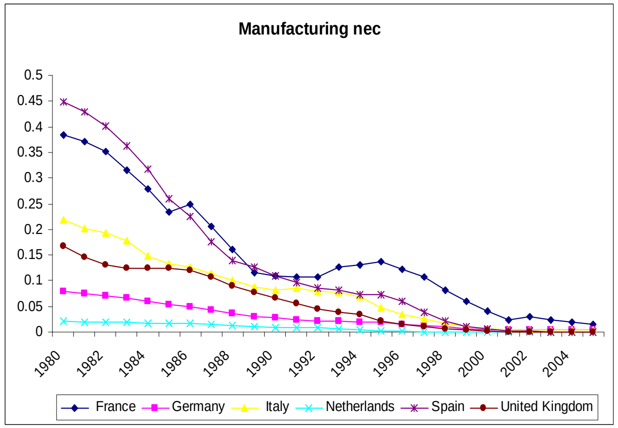
Electrical - Optical	Food - Beverages	Textiles

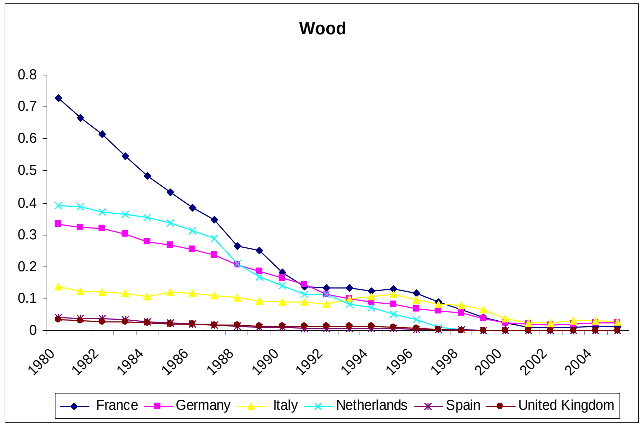


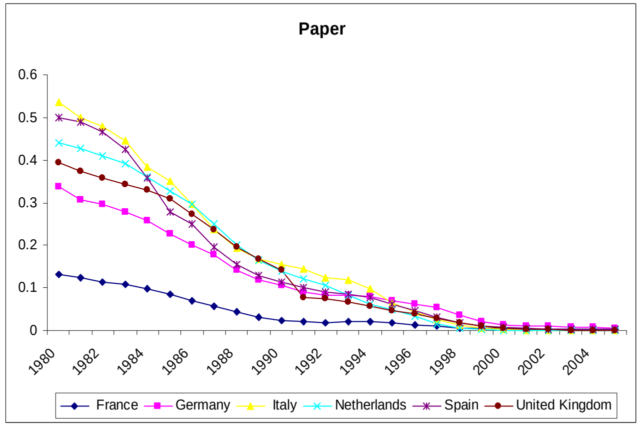


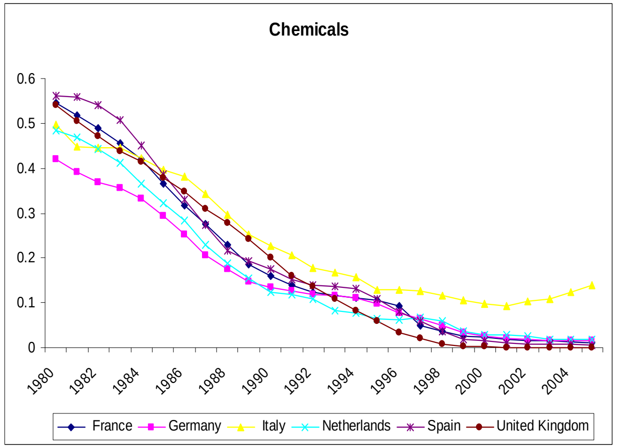
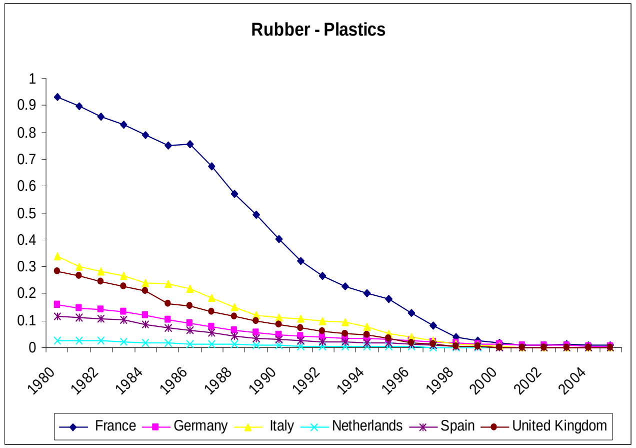
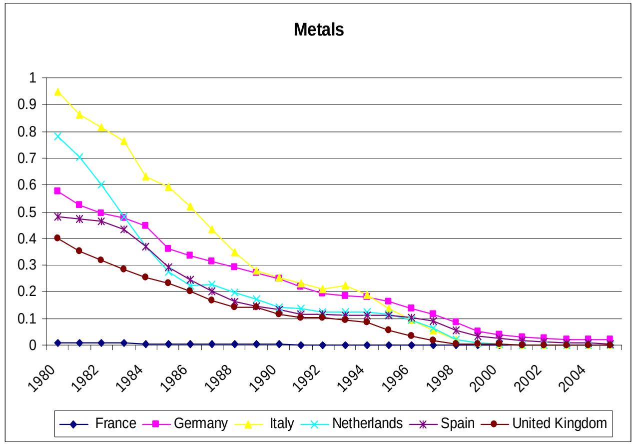


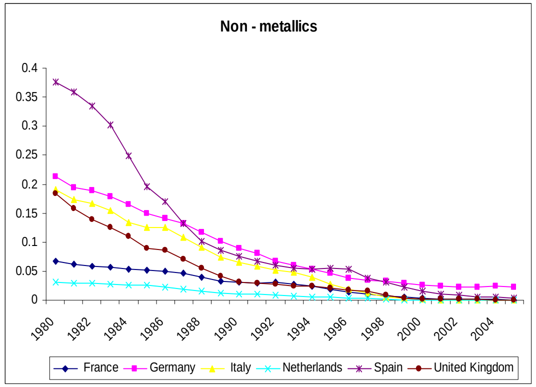
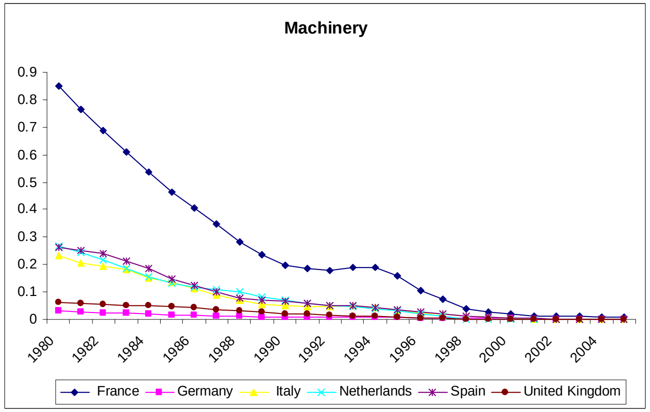
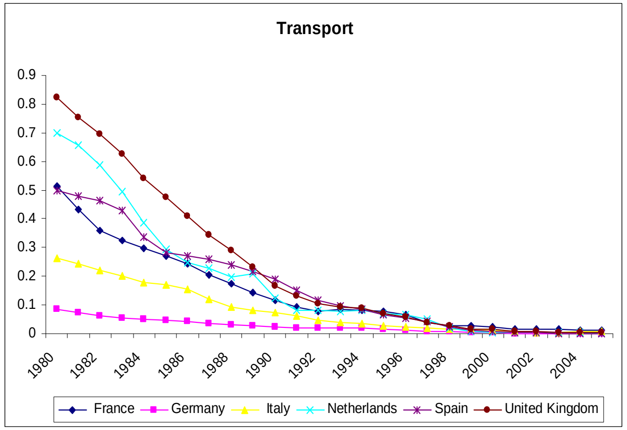
Manufacturing nec	Wood	Paper







Chemicals	Rubber - Plastics	Metals
		

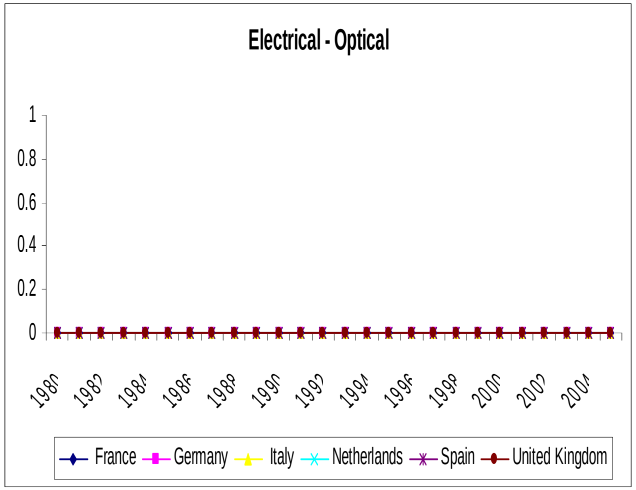
Non-metallic	**Machinery**	**Transport equipment**
		

Source: Own estimation

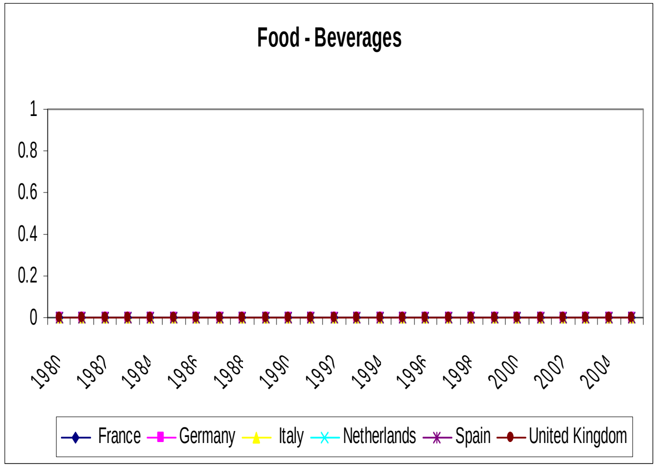
Similarly. model (15) presents time variant inefficiency. Even though with some inefficiency increases present in certain year and industries. the inefficiency level decreases over time in all the industries and countries. presenting overall higher efficiency improvement.

Figure A15. Inefficiency Analysis per Industry and country – Model 16

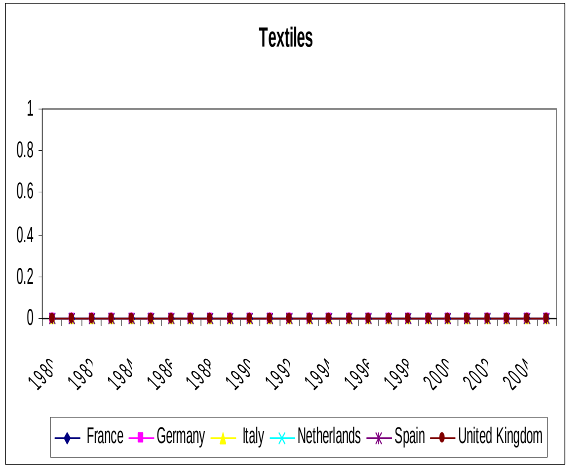
Electrical - Optical



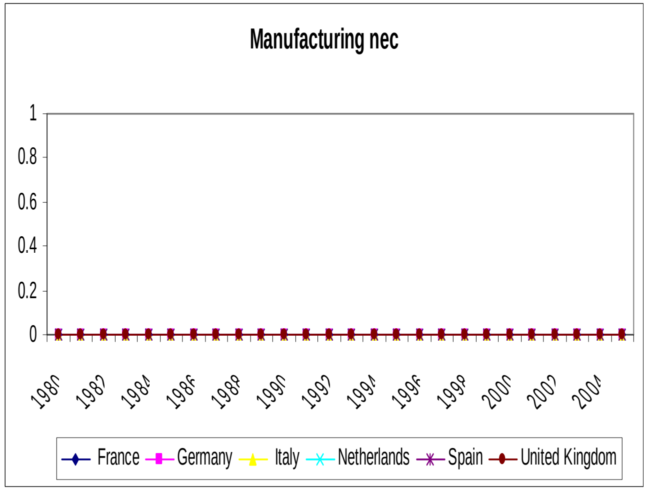
Food - Beverages



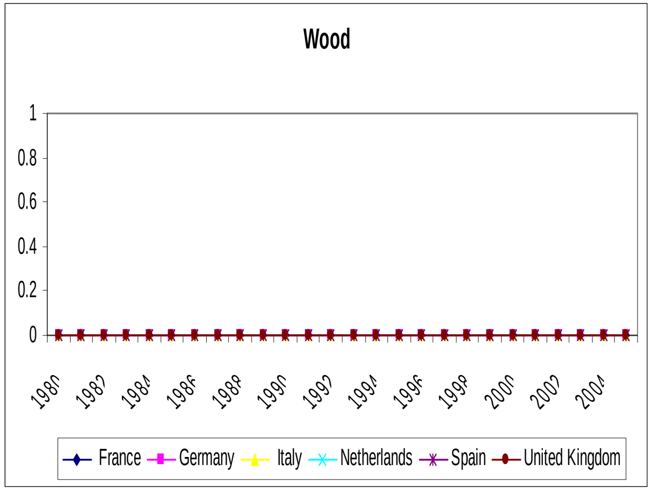
Textiles



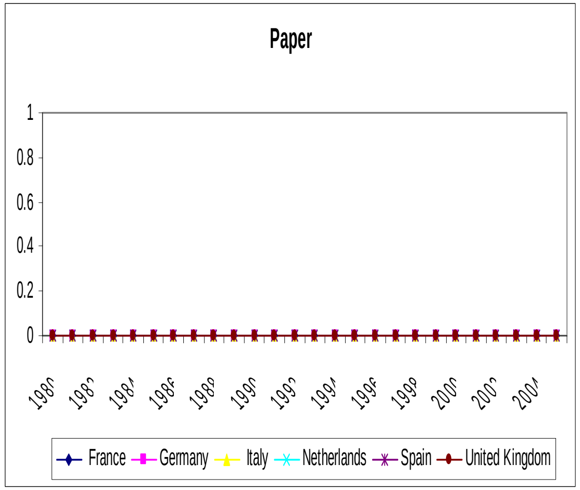
Manufacturing nec



Wood



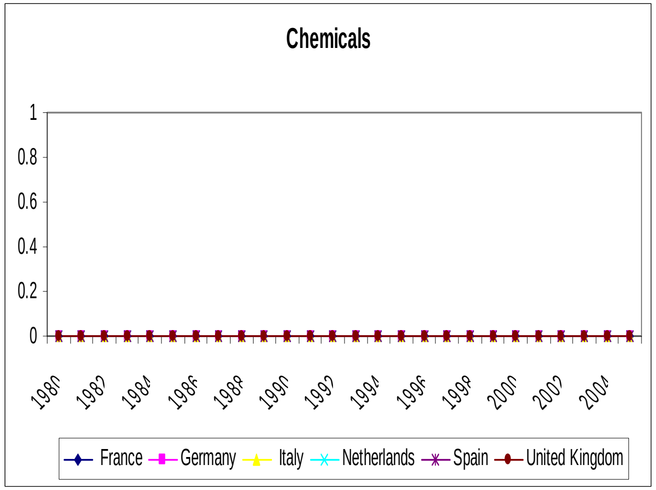
Paper

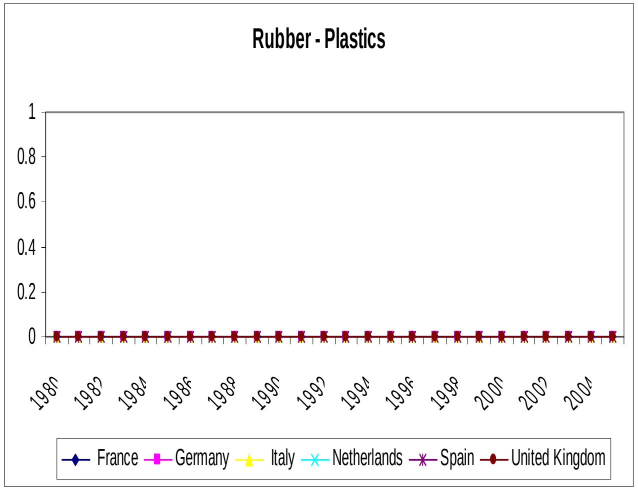


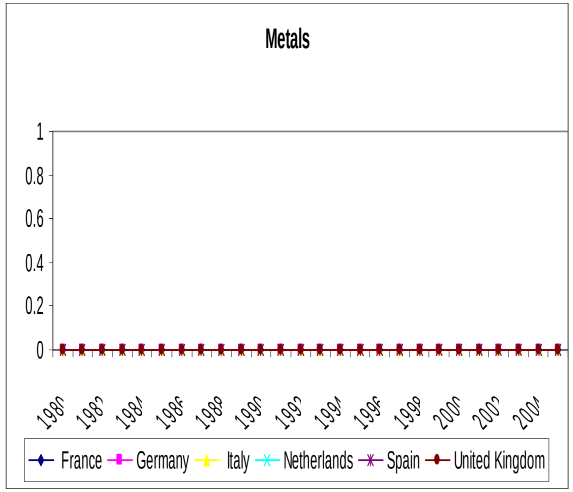
Chemicals

Rubber - Plastics

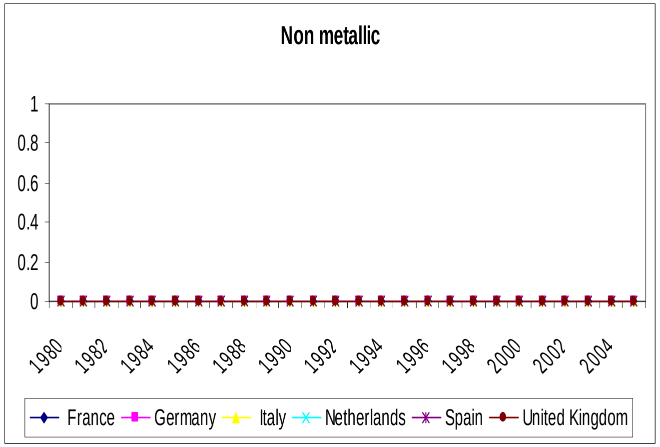
Metals



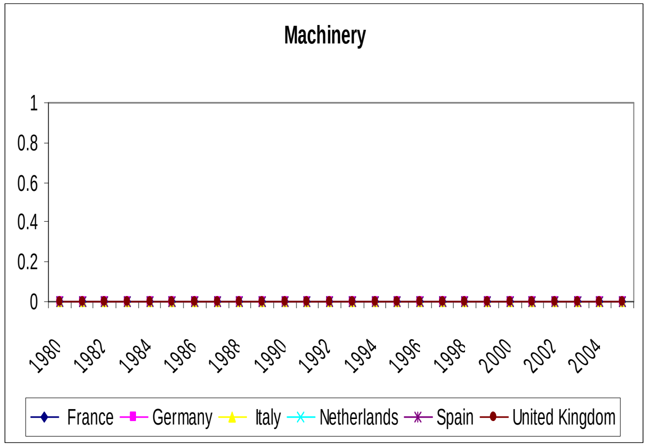




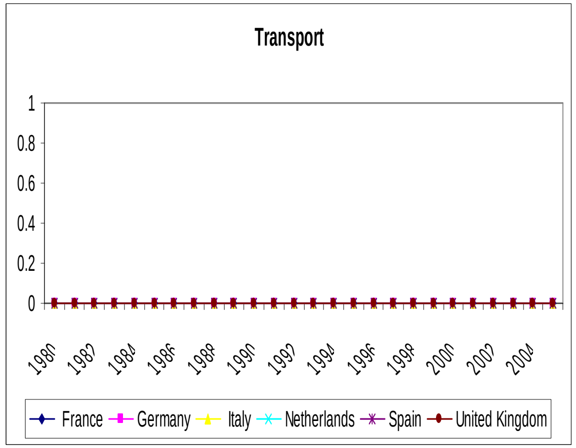
Non-metallic



Machinery



Transport equipment



Source: Own estimation

Model (16) does not produce any reliable results.