EFFICIENCY MEASUREMENT AND EFFICIENCY'S CONVERGENCE IN THE EUROPEAN INSURANCE MARKETS

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DIMITRIOS GIANTSIOS

CONTENTS

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Abstract

This thesis examines cost, revenue, and profit efficiency of the European life and non-life insurance firms operating in 22 and 24 European countries for the period 2006-2014 by employing the stochastic frontier approach. Then, β- convergence and σ-convergence criteria are examined for the period 2008-2014 in order to examine if convergence in EU has been achieved. We found that there have been significant improvement potentials. For the non-life European insurance sector we found that the average cost, revenue and profit efficiencies for the whole period were 0.836, 0.771, and 0.828 respectively. For the life sector the respective scores were 0.772, 0.792, and 0.881 respectively. Concerning efficiency convergence, for the non-life European insurance sector we found evidence of beta convergence for cost, revenue, and profit efficiencies but no evidence of sigma convergence. For the life European insurance markets we found evidence of beta and sigma convergence concerning cost and revenue efficiencies but no evidence of beta or sigma convergence for its profit efficiency. This thesis, one of the first to include a very large sample of countries and firms, extends the existing literature in two important aspects. First, it is the only study that provides cost, revenue, and profit efficiency estimates for a sample of insurers operating both in old and in new European countries that entered European Union after the so-called Fifth Enlargement Part II (in 2006), based on a flexible stochastic frontier. Second, we consider the level of convergence of the European insurance industry by estimating β-convergence and σ-convergence. To our knowledge, no other study has examined the efficiency convergence of the European insurance industry.

CHAPTER 1

INTRODUCTION

1.1 Motivation

Risk and uncertainty is an integral part of humans' and companies' daily life and it is not subject to the control of the power, the thought and the willingness of human being. People are mainly exposed to risks of loss or drop in income, property-liability, fluctuation in the value of invested assets, as well as risks to life and health, while corporations are exposed to market, credit, and price risks. From the very old times, people either in personal or in organized group level are striving for a form of collateral against the existing uncertainties. Teamwork symbiosis was the first sample of the effort and desire of individuals for both physical and psychological assurance and to protect their property. After thousands of years of evolution of the human life, in modern times the basic technique of risk reduction and response is insurance.

The general function of the insurance mechanism is to protect individuals and firms against such adverse events. This mechanism is complicated and intricate, and it is consequently difficult to find an accurate and commonly accepted definition. From an individual point of view, insurance is an economic device through which the individual substitutes a small certain cost called premium for a large uncertain financial loss (the contingency insured against) that would exist if it were not for insurance (Vaughan and Vaughan, 2008). From the social point of view, insurance is an economic device for reducing and eliminating risk through the process of combining a sufficient number of identical and homogenous exposures into a group to make the losses predictable for the group as a whole (Vaughan and Vaughan, 2008). The first point of view stresses the transfer of risk while the second point of view stresses the role of insurance in reducing risk by combining the risks of various clients in a pool (risk pooling) and spreading these risk over this usually large group of clients. The law of large numbers[1] favors this pooling arrangement since although some events appear to be a matter of chance, they actually occur with regularity over a large number of cases.

The contribution of private insurance in society and the economy is very important for the reasons explained below. In addition to the large number of their employees and the tax revenues they pose to their countries, private insurance companies offer multiple positive factors for the prosperity of a society. The existence and operation of a healthy insurance market contributes to the social stability as it helps to reduce the uncertainty of the individuals and businesses. Private insurance has a complementary role to the social security by operating health programs, accident programs, and paying lump pension funds. The existence of insurance encourages entrepreneurial initiative, as in the current context of globalization and competition the most

[1] The law of large numbers says that when many people are insured, the probability distribution of the losses will assume the normal distribution which allows accurate estimations.

innovative and thus risky business ventures would be much less if the entrepreneurs do not have the protective network of the insurance.

With private insurance, the need of individuals and business to maintain reserves in cases of future harmful potentials is reduced. The private insurers, with their experience and their know-how, can estimate with great accuracy the expected losses, and therefore the required reserves are much smaller than the total reserves should accumulate individuals themselves. Therefore, with the intervention of the insurers the best allocation of accumulated reserves of people and of enterprises as well as their efficient utilization is achieved. Also, insurers are one of the largest institutional investors nowadays. The funds collected from premiums are available stored funds which contribute to the creation of healthy and strong national financial markets. Insurance is also contributes indirectly in the creation of new investments since the increased supply of capital in the form of accumulated reserves leads to lower interest rates and thus in increased investments.

Insurance agencies contribute to a great extent to the improvement of the creditworthiness of person-entities under their protection by pooling the risks they cover and by reducing the cost of financial intermediation (Trainar, 2001). So, a company or an individual who has insurance coverage is easier to find some source of external financing than a corresponding uninsured one, as this coverage guarantees them required security and gives them higher certainty to rely on planned cash flow generated through their planned operating cycles. This fact shortly contributes to increased confidence that banks have in the creditworthiness and liquidity of their prospective clients. Also, funds collected from premiums are essentially available stored resources that can be channeled to the financial markets and thus enhance their liquidity and operating efficiency.

Apart from the above mentioned economic benefits of insurance coverage, there are also social benefits. The contribution of the insurance sector in health, stability, and cohesion of the family and the whole society is very important. The major benefits it offers are the sense of security and the reduction of anxiety and stress which cause psychological and organic diseases. Thus, insurance contributes to the mental and spiritual health of the individuals. The operation of private insurance as a supplementary to social insurance programs in issues relating to ensuring family income (e.g. inability to work, death, health, property damage) ensure to a certain degree the economic self-sufficiency of the policyholder and his family. So, with the existence of the insurance, social problems and inequalities are reduced.

Taking into account the important role played by the insurance companies in modern economies and the above mentioned economic and social benefits it provides, it is very important to analyze how efficiently they utilize their resources during the process of offering their services. Performance measurement plays an important role since it identifies and trucks progress against organizational goals and specifies opportunities for improvement. Technical, cost, revenue, and profit efficiencies estimated by using frontier efficiency methodologies are the most modern measures which are suitable for this purpose. Although the number of studies measuring efficiency of insurance industries by using frontier methodologies has increased with geometric pattern within the last three decades, only a few articles measured on the fingers of one hand study the efficiency of insurance industry in a European level by using common international frontiers (Fenn et. al., 2008; Vencappa et. al., 2013). Additionally, to the best of our knowledge there is no other research that attempts to examine if convergence in efficiency has been achieved in the European insurance market after the enactment of the life and non-life Third Generation Insurance Directives implemented in 1 July 1994. Taking into account this gap in insurance efficiency literature, this thesis tries to contribute to this gap by estimating cost, revenue, and profit efficiencies for a sample of European life and non-life insurers for the period 2006-2014 and by measuring the level of convergence for these forms of efficiency.

1.2 Services provided by insurers

Insurance companies are financial institutions and their primary function is to protect individuals and corporations (policyholders) from adverse events described in the insurance contracts signed. Insurers assume the risk on behalf of their customers in exchange for a fee, called premium. By accepting premiums, insurance companies promise policyholders compensation if the pre-specified events occur. Insurance companies usually make a profit by charging premiums that are sufficient large to pay the expected claims to the policyholder plus a profit margin. These services represent financial liabilities to the insurance companies and are reported on the right hand side of their balance sheets. On the other hand, insurance companies invest the premiums collected in financial securities such as bonds and stocks and display these assets on the left hand side of the balance sheet.

The insurance industry generally is classified into two major types of insurers: life and property-liability (non-life) insurers. In Europe, there is a wide variety of life and non-life insurance products that differ with respect to levels of protection, duration of the protection, and the financial subsidy of the national governments on a social welfare ground. Life insurance products provide coverage against the possibility of early and untimely death, illnesses, and retirement. Property-liability insurance products protect policyholders against personal injury and liability such as accidents, theft, and fire damages. Below each type of insurance coverage will be described analytically since there are many forms of insurance coverage in each category.

1.2.1 Types of life insurance

Generally, life insurance products allow policyholders and their beneficiaries (e.g. their children) to be protected against losses in income through premature death or retirement. By pooling many risks, life insurers transfer income-related uncertainties from the insured person to a group. The basic difference between life and non-life insurance is that some life policies provide not only insurance features but also saving components while non-life insurance policies have only insurance features concerning mainly property damages or liability losses. There are four basic classes or lines of life insurance distinguished by the manner in which they are sold or marketed to the customers (Saunders and Cornett, 2008). These categories of life insurers are (1) ordinary life, (2) group life, (3) industrial life, and (4) credit life.

1) Ordinary Life

Ordinary life insurance is a simple form of insurance coverage that involves policies marketed on an individual basis, on which policyholders make periodic premium payments. There are five basic contractual types of insurance in this category with the first three being traditional forms of ordinary life insurance and the last two being contractual types developed during the last two decades as a result of increased competition for savings from other segments of the financial services industry

(Saunders and Cornett, 2008). The basic features of each these contractual forms are described below:

- Term life: It is the simplest form of life insurance which pays out if the insured dies while the policy is in force. This form of policy contains no savings element and once the policy period ends there are no residual benefits (Saunders and Cornett, 2008).
- Whole life: This type of contracts protects the policyholder over an entire life time. In return for periodic or level premiums, the individual's beneficiaries receive the face value of the life insurance contract on death. Unlike term life, there is certainty that the insurance company will make a payment if the policyholder faithfully fulfils the obligations arising from the agreement (Saunders and Cornett, 2008).
- Endowment life: This life policy combines a pure insurance element with a savings element. It guarantees a payout to the beneficiaries of the policy if death occurs during some endowment period. An endowment policy also pays the face amount of the policy if the insured survives the policy term (Saunders and Cornett, 2008).
- Variable life: Unlike traditional policies that promise to pay the insured the fixed or face amount of a policy if a contingency arises, variable life insurance invests fixed premium payments in mutual funds of stocks, bonds, and money market instruments (Saunders and Cornett, 2008). This form of insurance is in fact a form of whole life insurance where now the policyholder is allowed to specify how the funds are invested. A minimum guaranteed payout on death is usually specified, but the payout can be higher if the investment does well.
- Universal life: Universal life allows both the premium amounts and the maturity of the life contract to be changed by the insured, unlike traditional policies that maintain premiums at a given level over a fixed contract period. For universal life products, insurers invest premiums in money, equity, or bond mutual funds (i.e. in fixed income products) so that the savings or investment component of the contract reflects market returns (Saunders and Cornett, 2008). The insurance company guarantees a certain minimum return on these funds. The policyholder can choose between two options. Under the first option, a fixed benefit is paid on death and under the second option, the policyholder's beneficiaries receive more than the fixed benefit if the investment return is greater than the guaranteed minimum (Saunders and Cornett, 2008). Needless to say, premiums are lower for the first option (Saunders and Cornett, 2008).
- Variable universal life: Variable universal life insurance blends the features found in variable life insurance and universal life insurance. The policyholder can choose between a number of alternatives for the investment of surplus premiums. The insurance company guarantees a certain minimum death benefit and interest on the investments can be applied toward premiums. Premiums can be reduced down to a specified minimum without the policy lapsing (Saunders and Cornett, 2008).

2) Group life

Group life insurance covers a large number of insured persons under a single policy. Usually issued to corporate employers, these policies may be either contributory (where both the employer and employee cover a share of the employee's cost of the insurance) or noncontributory (where the employee does not contribute to the cost of the insurance) for the employees (Saunders and Cornett, 2008). Group life coverage remains in force until the employment is terminated or until the specific term of coverage ends. The policyholder may have the option of converting his group coverage to an individual policy if he leave the employer. However, most people choose not to do this because these conversion premiums tend to be much higher than premiums for comparable policies available to individuals. Typically, only those who are otherwise uninsurable take advantage of this conversion option (Saunders and Cornett, 2008).

3) Industrial life

Industrial life insurance currently represents a very small area of coverage. It refers to an insurance which provides insurance coverage to industrial workers or people who are unable to afford insurance for bigger amounts. Here a fixed amount is given in case of accident or death. Industrial life usually involves weekly payments directly collected by representatives of the companies (Saunders and Cornett, 2008).

4) Credit life

Credit life insurance is sold to protect lenders against a borrower's death prior to the repayment of a debt contract such as a mortgage or car loan. Usually, the face amount of the insurance policy reflects the outstanding principal and interest on the loan (Saunders and Cornett, 2008).

5) Other life insurance activities

Three other activities are performed by life insurance companies that involve the sale of annuities, private pension plans, and accident and health insurance. These activities do not belong to the traditional life insurance activities but they were documented during the last two decades mainly due to competition from banks.

Annuities generally represent the reverse of life insurance activities. Whereas a life insurance contract has the effect of converting regular payments into a lump sum, an annuity contract has the opposite effect by converting a lump sum into regular payments. First, the policyholder makes a lump sum payment to the insurance company. Then, during the payout period this insurance company pays a specified amount of money at given time intervals (e.g., monthly) over an exactly specified length of time. An annuity that only pays until the annuitant dies is called a straight life annuity and an annuity that pays over a fixed period of time regardless of death is called an annuity certain (Harrington and Niehaus, 2004). Insurance companies offer many alternative pension plans to private employers in an effort to attract this business from other financial service companies, such as commercial banks and security firms (Saunders and Cornett, 2008). A pension plan is a form of insurance arranged by a company for its employees. It is designed to provide the employees with income for the rest of their lives once they have retired. Typically both the company and its employees make regular monthly contributions to the plan and the funds in the plan are invested to provide income for current and future retirees (Saunders and Cornett, 2008). Finally, accident and health insurance protect against morbidity, or ill health risk although life insurance mainly protects against mortality risk.

1.2.2 Types of property-liability insurance

Property and casualty (non-life) insurance protects again losses related to the real and personal property. These losses can be from fire, theft, storm, earthquake, explosion etc. Property insurance protects business and owners from the impact of risk associated with owning property. This includes replacement and loss of earnings from income-producing property as well as financial losses to owners of residential property (Harrington and Niehaus, 2004). Casualty insurance (or Liability insurance) protects against liability for harm the insured may cause to others as a result of product failure or accidents. It is important to note that the biggest difference between non-life and life insurance is the fact that the non-life insurance policies tend to be short-term (usually 1 year or less) while the life policies are long term policies. The main property-liability insurance lines are described below (Saunders and Cornett, 2008):

- Fire insurance and allied lines: This line protects against the perils of fire, lightning, and removal of property damaged in a fire case.
- Homeowners' multiple-peril insurance: This line protects against multiple perils of damage to a personal dwelling and personal property as well as providing liability coverage against the financial consequences of legal liability due to injury done to others.
- Commercial multiple-peril insurance: This line protects commercial firms against perils in a way analogous to homeowners' multiple-peril insurance.
- Automobile liability and physical damage insurance: It provides protection against losses resulting from legal liability due to the ownership or use of the vehicle (auto liability) and theft of or damage to vehicles (auto physical damage).
- Liability insurance (other than auto): This broad line of property-liability insurance provides either individuals or commercial firms with protection against non-automobile-related legal liability. For commercial firms, this includes protection against liabilities relating to their business operations (other than personal injury to employees covered by workers' compensation insurance) and product liability hazards.

1.3 Insurance regulation in EU

The insurance business is heavily regulated both in EU and in the United States and in most other developed countries, usually through prescribed methods to calculate premiums and technical provisions to cover expected future claims. Because of the nature of its activities, insurance business is plagued by asymmetric information problems. Insurance is subject to moral hazard when the contract outcome is partly influenced by the behavior of the insured and the insurer cannot observe (e.g. someone does not lock his car doors if he will be reimbursed by the insurer if the car is stolen), without costs, to which extent reported losses can be attributed to the behavior of the insured (Vaughan and Vaughan, 2008). Adverse selection is another case of asymmetric information problems that insurers face. The ex-ante information asymmetry arises because the insured generally knows more about his risk profile than the insurer. So, the risk type of the insured cannot be determined ex-ante by the insurer and he charges the same premium rate based on aggregate risk (Vaughan and Vaughan, 2008). The high risk types of persons (e.g. a person with chronic health problems) are the ones who are most eager to buy insurance, producing an undesirable outcome for the insurance company.

The first rationale for the regulation of insurance stems from its fiduciary nature since it is an industry vested in the public interest. Failures for an insurer can affect persons other than those directly involved in it. Policyholders purchase insurance to protect against future financial losses and it is important for the public welfare that the insurer promising to indemnify insurers for future losses fulfils its promises. The second rationale arises from the uncertainties inherent in the insurance pricing process. Competition in some fields of insurance, if left unregulated, would become excessive since the cost of production is not known until the contract has run its full term (Vaughan and Vaughan, 2008). Also, in an attempt to compete they might assume that their insurers are from the more desirable class and make unwarranted assumptions about their future costs (Vaughan and Vaughan, 2008). Thus, the goal of insurance regulation was to promote the welfare of the public by ensuring fair contracts at fair prices from financially strong companies. The market failures that insurance regulation was intended to correct were insolvencies (no matter what their source) and unfair treatment of insurers by insurers (Vaughan and Vaughan, 2008).

In insurance contracts, the time when the policyholders pay premiums is chronically very distant from the moment when insurers will pay out possible compensation. This is inconvenient for the insurer, as it does not know upfront if the premium will be sufficient, as well as for clients as they simply have to trust the insurer will meet its future obligations. This trust is the most important foundation of a financial institution. But due to their specific accounting rules, insurers' solvency and reliability are difficult to ascertain even by the most sophisticated investors. Thus, not everybody has the necessary expertise to judge the financial situation of an insurance company. For these reasons the supervision of insurers is therefore assigned to an independent supervisor.

The European insurance regulations in place date back to the 1970s. Since then, they have been adjusted to support the objective of a single European market of the European Union, or its predecessor the European Economic Community. These updates focused in particular on the licensing procedure and the rules for providing services in multiple member states (Doff, 2011). A major milestone in European insurance regulation was the first generation of Insurance Directives enacted in 1973. These directives regulated the process of insurance licensing such that the requirements for a license were consistent throughout Europe. They also set out financial requirements for technical provisions and capital, and included asset restrictions. In the context of European integration, it was important that insurance companies were allowed to open subsidiaries in all member states based on consistent licensing principles (Doff, 2011).

The second-generation directives were adopted in 1988 and 1990 for non-life and life insurance, respectively. They further opened up the European market for large risks. For these risks, insurance companies were allowed to provide services throughout Europe without having a licensed subsidiary in a member state (Doff, 2011). The third generation directives of 1992 really paved the way for a European market by applying the single-license principle. This principle allowed companies to operate throughout Europe with only one license. An important step in European harmonization is that throughout Europe all supervisors apply normative supervision, i.e., that there is no ex ante requirement for insurance supervisors to approve insurance companies' product conditions and rates (Doff, 2011). These directives have been updated in 2002 by adjusting a number of thresholds in the calculations that assess the financial soundness of the insurance company (SOLVENCY I).

SOLVENCY I introduced formally in February 2002 and it became fully operational in late 2004. This directive does not change the basic calculation of the solvency margin of insurance companies, as configured from the previous directives, but required some modifications to the existing legislation, and increased supervision entitling supervisors to intervene in cases where the capital constituted the solvency margin was below the desired levels. SOLVENCY I provided a uniformity in the calculation of the solvency of the insurers, mainly based on financial factors, without emphasizing the specific risks that may affect the solvency of an insurance company. The methods of valuation for the assets, the liabilities, and the technical provisions continued to vary from country to country, as well as the conditions for the calculation of the mathematical reserves. This remained an obstacle in assessing risks faced by insurers in relation to a single European insurance market. Therefore, the SOLVENCY I did not serve the needs for the European insurance market harmonization and the adjustment and the transition to SOLVENCY II was necessary.

The aforementioned country differences triggered a number of countries to develop their own frameworks, resulting in a patchwork of regulations for insurance firms throughout Europe. The Solvency II project of the European Commission aimed to revise the supervisory rules to overcome these issues by articulating the key principles with a three-pillar structure: risk-based supervision, increasing reliance on fair value and options for companies to use standard approaches and internal models to determine the requirements. The idea of the implementation of SOLVENCY II was based on the context of BASEL II, the corresponding European directive on capital requirements for banks, which sought to establish a uniform and stable framework for risk management in the banking sector. The SOLVENCY II was implemented in January 1, 2016.

The Solvency II framework is based on three mutually reinforcing pillars. The Pillar I (financial requirements) lays out the valuation of the technical provisions and capital requirements. In addition, it describes the criteria for eligible capital to cover the capital requirements. The Pillar II (supervisory review process) stress that insurance supervisor should have a complete and comprehensive overview of all risk and the risk management techniques that companies use internally. Pillar II sets out the criteria for a constructive dialogue between supervisors and the supervised companies to ensure that all material risks are adequately addressed. The underlying principle of Pillar II is that the company itself is responsible for risk management and ensuring adequate capital levels to withstand all material risks. Finally, Pillar III (disclosure and market discipline) entails supervisory reporting as well as public disclosure. By publishing risk management information, all market participants such as investors (and potentially policyholders) could gain insight into the risk profile of an insurance company. This could act as another incentive for companies to adopt good risk management practices. The supervisory reporting allows the supervisor to form an in-depth opinion of the insurance company.

Although it is too early to draw firm conclusions concerning the effectiveness of the SOLVENCY II, it is certain that it aspires to enhance risk awareness in the insurance industry both for companies and supervisors. This new regulatory conditions in European insurance market will result in more efficient capital allocations, which means that insurance capital is allocated to the areas where risks are identified. So, the adoption and the implementation of the SOLVENCY II will finally be beneficial for the stability of the industry.

1.4 Thesis structure and overview

Despite the plethora of studies measuring the efficiency of financial institutions, only a few papers, measured on the fingers of one hand, examine if efficiency convergence has been achieved in the European financial market. All these efforts measure cost efficiency convergence only for the European banking sector. To our knowledge, there is no analogous effort for the European insurance sector. The basic aim of this thesis is to contribute to this deficit of the literature by examining the impact of the EU integration tried during the last three decades on the level of the efficiency convergence in the European insurance industry.

Our analysis, one of the first to include a very large sample of countries and firms, extends the existing literature in several important aspects. First, we provide inefficiency estimates for cost, revenue, and profit functions at a European level based on a flexible stochastic frontier. Indeed, it is the first attempt to measure revenue efficiency for life and non-life European insurers in a European context. Second, we consider the level of convergence of the European life and non-life insurance industry by estimating β-convergence and σ-convergence. To our knowledge, no other study has examined the convergence of the European insurance industry. Third, unlike articles measuring banking efficiency convergence by estimating efficiency with Data Envelopment Analysis (DEA) or with the classical Stochastic Frontier Analysis (SFA) methods, this thesis uses the Battese and Coelli (1995) model for the efficiency estimations. This model has the advantage to permit the estimation of efficiency in a single stage while accounting for the impact of environmental variables (e.g. inflation). So, the measurement of β-convergence and σ-convergence concerning efficiency is more accurate than the respective convergence measures that derived by using the DEA or the classical SFA for the efficiency estimations. Finally, by the time this thesis is written, it is the only study that uses so recent data in its efficiency estimations.

This chapter has introduced the background of this thesis and specified the aims, objectives, motivation, and scope of the study. The structure of this thesis goes as follows: Chapter 2 critically reviews the literature concerning insurance sector's efficiency in an international level. It categorizes the existing literature in ten different categories according to the approach first used by Eling and Luhnen (2010). Chapter 3 develops a theoretical framework, which presents the possible existing methods of estimating efficiency. Parametric and non-parametric approaches are analyzed thoroughly while stressing the advantages and disadvantages of each approach. Chapter 4 thoroughly analyzes the way in which inputs and outputs needed for efficiency estimations are defined. The value added approach for determining outputs and inputs is used in the majority of literature and this thesis follows this method. Chapter 5 empirically estimates cost, revenue, and profit efficiency for the European life and non-life insurers during the period 2006-2014. SFA and more accurately the

Battese and Coelli (1995) model is used for the estimations by assuming the translog form for the respective equations. Chapter 6 estimates the levels of beta and sigma convergence concerning the efficiency of European life and non-life insurers for the period 2008-2014. Regulators in the EU sought to achieve a single European financial market (financial integration) during the last three decades and this thesis sheds light to this matter by estimating the efficiency convergence of the European insurers. The final chapter draws conclusions from the findings, discusses the contributions and limitations of the study and offers suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction to the efficiency measurement

In the last two decades the insurance sector has experienced great changes that influenced the structure and the operation of each insurance company operating in it. These changes affected not only the European insurance market but also the insurance sector around the world. An indication of these structural changes were the introduction of the Third Generation Insurance Directive in European Union in 1994, the deregulation of the Japanese financial system in 1996 and the attempt of the United States to relax regulations regarding the structure and the protection of domestic firms from outside competitors. All these things justify the interest of researchers for developing methods for measuring insurance sector efficiency.

The traditional methods of measuring efficiency based on financial and economic indexes, such as ROA and ROE, are not utilized now frequently. On the contrary, the known as frontier efficiency methodologies have received great attention by researchers in measuring and decomposing the efficiency in the insurance sector globally. These methods estimate the relative but not the absolute efficiency of each insurance firm because each one in the sample is compared with the best practice insurers in the sample used every time. Also, it is important to note that this category of methods includes two subcategories, the parametric or econometric and the non parametric or mathematical programming frontier efficiency measurement methods.

In the first category the most used version is the Stochastic Frontier Approach (SFA) firstly proposed by Aigner et al. (1977). As a first step, this method estimates the production, cost, revenue or profit function according to the needs of researcher each time so as to be able to determine the efficient frontier. At the second phase, it estimates the deviations from the efficient frontier attributed to inefficiency and to other random factors beyond inefficiency. The SFA assumes a composed error model where inefficiencies follow an asymmetric distribution and the random error term follows a symmetric distribution which is usually the normal distribution. Another version of this category is the Distribution Free Approach (DFA) which assumes that the efficiency component of the model is constant over time but the random noise component averages to zero. The last version of this category is the called Thick Frontier Approach (TFA) which makes no distributional assumptions concerning the inefficiency component and the error term but accepts that inefficiencies differ between the highest and the lowest quartile firms (e.g. Kumbhakar and Lovell, 2000).

In the non parametric category the most used version is the data envelopment analysis (DEA) introduced by Charnes, Cooper et al. in 1978. As its name suggests, this method uses mathematical programming in order to construct an efficient frontier which envelopes all input-output possible combinations of the sample. Like the preceding category, the efficient firms' input –output combinations are on the frontier while inefficient firms' input –output combinations are below the frontier. Another version of this category is the Free Disposal Hull (FDH) approach introduced by Deprins et al. in 1984. This method does not allow substitution among inputs or more accurately the points on the lines connecting the DEA vertices are excluded from the frontier and the convexity assumption on the efficient frontier is relaxed (Cooper et. al., 2007).

According to the review article by Eling and Luhnen (2010), there exists a common agreement among researchers as far as the selection of inputs for the estimation of the efficient frontier. Labor, business services and materials and capital are the most commonly used inputs for the measurement of efficiency. As far as the selection of the outputs, the situation is different. There are three different approaches for the output selection and measurement. The intermediation approach views the insurance company as selecting a sum of assets and converting them to money in order to pay claims, taxes and costs of operation. Next, the user cost approach receives a financial product as an input if it yields a return that exceeds the opportunity cost and as an output for the opposite case. Finally, the most common approach called value added approach presume outputs as important if they contribute a significant added value based on operating cost allocations.

An excellent article by Eling and Luhnen (2010b) reviews the literature on frontier efficiency methodologies used to measure performance in the insurance industry. This article reviews the article of Berger and Humphrey (1997) which concentrates mostly on banking and reviews eight studies of insurance efficiency and the review article of Cummins and Weiss (2000) which reviews twenty one studies respectively. Eling and Luhnen (2010b) were the first to systemize and classify the studies in ten different categories according to the topics each developed. In the following literature review, we will adopt this systemization but with the aim of incorporating all the new and updating articles.

2.2 Category of general level of efficiency and evolution over time

This category of literature review includes studies that plainly measure the general level of insurance sector efficiency in various countries. Here we quote the studies according to their alphabetic order but not to chronological order.

Talat Afza and Jam-E-Kausar (2008) estimated the technical efficiency of non-life insurance companies in Pakistan over the period 2003-2007. They used the input – oriented DEA approach for measuring technical efficiency and decomposed it to its pure technical and scale efficiency components. They used four inputs : labor, business services, debt and equity while for defining the outputs they followed the value added approach and defined as outputs the premiums earned along with the investment income. They used a non balanced sample of life insurers and the data they used came from the annual reports for the same period. They found that the non life insurance companies of the sample were 82.4% technical efficient while during the study period the general level of technical efficiency had improved from 80% in 2004 to 86% in 2007. In addition, they found significant variation (16.2%) in the level of efficiency amongst the insurers and that on average technical inefficiency in the non life insurance sector of Pakistan was due to both pure technical efficiency (91.4%) and scale efficiency (89.9%). Moreover, they classified the non life insurers into three groups; large, medium and small according to their total assets size and found that large non life insurers were more technical efficient as compared to medium and small size non life insurers. On average, the technical efficiency of the large non life insurers declined whereas the efficiency of small ones improved over the time period. Finally, the authors find that most of the non life insurers in Pakistan and particularly the small and medium size insurers are inefficient due to increasing return to scales while most of the large non life insurers are inefficient due to decreasing returns to scale.

Barros et al. (2005) calculated the output oriented Malmquist productivity index based on the DEA method and decomposed it to technical and technology efficiency change components. Additionally, they decomposed technical efficiency change component to its pure technical and scale efficiency subcomponents. They used data for 27 Portuguese life and non life insurance companies for the period 1995-2001. As inputs variables they used the wages paid, the capital used, the total investment income and the premiums issued while for the determination of output variables they followed the value added approach and they took claims paid and profits earned as output measures. They found that this index was one or higher than one for 20 of these companies, indicating that on average insurance sector in Portugal has experienced gains in total productivity in the period considered. They concluded that there were on average improvements for the technical efficiency component of this index over time while there was deterioration for the technological change component of the Malmquist productivity index. As a second stage they regressed the Malmquist productivity index toward four dummy variables using Tobit regression. These dummy variables account for the country of origin of each insurance company, for their size, for the fact that they entered the market after 1994 or before (the year of the inception of the insurance single market) and for their type (life or non life) respectively. From this stage they concluded that foreign own companies were more efficient than domestic insurance companies, that large companies were more efficient than small companies, that companies entered the market after 1994 were more efficient from other not entered after 1994 and that non life insurers were more efficient than life insurers.

Barros and Obijiaku (2007) used the DEA–CCR model, the DEA-BCC model, the cross-efficiency DEA model and the super-efficiency DEA model using output orientation in order to calculate technical, pure technical, and scale efficiency of 10 Nigerian life and non life insurance companies for the period 2001-2005. They used balanced panel data for these insurance firms and obtained them from the insurance companies annual reports and web sites. The variables for total capital, total operative costs, total number of employees and total investments were used as inputs while the profit, the net premiums, the settled claims, the outstanding claims and the investment income were used as output variables according to the value added approach. According to their estimates, Nigerian insurance companies are on average technical efficient (94.6% according to CCR and 100% according to BCC DEA models) but some of them do not display scale efficiency having decreasing returns to scale. They also test three hypotheses with the Mann-Whitney U-test using super-efficiency DEA scores obtained from the first stage. Firstly, they search for the fact that large insurance companies are more efficient than small insurance companies classifying them by their book value of their assets. Secondly, they test if insurance companies integrated into bank networks are more efficient than those not integrated into banks classifying them by their relationship with banks. Finally, they search if insurance companies with higher market shares are more efficient than those with lower market shares classifying them according to their estimated market share. Their main conclusions were: large insurance firms tend to have higher efficiency scores than their small counterparts; bank network-managed insurance companies have higher efficiency scores than those not managed within a bank network; insurance companies with higher market share tend to be more efficient than those with lower market share.

Biener et al. (2016) studied the technical, cost, revenue efficiencies and productivity of the Swiss insurance companies in the life, property/casualty, and reinsurance sectors from 1997 to 2013. The method used for these estimations was the DEA and the Malmquist index of total factor productivity respectively. According to the value added approach, they defined the present value of losses paid plus addition to reserves and the real value of total investments as outputs produced by Swiss insurers. Operating expenses, debt, and equity capital were used as inputs. They found that productivity and efficiency have improved with regard to property/casualty and reinsurers while in the case of life insurance productivity and efficiency diminished. Their work is the first empirical analysis of internationalization strategies of insurance companies. The ratio of premiums written abroad to total premiums written was used as an international diversification variable. They found that diversification strategies directed to the European market were more beneficial compared to those targeting markets outside of Europe.

Bikker and Leuvensteijn (2008) estimated scale and X-efficiency for the Dutch life insurance industry although their basic intention was to measure the competition of this sector indirectly from these two efficiency measures. Their sample data cover the period 1995-2003 but the number of the firms in the sample ranged from 84 to 105 life insurance firms. For the estimation of scale efficiency they used the translog cost function (TCF) where they took as inputs prices the reinsurance ratio and the acquisition ratio while as output only the premium income. For the measurement of X-efficiency they used the stochastic cost frontier function based on the TCF. As inputs they used acquisition costs and additionally other costs which include management cost, salaries, depreciation on capital equipment etc. The prices of these two input factors had been estimated as the ratio of the respective costs and the total assets. As outputs they used the annual premium income, the total number of outstanding policies, and the sum total of insured capital, the sum total of insured annuities and the unit-linked funds policies. According to their results, scale economies exist and amount to 20% on average, ranging from 10% for large insurers to 42% for small life insurers. Finally, the average cost X-efficiency was 72% on average, implying that costs were on average 28% higher than from the best practice firms.

Cummins et al. (1996) analyzed technical efficiency of life and non-life Italian insurance industry for the period 1985-1993. Using DEA method they estimated input technical efficiency and the Malmquist Productivity index decomposing it to its technical and technological change components. After eliminating small firms, inactive firms, and firms with data available for only part of the sample period, the complete panel sample consisted of 94 life and non- life insurance companies. For the determination of outputs they preferred the value added approach and defined as life insurers outputs the sum of life insurance benefits, the changes in reserves, and the invested assets for the intermediation function while they defined losses incurred and invested assets as non-life insurers' outputs. The geometric mean of technical efficiency for this period was 73.7% implying that insurance companies could have produced their output vectors with about 25% less inputs if they had operated on the production frontier. The geometric mean productivity change for this period was 96.5% implying that productivity declined on average during 1985-1993. Also, from Malmquist Productivity index decomposition to its technical and technological change components they found that the cumulative effect of technical efficiency change was slightly less than one (0.9925) while for the technological change was 0.7522 indicating that most of the deterioration in productivity over the period was attributable to technological regress. Finally, as a second stage they conduct an ex post regression analysis with technical efficiency scores as dependent variables and various firm characteristics as independent variables. Among their important results was the fact that mutual insurers had higher technical efficiency than stocks excluding the expense preference hypothesis and adopting managerial discretion hypothesis.

Cummins and Weiss (1993) measured cost efficiency for the property-liability (P-L) insurance sector in United States. Their sample included 261 P-L insurance firms including only firm with complete available data for all years in the sample and covered the period 1980-1988. For the determination of outputs they preferred the value added approach. They defined as outputs the discounted long-tail incurred losses for regulated and unregulated states, the discounted short-tail incurred losses for regulated and unregulated states, the loss settlement services, and the intermediation services. As inputs they considered the labour, the capital, and the intermediate materials while as input prices they used the wage index for labour, the net income/capital, and the price index for intermediate goods respectively. Using the stochastic frontier analysis method and adopting the flexible translog functional form they firstly estimated cost efficiency and secondly decomposed it to allocative and technical efficiency. They stratified the sample in three groups according to their size and estimated the system consisting of the equation of cost function and the associated first order cost minimization conditions for each of these groups. Moreover, they added the cost share equation for loss adjustment expenses to the above system and estimated the three-equation system again for each of the above three groups of insurers constituting the sample. They found that large insurance firms were on average 90.59% cost efficient if judged by the estimated mean of the inefficiency error term and 96.07% efficient if judged by the mode of the inefficiency error term. Additionally, average cost efficiency for the intermediate size firms is 79.1% based on the mean of the error term and 83.7% based on the mode. Small insurance firms found to have average cost efficiency of 87.7% based on mean errors and 92.2% based on modes. As far as loss settlement services concerned, they found that large insurers were over-produced this output while small and medium size firms were under-produced it. Finally, they concluded that large insurers were operated with mild scale diseconomies while small and medium size insurers were operating under potentially significant scale economies.

Fecher et al. (1993) measured technical efficiency of 327 life and non-life insurers in French insurance industry for the period 1984-1989. They used both the DEA and SFA methods for this purpose. Preferring value added approach, they used gross premiums as an output measure and labor cost and other outlays as input measures. For the non- life insurers they used three different DEA models. In the first model (DEA1) they used the aggregate gross premiums as the only output, in the second model (DEA2) they decomposed aggregate gross premiums to motor and non-motor branches premiums, and in the third model (DEA3) they used as outputs the gross premiums in civil- liability branch, in fire- property branch and in accident-health branch. In addition, they used the SFA method using one output (gross premiums) and represented the production frontier by the Cobb-Douglas function and estimated the parameters of the production frontier with the maximum likelihood method. They used three different DEA models for the life insurers. In the first model (DEA1) they used the gross premiums as the only output; in the second model (DEA2) they used both gross premiums and investment returns as outputs while in the third model (DEA3) they used gross premiums both in collective insurance and in other types of life insurance. As in non-life sector, for life sector they used the SFA method using one output (gross premiums) and representing the production frontier by the Cobb-Douglas function. For non-life insurers the average sample efficiencies were 50.4%, 52.3%, 53.7% and 41.2% for DEA1, DEA2, DEA3 and SFA method respectively. For life insurers the average sample efficiencies were 32.8%, 35.7%, 39.8% and 24.2% for DEA1, DEA2, DEA3 and SFA method respectively. Moreover they estimated the Kendall's rank correlation among the efficiency results of these four models and found high correlation between the results of parametric and non-parametric methods. They noted the wide dispersion of the efficiency rates across companies in the sample. Finally, they regressed efficiency results of DEA3 and SFA models across scale, reinsurance ratio, commission ratio, claims to premium ratio, and output structure both for life and non –life insurers separately and found that these factors explained 49% and 55% of the variance of efficiency for non-life and life insurers respectively.

Gardner and Grace (1993) measured cost efficiency for 561 life insurance companies operating in the United States. Their sample covered the period 1985-1990 and they used the Distribution Free Approach (DFA) as the main method for cost efficiency estimation. They also used the value added approach for the determination of output variables and considered as outputs the dollar amounts of ordinary life insurance premiums, the group life insurance premiums, the ordinary annuity considerations, the group annuity considerations and the group accident and health premiums. Moreover, they recognized the firm's investment activities by considering the dollar amount of securities investments as the last output variable. As inputs they took into account the labor, the physical capital and the miscellaneous items. The price of labor was computed by multiplying the average statewide salary of insurance workers by the proportion of business written in the state, and summing across all states. The price of the physical capital was computed as the ratio of physical capital expenses to the value of physical capital assets while the value of miscellaneous items was difficult to ascertain and considered constant across firms. It assumed that the cost function takes the hybrid trans-log form and following the DFA method it was estimated using the corresponding share equations with full information maximum likelihood. The mean efficiency which occurred after the above estimation procedures was dramatically low and amounted to 17%. At a second stage, taking efficiency scores as dependent variable and ten dummy variables as independent variables they used a cross-sectionally heteroscedastic time-wise autoregressive technique to analyze the fixed effect model. The model also assumed heteroscedasticity and autoregressive error exists and is estimated by generalized least squares. From this second stage it was found that firms with advertising expenses are more efficient than those not participating in advertising programs. Firms being subject to New York regulation are more efficient than those that are not and that Bureau and association fees are unrelated to efficiency scores of insurance firms.

Hao (2007) estimated cost efficiency for 26 life insurance companies in Taiwan and the sample covered the period 1981-2003. The DFA method was followed assuming that the cost function takes the trans-log form. As outputs he defined the dollar amounts of ordinary life insurance, the accident and health premium, the group life insurance premium and the investments according to the value added approach. Inputs variables include labor, physical capital, and claims. The price of labor is computed by multiplying the average salary of insurance worker reported by the life insurance association of the republic of China while the price of the physical capital can be found by the ratio of physical capital expenses to the value of physical capital assets and the price of claims is estimated by dividing ordinary life insurance claims by the number of life insurance policy. The average cost inefficiency in Taiwan insurance industry was 33.98%. At a second stage, a random effect model was estimated with dependent variables being the inefficiency scores and explanatory variables the market share of each insurance company, the form of the operations strategy (product focus or diversified), and the total assets of each company in the sample. It was found that insurance firms with large market shares tended to have higher cost efficiency scores and that those that followed product diversification strategies were not more efficient than those not following product focus strategies.

Hao and Chou (2005) estimated cost efficiency for 26 life insurance companies in Taiwan and the sample covered the period 1977-1999. They used two different methods for estimating cost efficiency. First, they followed the DFA and SFA methods assuming that the cost function was taking the trans-log form. They used as output variables the dollar amounts of ordinary life insurance, the accident and health premium, the group life insurance premium and the investments in line with value added approach. As input variables they considered the labor, the physical capital, and the claims. The price of labor is computed by multiplying the average salary of insurance worker reported by the life insurance association of the republic of China while the price of the physical capital can be found by the ratio of physical capital expenses to the value of physical capital assets and the price of claims is estimated by dividing ordinary life insurance claims by the number of life insurance policy. The average cost inefficiency was 33.98% according to the DFA and 81% according to SFA approach. In a second stage a random effect model was estimated with dependent variables being the inefficiency scores and explanatory variables the market share of each insurance company, the form of the operations strategy (product focus or diversified), and the total assets of each company in the sample. The authors concluded that firms with large market shares tended to be more profitable than those with small market shares. Firms that followed product diversification strategies were not more efficient than those not following product focus strategies.

Hardwick (1997) estimated the economic, scale and total inefficiency of 54 UK life insurance companies for the period 1989-1993. For the determination of outputs he followed the value added approach and used as output variables the total premiums from life insurance, the total premiums from pensions and annuities and the total premiums from permanent health insurance. As input variables he used the labour and capital expenses. The labour price was measured by the average gross weekly earnings of full time non manual insurance workers while the price of capital in this study was defined as the long term interest rate plus the annual depreciation rate in the life insurance industry less the expected annual rate of capital gain. He used the translog cost function and incorporated two independent dummy variables. The first dummy variable trying to capture the effect of location is set equal to zero for regional insurers and one for London based insurers. The second dummy variable tries to capture the effect of organizational form on total costs and takes the value zero for mutuals and one for stock insurance companies. For better comparison, insurance firms were separated in five non- overlapping groups according to their premium income. The mean cost efficiency for the whole sample was 70% indicating that total costs were 30% above the level achievable with a more efficient use of resources. Holding the same groups, Hardwick also estimated average scale efficiencies and total efficiency for each group and for the whole sample. He found statistically significant economies of scale for companies in the four lower groups and also evidence for scale economies in the upper group which contained insurers with the largest average premium incomes but this result was not statistically significant at the 0.05 level. Several statistic tests were performed to determine whether the measure of economic inefficiency was related to the size, organizational form and the location of insurance companies. Larger companies tended to have higher efficiency but this result was not statistically significant at the 0.05 level. At the end, it was proved that regionally based mutual life insurance companies were more economically efficient than London-based stock insurance companies but the results were not statistically significant at the 0.05 level.

Huang (2007) estimated cost and profit efficiency for a number of Chinese life and property-liability insurance companies covering the period 1999-2004. Using the value added approach, he used as outputs the actual premiums earned, the incurred benefits and additions to reserves, and the total invested assets. As inputs were defined the labor, the capital, and the business services. The price of labor was computed as the total cost of employees and agents divided by their total number but because there were no public available data author used the average salary in insurance for a proxy for labor price. As capital price considered the average book ROE for the five years prior to the year of analysis while as business services price considered the average salary in business sector. Using SFA method, he estimated the cost and the profit frontier both for life and property-liability insurers separately. It is important to note that this paper followed the alternative or nonstandard approach for the estimation of profit efficiency and not the standard approach because the first requires only input price and the output quantity for estimations.[2] The average cost and profit efficiencies were 37.12% and 11.79% respectively for the 1999-2004 period. The average cost efficiency showed a steady upward trend (1.3%) during the period while profit efficiency did not change much. State-owned and nonstate-owned insurance companies had 31.06% and 37.63% cost efficiency and 18.41% and 11.23% profit efficiency, respectively. Foreign-funded and Chinese insurance companies had 40.22% and 33.02% average cost efficiencies respectively while 10% and 14.24% profit efficiency respectively. The two-step regression approach for determining the factors that affect efficiency was rejected because impact factors are impossible to be exogenous completely and they are correlated with inputs and outputs variables and consequently the efficiency scores. So, in order to avoid incorrect estimation results, the author incorporated directly into the cost and profit trans-log functions five variables. Four of them were dummy variables capturing the property right structure,

[2] Data for output prices were not available so the nonstandard or alternative approach was used in this paper.

the organizational form, the marketing system, and the degree of product diversification. The fifth variable was the natural logarithm of total assets. The results showed that the property right structure did not have any effect on cost and profit efficiency, the group holding company had a positive effect on both the cost and profit efficiency, the adoption of direct marketing network had negative effect on cost efficiency but no effect on profit efficiency, the asset scale influence negatively affected cost efficiency and positively profit efficiency while the degree of product diversification had a positive influence on cost efficiency but no effect on profit efficiency.

Leverty et al. (2004) measured technical efficiency and decomposed it to its pure technical efficiency and its scale efficiency component for the Chinese life and property-casualty insurers for the period 1995-2002. Due to data availability they focused on property-liability insurers for the period 1995-2002 and on life insurers for the period 1999-2002. They followed the DEA method and estimated the efficiencies for each year separately. Following the value added approach, they used as outputs for life insurers the net premiums written for group, the net premiums written for personal lines and the real invested assets. For property-liability insurers, they utilized as outputs the losses incurred for short tail personal, long tail personal, short tail commercial and long tail commercial lines, and the real invested assets.

For the property-liability sector as a whole the average technical efficiency was 86.6% while technical efficiency for domestic and foreign property-liability insurers was 87.6% and 85.6% respectively. Pure technical efficiency was 90.2%, 91.7% and 88.6% for the property-liability sector as a whole and for domestic and foreign property-liability insurers respectively. Mean scale efficiency was 95.7%, 95.6% and 95.8% for the property-liability sector as a whole and for domestic and foreign property-liability insurers respectively. It is important to note that none of the differences between foreign and domestic efficiency (technical, pure technical, scale) were statistically significant.

In the life insurance sector the whole average technical efficiency was 97.6% while for the domestic, foreign and joint venture life insurers were 99%, 98.6%, and 95.4% respectively. Pure technical efficiency was 98.9%, 99.6%, 100%, and 97.2% for life insurers as a whole, domestic, and foreign and joint venture life insurers respectively. Scale efficiency was 98.7%, 99.3%, 98.6%, and 98.1% for the four above groups respectively. For the property liability sector it was found that 40% of the firms were operating with increasing returns to scale, 56% with constant returns to scale and 4% with decreasing returns to scale and that the difference in returns to scale between domestic and foreign property-liability insurers was not significant. For the life insurance sector, 18% of the firms exhibited increasing returns to scale, 75% constant returns to scale and 8% decreasing returns to scale.

The authors also estimated the Malmquist total factor productivity index and decomposed it to its technical and technological change components for life and property liability insurers separately. For the property-liability sector the average annual productivity growth was 15.8% while the mean technological change was 7.6% and the mean technical efficiency change was 10.7%. For life insurance sector the average annual productivity growth was 24.7% while the mean technological change was 2.7% and the mean technical efficiency change was 21.8%.

As a second step, the authors estimated a Tobit regression weighted by the square root of premiums written. As dependent variables they took the technical, pure technical and scale efficiencies while as explanatory variables the number of firms in each year, the log of total premiums written for each firm in each year, a dummy variable that equals one if the firm is a foreign insurer and zero otherwise and an interaction between size and the foreign firm dummy variable. This procedure was followed for life and property-liability insurers separately. Because the pure technical efficiency results for life insurer sample did not have enough variation to make Tobit regression consistently estimated, a weight least square regression was conducted for pure technical efficiency and with the same explanatory variables.

Moreover they estimated a count model regression and especially a Poisson regression model in order to analyze whether foreign firms (along with joint ventures for life insurers) were influencing the best-practice efficient frontier. As dependent variables they used the variables TE Frontier and PTE Frontier which counted the number of times a given firm is represented as a peer group efficient firm. For the property-liability insurers were used the following explanatory variables: the log of total premiums written for each firm in each year, a dummy variable that equals one if firm is a foreign insurer and zero otherwise and an interaction between size and the foreign firm dummy variable.

For life insurers they used the log of total premiums written for each firm in each year, a dummy variable that equals one if the firm is a foreign insurer and zero otherwise, a dummy variable that equals one if firm is a joint venture insurer and zero otherwise, an interaction between size and the foreign firm dummy variable and an interaction between size and joint venture firm dummy variable. Also, they estimated a weight least square regression using as dependent variable each time the technological change, the technical efficiency change and the total factor productivity change. For property-liability sector the independent variables include size, the number of firms examined in each two-year period, a dummy variable being one if the insurer is a domestic firm and zero otherwise and an interaction variable between size and the above dummy variable. They found that domestic insurers realized greater efficiencies, higher growth in productivity changes and a realization of an improvement in productivity of the sample period. The authors conclude that foreign property-casualty insurers were less likely to encompass the PTE best-practice efficiency frontier, the technological change and technical efficiency change in the property-liability sector were significantly greater for domestic firms than for foreign firms. For the life insurance sector the joint venture insurer was not as efficient as a solely owned domestic or foreign firm insurer and the joint ventures firms were less likely to be represented in the TE frontier than domestic firms.

Luhnen (2008) measured technical, cost, allocative and scale efficiency for 148 property-liability insurance companies operating in Germany using data for the period 1995-2006. Following the value added approach, the claims incurred net of reinsurance plus addition to reserves and the total invested assets were the two outputs used. Labor and business services, the debt capital, and the equity capital were used as inputs. The price for labor and business services is considered equal to the annual wage for the German insurance sector. The price of financial debt capital obtained using the 10-year average return of German Government Rentenindex while the price of equity capital was obtained using the 10-year average return of the German primary stock index Deutscher Aktienindex. The author used the non-parametric DEA method and assumed input orientation and variable returns to scale. Furthermore, Malmquist index of total factor productivity was estimated and decomposed to its technical change and technical efficiency change components.

The technical efficiency change further decomposed into pure technical and scale efficiency change components. Mean technical efficiency for the period 1995-2006 found to be 84% while cost, allocative, and scale were found to be 54%, 64% and 96% respectively. The majority of large (81%) and medium (45%) property-liability insurers operated under decreasing returns to scale while the majority of small (73%) property-liability insurers operated under increasing returns to scale. Total factor productivity growth over the entire period was only 1.3%. This was attributable about 7% to technical change and about 6% to technical efficiency change, the latter of which was mainly defined by pure technical efficiency change (4%) and less by scale efficiency change (2%).

At a second stage the author tried to find the influence on cost and technical efficiency separately of the following contextual variables and their subcategories: size (small, medium, large), distribution channels (exclusive agents, independent agents, direct insurers), ownership form (mutual, stock, public), specialization (specialized, non-specialized), leverage (leverage above median, leverage below median), and growth (above median premium growth, below median premium growth). Next, a truncated regression followed by bootstrapping and reestimation of the regression coefficients was estimated, as proposed by Simar and Wilson (2007). The main findings of the paper were : a) large firms were both more technically and cost efficient than medium and small sized firms, b) exclusive agent insurers which grouped together with direct insurers in order to use a dummy variable were more technically and cost efficient than independent agent insurers and that mutual, stock and public insurers were equally technical efficient but mutual were more cost efficient than stocks and equally as cost efficient as public insurers, c) specialized firms were more cost and technical efficient than non-specialized, d) insurance firms with above median leverage were more technical efficient but equally cost efficient than insurers with below median leverage but the coefficient for this variable was not statistically significant, e) insurance companies with below- median premium growth were more cost and technical efficient than those with above-median premium growth.

Nektarios and Barros (2010) estimated technical efficiency and productivity for a sample of almost all Greek insurance companies (life, non-lie, and composite) for the period 1994-2003. Efficiency and productivity measures were estimated by means of DEA methodology. They proxied outputs produced by using losses incurred, invested assets, reinsurance reserves, and own reserves. Labor cost, non-labor cost, and equity capital were used as inputs used by insurers. They showed that the life insurance sector experienced an annual productivity growth of 16.1%, the non-life insurance sector a rate of 6.5%, and the composite insurers had the lowest productivity rate of 3.3%.

Noulas et al. (2001) estimated technical efficiency for the Greek non-life insurance sector for the period 1991-1996. The sample included 11 companies in 1991, 12 in

1992, nine in 1993, 11 in 1994, 10 in 1995, and 10 in 1996 and accounted on average for the 65% of total premiums written in Greek insurance market. Following the value added approach they defined as outputs the premium income (revenue from insurance related activities) and the revenues from investment activities. In this paper the sum of payments to the insured and the expenses incurred in the production of services was the first input while the salaries and expenses was the second input in the production process. They used the DEA method with an input orientation and found the technical efficiency for each year for each firm in the sample. The average industry technical efficiency for the whole period was 64.69% with an average inefficiency of 35%. Large variations in the degree of inefficiency levels among the firms in the sample were detected.

Pestana-Barros et al. (2010) estimated technical efficiency using a sample of 71 life and non-life Greek insurance companies for the years 1994-2003. They used the two-stage procedure of Simar and Wilson (2007) to analyze the effects of deregulation on the efficiency of the Greek insurance industry. At the first stage the technical efficiency was estimated by means of DEA methodology. At the second stage of this procedure they used bootstrapping techniques in order to approximate the distribution of the estimator via re-sampling and recalculation of the DEA efficiency score. They found that the average efficiency for this period was 0.88 while competition for market share was the main driver of efficiency in the Greek insurance market.

Qiu and Chen (2006) measured technical, pure technical and scale efficiency for a number of Chinese life insurance companies. The number of the companies in the sample was not stable but ranged between 14 and 32 and the data used were covering period 2000-2003. They used the annuity payment, the benefits of death, injury and medical treatment, addition to reserves and yield of investments as the four output variables of the industry. They defined the amount of labor, the equity capital and the agent cost and others as the three input variables of the industry. The DEA method then was used in order to estimate the above mentioned measures of efficiency. At the first stage the authors measured technical, pure technical and scale efficiency separately for each company in the sample and concluded that the efficiency of Chinese life insurers was diversified and relatively stable and that technical inefficiency was not only attributed to pure technical inefficiency but also attributed to scale inefficiency. Next, they separated life insurers into two groups: state-owned Chinese life insurers and international insurers and the joint ventures by a Chinese company and an international insurer. For each of these two groups they estimated the mean and variance of technical, pure technical and scale efficiency for each year in the sample and found that international insurers were more purely technical efficient than Chinese life insurers but their scale efficiency was much lower than that of Chinese life insurers. They found that Chinese life insurers were both pure technical and scale inefficient and that generally the market as a whole were diversified as it is obvious by the size of the variances. Additionally, they grouped life insurers regarding insurers registered before 1998 as traditional life insurers and those registered after 1998 as new-coming life insurers. In the same way as previously, for each of these two groups they estimated the mean and variance of technical, pure technical and scale efficiency for each year in the sample. They concluded that the average technical efficiency was decreasing year by year and that efficiency of traditional life insurers was higher than that of new-coming life insurers. The new comers were not at all worse than traditional insurers and that traditional insurers were more scale efficient than new-comers. Most life insurers were of increasing returns to scale while the average technical efficiency were relatively low (56%) and declining over time. At the late stage they estimated the Malmquist productivity index and its technical efficiency and technological change component. But because for these calculations were required the same sample size in each year, the authors defined as the base sample the life insurers existed in 2000. They found that technological change was the major factor that drives the productivity improvement in the Chinese life insurance industry although some companies' productivity progress is attributed both to technical efficiency and technical progress.

Tone and Sahoo (2005) measured technical, allocative, cost and scale efficiencies for the Life Insurance Corporation of India (LIC) for the period 1982-2001. The data were obtained from the annual statement of LIC which includes the aggregate figures of necessary operational and financial data of all its branches. Following a modified version of the value added approach, they considered as the first output the present value of real losses incurred deflated by the year's 1994 consumer price index and the ratio of liquid assets to liability as a second output variable. The input variables used were the business services, the labor, the debt capital and the equity capital. The price for business services was taken as the ratio of total deflated commission to agents to the number of total active agents. The price of labor was calculated by dividing total deflated salary and other benefits to employees with total employees. The price of debt capital was considered as the rate of interest realized on the mean life insurance fund while the price of equity capital was considered as 9% plus the rate of inflation in each year. A variant of DEA method was used in order to estimate the efficiencies. They reported that although the technical and scale efficiency scores exhibit a slightly upward trend, efficiency scores were high (around one) since 1994-1995. Also this research showed increasing allocative inefficiency after 1994 while the cost efficiency showed an upward trend in 2000. Finally, they stressed that LIC operated under increasing returns to scale for the first two years, constant returns to scale for the year 1984-1985 and decreasing returns to scale for the remaining years of the specified sample period.

Weiss (1991) measured technical, scale, and allocative efficiency of the largest 100 U.S property-liability insurers for the period 1980-1984. Following the value added approach she identified as output variables the incurred loses for each line of business and the reserves invested. The price of incurred losses was defined as the difference between premiums earned and losses incurred by each line of business while the price of reserves invested was considered equal to the three month Treasury bill rate for each year multiplied by policyholder' funds. She also used as input variables the labor, material and capital where labor input included agents, supervisory labor and non-supervisory labor costs. Labor price was defined as a labor wage index for employees and agents of insurers. The price of materials was taken equal to the current dollar value of materials divided by its real value while the price of capital was taken equal to the net income divided by average surplus. The method used was SFA and she estimated the profit function for the sample insurer assuming that it has taken the generalized Leontief form. Her aim mainly was the estimation of costs associated with inefficiency. From the estimates it was concluded that excessive costs of \$121.8 to \$318 million was observed due to inefficiencies and this cost represented 12.6% to 33 % of premiums written respectively.

Worthington and Hurley (2002) measured pure technical, scale, allocative and cost efficiency for 46 Australian General Insurers only for the year 1998. Following the value added approach, they defined as output variables the housing-related insurance net premium income, the transport-related insurance net premium income, the indemnity-related insurance net premium income, the mortgage-related insurance net premium income and the other insurance net premium income. Also, they considered invested assets as the last output variable representing the intermediation function of insurers. The inputs selected were labor, information technology, and other physical capital expenses and the financial capital invested. The price of labor was set equal to the gross weakly earnings of all persons employed in finance and insurance sector. The price of information technology was the prime cost depreciation rate over five years for computers, the price of the other physical capital was the prime cost depreciation rate over 15 years while the price of the financial capital was the long-term rate of return on Australian equity. Using the DEA method, they found that the average pure technical, scale, allocative and cost efficiencies for all firms in the sample were 76.2%, 72.9%, 30.9% and 29.6%, respectively. Based on their estimates, they stressed that the larger portion of overall cost inefficiency was attributed to allocative inefficiency rather than to technical inefficiency. In order to test for differences in efficiency among these groups, they divided general insurers into five equally sized groups according to their book value of total assets. Using the Mann-Whitney and Kolmogorov-Smirnov tests they concluded that the largest 20% of insurers were significantly more efficient than the remaining general insurers. Finally, they estimated four Tobit regressions with dependent variable the pure technical, scale, allocative and cost efficiency separately in each of these regressions. The explanatory variables used were the log of total assets, the log of total assets squared, a dummy variable indicating whether the insurance company is listed or unlisted and a Herfindahl index of product market specialization. They concluded that cost efficiency was closely related to asset size but not to stock exchange listing or product diversification.

Yao et al. (2007) measured technical efficiency for 22 Chines life and non-life insurers for the period 1999-2004. They estimated the efficient frontier using DEA approach without separating this sample in life and non-life insurers. Following the value added approach, they defined total premiums written and investment income as outputs. They defined labor, capital and payments and benefits as input variables in order to estimate efficiency. Adopting the input oriented constant return to scale hypothesis, they found that the average technical efficiency for non-life insurers was 77% and 70% for life insurers. They estimated also the Malmquist productivity change index for this period for life and non-life insurers separately giving simultaneously its efficiency change component and its frontier change component for each company in the sample. The Malmquist index revealed that inefficiencies can be vanished either by improving technical efficiency or by making technological advances with the suitable methods. At a second stage, they estimated a Tobit regression with technical efficiency as dependent variable and total assets, three dummy variables representing the ownership, the distribution system and the mode of business and a variable giving the proportion of labor force with higher education in total labor force as dependent variables. They concluded that larger insurers were more efficient than smaller ones and the insurers using direct sales were more efficiency than those using indirect sales. However, in contrast with the literature, they did not find significant evidence to prove that non-state insurers were more efficient than state insurers because Chinese insurance market still gives special attention in protecting state-owned insurers. Finally, they stressed that insurance firms with a high portion of labor force having higher education were more efficient than those not possessing this advantage.

Ysu and Petchsakulwong (2010) estimated technical, cost, and revenue efficiency of public non-life insurance companies in Thailand over the period 2000-2007. DEA methodology was used to compute an insurer’s efficiency performance. Losses incurred and invested assets were used as outputs while labour, equity capital, and materials and business services were used as inputs. They primarily examined the relationship between corporate governance and efficiency performance of these non-life insurers. Employing truncated bootstrapped regression, they found that board independence, diligence, and firm size had a positive impact on the efficiency while audit committee size, board tenure, board age, and board ownership had a negative impact on the efficiency performance.

2.3 Category of regulation change

This category of papers deals mainly with the deregulation of financial services sector and especially the insurance providing sector. Deregulation generally is acted in order to improve market efficiency through higher competition among insurance providers and hence improve consumer social and economic status.

Badunenko et al. (2006) measured technical and scale efficiency for 163 life and non-life insurers in Ukraine during the period 2003-2005. They primarily searched whether the increased capitalization requirements for Ukrainian insurance firms influenced their technical and scale efficiency. Using DEA method, in the first model they used premiums written for personal, property and liability insurance lines as output variables (value added approach) and fixed and current assets as input variables. In the second model, they used the same output variables but they used liabilities and equity as input variables. Average technical efficiency for the industry as a whole was found to be 56% by the first model and 61% by the second model. They also estimated the Malmquist productivity index and its technical efficiency change component, its technological change component and its scale change component. The authors stressed that deregulation improved efficiency about 40%, the number of small firms dropped impressively while the number of large and middle insurers remained on average unchanged. However, they concluded that the increase in size of the firms was not exclusively attributed to deregulation. But the fact that scale inefficient firms were operating under increasing return to scale conditions created the suitable conditions for mergers and acquisitions and as a consequence for size increases.

Boonyasai et al. (2002) measured technical, pure technical and scale efficiencies for the life insurance sector in Korea, Philippines, Taiwan and Thailand. Their research covered the period 1978-1997 and the number of firms in the sample ranged between 49 and 110, depending on the availability of data. They defined the output variables according to the value added approach and used premium income and net investment income as their two output variables. As input variables they defined labor, capital and materials. Using DEA method they also estimated the Malmquist productivity index and it’s technical, pure technical, technological and scale efficiency change components. For each of the above mentioned countries they estimated three Tobit regressions, using in each of these regressions the technical, pure technical and scale efficiency variable as a dependent variable separately. With this process they tried to discover if the liberalization and deregulation of these insurance markets had a positive, negative or no effect in productivity and efficiency. Also, they used a t-test in order to identify whether the Malmquist productivity index and it’s technical, pure technical, technological and scale efficiency change components were substantially different before and after the year of liberalization or deregulation. According to their results, liberalization and deregulation of the Korean and Philippine life insurance industries had positive effects on productivity. On the other hand, liberalization of the Taiwanese and Thai life insurance industries had little effect on productivity. The authors concluded with the suggestion that liberalization must be followed by deregulation efforts in order to promote positive competition and to increase efficiency and productivity.

Cummins and Rubio-Misas (2006) estimated cost, pure technical, allocative and scale efficiency for all life and non-life operating insurance companies in Spain, excluding those having data problems such as non-positive premiums or net worth for the period 1989-1998. They used the non-life losses incurred, the life losses incurred, the reinsurance reserves and the invested assets as output variables following the modified value added approach. As input variables they used the labor, the business services, the debt capital and the equity capital. They first categorized the insurance firms into four quartiles according to their asset size and measured the average price for the above mentioned sort of efficiencies. Additionally, they measured Malmqist’s average total factor productivity index with its technical, pure technical and scale change components firstly for the complete panel of firms presented in all of the years 1989-1998 and secondly for the firms present in each of the adjacent two-year comparison periods. Next, they repeated the above process categorizing insurers in firms acquired by other, in firms leaving the market for other reasons such as insolvency or voluntary liquidation, in firms entering the market, in firms participating in mergers and acquisition process (M&A) and in firms remaining in the market that have not engaged in M&A activities. They argued that deregulation and consolidation had positive important effects as far as total factor productivity growth is concerned. But the productivity gains were attributed to technical efficiency progress and not to technological progress. The number of insurers in the market declined by 35% while average firm size increased by 275% during the sample period. As far as M&A activities, they stressed that consolidation increased average firm size by removing small firms from the market and permitting large firms to grow through acquisitions. Finally, they found that consolidation reduced the number of insurance providers with increasing return to scale productions and at the same time increased the number of insurers having decreasing return to scales operations.

Ennsfellner et al. (2004) estimated technical efficiency for a sample of life/health and non-life Austrian insurers during the period 1994-1999. The sample was not stable for each year of this period but ranged between 97 and 105. They primarily estimated technical efficiency in order to find out if deregulation and more accurately the adoption of the Insurance Directives of the European single insurance market in 1994 affected the production efficiency of the Austrian insurance industry. Using the value added approach, they used incurred benefits, changes in reserves and total invested assets as health/life output variables and losses incurred and total invested assets as non-life output variables. Net operating expenses, equity capital and technical provisions were the input variables for the production process. They estimated the SFA production function first separately for life and health insurers and secondly for non-life insurers. Additionally, they estimated a single production function for the above two categories of insurers. It is also important to note that they used the Bayesian technique for the estimation of the required variables. Finally, they used Lewis-Anderson methodology to test whether the industry efficiency between periods 1994-1996 and 1997-1999 progressed or regressed. They found that the deregulation had important positive effects in the productive efficiency and that technical efficiency both for life/health and non-life sector was substantially higher during the period 1997-1999 than technical efficiency in the period 1994-1996.

Hussels and Ward (2006) measured cost, technical, allocative and scale efficiency for 47 U.K life insurance companies and 31 German life insurance companies during the 1991-2002 period. Their first objective was to find whether deregulation in these two economies had a positive impact on insurance sector efficiency. According to the value added approach, they used net written premiums and addition to reserves as output variables and labor and capital as input variables. For their efficiency estimation they used both DEA and DFA and found that DEA produced larger efficiency measures than DFA. The average mean efficiency for Germany was 57.4% with DEA and 44.4% with DFA while for UK average mean efficiency was 74.4% with DEA and 53.1% with DFA. They also estimated the Malmquist productivity index and decomposed it into its technical efficiency and technological change components. At a second stage they regressed the various measures of efficiency on a variety of organizational variables and time dummies using the Tobit specification. Only the 1996 time dummy for UK was significant, indicating that there were no statistically important evidence to show that deregulation had positive effects on efficiency measures.

Mahlberg and Url (2000) measured technical efficiency for a panel of German life, health and property-liability insurers for the period 1992-1996. Their primary concern was to ascertain whether transition to the single market in the German insurance industry had positive effects on efficiency. Preferring the value added approach they used claims, net change in provisions, allocated investment returns and bonuses and returned premiums as output variables and selected administration and distribution cost as the unique input variable. They used the DEA method to complete their efficiency estimations and estimated the Malmquist productivity index with its technical efficiency change and technological change components. According to their results, costs saving potentials yet existed as well as an increasing divergence between fully efficient firms and efficiency laggards. They stressed that average cost curve had an L-shaped form and so there exists low cost saving potentials from merging activities indicating that the transition to the single market in the German insurance industry had not achieved the maximum cost saving potentials and therefore there were opportunities for further developments.

Mahlberg and Url (2003) measured technical efficiency for a sample of life, health and property-liability Austrian insurers for the period 1992-1999. Preferring the value added approach they used claims, net change in provisions, allocated investment returns and bonuses and returned premiums as output variables and they defined the administration and distribution cost as well as the cost of capital investments as input variables. They used the DEA method to complete their efficiency estimations and estimated the Malmquist productivity index with its efficiency progress and technical progress components. Following the constant returns to scale hypothesis, they found that the average geometric mean efficiency was 42%, while average geometric mean efficiency was 66% according to the variable returns to scale hypothesis. The average geometric mean scale efficiency was 65% for the whole sample period. At a second stage, they also estimated some Tobit regressions in order to find if some firm specific characteristics had important effects on efficiency. They found that Austrian insurance industry showed increased productivity during the period 1992-1999 and especially it averaged 10% between 1992 and 1999. They concluded that the Austrian insurance market was still inefficient at a high level implying that the implementation of single market had not exploited wholly the opportunities for efficiency improvement.

Rees et al. (1999) described the regulation of insurance sector in Germany and in U.K and measured the technical efficiency for the above two life insurance markets for the period 1992-1994 in order to find out if pre-1994 deregulation affected the efficiency. Preferring value added approach for output variables definition they used total premium income and change in total premium income as output variable for the U.K life insurance sector and aggregate sum insured and change in aggregate sum insured as output variable for the German life insurance sector. They used as input variables the distribution cost and the administration cost. Using the DEA approach, they found that the average level of efficiency of the German firms was 47.6% and56.8% for the British firms. Light regulation, competition and the possibility for bankruptcy had improved the efficiency causing a significantly higher proportion of firms to achieve efficiency level closer to those of the most efficient firms. They stressed that the European Commission's policy may have improved the welfare of insurance buyers in previously highly regulated countries such as Germany. Finally, they argued that tighter solvency regulation allows the survival of a large proportion of higher-cost firms.

Ryan and Schellhorn (2000) measured cost efficiency for 321 life insurers in U.S during the period 1990-1995 and their main objective was to search for improvements in efficiency after the implementation of risk-based capital (RBC) requirements developed by the National Association of Insurance Commissioners (NAIC). They followed the value-added approach in defining of outputs. These were benefit payments for individual life insurance, for group life insurance, for individual annuities, for group annuities and for accident and health insurance. Also they used the addition to reserves as output variable simulating the intermediation services provided by life insurers. They used labor, financial capital and materials as input variables in the production function of the life insurance sector in U.S. They used the DFA for their estimations and more accurately they specified the translog cost function for the six outputs and the three inputs described above. They divided the sample in four quartiles according to their size and estimated average cost efficiency for each of the quartiles and for the whole sample. Next, they used the mean t-tests and the non-parametric Wilcoxon tests in order to test whether average X-efficiency was equal during period 1990-1992 and during period 1993-1995. They found that average X-efficiency for the industry was about 31% in both 1990-1992 and 1993-1995 periods. These results indicated that the X-efficiency of life insurance sector in

U.S remained visibly unchanged after the implementation of RBC requirements. Finally, they estimated a fixed effect model using firstly ordinary least squares, secondly generalized least squares and finally a Tobit regression using as dependent variable the cost efficiencies founded above. As independent variables they used many dummies variables. Among their most important results were the fact that efficiency was enhanced by multiple product offerings, that mid-sized insurers were the least efficient and that mutual insurance companies were relatively more efficient than stock companies.

Trigo Gamarra (2008) measured cost and profit efficiency for a non-balanced panel of German life insurance corporations for the period 1995-2002. The basic aim was to examine the effects of liberalization and deregulation on the performance of German life insurance sector. Following the value added approach for the determination of outputs they defined incurred benefits, addition to reserves and bonuses and rebates as the output variables of the production process. They defined acquisition and administration expenses according with equity capital as the two main input variables in the production process of the insurance sector. Using the SFA method the author estimated a parametric input distance function with the Translog functional form. The author estimated the total factor productivity index and its cost efficiency change, technical change and scale efficiency change components. Average technical cost efficiency for the whole sample period amounted to 67.78% while average profit efficiency amounted to 91.37% for the same period. It was found that technical cost and profit efficiencies remained stable on average and there was no clear upward trend for these efficiencies in the German life insurance industry. The average total factor productivity change for this period amounted to 12.5% and it was mainly driven by improvements in technology change. In contrast, German insurance firms had realized important increases in scale efficiency as the industry experienced a significant positive scale efficiency of 5.83% on average and they were on average operating under increasing returns to scale. Finally, the author stressed that liberalization, which intended to increase competition, had resulted in higher market concentration and efficiency gains for life insurers.

Turchetti and Daraio (2004) estimated technical, cost, allocative and scale efficiency for the Italian motor insurance industry in order to find out how deregulation shaped the market structure and the efficiency of this industry. The sample used (45 insurers) included insurers operating in Italy, active and working in the motor liability sector during the period 1982-2000. Using the value added approach, they used motor property incurred losses, motor liability incurred losses, other liability incurred losses, other properties incurred losses and invested assets as the main outputs. They defined acquisition production and organization costs, overheads and administrative expenses, fixed capital, financial equity capital and policyholder debt capital as inputs. The method used for measuring the above mentioned efficiencies was the DEA and they also estimated the Malmquist productivity index as well as its technical efficiency change and technological change components. They separated the sample between companies hit by the Antitrust measure (FINED=1) and companies not hit by the Antitrust measure (FINED=0). They found that cost efficiency increased during the sample period and especially during the second half of the 1990s. Also, the total factor productivity index was increased and this increase was mainly due to technological changes rather than to efficiency changes. The authors concluded that fined firms presented higher level of efficiency during almost the whole period and that among fined companies, generalist ones presented better results than specialist ones.

Yuan and Phillips (2008) used the composite production function proposed by Pulley and Braunstein (1992) in order to estimate the cost, revenue and profit functions for U.S life, property-liability, commercial banks and thrifts institutions. At a second stage, they estimated the cost, revenue and profit scope economies and tried to find out if the Gramm-Leach-Bliley (GLB) act of 1999 had any productive efficiency effects as it allowing the formulation of an integrated financial service company. They estimated separate functions for banking and insurance subsidiaries, of specialists firms and joint producers which are firms jointly producing both banking and life insurance banking and property-liability insurance, and firms participating in all three sectors. Using the value added approach for output definition they used present value of real losses incurred as output variable for P-L insurers and incurred benefits plus addition to reserves as output variable for life insurers. As input variables in the production process they used labor (administrative and agent), material and physical capital, financial equity capital and debt capital. They followed the SFA approach for the estimation of the demanded coefficients using non-linear least squares techniques. They stressed that in the post-GLB integrated banking and insurance sectors were existing significant number of cost scope diseconomies, revenue scope economies and weak profit scope economies. After that, they regressed the cost, revenue and profit scope economy scores on a set of firm characteristic variables respectively using Tobit methodology. Among their results: Small firms were more likely to benefit from cost saving while large firms were more likely to benefit from revenue and profit increases when jointly producing banking and insurance products; Firms offering a more narrow set of products from their insurance division were less likely to exploit cost scope economies but were more likely to exploit revenue and profit scope economies; Firms which were more profit x-efficient in the individual subsidiaries were also shown to be overall more profit scope efficient.

2.4 Category of intercountry comparisons

This category of papers engages in measuring and comparing efficiency scores among insurance sectors of different countries. The majority of the articles included in this category compare life or non-life insurance sectors belonging mainly to EU countries.

Bertoni and Croce (2011) estimated technical efficiency and productivity for a sample of European life insurers for the period 1997-2004. They applied DEA method for the efficiency estimations and the Malmquist index for productivity estimations respectively. They used net premiums written as a proxy for the output produced by insurers and equity, total other liabilities, net technical reserves, and total operating and management expenses as input proxies. Their basic aim was to investigate the drivers of productivity evolution in the aftermath of the enforcement of the Third Directive in European insurance market. They found that productivity increased on an annual basis by 6.71% and this increase has been mostly due to innovations in best practices (6.67%), while best practice adoption contributed by a mere 0.04%. Finally, they found no evidence that productivity has been driven by a shift in the risk profile of European insurers.

Biener and Eling (2012) estimated technical, cost, and allocative efficiency for a sample of insurers operating in 21 countries from northern America and the European Union for the years 2002-2006. They employed cross-frontier analysis, an innovative technique based on DEA, to provide new insights into the relationship between organizational form and efficiency in international insurance markets. The cross-frontier efficiency scores are calculated as the output/input ratio of insurer-i in relation to the maximum output/input ratio of all stock insurers in the sample (if insurer-i is a mutual insurer) or mutual insurers in the sample (if insurer-i is a stock insurer). They found evidence for the efficient structure hypothesis in selected market segments, but no evidence for the expense preference hypothesis.

Delhausse et al. (1995) estimated technical and scale efficiency for a sample of 243 France and 191 Belgian non-life insurance companies covering the period 1984-1988. According to the value added approach they defined gross premiums as the only output variable and used labor cost and a composite item consisting of various outlays such as capital consumption, purchase of equipment and supplies as the two main input variables in the production process of the insurance sector. They used both DEA and SFA methods in order to estimate production frontier for France, Belgium and the merged insurance market consisting of these two markets. Generally, they found low and widely dispersed efficiency scores for the two insurance markets. They found that Belgian non-life insurers were on average less efficient than the French ones by 7.8% and 10.4% for the SFA and DEA approaches respectively.

Diacon (2001) measured technical efficiency for 431 specialist general and composite insurers operating in six European countries, namely France, Germany, Italy, the Netherlands, Switzerland and the United Kingdom. He defined net earned premiums and total investment income as the main output variables in the production process. Total operating expenses, total capital, total technical reserves and total borrowing from creditors used as the main inputs. Firstly, he estimated average local technical efficiency for each country`s insurance sector using the variable returns to scale DEA approach. Secondly, he projected each insurer to its local efficiency frontier and a second DEA analysis was undertaken producing the projected global efficiency scores. Finally, a global score for each general insurer in the sample was obtained by multiplying local and projected global efficiency scores. The results showed that United Kingdom insurers had the highest average technical efficiency score with Germany insurers coming second. Specifically, UK`s insurance market had an average technical efficiency of 77%. France, Germany, Italy, the Netherlands and Switzerland insurance sectors had 67%, 70%, 56%, 69% and 66% technical efficiencies respectively. Using a variety of environmental variables as independent factors he estimated Tobit regressions with dependent variables the global and projected global efficiencies respectively. Among the most important result was the fact that both small and large insurers were more efficient than medium-sized insurers and that mutual insurers were more efficient than stock insurers.

Diacon et al. (2002) measured pure technical, scale and mix efficiencies for 454 life (including pension and health insurers) insurers belonging to 15 different European countries for the period 1996-1999. According to the value added approach, they used general insurance net earned premiums, long-term insurance net earned premiums and total investment income as the main outputs. They used total operating expenses, total capital, total technical reserves and total borrowing from creditors as inputs.

Efficiency estimates were obtained by using the input-oriented variable returns to scale formulation of DEA methodology and they presented average pure technical, scale and mix efficiencies for each of the 15 countries and average pure technical, scale and mix efficiency considering all the insurers as a unified sample. The average pure technical, scale and mix efficiency for the whole international sample of these insurers were 55.73%, 80.05% and 86.84% respectively. They stressed that there was evidence of substantial variations in international efficiency and that in general the average level of pure technical efficiency had declined since 1996. Using the pooled data, they estimated three Tobit regressions with dependent variable the pure technical, scale and mix efficiency each time and explanatory variables a galore of environmental and year with country dummy variables. Among the most important results were that technical and scale efficiency scores were associated with insurer size with clear evidence of a U-shaped relationship, and that mutual insurers were more technical efficient and less mix efficient than stock insurers.

Donni and Fecher (1997) measured technical efficiency for a sample of life and non-life insurers belonging to 15 OECD countries for the period 1983-1991. They determined net premiums earned as the only output variable according to the value added approach and labor as the only input variable. Using the DEA method they estimated average technical efficiency for each country and the average technical efficiency for all 15 countries which amounted to 70%. It appeared that there was an important variation in efficiency level among these countries and that most of the industrialized countries (United States, United Kingdom, France, Germany) were more technically efficient than others according to their insurance sectors technical efficiency. Moreover, they estimated Malmquist productivity index and its technical efficiency change and technological change components and found important growth in productivity (5.5%) for all countries in the sample with this growth coming from improvements in technical progress. Finally, they estimated a Tobit regression using technical efficiency as the dependent variable and concluded that reinsurance ratio and market shares in OECD insurance markets tended to favor efficiency levels.

Eling and Luhnen (2010a) estimated technical and cost efficiency for a sample of 6462 life and non-life insurers operating in 36 different countries for the period 2002-2006. According to the value added approach, they determined claims plus additions to reserves and benefits plus addition to reserves as output variables for non-life and life insurers respectively. Also, they defined investments as the third output of the production process in the insurance sector. Labor and business service, financial debt capital and equity capital were used as the main input variables. They used DEA method assuming input orientation and variable returns to scale. Technical efficiency for life insurance was, on average, 71% and 50% in non-life insurance. Cost efficiency was on average lower than technical efficiency with a value of 38% in non-life and 59% in life insurance. They also used SFA method and for the calculation of technical efficiency they specified a translog stochastic input distance function while for the calculation of cost efficiency they specified a translog stochastic cost function. The results were quite similar with those obtained with DEA method. They found generally technical and cost efficiency growth in the international insurance markets during the period 2002-2006 but with large differences across countries. Moreover, it is important to note that Denmark and Japan had the highest average efficiency while Philippines had the lowest efficiency. At a second stage, they used conditional mean approach and estimated two regression equations with dependent variable the technical and cost efficiency score separately and explanatory variables a vector of firm and country specific variables. They showed that both life and non-life mutual insurers had higher cost and technical efficiencies than stock insurers. Finally, they stressed that under the conditional mean approach the size advantage of large insurers was only confirmed for non-life insurers.

Eling and Huang (2013) measured technical efficiency of 821 non-life insurers in the BRIC (Brazil, Russia, India and China) countries over the period 2000-2008. The innovative characteristic of this paper was the incorporation of uncontrollable variables in the efficiency analysis so as to distinguish between managerial inefficiency and inefficiency due to environmental conditions. According to the value added approach, they used net premium written and total invested assets as output variables. They used the number of employees, the equity capital and the debt capital as inputs. The environmental variables include macroeconomic, regulatory and insurance industry conditions that are important factors in demand and operational efficiency of non-life companies. Using DEA method (Model 1), they first measured efficiency without considering differences in the environmental conditions and found that Brazilian insurers were the most efficient while Chinese insurers were the least efficient. They adopted a multi-stage DEA model, obtained slacks filtered for the impact of uncontrollable variables by regressions, and adjusting the values of primary inputs by using Tobit regressions (Model 2) and stochastic frontier analysis slack regressions (Model 3) to eliminate the impact of different environmental conditions. From the adjusted models entailed that Indian insurers were less efficient than the other BRIC insurers while Brazilian insures were the most efficient with Russian and Chinese coming second and third respectively. They analyzed total factor productivity growth and found, on average, a decrease in efficiency over time. Finally, they estimated a Tobit model in order to investigate the relationship between efficiency scores and firm-specific variables. They detected that three firm-level factors- return on equity, ratio of claims paid to premiums and ratio of equity capital to total assets-had important explanatory power for technical efficiency.

Klumpes and Schuermann (2011) estimated cost, revenue, and profit efficiencies for a sample of life insurers that operate in European markets from 2003 to 2007. They used the present value of future claims as output and total capital and reserves, labour, and debt capital as inputs used by the insurers. The DEA method was used for the efficiency estimations. Their basic aim was the examination of the relationship between efficiency and the strategic mix of product, marketing and asset/liability structure of insures. Utilizing multiple regression analysis they supported the prediction of the market imperfection hypothesis. This hypothesis states that firms with non-exclusive distribution systems are less costly and profit efficient than firms with exclusive ones.

Rai (1996) measured cost efficiency for a sample of 106 life and non-life insurance companies operating in 11 OECD countries for the period 1988-1992. Life premiums and non-life premiums were used as outputs and labor, capital and benefits plus claims as inputs. He used both SFA and DFA methods in order to estimate cost efficiency for the whole sample and for the large and small firms separately. For both methods it was assumed that the cost function had the translog form. The results showed that insurers operating in Finland and France were the most efficient while those operating in UK were the least efficient. At a second stage, he regressed cost inefficiency estimates against some firm-specific variables. The basic results were that small insurers were more cost efficient than large insurers and that specialized insurers were more cost efficient than diversified insurance companies.

Vencappa et al. (2008) estimated technical efficiency for a sample of life and non-life insurers operating in 14 European countries for the period 1995-2001. Also, they estimated and decomposed productivity growth for each of these countries. Specifically, they estimated and decomposed productivity growth into technical change factor, technical efficiency change factor and scale efficiency change factor separately for life and non-life insurers. They proceed in decomposition with two methods. Firstly, they decomposed productivity growth using time trend for technical change and secondly using the Baltagi and Griffin general index. For their estimation they used the SFA method and they assumed that the production function had the Flexible Fourier functional form. Incurred benefits were used as output and labor including materials, financial capital and debt capital as inputs. They found temporal variations in the rate of the overall productivity growth for life and non-life insurers. These variations were driven by patterns of technological progress and regress, together with consistent positive contributions from scale efficiency. Finally, in most years they found evidence of modest growth in technical efficiency with important differences existing across EU member states.

Zanghieri (2008) estimated cost and profit efficiency using balance sheet data on a sample of European life and non-life insurance companies operating in 14 different countries for the period 1997-2006. According to the value added approach, the author defined claims paid plus additions to reserves as output variables for life insurers and claims paid only as output variable for non-life insurers and defined technical reserves, labor, and equity and debt capital as the four main inputs for the production process. He estimated cost and profit efficiency separately for life and non-life insurers using SFA method and assumed that cost and profit function followed the standard translog form. At a second stage, he tried to relate the estimated efficiency scores with some structural factors related to the characteristics of a firm and with some environmental variables related to the country in which each company is registered. For this aim he used the one-stage methodology put forward by Khumbakhar and Lovell (2000), which assumes a zero mean half normal distribution for the efficiency term and an impact of the exogenous variables on heteroscedasticity of both the efficiency and the error terms. For life insurers, the size had a negative effect on cost efficiency but on the contrary, insurers with larger market shares were more cost efficient than those with smaller market shares. For non-life insurers, the size was positively correlated with cost efficiency as well as market share was. Additionally, larger life insurance firms were less profit efficient than smaller ones and market shares were positively related with profit efficiency. For non-life insurers size was positively related to profit efficiency while market share was negatively related to profit efficiency. The author stressed that country-specific factors (e.g. size of insurance sector, index of regulation quality provided by the World Bank) did not seem to influence the efficiency of life insurance sector but they did have a strong effect on efficiency of non-life insurance sector.

2.5 Category of methodology issues, comparing different techniques or assumptions

This category of literature includes mainly articles which primarily solve methodological issues or compare different techniques or assumptions as far as estimation of unknown parameters is concerned. Here the most important paper belongs to Cummins and Zi (1998) who compared the following different frontier efficiency methods: DEA, DFA, FDA, and SFA.

Brocket et. al. (2004b) measured technical efficiency for 538 HMO health insurers operating in U.S only for the year 1995. HMOs insurers are organizations that provide basic health services for a fixed periodic payment under a community rate system and were defined by the Health Maintenance Organization Act (HMO) of 1973. The authors estimated and compared the efficiency between two principle HMO categories, the less autonomous Staff/Group arrangement and the more autonomous Independent Practice Association (IPA) arrangement both from consumer's perspective and from societal perspective. They defined as output variables the number of outpatient visits made by the members of an HMO, the number of hospital days (the total number of days enrollees of HMOs are hospitalized), and the total member months (the total enrollment of group and individuals subscribers of HMOs expressed in months). From consumer's perspective they determined premiums as input variable for the production process while from societal perspective they determined the total HMO expenses as the sole input for the production process. They used the DEA method and more accurately a new game-theoretic DEA model[3] for their estimations. They found that Independent Practice Associations (IPAs) were more efficient than the Staff/Group arrangement HMOs both from the societal and from consumer's perspective.

Cummins and Zi (1998) measured cost, technical and allocative efficiency for a sample of 445 life insurance companies operating in U.S market for the period 1988-1992. The methods used include DEA, FDH and seven econometric methods which were depending on the distribution assumptions followed each time by the inefficiency error term. They defined incurred benefits and additions to reserves as the main outputs from the production process and labor, capital and materials as inputs for ordinary life insurance, for group life insurance, for individual annuities, for group annuities and for accident and health insurance. They found that the choice of estimation method has a significant effect on the conclusions of an efficiency study. The authors stressed that the efficiency rankings for the insurance firms in the sample were well-preserved within the set of econometric methods. The rankings were less well-preserved between the econometric and mathematical programming methods and likewise between the DEA and FDH methods. Additionally, it was stressed that both the econometric and mathematical programming efficiency scores were significantly correlated with the conventional performance measures, but the correlations tend to be somewhat higher for the mathematical programming methods. Also, they showed that insurers with less than $300 million in assets exhibited increasing returns to scale while insurers with more than $1 billion in assets exhibited decreasing return to

[3] It is a cross-frontier methodology that estimates efficiency of mutuals insurers for example by using the set of the stock insurers in order to estimate their efficiency scores. See Rousseau, J. J., and J. Semple, 1995, Two-Person Ratio Efficiency Games, Management Science, 41, 3:435-441.

scales. Finally, they found no evidence that mutual insurers were less efficient than stock insurers.

Fuentes et al. (2001) measured technical efficiency and estimated as well as decomposed two alternative, deterministic and stochastic parametric Malmquist indexes of a panel of Spanish health, life and non-life insurers over the period 1987-1994. For their estimations they adopted a multi-output distance function which was specified in a translog form. They defined as output variables the total annual premiums in health, life and non-life insurance and labor costs and a composite input as the two input variables. Following the SFA method, they decomposed Malmquist index for each year to its efficiency change and technical change components. Moreover, technical change component decomposed further to its bias index, output bias and input bias components. They showed that under the deterministic approach average technical efficiency was lower and more widespread than under the stochastic model. They stated that although the period analyzed was a period of deregulation of insurance markets in Europe, the sector showed very low rates of productivity growth. Finally, they showed that Malmquist index's estimation can be accomplished with parametric frontier approaches in a similar way to non-parametric frontier approaches.

Fukuyama and Weber (2001) estimated the Farrell, Russell and Zieschang measures of technical efficiency for a sample of 17 non-life insurers operating in Japan during the period 1983-1994. These three efficiency measures were then used to construct the Malmquist index of productivity growth which additionally decomposed into an index of efficiency change and an index of technological change. Preferring the financial intermediary approach for output definition, they assumed that insurers were employing reserves as an output as they can be considered financial firms that utilize labor and capital as inputs in order to produce reserves, loans and investments. For all the above mentioned estimations they followed the non-parametric DEA method. They concluded that from 1983 to 1990 all three productivity indexes showed productivity growth with technological progress tending to be the dominant factor of growth. After 1990 there was no significant change in productivity while during 1992-1993 all efficiency measures showed a significant decline. They found that most non-life insurance companies operated with decreasing return to scales throughout the period. They stressed that non-life insurance companies in Japan experienced much of the improved productivity and technological progress enjoyed by other financial services firms.

Hwang and Kao (2008) measured efficiency for a sample of 24 Taiwan non-life insurance firms for the period 2001-2002. They estimated efficiency both with the two-stage independent model which measures efficiency in each stage of production process using the conventional DEA method and the relational two-stage DEA model which uses the outputs of the first stage as inputs of the second stage. The efficiency of the first stage measures the performance in marketing while the efficiency of the second stage measures the performance in generating profits and the product of these two efficiencies is the efficiency of the whole process. They used direct written premiums and reinsurance premiums as first stage outputs while they used underwriting income along with investment income as second stage outputs. They also used operation expenses as well as insurance expenses as inputs of the system which are also the inputs of the first stage. They stressed that the low average efficiency of the whole production process was mainly due to the low efficiency score of the second stage which includes the profit earning process. They concluded that the independent model was less reliable than the relational model because the first may produce unusual results for several companies while the second always produces meaningful results for all companies.

Leverty and Grace (2008) measured pure technical, technical, scale, allocative, cost and revenue efficiency for a sample of U.S property-liability insurers from 1989 to 2000. They compared the production and the flow or financial intermediation approach with the aim to search for differences in efficiency scores. For the production approach they used real losses incurred for the different lines of business and real invested assets as output variables while they used ROI, liquid assets to liabilities ratio and the solvency score as output variables for the flow approach. They used labor, material and business services, financial equity capital and policyholder supplied debt capital as input variables for the production approach. Also, they used policyholder surplus, underwriting and investment expenses and policyholder supplied debt capital as input variables for the flow approach. DEA and Range Adjusted Measure (RAM) used separately for each approach and for each year in the sample. They showed that the production and the flow or financial intermediation approach are not consistent. Also, they found that the production approach was more closely related to traditional measures of firm performance. They stressed that firms operating efficiently according to the production approach were generally significantly less likely to fail while those operating efficiently according to the flow approach were generally more likely to fail.

Pestana-Barros and Wanke (2014) analyzed the technical efficiency of a sample of Angolan life and non-life insurers using a two-stage DEA methodology for the period 2002-2011. They found that the average technical efficiency was 0.74 and 0.94 for the constant return to scale and variable return to scale models respectively. Additionally, they developed a neural network model which predicts insurers' insolvency by assessing how the age, the market share, and the company origin impact efficiency. They concluded that there is a capacity shortfall in this insurance market and that the output-increasing potentials are severely constrained.

Pestana-Barros and Wanke (2017) estimated technical efficiency for a sample of major insurance life and non-life companies operating in Angola and Mozambique between 2003 and 2012. They applied both the input and output oriented DEA methodology and used a bootstrap technique in order to estimate confidence intervals for their efficiency scores. They also used the meta-frontier approach in order to estimate the technology gap ratio which is the ratio of technical efficiency of an insurer according to the whole sample frontier (both Angolan and Mozambique insurers) to its technical efficiency according to its national sample frontier. They found that the average technical efficiency was 0.68 and 0.82 for the constant return to scale and variable return to scale models respectively. They concluded that there is a capacity shortfall in these two African countries and that their performance is quite similar towards a common meta-frontier.

Wu et al. (2007) measured systematic[4], production and investment efficiency for a sample of Canadian life insurance companies for the period1996-1998. A new DEA model was used which simultaneously could analyze both production and investment efficiencies within a systematic organization. For the production function they used labor expenses, operating expenses, capital equity and claims incurred as input variables and net premium written as well as net income as output variables for the same function. For the investment function they used net actuarial reserves, investment expenses, total investments, and total segregated funds as input variables while for the same function they used investment gains in bonds and mortgages and investment gains in equity and real estate as the main output variables. They found that Canadian life insurance industry was highly efficient for the examined time period and that no scale efficiency was found. Finally, as far as efficiency and insurer size is concerned, they stressed that asset size was independent of the efficiency scores.

Yang (2006) measured systematic, technical (production) and investment efficiency for 72 Canadian life insurance companies for the year 1998 only. He used a new two-stage DEA model in order to evaluate systematic efficiency, which allowed the integration of the production and investment performance for each insurance company in the sample. For the production function he used labor expenses, general operating expenses, capital equity and claims incurred as input variables and net premium written as well net income as output variables for the same function. For the investment function he used net actuarial reserves, investment expenses, total investments, and total segregated funds as input variables while for the same function author used investment gains in bonds and mortgages and investment gains in equity and real estate as the main output variables. The results showed that the Canadian life insurance industry operated fairly efficiently during the examined period while scale efficiency was found for this industry. Finally, he found that a variable return to scale (VRS) mechanism was at work both from the production and investment viewpoint.

2.6 Category of organizational form, corporate governance issues

This category of literature deals mainly with the effect of organizational form on efficiency of insurance industry. The main hypotheses developed in this area are the expense preference hypothesis and the managerial discretion hypothesis. The first states that stock insurers are generally more efficient than mutual insurers due to unresolved agency conflicts while the second states that the two organizational forms use different technologies and that mutual are more efficient in areas with low managerial discretion.

Brockett et al. (2005) examined the efficiency for a sample of 1524 US property-liability insurers for the year 1989. More accurately, viewing the insurer as a financial intermediary they examined the efficiency of the marketing distribution channels and the efficiency of the organizational structure of the insurers. They used the Range Adjusted Measure (RAM) method which is a variant of the additive DEA model. According to the financial intermediary approach, they selected the surplus of the

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[4] For the estimation of systematic efficiency firstly they separately calculate production and investment efficiencies by DEA method and then as a second step they average these two efficiencies.

previous year, change in capital and surplus, underwriting and investment expenses, and policy-holders-supplied debt capital as input variables and rate of return on investments, liquid assets to liabilities, and solvency scores as output variables for the production process of the insurers. Also, they used the Mann-Whitney rank-order test in order to find whether one type of organizational form was more efficient than the other. They found that stock insurance companies were more efficient than mutual insurance companies and that the agency marketing system was more efficient than the direct marketing system. Finally, they stressed that stock insurers tended to have more inefficiency in the input dimension than did the mutual organizational form while mutual insurers showed much higher shortfall in all areas of outputs.

Cummins et al. (2004) measured technical, allocative, cost and revenue efficiency for a sample of 347 life and non-life insurance companies operating in Spain for the period 1989-1997. They estimated efficiencies year by year for all stock and mutual insurers, leading to pooled efficient frontiers. Next, they estimated own-group frontiers for the stock and mutual sub-samples for each year in the sample period. Also, the cross-frontier method was used for the estimation of the efficiency scores. They used life and non-life insurance losses incurred as output variables according always with the value added approach and labor, business services, and debt and equity capital as input variables. They used the average rate of total return on the Madrid Stock Exchange Index and the one-year Spanish Treasury bill rate as prices for the equity and debt capital inputs respectively. They also used the DEA method for all their estimations. They showed that stocks and mutuals were operating at different production, cost, and revenue frontiers representing different technologies. Moreover, they found that in cost and revenue efficiency, stock of all sizes dominated mutuals in the production of stock output vectors, and smaller mutuals dominated stocks in the production of mutual output vectors. Larger mutuals were neither dominated by nor dominant over stocks in the cost and revenue comparisons. Finally, they conducted a multiple regression analysis with cross-to-own frontier ratios as dependent variables and firm characteristics as independent variables. The results provided strong support for the efficient structure hypothesis based on technical efficiency but somewhat weaker support for this hypothesis based on cost and revenue efficiency.

Cummins et al. (1999b) measured technical and cost efficiency for a sample of 417 property-liability insurance companies operating in US for the period 1981-1990 testing agency-theoretic hypothesis about organizational form by using cross-frontier analysis. They adopted a modified version of the value added approach to measure outputs and so they defined present value of real losses incurred and total invested assets as the outputs and labor, materials, debt and equity capital as inputs. They used the DEA method assuming that property-liability insurers were operating under constant return to scale. They showed first that stock and mutual were operating on separate production and cost frontiers and thus representing distinct technologies, that stock technology dominated the mutual technology for producing stock outputs and the mutual technology dominated the stock technology for producing mutual outputs as the managerial discretion hypothesis would support. They concluded that the stock cost frontier dominated the mutual cost frontier, a thing that the expense preference hypothesis would support.

Diboky and Ubl (2007) measured technical, cost, and allocative efficiency for a sample of 90 life insurers operated in Germany for the period 2002-2005. Following the value added approach, they considered gross premium written and net income as output variables and labor, business services, financial debt capital and equity capital as inputs. They used the traditional constant return to scale DEA method as well as the Simar-Wilson bootstrapping method in order to correct the bias of DEA estimators. They first pooled all insurers in order to calculate the efficiency for stock, mutual, and public insurers according to a joint production and a joint cost frontier. Additionally, they estimated cross efficiency measures where it was estimated the distance of stock firms to the mutual and the public frontier, the distance of mutual firms to the stock and the public frontier, and the distance of public firms to the stock and the mutual frontier. They found evidence that stock, mutual, and public life insurers do not operate on a joint production and a joint cost frontier. Also, their results gave strong support to the expense preference hypothesis while they found no evidence that public ownership is an efficient corporate structure for life insurers. Finally, they concluded that stock ownership was superior to mutual and public structure with smaller stock insurers being even more dominant in production technology.

Erhemjamts and Leverty (2007) measured technical efficiency for a sample of 1050 life insurers operated in US for the period 1995-2004. Using the DEA method they estimated own-frontier and cross-frontier efficiency of demutualized firms five year before conversion through five years after conversion. Following the value added approach, they determined incurred benefits and additions to reserves as the main output variables while they defined labor, business services, equity capital, and policy-holder supplied debt capital as input variables. They found that during the sample period the stock and mutual life insurers operated on separate production frontiers and that the stock technology dominated the mutual technology for producing life insurer outputs. Also, their results were indicating that mutual that were the most remote from the mutual efficient frontier were more prone to demutualization. Finally, they estimated a multinomial logit model in order to analyze the determinants of demutualization process. They found that access to capital was an important determinant of this conversion, but only for mutual that fully demutualized and not for firms that convert using a mutual holding company structure.

Fukuyama (1997) estimated technical, pure technical, allocative and scale efficiency for 25 Japanese life insurance companies using panel data for the 1988-1993 period. Using the financial intermediary approach, he determined insurance reserves and loans as the main output variables. Also, capital measured by the asset value of company premises and real estate, office workers or internal personnel as well as tied agents or sales representatives were used as input variables needed for the production process taking place in life insurance sector. The method used was the DEA and two set of assumptions were used. With respect to the scale of production, both variable and constant returns to scale were considered while in reference to input disposability weak and strong disposability of inputs were considered. He found that the major sources of technical inefficiency were pure technical inefficiency for mutuals and scale inefficiency for stocks. Additionally, it was showed that total productivity growth of the entire sample was primarily due to technological progress. Fukuyama stressed that during the economic boom, stock companies were quicker in adopting innovations than mutual companies.

Greene and Segal (2004) estimated cost efficiency for a sample of 136 life insurance companies operating in US using panel data for the period 1995-1998 and explored the association between cost inefficiency and profitability. Following the value added approach, they determined the dollar value of investments, the amount of life insurance sold, the total annuity considerations and the total accident and health premiums as output variables and labor, capital and material as input variables. They used the SFA method for their estimations of the translog cost function. Also, they estimated cumulative regressions with return on equity (ROE) and return on assets (ROA) as dependent variables. The explanatory variables included the inefficiency estimate, the type of organizational form, the size and the mix of life insurance policies and growth. They found that the life insurance industry was on average 20% inefficient. Also, they stressed that there were no significant relationship between inefficiency and organizational form but the mutual companies were as efficient and profitable as stock companies. Finally, they found that inefficiency was negatively related with the ROE and ROA ratios, and efficient companies on average had higher cumulative return on equity and on assets.

Hardwick et al. (2004) measured technical, allocative and cost efficiency for a sample of 50 UK life insurers from 1994 to 2001 in order to examine empirically the linkage between various corporate governance mechanisms and the efficiency scores of the UK life insurance companies. They defined incurred benefits and additions to reserves as insurance outputs and labor and capital as insurance inputs, employing the DEA method. At a second stage, they estimated some cross-sectional regressions in order to investigate the linkage between corporate governance mechanisms and cost efficiency. According to their results, cost efficiency appeared to be positively related to the size of board of directors but negatively related to the proportion of outside directors on the board. They stressed that firm size had a non-linear impact on cost efficiencies, indicating that large firms were able to benefit more from corporate governance than small firms, and that the effect of some governance mechanisms on cost efficiency was varied between mutual and stock life insurers.

He et al. (2011) estimated cost and revenue efficiency for a sample of property/liability insurers in US for the period 1996-2004. They used the DEA method for their estimations and defined the present value of losses incurred and the average of the beginning and end-of-year invested assets as outputs. Administrative labor, agent labor, materials and business services, and financial equity capital were used as inputs. Their main concern was the investigation of the impacts the turnover of a Chief Executive Officer (CEO) has on insurers' efficiency. They found strong evidence that firms with a CEO turnover experience more favorable performance changes than firms without a CEO turnover. More accurately, firms with CEO changes experience higher cost and revenue efficiency improvements than those without CEO changes.

Huang et al. (2011) estimated technical and cost efficiency of the U.S property-liability insurance industry during the period 2000-2007. They followed the value-added approach and defined insurance outputs as losses incurred and total invested assets. The inputs defined in this study were: labor, business services, and equity capital. In order to correct the bias in DEA estimations, they implemented the bootstrapping procedure proposed by Simar and Wilson (2007). Their main concern was the examination of the relation between corporate governance and the efficiency. Using multiple regressions, they found significant relation between efficiency and corporate governance (e.g. board size, proportion of independent directors on the audit committee, director tenure, auditor dependence).

Jeng and Lai (2005) measured technical and cost efficiency for 19 Japanese non-life insurers for the 1985-1994 period trying to examine if the organizational form of Keiratsu, no specialized independent (NSIFs), and specialized independent firms (SIFs) had some effect on efficiency scores. They used both the value added approach and the financial intermediary approach for their estimations. Under the financial intermediary approach they conducted analysis using both the cross-frontier methodology and the RAM version of DEA. Under the value added approach, they defined the number of policies in short-tail, long-tail and saving-type lines and the total invested assets as output variables while they defined labor, business services and capital (debt and equity) as input variables. Also, under the financial intermediary approach they defined return on assets and three principal components of financial conditions as output variables while they defined the rates: surplus previous year/assets, change in surplus/assets, underwriting + investment expenses/ assets, and policyholders debt capital/assets as input variables. With all these approaches, authors were unable to reject the null hypotheses that one form of organizational structure dominated the others as far as the efficiency was concerned. Only Keiratsu firms were found to be more cost efficient than no specialized independent firms. They also estimated the Malmquist indexes for the sample period and found that overall efficiencies of Keiratsu, NSIFs, and SIFs firms deteriorated during the sample period. Finally, they stressed that the two output measurement approaches showed different but complementary results.

Jeng et al. (2007) measured cost, technical, and allocative efficiency for a sample of 11 U.S. life insurance corporations for the 1980-1995 period and examined the efficiency changes of U.S. life insurers before and after demutualization taking place in the 1980s and 1990s. Based on the DEA method, they used both the value added approach and the financial intermediary approach for their estimations. Under the value added approach, they used death benefits, annuity benefits, surrender benefits, and accident and health benefits as output variables while they used labor, business services, and equity capital as input variables. Under the financial intermediary approach, they used return on assets and three principal components of financial conditions as output variables while they defined the rates: surplus previous year/assets, change in surplus/assets, underwriting + investment expenses/ assets, and policyholders debt capital/assets as input variables. They stressed that the results of both approaches suggested that there were no efficiency improvement after demutualization. More accurately, according to value added approach the demutualized life insurers improved their efficiency before demutualization. On the other hand, under the financial intermediary approach the efficiency of the demutualized life insurers relative to mutual control insurers deteriorated before demutualization and improved after conversion. Finally, they concluded that the only efficiency improvement which took place was the improvement relative to mutual control insurers when the financial intermediary approach was used.

Wende et al. (2008) measured technical, allocative and cost efficiency for a sample of 40 property-liability insurance companies, including public insurers, operating in

Germany during the 1988-2005. More accurately, they examined the relationship between efficiency and organizational form and the effect of the regulatory framework on the relative efficiency of alternative organizational forms. They defined the present value of claims incurred and the total invested assets as output variables and labor and business services, equity capital, and debt capital as input variables. They applied the input oriented DEA method and estimated the cross-frontier efficiencies. They found that regulation influenced the comparative advantages of organizational forms in terms of efficiency. The stock cost frontier did not dominate the cost frontier of the public and mutual insurers respectively during the period with strict regulation. On the other hand, the stock cost frontier dominated the public cost frontier after the deregulation started in 1994. Performing a regression analysis of the cross-to-own efficiency ratios for technical and cost efficiency showed analogous results.

Xie (2010) measured scale, technical, allocative, cost, and revenue efficiency by using DEA method and by analyzing property-liability insurers that issued initial public offerings (IPOs) from 1994 to 2005 in US, using private insurers as the benchmark. He used the modified value added approach and defined the present value of losses incurred in personal lines short-tail insurance, in personal lines long-tail insurance, in commercial lines short-tail, and in commercial lines long-tail insurance as well as the real invested assets as insurance outputs. Also, the administrative labor, the agent labor, the materials and business services, and the financial equity capital were used as insurance inputs. He conducted a univariate analysis and a probit regression in order to find out the determinants of issuing IPOs. The results indicated that IPO firms in US property-liability insurance industry were usually large firms with high possibility in facing capital constraints. Also, Xie estimated some fixed-effect regressions using an unbalanced panel for all IPO and private firms in order to examine the results of IPO on firm performance and financials. Xie found that there was no post-issue underperformance for the IPO firms as far as efficiency, return on assets, or stock return were concerned. There was some evidence suggesting that IPO firms were able to improve their cost and allocative efficiency scores after the IPO. In conclusion, the author stressed that the main reason for going public for property-liability insurers was the desire to avoid capital constraints and that IPO firms had nothing to envy private insurers as far as cost and profit efficiency were concerned.

Xie et al. (2011) estimated technical and cost efficiencies for a sample of U.S life insurers from 1993 to 2003. They used incurred benefits plus additions to reserves and the average of the beginning-and end-of-year invested assets as outputs. Four inputs were used in efficiency estimation: administrative labor, agent labor, materials and business services, and financial equity capital. They mainly tried to examine the role of corporate governance in the demutualization wave in the U.S life insurance industry during the 1990s and 2000s. they showed that demutualization was value-enhancing for firms converting through Initial Public Offerings (IPOs), but value-neutral for firms that convert but stay private. Also, firms converting into public companies experience increased CEO turnover that leads to efficiency improvements.

2.7 Category of distribution systems

This category of literature deals mainly with the effect of the type of distribution system used by insurers on efficiency of insurance industry. Two different hypotheses have been presented in this field, which have tried to explain the coexistence of different distribution systems in the insurance industry. The market-imperfections hypothesis states that independent-agency insurers survive providing the same services as direct-writing insurers due to market imperfections. The product-quality hypothesis states that the higher costs of independent-agency insurers can be justified because they provide higher product and service quality.

Berger et al. (1997) measured both cost and profit efficiency for 472 direct-writing and independent–agency property-liability insurers operating in US for the period 1981-1990. Their primary goal was the examination of long-run coexistence of the direct-writing and independent-agency property-liability insurers. They defined total real invested assets and the present value of losses incurred as output variables according to the value-added approach and labor, business services, equity, and debt capital as insurance inputs. They used the DFA method for their estimations and assumed that cost and profit function had the flexible Fourier form. They found that independent-agency property-liability insurers were less cost efficient but equally profit efficient than direct-writing insurers. Finally, they stressed that these tests provided more support for the product-quality hypothesis than for the market-imperfections hypothesis.

Brocket et al. (1998) measured efficiency for a sample of 1524 property-liability insurers operating in US for the year 1989 and tried to examine the effects of organizational form and distribution system had on the efficiency scores. They defined ROI, liquid assets to liabilities, and solvency scores as insurance outputs and surplus from the previous year, change in capital and surplus, underwriting and investment expense, and policy-holder supplied debt capital as insurance input variables. The RAM version of DEA were used for the needed estimations. They found that generally the agency marketing system was more efficient than direct. Also, they stressed that stock insurers were more efficient than mutual insurers. Finally, they concluded that stock companies using agency as their marketing channel was the most efficient form while mutual insurance companies using agency as their marketing channel was the least efficient form.

Klumpes (2004) measured cost and profit efficiency for a sample of 40 UK life insurers for the 1994-1999 period. Consistent with the value added approach, five variable outputs were specified: claims on standard business line and three types of individual line (individual life and saving plans, endowment policies, and pension policies) and real invested assets. He defined labor and business services as variable insurance inputs and policy-supplied debt capital and financial equity capital as fixed insurance inputs. Klumpes used the SFA method for the needed estimations assuming that cost and profit functions had the Fourier-flexible form. The author concluded that life insurers sold their products via independent financial advisers (IFAs) were less cost and profit efficient than life insurers sold their products via their own sales force (AR/CR). Klumpes also used regression analysis in order to control for other firm characteristics affecting efficiency such as size, organizational form, and product mix. These tests provided evidence that there existed variation in profit and cost inefficiencies between IFA-based and AR/CR-based life insurers was explained by the market imperfections hypothesis.

Trigo Gamarra and Growitsch (2008) estimated cost, profit and scale efficiencies for a sample of 115 German life insurers differing in their distribution system for the 1997-2005 period trying to search the differences in efficiency among multichannel, direct, and independent-agent life insurers. They defined incurred benefits, additions to reserves, and bonuses and rebates as insurance outputs and acquisition and administration expenses and equity capital as insurance inputs. They used the non-parametric DEA methodology for their estimations. Additionally, they employed the nonparametric Mann-Whitney-U test in order to compare the mean efficiencies of the insurers used different distribution systems. From their results, is clear that specialized single-channel insurers (direct and independent-agent insurers) did not outperformed multi-channel insurers as far as cost and profit efficiency were concerned. The authors stressed that the majority of the life insurance companies in Germany was operating under increasing returns to scale.

Ward (2002) measured cost, revenue, and profit efficiencies for a sample of 44 life insurance companies operating in UK during 1990-1997 and tried to provide an insight in the costs of the alternatives distribution systems used by these life insurers. Following the value added approach, they defined claims and additions to reserves for the lines of life, pension, and PHI and labor and capital an life insurance inputs. Ward first estimated deterministic cost, revenue, and profit functions and then using the SFA approach estimated the stochastic cost, revenue, and profit functions assuming that these functions had taken the translog form. The results from the deterministic estimations showed that the use of the independent mode of distribution could increase costs but these costs could be offset by associated increases in the related revenues and profits. Also, these results provided strong support for the product-quality hypothesis. However, the stochastic estimation results showed that insurance firms could achieve cost benefits by focusing on one mode of distribution channels and failed to provide additional evidence for the product-quality hypothesis.

2.8 Category of financial and risk management, capital utilization

This part of literature deals with the effect of risk management, financial intermediation, and solvency on economic efficiency of any insurance sector. Cummins's et al (2009) article is a representative work that tries to estimate the above mentioned relationship for the US property-liability insurance sector.

Brocket et al. (2004a) estimated efficiency for a sample of 1524 property-liability insurers operated in US only for year 1989 and tried to estimate the relationship between solvency and efficiency. Using the financial intermediary approach, they defined ROI, liquid assets to liabilities, and solvency scores as insurance outputs. They defined surplus previous year, change in capital and surplus, underwriting and investment expense, and policy-holder supplied debt capital as insurance inputs. Using the DEA method, they estimated efficiency for each firm in the sample two times. In the first time the used solvency score as output variable while in the second time they did not used solvency score as an output. Examining the number of firms in the sample that changed from the efficient to inefficient status and vice versa, they concluded that omitting this variable as an output would not have important effects on efficiency. Finally, they estimated efficiency for mutual or stock insurers and efficiency for insurers using agency versus direct marketing arrangements. They concluded that stocks were more efficient than mutual and that agency form was more efficient than direct form.

Cummins et al. (2009) measured cost efficiency for a sample of 613 property-liability insurers operating in US during the period 1995-2003. Their main concern was to test how risk management and financial intermediation could create value for insurers usually by reducing costs. According to value added approach, they defined the present value of losses incurred, the total invested assets, and the dollar duration of surplus as insurance outputs. They defined labor, material and business services expenses, debt, and equity capital as insurance inputs. They used the SFA approach in order to complete their estimations assuming also that the cost function followed the translog functional form. Because the prices of risk management and financial intermediation were unobservable, they considered these two activities as intermediary outputs and tried to estimate their shadow prices. Finally, they noted that average shadow prices were positive indicating that these two above mentioned activities could allow insurance firms to reduce further their costs by increasing the level of these activities.

Cummins and Nini (2002) measured technical, allocative, cost, and revenue efficiency for a sample ranging between 770 and 970 property-liability insurers operating in US during the 1993-1998 period. Their original aim was to investigate whether sub-optimal capital utilization is determined as a response to changing market conditions or as true inefficiency. Following the value added approach, they defined the present value of real losses incurred for personal short-tail, personal long-tail, commercial short-tail, and commercial long-tail coverage as well as total invested assets as insurance outputs. They defined labor, material and business services, and equity capital as input variables. They preferred the non-parametric DEA approach for measuring the above mentioned efficiencies. Average cost efficiency amounted to 40.6% while average revenue efficiency amounted to 27.1%. At a second stage, they estimated three regression equations with dependent variables the ratio of the insurer’s actual to optimal capital, revenue efficiency, and ROE respectively. It is important to note that they used as an explanatory variable the sub-optimal capital-to-assets ratio, defined as the ratio of actual minus optimal capital-to-assets, in order to estimate the relationship between efficiency and capital utilization. Based on their results, they concluded that capital over-utilization reflected inefficiency while capital under-utilization was not significantly related to either revenue efficiency or ROE score.

2.9 Category of market structure

This category of bibliography deals with the relationship between market structure and efficiency of insurers. Three main hypotheses have been developed coming from the industrial organization literature. (a) The structure-conduct-performance (SCP) which predicts that increased market concentration leads to higher prices and profits. (b) The relative market power hypothesis (RMP) which predicts that firms with large market power will charge higher prices. (c) The efficient-structure (ES) hypothesis which predicts that efficient firms charge lower prices and so they achieve larger market shares.

Berry-Stolzle et al. (2011) estimated cost, revenue, and scale efficiency using DEA for a sample of European insurers operating in 12 member states for the period 2003-2007. The purpose of this work was to test the structure-conduct-performance (SCP), relative market power (RMP), and efficient structure hypotheses in the European property-liability insurance industry. Using both group and company data, they found strong support for the efficient structure hypothesis and little or no support for the structure-conduct-performance hypothesis or the relative market power hypothesis.

Bikker and Gorter (2011) estimated cost efficiency for a sample of Dutch non-life insurers during the 1995-2005. They used the Thick Frontier Approach for their estimations. In their work they mainly investigated the restructuring of the Dutch non-life insurance market from a cost efficiency perspective. They defined premiums net of reinsurance ceded, losses net of reinsurance received, and total investments as the three outputs used and labor, financial equity capital, and debt capital as inputs respectively. They observed substantial economies of scale that were even larger for smaller insurers. Also, they found that both efficient structure and strategic focus hypotheses have effects since both stock and mutual have comparative cost advantages and since the more specialized insurers have lower costs respectively.

Choi and Weiss (2005) measured cost and revenue efficiency by examining the relationship between market structure and performance for the property-liability insurers operating in US over the period 1992-1998 using data at the company and group levels. Using the value added approach, they defined the present value of losses incurred and the total invested assets as outputs. They defined labor (agent and non-agent), materials, and equity capital as inputs used in the production process from the property-liability insurers. For the efficiency estimations they used the SFA approach assuming that cost and revenue functions followed the translog form. Moreover, they estimated the profitability and price models based on multivariate regression analysis, using as dependent variables the profit and price of each insurer respectively and the concentration, market share, cost and revenue efficiencies along with a vector of control variables for each insurer as dependent variables. Their results provided support for the ES hypothesis, which supports that cost-efficient firms charge lower prices than their competitors and so they capture larger market shares and economic rents. The authors stressed that prices and profits were higher for the revenue-efficient firms.

Choi and Weiss (2008) measured cost and revenue efficiency with the aim of examining the impact of regulation on state automobile insurance markets while controlling for other state insurance market characteristics related to performance. Cross-sectional time series data for the period 1992-1998 concerning the US auto insurers were used for their estimations. They defined the present value of losses incurred and the total invested assets as outputs and labor (agent and non-agent), materials, and equity capital as inputs. They used the SFA approach for the efficiency estimations assuming that cost and revenue functions followed the translog form. Additionally, they estimated the profitability and price models based on multivariate regression analysis and using the same dependent and explanatory variables as in their paper issued in 2005. Separate regressions were conducted for insurers operating in stringently regulated, non-stringently regulated, and competitive states. They estimated three regressions with cost, cost-scale, and revenue X-efficiency as dependent variables respectively and market share, concentration, and a dummy variable concerning the type of regulation along with a vector of control variables for each insurer as explanatory variables. The RMP hypothesis was supported from their results only for competitive and non-stringently regulated states and so they could benefit from market power by charging higher unit prices. Additionally, in these two types of states insurers were on average more cost X-efficient and these cost X-efficient insurers charged lower prices and earned smaller profits. Finally, they stressed that in some rate regulated states firms were less revenue and cost-scale efficient than in competitive states.

Fenn et al. (2008) measured cost efficiency for a sample of life, non-life, and composite insurance companies operating in 14 different European markets during the period 1995-2001and tried to estimate the impact of firm size and market structure on efficiency. According to value added approach, they defined net incurred claims for life and non-life insurers as outputs. They defined the real value of total capital and total technical provisions as fixed inputs and labor and real debt capital as variable inputs. They used the SFA method for the efficiency estimations assuming that the cost function followed the Fourier-flexible form. They used a one-stage approach to estimate the effects of firm size and market structure on efficiency which simultaneously controlled for these effects without using two-stage regressions, and also corrected for potential estimation bias arising from heteroskedastic error terms. Moreover, separate frontiers were estimated for life, non-life, and composite insurers. Their results generally showed that size and domestic market share were associated with higher levels of cost inefficiency and that most European insurers operated under increasing returns to scale technologies.

2.10 Category of mergers

This category of literature deals with the effects of mergers and acquisitions (M&A) on the efficiency of firms. The papers included here measure efficiency scores based on efficient frontier methodologies and not on the event study or cash flow analysis methods used by some authors.

Cummins et al. (1999a) measured cost, technical, allocative, scale, and revenue efficiency for a sample of 750 life insurers operating in US during the period 1988-1995 and tried to find the relationship between M&A and efficiency in the US life insurance industry. Following the value added approach, they defined incurred benefits and additions to reserves as outputs. They defined home-office labor, agent labor, business services, and financial capital as inputs. They used the non-parametric DEA method and also conducted the Malmquist analysis. At a second stage, they conducted regression analysis with the dependent variables the changes in various types of efficiencies over a period ranging from two years prior acquisition to two years after acquisition. They used a dummy equal to one for firms participating in M&A activities and zero for the other circumstances in order to compare the differences among firms participating and non-participating in M&A activities. They found strong evidence that M&A were beneficial for efficiency because acquired firms achieved greater gains in technical, cost, and revenue efficiency than firms not participating in M&A. The probit analysis showed that financially vulnerable life insurers were more likely to be acquired than financially healthy firms.

Cummins and Xie (2008) measured cost, technical, allocative, scale, and revenue efficiency for a sample of 1550 property-liability insurers operating in US during the period 1994-2003 and tried to describe the productivity and efficiency effects of M&A in the US property-liability insurance industry. According to the value added approach, they defined the present value of losses incurred and the real invested assets as outputs. They defined labor, materials and business services, as well as financial equity capital as inputs. The non-parametric DEA method was used for efficiency estimations across with the respective Malmquist productivity indices in order to measure the productivity change of firms. Regression analysis with productivity and efficiency change as dependent variables was used to analyze firm characteristics associated with performance gains. They used a dummy equal to one for firms participating in M&A activities and zero for the other circumstances in order to compare the differences among firms participating and non-participating in M&A activities. The analysis was conducted both at a company and at a group level. According to their results, M&A activities in the US property-liability insurance industry were value enhancing. More accurately, these M&A activities had leaded to significant revenue efficiency gains for acquirers and to significant cost and allocative efficiency gains for targets. They also estimated the probability that firms become involved in M&A activities as acquirers or targets using probit analysis and found strong evidence that financially vulnerable firms were more likely to be takeover targets than stronger firms.

Davutyan and Klumpes (2008) measured technical, pure technical, and scale efficiency for a sample of 472 life and non-life insurers operating in 7 different European countries for the period 1996-2002. Their principal aim was the examination of the relationship among M&A, efficiency and scale economies in these European insurance markets. According to the value added approach, they defined the present value of losses incurred, the premiums, and the total invested assets as outputs. They used labor, business services, and equity capital as discretionary inputs. But they also used life and non-life insurance penetration potential across with regulatory quality as non-discretionary insurance inputs. They used for their estimations the DEA method and analyzed separately the characteristics of life and non-life insurance targets and acquiring firms. They included in the sample and insurance firms not participating in M&A activities as a reference set and that only company level analysis was conducted for measuring efficiency and productivity for both acquirers and targets. At a second stage, regression analysis with technical, pure technical, and scale efficiency scores as dependent variables respectively was conducted. According to their results, post consolidation technical efficiency was generally improved but scale efficiency was deteriorated and the conclusions for the non-life sector were stronger than that of the life sector. Finally, they conducted multinomial logit analysis in order to explain the drivers of M&A activities and found that in life insurance sector business inputs replaced labor for both target and acquirers after mergers and those merger activities did not impact significantly acquirer behaviors.

Klumpes (2007) estimated cost, technical, allocative, revenue and scale efficiency for a sample of 1183 life and general insurers operating in seven (7) different European countries during the 1997-2001 period with the aim to examine the relationship between M&A, efficiency, and scale economies in these insurance markets. According to the value added approach, Klumpes defined premiums and claims and investment income as outputs, and labor, business services, debt, and equity capital were used as inputs. The non-parametric DEA method was used for the efficiency estimations and for the estimation and decomposition of the Malmquist productivity indexes. At a second stage, the author conducted regression analysis where the dependent variables represented changes in various types of efficiency over a period ranging from three years prior to the year of acquisition to three years after this year. In order to determine whether M&A improve firm efficiency, Klumpes included a dummy variable equal to one for firms non-participating in M&A activities and zero otherwise. The results of these regressions revealed that acquiring firms experienced significantly greater gains in cost, allocative, and pure technical efficiency than non-acquiring firms. By contrast, target firms experienced significantly higher gains in only allocative efficiency than did non-target firms. Finally, the author conducted a probit analysis where the dependent variable was set equal to one for target firms and zero for firms with non-M&A activities and found that these M&A activities were driven primarily by solvency objectives.

2.11 Category of scale and scope economies

This category of literature tries to explore the relationship between scale and scope economies and the level of efficiency of insurance markets. As far as scale economies are concerned, the results vary across studies because there are many differences in the methods used and the time horizons employed. On the other hand, two different hypotheses were developed as far as scope economies are concerned. The first is known as conglomeration hypothesis and states that operating many lines of business can add value by exploiting cost and revenue scope economies (see Cummins et. al. 2010). The other is the strategic focus hypothesis and states that firms can add value better by concentrating in core lines of businesses.

Berger et al. (2000) measured cost, revenue, and profit efficiencies for a sample of 684 life, property-liability and composite insurers operating in US during the 1988-1992 period in order to estimate the analogous scope economies. Their main concern was the justification of the long-run coexistence of joint producers and specialists in the US insurance market. Following the value added approach, they defined invested assets and the present value of real losses incurred as P/L insurance outputs and invested assets as well as the incurred benefits as insurance outputs for life insurers. They used the SFA method assuming that cost, revenue, and profit functions followed the composite functional form. The scope economies were estimated both with traditional and with the preferred approach. The first method used a single cost, revenue, and profit function only for joint producers which assumed to apply to specialists as well. The preferred method used a separate cost, revenue, and profit function for joint and specialist insurers and also a separate cost, revenue, and profit function for the life and P/L divisions of the joint insurers. Their results provided strong evidence on the validity of the conglomeration versus the strategic focus hypothesis. Moreover, they attributed the long-run coexistence of joint producers and specialists to the fact that substantial profit scope economies hold for some types of insurers and substantial profit scope diseconomies hold for other types of insures. Finally, they estimated some regressions with dependent variables the cost, revenue, and profit scope economies and with some firm characteristics as exogenous variables. Their results showed that joint production was more efficient and may apply more to insurers that are large, emphasize personal lines of business, use vertical integrated distribution systems, and are relatively profit efficient. The opposite results were found for specialist insurers.

Cummins et al. (2010) estimated cost, revenue, and profit efficiency for a sample of 846 US life, property-liability, and joint insurers and tried to find out if there were evidence for scope economies existence in the US insurance market during the 1993-2006 period. According to the value added approach, they defined real invested assets and the real value of incurred benefits and additions to reserves for individual life, individual annuities, group life, group annuities, and accident-health insurance as life-health insurance outputs. They defined real invested assets and the present values of real losses incurred for short and long-tail personal and commercial lines as P/L insurance outputs. They defined administrative labor, agent labor, materials and business services, and financial equity capital as inputs both for life and P/L insurers. They used the non-parametric DEA method for the estimation of the efficiency scores. At a second stage, they conducted multiple regressions with efficiency score as dependent variable and firm characteristics such as size, business mix, organizational form, and type of distribution system as explanatory variables. Moreover, they used a dummy variable which equaled to one for focused firms and zero for diversified firms in order to measure the effects of strategic focus versus diversification. Their results showed that property-liability insurers realized cost scope economies but they were more than offset by revenue scope diseconomies. On the other hand, life-health insurers appeared to have both cost and revenue scope diseconomies. They finally concluded that the strategic focus was superior to conglomeration in the US insurance market.

Fecher et al. (1991) estimated cost efficiency for a sample of 327 life and non-life insurance companies operating in France for the period 1984-1989 and provided a measurement of the economies of scale in this insurance market. Following the value added approach, gross premiums were defined as output and labor costs and other outlays as inputs. The method used for their estimations was the SFA with cost function taking the translog form for the scale economies estimation and the Cobb-Douglas form for the productive efficiency estimation. Their results suggested that there were increasing returns to scale and a wide dispersion in the rates of efficiency across insurance companies. Finally, they suggested that this wide dispersion in efficiency stemmed from the huge segmentation of the French insurance industry.

Fuentes et al. (2005) estimated technical efficiency and productivity change for a sample of Spanish insurance companies for the period 1987-1997. They focused on health, property-liability, health and property-liability, and on health, property-liabilities and life branches. They defined annual premiums as output variables and labor cost and operated expenses as insurance inputs. They used the SFA method assuming that the output distance functions followed the translog specification. The technical efficiency was found to be very different depending of the branch type. More accurately, the technical efficiency for the health, property-liability, health and property-liability, and health, property-liabilities and life branch were found to be about 40%, 68%, 73% and 80% respectively. Also, in all cases the Malmquist productivity index was less than 2% per year in the sample period. Their results also showed that insurance firms combining two or three product lines were more efficient in providing insurance than those concentrating in one product line.

Hirao and Inoue (2004) measured cost efficiency for a sample of 20 Japanese and 13 foreign-owned property-liability insurance firms operating in Japan for the period 1980-1995. They tried to examine economies of scale and economies of scope between third-sector products (personal accident, medical expenses and nursing care expense insurance) and the products offered by the rest of the P/L insurance lines. They followed the value added approach and defined real incurred losses which equaled net claims paid and changes in loss reserves as insurance output, and labor, agencies, and materials as insurance inputs. They used the SFA method for their estimations by fitting a composite cost function on a set of panel data and employing an error components model. Their results showed that significant economies of scale were observed both for Japanese and foreign P/L insurers operating in Japan. Finally, they stressed that there existed statistically significant scope economies between the third-sector products and the rest of the P/L insurance lines both for Japanese insurers and the majority of the foreign insurers operating in Japanese insurance market. However, these scope economies were greater for larger insurers than for smaller ones.

Meador et al. (2000) measured cost efficiency for a sample of 358 life insurance companies operating in US during 1990-1995 with the aim of testing for a relationship between a firm's output choice and measures of X-efficiency. Following the value added approach, they defined ordinary life insurance premiums, ordinary annuity considerations, group life insurance premiums, group annuities considerations, group accident and health premiums, and the securities investments as insurance outputs, and labor, physical capital, and miscellaneous items as insurance inputs. They used the DFA approach for their efficiency estimations assuming that cost function had followed the translog form. Also, they estimated a firm specific Herfindahl index calculated across each firm's product line premiums in order to measure the product focus of each firm. The average X-efficiency for the sample period was found to be 41,6%. Additionally, they conducted a univariate comparison of means and medians for focused versus diversified firms for the sample period. They found that diversified firms were on average more X-efficient than focused firms with the results to be even stronger in the case of comparisons based on medians. At a second stage, they estimated a multivariate fixed-effect regression model which included other firm specific and environmental factors that influence insurance efficiency scores. The results from this fixed-effect model suggested that life insurers with product diversification across both insurance and investment product lines were more X-efficient than focused ones.

Toivanen (1997) measured cost efficiency during 1989-1991 for a sample of 21 Finish non-life insurance companies with the aim to search for the existence of scale and scope economies. Following the physical approach, the author defined the number of units produced as insurance output and the labor expenses was used as the only insurance input. The SFA method was used with cost function assumed to follow a quadratic specification. It is important also to note that the production process was separated into cost and portfolio management function and the analysis was conducted both at the branch and at the firm level. Also, for the portfolio management estimations the sample period was expanded from 1984 to 1991 and a random effect as well as a fixed-effect model were estimated for this time period. From the results it was concluded that there were constant returns to scale at the branch level and diseconomies of scale at the firm level. Economies of scope were found in production but they were modest in size.

Yuengert (1993) estimated cost and scale efficiencies for a sample of 765 life insurance firms operating in US only for the 1989 year with the view to measure the existing scale and scope economies. Following the value added approach, Yuengert defined reserves and addition to reserves as insurance outputs and the labor and the physical capital as inputs. The author used both the SFA and the TFA methods for the needed estimations. The cost function assumed to follow the translog form. Yuengert also used a mixed-error (normal-gamma) model in order to estimate the X-efficiency scores. Moreover, he used weight least squares (WLS), TFA and a half-normal specification for the inefficiency error term for comparison reasons. The results provided strong evidence that this insurance market showed great amount of X-inefficiency, ranging from 35% to 50%, but the differences across firm size were insignificant. Finally, there was evidence for ray scale economies in US life insurance market up to $15 billion in assets but no evidence for any product mix economies.

2.12 Summary of the literature

In this chapter a comprehensive survey of the existing literature on frontier efficiency measurement in insurance is provided. We categorized the existing studies into 10 different areas of application as in Eling and Luhnen (2010b). The main conclusions can be drawn from this literature review are: (a) Non-parametric approaches, and especially DEA, are the most frequently applied methods of frontier efficiency analysis in insurance industry (b) There is a widespread agreement in literature with regard to the choice of input factors since most studies define labour, capital, and business services as inputs of an insurance company. There is also agreement with regard to output measurement as most studies employ the so called value-added approach. However, there is disagreement among researchers as to whether premiums or claims are the more adequate proxy for value added (e.g. Yuengert, 1993) (c) Finally, just recently was observed an expansion of frontier methodologies to new fields of application such as market structure and risk management (e.g. Fenn et. al., 2008 ; Cummins and Nini, 2002) while the geographic scope has noticeably expanded beyond its former U.S. focus to encompass a broad array of countries including emerging markets such as China, Taiwan, and Malaysia (e.g. Eling and Luhnen, 2010a).

Frontier efficiency methods have been applied to a wide range of countries as well as to all major lines of business. Furthermore, frontier efficiency methods have been used to investigate various economic questions. These include risk management, market structure, organizational forms, and mergers. However, it should be noted that findings regarding the same economic issues often vary depending on country, line of business, time horizon, and method considered in the different studies. Given the broad range of countries and time horizons employed, findings regarding efficiency and productivity scores are mixed. However, nearly all studies note that there are significant levels of inefficiency with corresponding room for efficiency improvements. Table 1 summarizes the main findings for each of the ten categories that we discussed above in this chapter.

Table 1. Main Findings of the Existing Literature

Category	Main Results
General level of efficiency and evolution over time	Significant levels of inefficiency with corresponding room for improvement world (e.g. Eling and Luhnen, 2010a ; Biener and Eling, 2012). The existing literature examines both developed and developing countries (e.g. Pestana-Barros and Wanke, 2017).
Regulation change	Modest efficiency improvements from deregulation in Europe (Rees et al., 1999; Hussels and Ward, 2006). Efficiency gains in Asia due to deregulation (Boonyasai et al., 2002). Not important efficiency change with risk-based capital requirements implementation in the U.S. (Ryan and Schellhorn (2000).
Intercountry comparisons	Important international differences in average efficiency scores (e.g. Eling and Luhnen, 2010a). Efficiency in developed countries is on average higher than that in emerging markets and technical progress has increased productivity and efficiency around the world (e.g. Eling and Luhnen, 2010a).
Methodology issues, comparing different techniques or assumptions	Average efficiencies can differ significantly across methods (e.g. Cummins and Zi, 1998).
Organizational form, corporate governance issues	Most authors find that stock companies are more efficient than mutuals-i.e. the expense preference hypothesis is valid (e.g. Cummins et al., 1999a; Cummins et al., 2010).
Distribution systems	In most studies, independent agent distribution systems are more efficient than direct systems (e.g. Brockett et al., 2004a, b; Klumpes, 2004) confirming the market imperfections hypothesis, while insurers with one distribution system are more efficient than those employing more than one (e.g. Ward, 2002).
Financial and risk management, capital Utilization	Risk management and financial intermediation affect positively efficiency levels (e.g. Cummins et al., 2006). Solvency scores seem to have limited impact on efficiency (e.g. Brockett et al., 2004a;2004b).
Market structure	More efficient firms charge lower prices than their competitors (e.g. Choi and Weiss, 2005) while large firms with high market shares tend to be less cost efficient than small ones (Fenn et al., 2008).
Mergers	Mergers are beneficial for the efficiency of acquiring and target firm (e.g. Cummins et al., 1999a; Cummins and Xie., 2008). Mergers and acquisitions, facilitated by the liberalization of

	the EU insurance market, have led to efficiency gains (e.g. Fenn et al., 2008).
Scale and scope economies	Increasing returns to scale were found for U.S. insurance companies with up to US$1 billion in assets (e.g. Cummins and Zi, 1998). Evidence concerning the economies of scope are mixed. In some studies conglomeration hypothesis is valid (e.g. Cummins et al., 2010) while in some other studies the strategic focus hypothesis is valid (e.g. Berger et al., 2000).

CHAPTER 3

FRONTIER METHODOLOGIES

3.1 Introduction

Traditional microeconomic theory assumes that all producers minimize cost and maximize revenues and profits and that firms not succeeded in attaining these objectives are not of interest because they will be eliminated by the market forces. According to this theory, producers are assumed to operate on their production functions, maximizing outputs (output orientation) obtainable from the inputs they have at their disposal. Producers also are assumed to satisfy the first-order conditions for cost minimization, allocating inputs efficiently and ending up on their cost functions. Finally, producers are assumed to satisfy the first-order conditions for profit maximization, allocating outputs and inputs efficiently and ending up on their profit functions.

However, the failure of at least some producers to optimize has transferred the analysis of production, cost, revenue, and profit away from the traditional functions toward frontiers. A production frontier (Kumbhakar and Lovell, 2000) characterizes the minimum input bundles required to produce various outputs, or the maximum output producible with various input bundles, and a given technology. According to them, a cost frontier characterizes the minimum expenditure required to produce a given bundle of outputs, given the prices of the inputs used and the used technology. The revenue frontier characterizes the maximum revenue obtainable from a given bundle of inputs, given the prices of the outputs produced with a given technology. A profit frontier characterizes the maximum profit obtainable from production, given the prices of the inputs used and the prices of the outputs produced and the given technology. Thus, producers operate on the production, cost, revenue, and profit frontier are called productive, cost, revenue, and profit efficient respectively. At the opposite case they are called productive, cost, revenue, and profit inefficient respectively.

The above mentioned development in modern economics has led to the abandonment of the traditional methods used for measuring efficiencies. These traditional methods were based on conventional financial ratios such as return on equity, return on assets, and expense to premium ratios, etc (Cummins and Weiss, 2012). During the last few decades, frontier methodologies have been the most commonly used approach for estimating efficiency and productivity for producers. These methodologies summarize firm performance in a single statistic that controls for differences among firms in a multidimensional framework. These frontier efficiency methodologies are separated in two different categories: (1) non-parametric approaches which utilize mathematical programming techniques to estimate the frontier, such as DEA (Cooper et al, 2000) and (2) econometric approaches which utilize econometric techniques to estimate the frontier, such as SFA (Greene, 2008).

The measurement of efficiency and productivity by frontier methodologies is useful for many reasons. First of all, these measures are used as indicators by which production units are evaluated. By measuring efficiency and productivity, and separating the effects of the production environment on these indicators, we are able to test many economic hypotheses. For example, we can estimate the effects of the market structure, the type distribution system used, or the organizational form on the economic (cost, revenue, and profit) and technical efficiency of the producers. The measures of efficiency are also important indicators for regulators regarding the institution of public and private policies designed to improve performance in an industry or the whole economy. Finally, with the use of the frontier efficiency methodologies we can also compare economic performance across countries or across departments, divisions, and branches within the same firm.

3.2 Definitions of efficiency and productivity

Generally, efficiency refers to the success of the firm in minimizing costs, maximizing revenues, or maximizing profits given the existing technology. By productivity of a firm we mean the ratio of its output to its input. So, productivity refers to the changes in technology over time, such that firms can produce more output with a given amount of inputs (technical progress) or produce less output utilizing a given amount of inputs (technical regress). But, before starting to give the definitions of the efficiency and productivity concepts it is important to introduce some notation and terminology.

We assume that producers use the inputs $x = (x_1,\dots,x_N) \in R^N_+$ to produce the outputs $y = (y_1,\dots,y_M) \in R^M_+$. The production technology can be represented by the production set:

$T = \{(y, x\}: x \text{ can produce } y\}$ [3.1]

Production technology can also be represented by input sets which defined as:

$L(y) = \{x: (y,x) \in T\}$ [3.2]

which for every $y \in R^M_+$ have input isoquants:

$I(y) = \{x: x \in L(y), \lambda x \notin L(y), \lambda < 1\}$ [3.3]

and input efficient subsets:

$E(y) = \{x: x \in L(y), x' \notin L(y), \text{ for every } x' \leq x\}$ [3.4]

with E(y), I(y), and L(y) satisfying the following inequality:

$E(y) \subseteq I(y) \subseteq L(y)$, where the symbol $\subseteq$ depicts that each is subset of the other.

When multiple inputs are used to produce multiple outputs, Shephard's (1953,1970) distance functions provide a functional representation of production technology. Input distance functions characterize input sets while output distance functions characterize output sets. The mathematical representation of the input distance function is:

$D_I(y,x) = \max \{\lambda: (x/\lambda) \in L(y)\}$ [3.5]

where for $x \in L(y)$, $D_I(y,x) \geqq 1$, and for $x \in I(y)$, $D_I(y,x) = 1$.

However, in some cases output augmentation is the objective of the management process. So, in these cases an output orientation must be used and the production technology can be represented by output sets as follows:

$P(x) = \{y: (x,y) \in T\}$ [3.6]

which for every $x \in R^N_+$ have output isoquants:

$I(x) = \{y: y \in P(x), \lambda y \notin P(x), \lambda > 1\}$ [3.7]

and output efficient subsets:

$E(x) = \{y: y \in P(x), y' \notin P(x), \text{ for every } y' \geq y\}$ [3.8]

With E(x), I(x), and P(x) satisfying the following inequality:

$E(x) \subseteq I(x) \subseteq P(x)$.

The Shephard's (1953,1970) output distance function is:

$D_O(x,y) = \min \{\lambda: (y/\lambda) \in P(x)\}$ [3.9]

where for $y \in P(x)$, $D_O(x,y) \leqq 1$, and for $y \in I(x)$, $D_O(x,y) = 1$

In general terms, technical efficiency refers to the ability of a producer to minimize input use in the production of given output vector, or the ability to obtain maximum output from a given input vector. Koopmans (1951) was the first to give a formal definition of technical efficiency. According to this definition, a producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if a reduction in any input requires an increase in at least one other input or a reduction in at least one output. The mathematical formulation of Koopmans definition is as follow:

$(y,x) \in T$ is technically efficient if, and only if, $(y',x') \notin T$ for $(y',-x') \geq (y,-x)$ [3.10]

Debreu (1951) and Farrell (1957) provide alternative definitions for technical efficiency. In bibliography these definitions are often referred as Debreu-Farrell measures of technical efficiency. According to them, if an input conserving is used then technical efficiency is defined as (one minus) the maximum equiproportionate (i.e., radial) reduction in all inputs that is feasible with given technology and outputs. On the other hand, when an output augmenting orientation is used then technical efficiency is defined as the maximum radial expansion in all outputs that is feasible with given technology and inputs. The mathematical formulations for these definitions are:

$TE_I(y,x) = \min \{\theta: \theta x \in L(y)\}$ or $TE_I(y,x) = [D_I(y,x)]^{-1}$ [3.11]

for input orientation and

$TE_O(x,y) = \max \{\varphi: \varphi y \in P(x)\}$ or $TE_O(x,y) = [Do(x,y)]^{-1}$ [3.12] for an output orientation.[5]

For the above definitions we implicitly assumed that the numbers of the inputs used and the output produced are greater than one (N>1and M>1). In the single input case we have:

$D_I(y,x) = x/g(y) \geqq 1 \Leftrightarrow x \geqq g(y)$ [3.13]

where $g(y) = \min\{x\colon x \in L(y)\}$ is an input requirement frontier that defines the minimum amount of scalar input x required to produce output vector y (Fried, Lovell and Schmidt, 2008) and the input technical efficiency is the ratio of minimum to actual input.

Similarly, in the single output case we have:

$D_O(x,y) = y/f(x) \leqq 1 \Leftrightarrow y \leqq f(x)$ [3.14]

where $f(x) = \max\{y\colon y \in P(x)\}$ is a production frontier that defines the maximum amount of scalar output that can be produced with input vector x and the output oriented efficiency is the ratio of maximum to actual output.

The output and input oriented technical efficiency measures are depicted in figures 3.1-3.3. The basic difference among these figures is that technology is smooth in figure 3.1 and piecewise linear in figures 3.2 and 3.3 respectively. The econometric approach of estimating efficiency (e.g. SFA) assumes and estimates smooth parametric frontiers, while the non-parametric mathematical programming approach (e.g. DEA) estimates piecewise linear non-parametric frontiers (Fried et al., 2008). In figure 3.1, the producer A is located on the interior of production set T and its technical efficiency can be measured horizontally with an input-conserving orientation using equation [3.11] or vertically with an output-augmenting orientation using equation [3.12].

[5] For our technical efficiency definitions it is always true that $TE_I(y,x) \leqq 1$ and $TE_O(y,x) \geqq 1$. Some authors define $TE_O(x,y) = [\max\{\varphi\colon \varphi y \in P(x)\}]^{-1} = D_O(x,y)$, so that $TE_O(x,y) \leqq 1$ just as $TE_I(y,x) \leqq 1$.

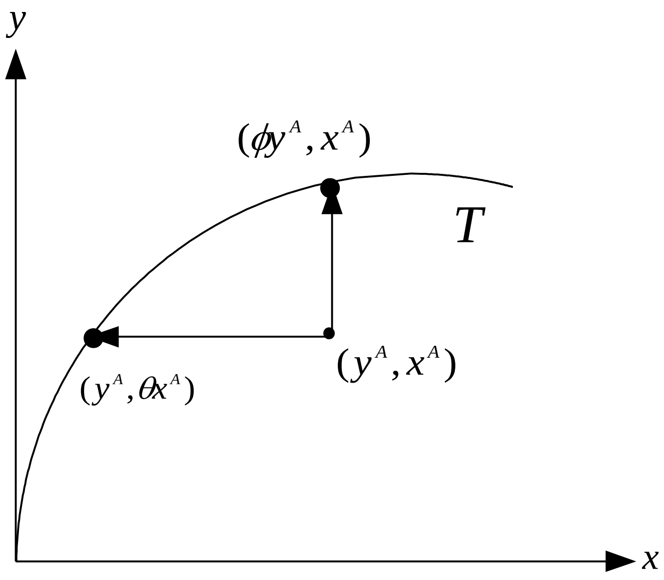

Figure 3.1. Technical Efficiency.

In figure 3.2, input vectors x^A and x^B are on the interior of the input set L(y) and both can be contracted radially and still remain capable of producing output vector y. Input vectors x^C and x^D cannot be contracted radially and still remain capable of producing output vector y because they are located on the input isoquant I(y). Figure 3.3 repeats exactly the same story but with an output orientation. Output vectors y^C and y^D are technically efficient given input usage x, and output vectors y^A and y^B are not technically efficient. Radially scaled output vectors $\phi^{\mathrm{A}} y^A$ and $\phi^{\mathrm{B}} y^B$ are technically efficient even though slack in output y_2 remains at $\phi^{\mathrm{B}} y^B$ (Fried et al., 2008).

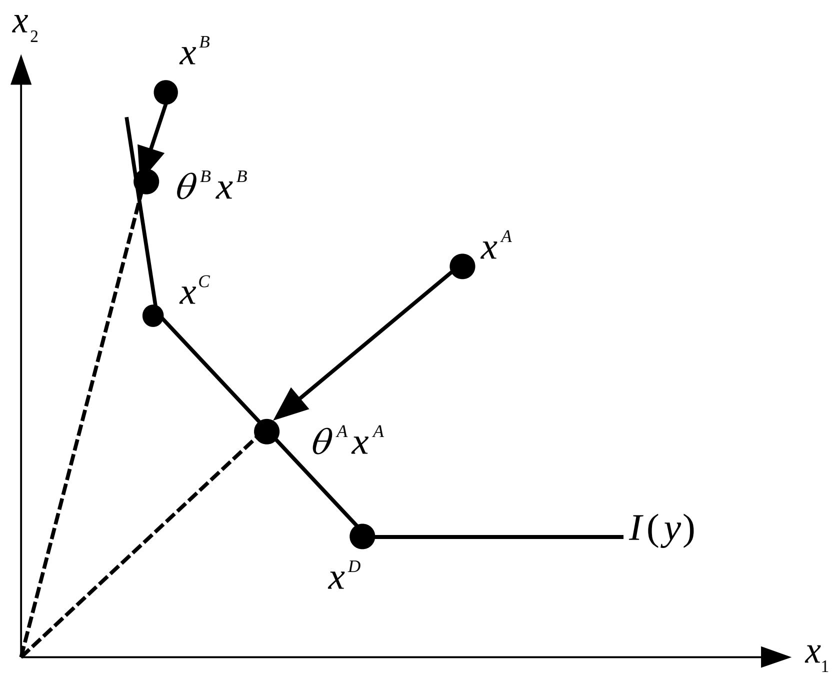

Figure 3.2 Input-Oriented Technical Efficiency.

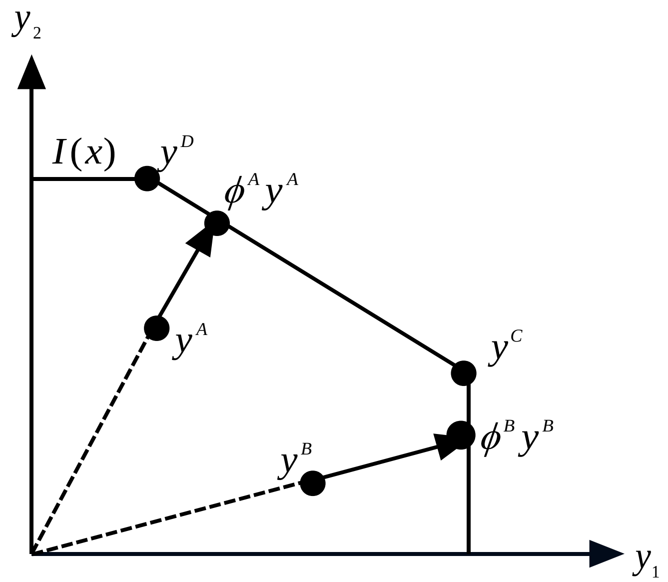

Figure 3.3. Output- Oriented Technical Efficiency.

If a behavioral objective of cost minimization is adopted by a producer, then the standard against which his performance is evaluated shifts from the production frontier to the cost frontier. A measure of cost efficiency is provided by the ratio of minimum feasible cost to actual cost and depends on the available input prices. Generally, the achievement of input-oriented technical efficiency is necessary but not sufficient, for the achievement of cost efficiency. This can occur because a technically efficient producer could use an inappropriate input mix (input allocative inefficiency) given the input prices it faces. A measure of the input allocative efficiency is obtained residually as the ratio of the measure of cost efficiency to the input-oriented measure of technical efficiency.

For the mathematical definition of the cost efficiency we assume that producers face input prices $w = (w_1,\ldots,w_N) \in R^N_{++}$ and seek to minimize cost w^Tx they incur in producing the outputs $y \in R^M_+$ they choose to produce. Then a minimum cost function or a cost frontier is defined as:

$c(y,w) = \min_x \{w^Tx: D_I(y,x) \geqq 1\}$[6] [3.15]

If the input sets L(y) are closed and convex, and if inputs are freely disposable, the cost frontier is dual to the input distance function and so we have:

$D_I(y,x) = \min_w \{w^T x: c(y,w) \geqq 1\}$ [3.16]

The measure of cost efficiency is provided by the ratio of minimum cost to actual cost:

$CE(x,y,w) = c(y,w) / w^T x$ [3.17]

while the measure of the input allocative efficiency is defined as:

$AE_I(x,y,w) = CE(x,y,w) / TE_I(y,x)$ [3.18]

i.e cost efficiency is the the product of technical by allocative efficiency. Finally, it is important to note that CE, TE_I, and AE_I efficiencies are bounded above by unity.

The graphical display of the measurement of cost efficiency is illustrated in figure 3.4. In this figure the input vector x^E minimizes the cost of producing output vector y at input prices levels w, so $w^T x^E = c(y,w)$. The cost efficiency of x^A is given by the ratio $w^T x^E / w^T x^A = c(y,w) / w^T x^A$ while its input-allocative efficiency is determined residually as the ratio of cost efficiency to technical efficiency, or by the ratio $w^T x^E / w^T (\theta^A x^A)$ (Fried et al., 2008).

[6] T denotes a vector transpose.

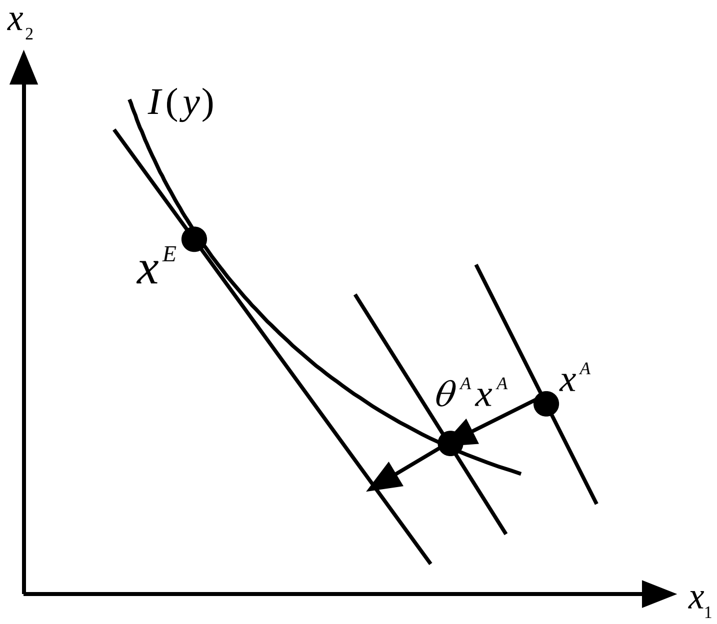

Figure 3.4. Cost Efficiency.

As we mentioned above, if a revenue maximization objective is adopted by producers, then the standard against which their performance is evaluated is provided by the revenue frontier. The process followed above for estimating and decomposing cost efficiency is used now for the revenue efficiency determination. Only orientation changes from the input-contraction to the output-maximization. More accurately, we assume that producers face output prices $p = (p_1,\dots,p_M) \in R^M{++}$ and seek to maximize the revenue p^T y they can generate from the input vector $x \in R^M+$ they use. The failure to achieve revenue maximization can be attributed either or both to the output-oriented technical inefficiency or to the production of an inappropriate output mix (output allocative inefficiency) given the prevailing output price vector. Mathematically, a maximum revenue function, or a revenue frontier, is defined as:

$r(x,p) = \max_y \{p^T y: D_O(x,y) \leqq 1\}$ [3.19]

In the case where the output sets P(x) are closed and convex, and if outputs are freely disposable, the revenue frontier is dual to the output distance function and so we have:

$Do(x,y) = \max_p (p^T y: r(x,p) \leqq 1\}$ [3.20]

The measure of revenue efficiency is provided by the ratio of maximum revenue to actual revenue:

$RE(y,x,p) = r(x,p) / p^T y$ [3.21]

while the measure of the output allocative efficiency is defined as:

$AE_O(y,x,p) = RE(y,x,p) / TE_O(x,y)$ [3.22] i.e revenue efficiency is the product of technical by allocative efficiency, while the RE, TE_O, and AE_O efficiencies are bounded bellow by unity.

The measurement of revenue efficiency is illustrated in figure 3.5. In this figure the output vector y^E maximizes the revenues can be generated from the input vector x at out prices p, so $p^T y^E = r(x,p)$. The revenue efficiency of y^A is given by the ratio $p^T y^E / p^T y^A = r(x,p) / p^T y^A$. The output-allocative of y^A is determined as the ratio of revenue efficiency to technical efficiency, or by the ratio $p^T y^E / p^T(\phi^A y^A)$ (Fried et al., 2008).

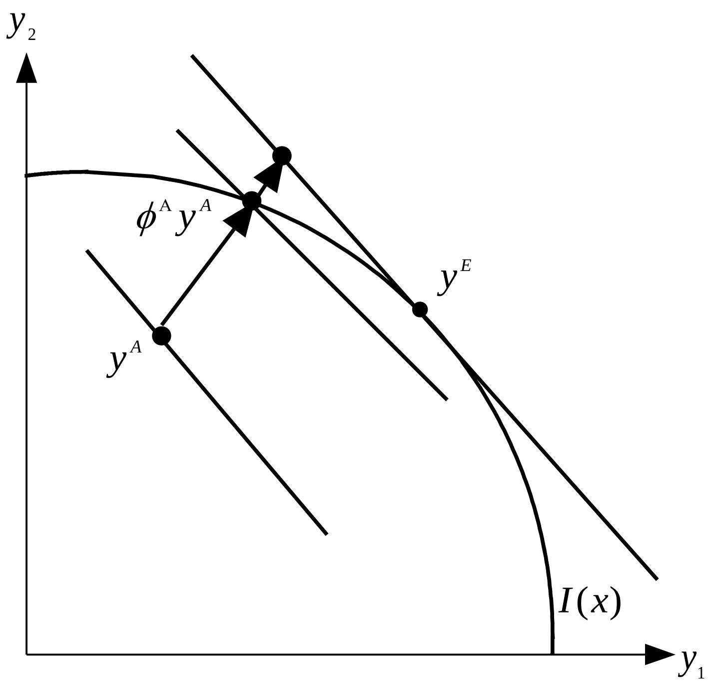

Figure 3.5. Revenue Efficiency

Cost efficiency and revenue efficiency are important performance indicators but each reflects just one dimension (input or output orientation) of a firm's overall performance. While these measures of efficiency are necessary for the achievement of profit efficiency, none by itself is sufficient. This occurs because (input or output oriented) technical efficiency and both input and output allocative efficiencies are required for the determination of profit efficiency. But except that, technical and both input and output allocative efficiencies must be achieved at the proper scale of production. So, a scale efficiency component is required for the estimation of profit efficiency.

We assume that producers face output prices p= $(p_1, p_2, \ldots, p_M) \in R^M_{++}$ and input prices $w \in R^N_{++}$, and seek to maximize the profit $(p^T y - w^T x)$ they obtain from using $x = (x_1, \ldots, x_N) \in R^N_+$ to produce the outputs $y = (y_1, \ldots, y_M) \in R^M_+$. Mathematically, the maximum profit function, or profit frontier, is defined as:

$\pi(p,w) = \max_{y,x} \{(p^T y - w^T x): (y,x) \in T\}$ [3.23]

In the case where the production set T is closed and convex, and if outputs and inputs are freely disposable, the profit frontier is dual to T and so we have:

$T = \{(y,x): (p^T y - w^T x) \leqq \pi(p,w)\ \forall\ p \in R^M{}_{++},\ w \in R^N{}_{++}\}$ [3.24]

As in the other cases above, a measure of profit efficiency is provided by the ratio of maximum profit to actual profit and is written as:

$\pi E(y,x,p,w) = \pi(p,w)/(p^T y - w^T x)$ [3.25]

provided that $(p^T y - w^T x) > 0$, in which case $\pi E(y,x,p,w)$ is bounded below by unity.

The measurement and decomposition of profit efficiency is partially depicted by figure 3.6. Profit at the internal point (y^A, x^A) is less than maximum profit at the point (y^E, x^E) and two possible decompositions of profit efficiency are illustrated (Fried et al., 2008). The first takes input-conserving orientation to the measurement of technical efficiency and the residual allocative component follows the path from $(y^A, \theta x^A)$ to (y^E, x^E) (Fried et al., 2008). The second decomposition takes an output-augmented orientation to the measurement of technical efficiency with the residual allocative component following the path from $(\phi y^A, x^A)$ to (y^E, x^E) (Fried et al., 2008). These two residual allocative efficiency components are hidden from view in figure 3.6 since it is impossible to depict them in a two-dimensional space (Fried et al., 2008).

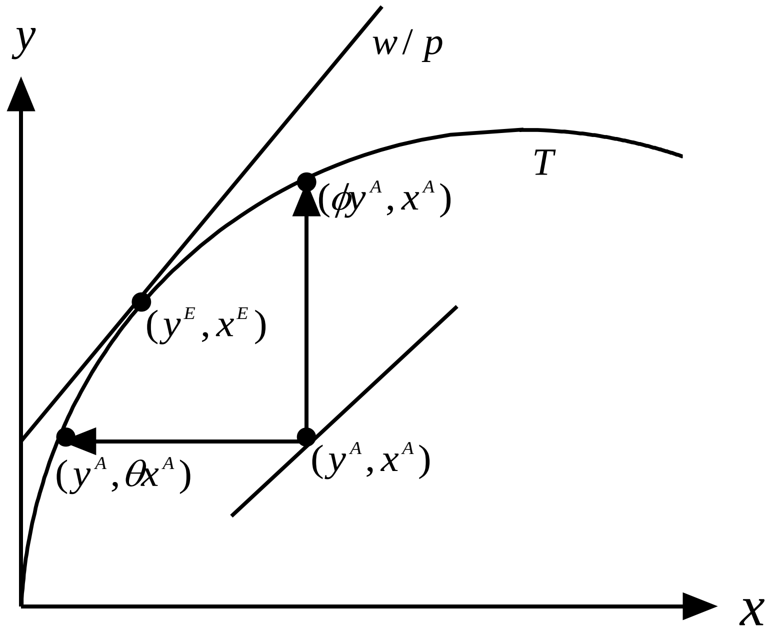

Figure 3.6. Profit Efficiency.

As a conclusion, we can assert that whatever the orientation of the technical efficiency measure, profit inefficiency is attributable to the technical inefficiency, to an inappropriate scale of operation, to the production of an inappropriate output mix, and to the selection of an inappropriate input mix. Thus the attainment of maximum profit requires technical efficiency, use of the right input mix in light of w, production of the right output mix in light of p, and operation at the right scale in light of p and w.

3.3 Mathematical programming methods

The mathematical programming approaches are based on an empirical implementation of Shepherd's distance functions (Shephard, 1970). All methodologies belonging to this category of estimating efficiency and productivity are non-parametric and do not adopt neither a specified functional form nor a specified error term structure. This methodology estimates the relevant efficiency of each firm because estimates are based on the given firm's reference set. If the efficiency is equal to one then the given firm is considered efficient and inefficient if the efficiency score is less than one.

The most important method in this category is the Data Envelopment Analysis (DEA). This name stems from the fact that the approach envelops the observed input-output correspondences in the course of carrying out an assessment of performance. If the quantities of inputs and outputs are only available, then only technical efficiency can be estimated. While, with quantities and prices for inputs and outputs available we can estimate and decompose economic efficiency into its technical and allocative components.

We assume that producers use the inputs $x = (x_1,\dots,x_N) \in R^N_+$ to produce the outputs $y = (y_1,\dots,y_M) \in R^M_+$ and that there are S firms in the sample. For each firm s=1,2,…,S, in each year of the sample period the DEA input-oriented technical efficiency is calculated by solving the following linear programming problem:

$$(D_I(y_s , x_s))^{-1} = TE_I(y_s , x_s) = \min \theta_s \qquad [3.26]$$

Subject to:

$$Y\lambda_s \geq y_s$$
$$X\lambda_s \leq \theta_s x_s$$
$$\lambda_s \geq 0$$

where Y is an M x S output matrix and X is a N x S input matrix for all firms in the sample, ys is a M x1 output vector and xs an N x 1 input vector for firm s, and λs is an S x1intensity vector for firm s. The input oriented technical efficiency is by definition equal to the optimal value θ_s^* of the above minimization problem. It is important to note that the last constraint ($\lambda s \geq 0$) imposes constant returns to scale to the above problem of technical estimation. Finally, the firms for which the elements of λs are non-zero constitute the firm s's reference set.

The output-oriented technical efficiency for each firm s=1,2,…,S, in each year of the sample period is calculated by solving the following linear programming problem:

$$[D_O(x_s,y_s)]^{-1} = TE_O(x_s,y_s) = \max h_s \qquad [3.27]$$

Subject to:

$Y\lambda_s \geq h_s y_s$
$X\lambda_s \leq x_s$
$\lambda_s \geq 0$

By definition the technical output efficiency of firm s is $1/h_s^*$ where h_s^* is the optimal value for h_s in the above maximization problem. Imposing the additional constraint $\sum_{i=1}^{S} \lambda_{si} = 1$, where λ_{si} is the s-th element of the vector λs, we allow for variable returns to scale (VRS) production and so we can estimate pure technical efficiency[7]. Then, by imposing $\sum_{i=1}^{S} \lambda_{si} \leq 1$ the above DEA problems are estimating the frontier under non-increasing returns to scale (NIRS). At these cases technical efficiency is the product of pure technical by scale efficiency with technical efficiency being equal to pure technical efficiency if and only if CRS is followed by the s firm.

If price data for inputs and output are available then a behavioral objective such as cost minimization or revenue or profit maximization can be adopted. In these cases it is possible to measure allocative efficiencies as well as technical efficiencies. For the cost efficiency estimation we must first adopt an input-orientation and calculate technical efficiency, while for the estimation of revenue efficiency me must first adopt an output orientation and calculate the technical output efficiency. However, for the estimation of profit efficiency we can adopt either an output or an input orientation in order to estimate technical efficiency.

As above, again we assume that producers face input prices $w = (w_1,\ldots,w_N) \in R^N_{++}$ and seek to minimize cost $w^T x$ they incur in producing the outputs $y \in R^M_+$ they choose to produce. The DEA-cost efficiency for each firm s=1, 2…,S in the sample can be estimated by solving the following linear programming problem:

$\text{Min}_{xs}\, w_s^T x_s$ [3.28]

Subject to:

$Y\lambda_s \geq y_s$
$X\lambda_s \leq x_s$
$\lambda_s \geq 0$

At a second stage firm s's cost efficiency is the ratio $0 < CE = w_s^T x_s^* / w_s^T x_s \leq 1$, indicating the ratio of minimum frontier costs to actual costs. The vector x_s^* is the cost-minimizing input vector for the input price vector w_s and the output vector y_s. Also, cost efficiency is the product of input allocative efficiency by the input technical efficiency.

For revenue maximization behavioral objective it is required to assume that producers face output prices $p = (p_1,\ldots,p_M) \in R^M{}_{++}$ and seek to maximize the revenue $p^T y$ they can generate from the input vector $x \in R^M{}_+$ they use. Then, the DEA-revenue

[7] Pure technical efficiency is defined as the distance of the firm's input-output bundle from the VRS frontier.

efficiency for each firm s=1, 2,...,S in the sample can be estimated by solving the following linear programming problem:

$$\mathrm{Max}_{ys}\ p^{T}_{s}\, y_s \quad [3.29]$$

Subject to:

$Y\lambda_s \geq y_s$
$X\lambda_s \leq x_s$
$\lambda_s \geq 0$

At a second stage firm s's revenue efficiency is the ratio $0<RE= p^{T}_{s}\, y_s / p^{T}_{s}\, y_s^{*} \leq 1$, indicating the ratio of observed to maximum revenue. The vector y_s^{*} is the revenue maximization output vector for the output price vector p_s and the input vector x_s. The revenue efficiency is also equal to the product of output allocative efficiency by the output technical efficiency.

For the estimation of profit efficiency we assume that producers face output prices $p= (p_1, p_2, \ldots, p_M) \in R^{M}{}_{++}$ and input prices $w= (w_1, \ldots, w_N) \in R^{N}{}_{++}$, and seek to maximize the profit $(p^T y - w^T x)$ they obtain from using $x = (x_1, \ldots, x_N) \in R^{N}_{+}$ to produce the outputs $y = (y_1, \ldots, y_M) \in R^{M}_{+}$. For the specification of the DEA-profit efficiency we describe first a model determined by Fare et al. (2004) and Ray (2004). This model imposes variable returns to scale[8] in the production and takes the following form:

$$\mathrm{Max}_{x,y}\ p_s^{T}\, y_s - w_s^{T}\, x_s \quad [3.30]$$

Subject to:

$Y\lambda_s \geq y_s$
$X\lambda_s \leq x_s$
$\sum_{i=1}^{S} \lambda_{si} = 1$
$\lambda_s \geq 0$

At a second stage, profit inefficiency for each firm s=1,2,…,S in the sample is estimated as:

$$\pi IE_s = (p_s^{T}\, y_s^{*} - w_s^{T}\, x_s^{*}) - (p_s^{T}\, y_s - w_s^{T}\, x_s) \quad [3.31]$$

However, πIE_s for the given firm s can be normalized by dividing it by the sum of actual costs and revenues (Färe and Grosskopf, 2004). Finally, it is important to note that profit efficiency, unlike the efficiency ratios, does not have to be between 0 and 1.

[8] If we assume CRS the solution is indeterminate because for each solution (λ^*, x^*, y^*) and each $t>0$ the $(t\lambda^*, tx^*, ty^*)$ is also a solution.

Another DEA- based model for estimating profit efficiency that is used very often was first specified by Cooper et al (2000). They estimate the profit efficiency for each firm s=1,2,…,S in the sample by solving the following linear programming problem:

$\mathrm{Max}_{x,y}\ p_s^T y_s - w_s^T x_s$ [3.32]

Subject to:

$Y\lambda_s \geq y_s$
$X\lambda_s \leq x_s$
$\lambda_s \geq 0$

Now, the ith row of y_s and the jth row of x_s in the above objective function are defined as:

$y_{is} = \sum_{k=1}^{S} y_{iks}\,\lambda_{ks}$, i=1,2,…., M [3.33]

$x_{js} = \sum_{k=1}^{S} x_{jks}\,\lambda_{ks}$ j=1,2,…..,N [3.34]

where x_{jks} is the jk-th element of the jth row of X and y_{iks} is the ik-th element of the ith row of Y. Again, profit inefficiency for the given firm s is defined as:

$\pi IE_s = (p_s^T y_s^* - w_s^T x_s^*) - (p_s^T y_s - w_s^T x_s)$ [3.35]

Usually, the data used for the estimation of the above described efficiencies are in the panel data form because we always have T periods and S insurers in each time period. One possibility is to pool the data and estimate a single common frontier after assuming that there exists an unvarying best practice technology. At the other extreme, it is possible to estimate T different frontiers, one for each year in the sample. This approach is considered more accurate because we can find if technical progress or regress exists. However, in this case the possibility of excessive volatility in efficiency scores resulting from excessive variation in temporally independent period frontiers is high.

Another non-parametric method for estimating efficiencies is the Free Disposal Hull (FDH) first proposed by Deprins et al. (1984). The name of this method comes from the fact that they maintained the assumption of free disposability of the DEA method, which for example implies that outputs do not decrease if some inputs are increased (strong disposability of inputs). Deprins et al. (1984) criticize the DEA for imposing convexity because it leads to a poor fit to the data as it does not allow for local non-convexities. So in their suggested method they relaxed convexity while maintained strong disposability and allowed local non-convexities. Mathematically, the FDH methods occurs if we additionally include the integral constraint $\lambda_i \in \{0,1\}$ for i=1,2,…,S in the DEA models described above. Finally, it has been shown to envelop the data more closely than DEA and that FDH efficiencies tended to be higher than those coming from the DEA method (Cummins and Zi, 1998).

3.4 Econometric or parametric methods

3.4.1 Estimation of technical efficiency

Benchmarking with parametric techniques of efficiency estimation is based mainly on regression analysis. Within this class of methods, the vast majority of existing applications utilize Stochastic Frontier Analysis (SFA). The SFA was developed independently by Aigner et al. (1977) and Meeusen and Van De Broeck (1977). The first stage of this method includes the estimation of an appropriate function, such as production, cost, revenue, or profit functions using an econometric technique (usually ordinary least squares). At the second stage it tries to decompose the residual of the frontier into a random error component (usually two-sided) and an inefficiency component (usually one-sided). Thus, according to the above characteristics of the SFA, a researcher must choose the functional form of the production, cost, revenue, or profit function and the approach for decomposing the random and inefficiency components of the error term.

3.4.1.1 Cross-sectional models

Before starting to describe the stochastic frontiers, it is essential to see how the respective deterministic models are estimated. We suppose that the producer i, i=1,2,..,I uses N inputs to produce one output. The production frontier can take the following general form:

$y_i = f(x_i , \beta) \times \exp \{-u_i \}$ [3.36]

where $TE_i = \exp \{-u_i \}$ is defined as the ratio of observed output to maximum feasible output and $u_i \geq 0$ since it is required that $TE_i \leq 1$. But because in most industries and especially in the service sector (e.g. banking) the true functional form is not known, researchers usually use approximations, with the Cobb-Douglas form to be the most commonly used. Now, assuming that $f(x_i , \beta)$ take this log-linear Cobb-Douglas form the deterministic production frontier can be written as:

$$\ln y_i = \beta_o + \sum_{i=1}^{N} \beta_n \ln x_{ni} - u_i \quad [3.37]$$

Aigner and Chu (1968) estimated the above deterministic problem using a linear programming and a quadratic programming model. The linear programming model of them tries to calculate a parametric vector β for which the sum of the proportionate deviations of the observed output of each producer beneath maximum feasible output is minimized. Mathematically, this model is written as:

$$\min \sum_{i} u_i \quad [3.38]$$

subject to $\beta_o + \sum_{i=1}^{N} \beta_n \ln x_{ni} \geq \ln y_i$ where i=1,2,…,I.

The respective quadratic programming model tries to calculate the parameter vector β for which the sum of squared deviations of the observed output of each producer beneath maximum feasible output is minimized. This model has the following mathematical form:

$$\min \sum_i u_i^2 \quad [3.39]$$

subject to $\beta_o + \sum_{i=1}^{N} \beta_n \ln x_{ni} \geq \ln y_i$ where i=1,2,…,I.

The technical efficiency of each producer in the sample can be now estimated from the equation $TE_i = \exp\{-u_i\}$ where $u_i = \beta_o + \sum_{i=1}^{N} \beta_n \ln x_{ni} - \ln y_i$ where i=1,2,…,I. However, the parameters β are calculated rather than estimated (Kumbhakar and Lovell, 2000) which complicates statistical inferences about these parameters. So, many other statistical methods have been developed in literature in order to estimate these deterministic frontier problems. These methods are the corrected ordinary least squares (COLS), the modified ordinary least squares (MOLS) and the maximum likelihood (MLE) and will be illustrated below.

COLS approach was first proposed by Winsten (1957) and it makes no assumption concerning the functional form of the nonpositive efficient u_i. The method at the first step uses ordinary least squares (OLS) to obtain consistent and unbiased estimates of the slope parameters (β vector) and a consistent but biased estimate of the intercept term. The model corrects the downward bias in the estimated OLS intercept by shifting it up until all corrected residuals are nonpositive and at least one is zero. At the second step the corrected residuals are used in $TE_i = \exp\{-u_i\}$ in order to calculate technical efficiency for each producer in the sample.

MOLS approach is an interesting variation of COLS and first proposed by Afriat (1972) and Richmond (1974). They argued that the deterministic production frontier described above could be estimated by OLS, but under the assumption that the disturbance term follows an explicit one-sided distribution, such as exponential or half normal. As in COLS approach, MOLS at the first step estimates the technology parameters by OLS method and modifies the estimated OLS intercept by shifting it up by minus the estimated mean of u_i, which is extracted from the moments of the OLS residuals. The OLS residuals are modified in the opposite direction and used in $TE_i = \exp\{-u_i\}$ in order to obtain consistent estimates of the technical efficiency of each producer. However, there is no guarantee that this approach shifts the estimated intercept up far enough to cover all the observations, so it is possible to find $TE_i>1$ for some producers.

MLE approach was first suggested by Afriat (1972) and apparently first used by Greene (1980a) and Stevenson (1980). As in MOLS approach, MLE approach is implementing by assuming a functional form for the nonpositive efficiency component u_i, and simultaneously estimating all the technology parameters of the deterministic production frontier and the parameters of the distribution of u_i. Then at the second phase the MLS residuals are inserted in equation $TE_i = \exp\{-u_i\}$ in order to obtain consistent estimates of technical efficiencies of each producer in the sample.

The above deterministic models allow for technical inefficiency only. But there are random shocks outside the control of producers that can affect output. Obviously, this problem with the deterministic frontiers does not allow researchers to disentangle the stochastic shock from the inefficiency in the residual. So, deterministic models have been abandoned in favor of stochastic methods, first suggested by Aigner et al. (1977) and Meeusen and Van De Broeck (1977).

For simplicity we again assume that producers use N inputs to produce one output with the production function taking the log-linear Cobb-Douglas form. Then the stochastic production model can be written mathematically as:

$$\ln y_i = \beta_o + \sum_{i=1}^{N} \beta_n \ln x_{ni} + \nu_i - u_i \quad [3.40]$$

where ν_i stands for the two-sided noise component and u_i is the non-negative technical inefficiency component of the error term. Since the error term has two components, the stochastic production frontier model is often referred to as a composed error model. The noise component ν_i is assumed to be independent, identically distributed (iid) and symmetric, distributed independently of u_i. Thus $\varepsilon_i = \nu_i - u_i$ is asymmetric since $u_i \geq 0$. The estimation of the above stochastic frontier by the OLS method, if we assume that ν_i and u_i are distributed independently of x_i s, provides consistent estimates of the β_ns, but not of β_o. Also, the OLS method does not provide estimates of producer-specific technical efficiency.

For the stochastic frontier models additional assumptions and a different estimation technique are required to obtain a consistent estimate of the intercept and estimates of the technical efficiency of each producer. More accurately, the above production frontier must be estimated by the ML method and the estimated residual is then decomposed into inefficiency and stochastic noise, by using the formula proposed by Jondrow, Lovell, Materov, and Schmidt (JLMS) (1982). However, both the ML estimation and the JLMS decomposition require distributional assumptions on the two components of the errors. Therefore, different formulations of the log-likelihood to maximize and of the JLMS decomposition have been derived under different distributions of the inefficiency term. Below, empirical applications with different distributional assumptions that appeared in bibliography are shown.

The Normal-Half Normal model makes the following assumptions:

- $\nu_i \sim$ iid $N(0,\sigma_\nu^2)$
- $u_i \sim$ iid $N^+(0,\sigma_u^2)$
- ν_i and u_i are distributed independently of each other, and of the regressors.

The density function of the u is given by:

f (u) = $\frac{2}{\sqrt{2\pi}}\frac{1}{\sigma_u}$exp { - $\frac{u^2}{2\sigma_u^2}$} [3.41]

while the density function of ν is given by:

f (ν) = $\frac{1}{\sqrt{2\pi}}\frac{1}{\sigma_\nu}$exp { - $\frac{\nu^2}{2\sigma_\nu^2}$} [3.42]

Because the u and ν factors are assumed to be independent, the joint density function of u and ν is the product of their individual density functions and is written mathematically as:

f (u, ν) = $\frac{2}{2\pi\sigma_u\sigma_\nu}\exp\left\{-\frac{u^2}{2\sigma_u^2}-\frac{\nu^2}{2\sigma_\nu^2}\right\}$ [3.43]

Since ε= ν-u the joint density function for u and ε is written mathematically as:

f (u, ε) = $\frac{2}{2\pi\sigma_u\sigma_\nu}\exp\left\{-\frac{u^2}{2\sigma_u^2}-\frac{(\varepsilon+u)^2}{2\sigma_\nu^2}\right\}$ [3.44]

The marginal density function of ε is obtained by integrating u out of f (u, ε), which will give the following mathematic equation:

f(ε) = $\int_0^\infty f(u,\varepsilon)du = \frac{2}{\sigma}\varphi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right)$ [3.45]

where σ = $\left(\sigma_u^2+\sigma_\nu^2\right)^{1/2}$, λ=$\frac{\sigma_u}{\sigma_\nu}$, and Φ(·) and φ (·) are the standard normal cumulative distribution and density functions.

According to the MLE method, we must estimate the log likelihood function for a sample of I producers. Using the marginal density function of ε, the log likelihood function is written mathematically as:

ln L = $c-\mathrm{I}\ln\sigma+\sum_i \ln\Phi\left(-\frac{\varepsilon_i\lambda}{\sigma}\right)-\frac{1}{2\sigma^2}\sum_i\varepsilon_i^2$ [3.46]

where c is a constant.

Next, this log likelihood function can be maximized with respect to the parameters to obtain maximum likelihood estimates of all parameters we need. However, the objective of each researcher is to obtain estimates of the technical efficiency of each producer in the sample. A possible solution to this problem is obtained from the conditional distribution of u_i given ε_i, which contains whatever information ε_i contains concerning u_i. According to the bibliography (Kumbhakar and Lovell, 2000), Jondrow et al. (JLMS) (1982) showed that if $u_i \sim N^+(0,\sigma_u^2)$, the conditional distribution of u given ε is given by:

$$\text{f(u/ε)} = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi}\sigma_*}\exp\left\{-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right\} / \left[1-\Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right] \quad [3.47]$$

where $\mu_* = -\varepsilon\sigma_u^2/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$.

Since f(u/ε) is distributed as $N^+\left(\mu_{*,}\sigma_*^2\right)$, either the mean or the mode of this distribution can serve as a point estimator for u_i. They are given respectively by:

$$\mathrm{E}\left(u_i/\varepsilon_i\right) = \sigma_*\left[\frac{\varphi\left(\varepsilon_i\lambda/\sigma\right)}{1-\Phi\left(\varepsilon_i\lambda/\sigma\right)} - \left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right]$$

and

$$\mathrm{M}\left(u_i/\varepsilon_i\right) = -\varepsilon_i\left(\frac{\sigma_u^2}{\sigma^2}\right) \text{if } \varepsilon_i \le 0 \text{ or } \mathrm{M}\left(u_i/\varepsilon_i\right) = 0 \text{ otherwise.}$$

The last step in the process is the estimation of the technical efficiency of each producer in the sample. Once point estimates of u_i are obtained estimates of the technical efficiency of each producer can be found by:

$$TE_i = \exp\left\{-\hat{u}_i\right\} \quad [3.48]$$

where $\hat{u}_i$ is either the mean or the mode of the above distribution.

Also, Battese and Coelli (1988) proposed an alternative point estimator for the technical efficiency of each producer in the sample, given mathematically by:

$$TE_i = E\left(\exp\{-u_i\}/\varepsilon_i\right) = \left[\frac{1-\Phi\left(\sigma_* - \frac{\mu_{*i}}{\sigma_*}\right)}{1-\Phi\left(-\mu_{*i}/\sigma_*\right)}\right]\exp\left\{-\mu_{*i} + \frac{1}{2}\sigma_*^2\right\} \quad [3.49]$$

Regardless of which estimator is used, the estimates of technical efficiency are inconsistent (Kumbhakar and Lovell, 2000). This is happens because the variation associated with the distribution of (u_i/ε_i) is independent of i.

The Normal-Exponential model makes the following assumptions:

- $v_i \sim$ iid $N(0,\sigma_v^2)$

- u_i ~ iid exponential
- v_i and u_i are distributed independently of each other, and of the regressors.

As in the Normal-Half normal model, we assume that the production function takes the log-linear Cobb-Douglas form. The density function for u_i is given mathematically by:

$$f(u) = \frac{1}{\sigma_u}\exp\left\{-\frac{u}{\sigma_u}\right\} \quad [3.50]$$

while the density function of ν is given by:

$$f(\nu) = \frac{1}{\sqrt{2\pi}}\frac{1}{\sigma_\nu}\exp\left\{-\frac{\nu^2}{2\sigma_\nu^2}\right\} \quad [3.51]$$

As a consequence of the independence assumption, the joint density function of u and ν is the product of their individual density functions, and so it is written mathematically as:

$$f(u, \nu) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_\nu}\exp\left\{-\frac{u}{\sigma_u}-\frac{\nu^2}{2\sigma_\nu^2}\right\} \quad [3.52]$$

The joint density of u and ε is:

$$f(u, \varepsilon) = \frac{1}{\sqrt{2\pi}\sigma_u\sigma_\nu}\exp\left\{-\frac{u}{\sigma_u}-\frac{1}{2\sigma_\nu^2}(u+\varepsilon)^2\right\} \quad [3.53]$$

Thus the marginal density function of ε is:

$$f(\varepsilon) = f(\varepsilon) = \int_0^\infty f(u,\varepsilon)du = \left(\frac{1}{\sigma_u}\right)\Phi\left(-\frac{\varepsilon}{\sigma_\nu}-\frac{\sigma_\nu}{\sigma_u}\right)\exp\left\{\frac{\varepsilon}{\sigma_u}+\frac{\sigma_\nu^2}{2\sigma_u^2}\right\} \quad [3.54]$$

where again Φ (·) is the standard normal cumulative distribution function.

As in the previous model, we must estimate the log likelihood function for a sample of I producers. Using the marginal density function of ε, the log likelihood function for a sample of I producers is written mathematically as:

$$\ln L = c - I\ln\sigma_u + I\left(\frac{\sigma_\nu^2}{2\sigma_u^2}\right)+\sum_i \ln\Phi(-A)+\sum_i\frac{\varepsilon_i}{\sigma_u}, \text{ c constant} \quad [3.55]$$

where A= $-\tilde{\mu}/\sigma_\nu$ and $\tilde{\mu} = -\varepsilon-\left(\frac{\sigma_\nu^2}{\sigma_u}\right)$.

As in the previous model, we can maximize the log likelihood function with respect to the parameters to obtain maximum likelihood of all parameters appeared in the production function. But the point estimates of technical efficiency can be obtained from either the mean or the mode of the conditional distribution of u given ε. The conditional distribution f(u/ε) is written mathematically as:

$$f(u/\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi}\sigma_v \Phi(-\tilde{\mu}/\sigma_v)} \exp\left\{-\frac{(u-\tilde{\mu})^2}{2\sigma^2}\right\} \quad [3.56]$$

with mean:

$$E(u_i/\varepsilon_i) = \sigma_v \left[\frac{\varphi(A)}{\Phi(-A)} - A\right] \quad [3.57]$$

and with mode:

$M(u_i/\varepsilon_i) = \tilde{\mu}_\iota$ if $\tilde{\mu}_\iota \geq 0$ and 0 otherwise.

Finally, by substituting either this mean or mode in $TE_i = \exp\left\{-\hat{u}_i\right\}$ or in $TE_i = E\left(\exp\{-u_i\}/\varepsilon_i\right)$ suggested by Battese and Coelli (1988), we can take producer specific estimates of technical efficiency. However, these estimates are unbiased, but not consistent.

The Normal-Truncated Normal Model was first introduced by Stevenson (1980) and makes the following assumptions:

- $v_i \sim$ iid $N(0,\sigma_v^2)$
- $u_i \sim$ iid $N^+(\mu,\sigma_u^2)$
- v_i and u_i are distributed independently of each other, and of the regressors.

The truncated normal density function for u≥0 is given mathematically by:

$$f(u) = \frac{1}{\sqrt{2\pi}\sigma_u \Phi(\mu/\sigma_u)} \exp\left\{-\frac{(u-\mu)^2}{2\sigma_u^2}\right\} \quad [3.58],$$

(μ is the mode of the normal distribution)

while, the density function for ν is given mathematically by:

$$f(v) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_v} \exp\left\{-\frac{v^2}{2\sigma_v^2}\right\} \quad [3.59]$$

As in the previous models, the joint density function of u and ν is the product of their individual density functions, and so is written mathematically as:

$$f(u,v) = \frac{1}{2\pi\sigma_u\sigma_v\Phi(\mu/\sigma_u)} \exp\left\{-\frac{(u-\mu)^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right\} \quad [3.60]$$

The joint density function of u and ε is given mathematically by:

$$f(u, \varepsilon) = \frac{1}{2\pi\sigma_u\sigma_v\Phi\left(\mu/\sigma_u\right)}\exp\left\{-\frac{\left(u-\mu\right)^2}{2\sigma_u^2}-\frac{\left(\varepsilon+u\right)^2}{2\sigma_v^2}\right\} \quad [3.61]$$

Thus, the marginal density function of ε is given mathematically by the following equation:

$$f(\varepsilon) = \int_0^\infty f(u,\varepsilon)du = \frac{1}{\sigma}\varphi\left(\frac{\varepsilon+\mu}{\sigma}\right)\Phi\left(\frac{\mu}{\sigma\lambda}-\frac{\varepsilon\lambda}{\sigma}\right)\left[\Phi\left(\frac{\mu}{\sigma_u}\right)\right]^{-1} \quad [3.62]$$

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

Using the marginal density function of ε, the log likelihood function for a sample of I producers is written mathematically as:

$$\ln L = c - I\ln\sigma - I\ln\Phi\left(\frac{\mu}{\sigma_u}\right)+\sum_i \ln\Phi\left(\frac{\mu}{\sigma\lambda}-\frac{\varepsilon_i\lambda}{\sigma}\right)-\frac{1}{2}\sum_i\left(\frac{\varepsilon_i+\mu}{\sigma}\right)^2 \quad [3.63]$$

where c is a constant and $\sigma_u = \sigma\lambda/\sqrt{1+\lambda^2}$.

As in the previous models, the log likelihood function can be maximized with respect to the parameters to obtain maximum likelihood estimates of all the parameters appeared in the production function. However, we must use the conditional distribution f(u/ε) in order to obtain point estimates of technical efficiency for each producer in the sample. The conditional distribution f(u/ε) is written mathematically as:

$$f(u/\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi}\sigma_*\left[1-\Phi\left(-\frac{\tilde{\mu}}{\sigma_*}\right)\right]}\exp\left\{-\frac{\left(u-\tilde{\mu}\right)^2}{2\sigma_*^2}\right\} \quad [3.64]$$

where $\tilde{\mu}_i = \left(-\sigma_u^2\varepsilon_i+\mu\sigma_v^2\right)/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$.

The mean of the f(u/ε) is given mathematically by:

$$E\left(u_i/\varepsilon_i\right) = \sigma_*\left[\frac{\tilde{\mu}_i}{\sigma_*}+\frac{\varphi\left(\frac{\tilde{\mu}_i}{\sigma_*}\right)}{1-\Phi\left(-\frac{\tilde{\mu}_i}{\sigma_*}\right)}\right] \quad [3.65]$$

While the mode by:

$M\left(u_i / \varepsilon_i\right) = \tilde{\mu}_i$ if $\tilde{\mu}_i \geq 0$ and 0 otherwise.

Finally, as in previous models we must substitute either $E\left(u_i / \varepsilon_i\right)$ or $M\left(u_i / \varepsilon_i\right)$ in the equation:

$$TE_i = \exp\left\{-\hat{u}_i\right\} \quad [3.66]$$

or in $TE_i = E\left(\exp\left\{-u_i\right\} / \varepsilon_i\right)$ suggested by Battese and Coelli (1998), in order to obtain point estimates of technical efficiency for each producer in the sample.

Finally, the Normal-Gamma stochastic frontier model was first introduced by Greene (1980a, b), extended by Greene (1990) and makes the following distributional assumptions:

- $\nu_i \sim$ iid $N(0,\sigma_\nu^2)$
- $u_i \sim$ iid gamma
- ν_i and u_i are distributed independently of each other, and of the regressors.

The gamma density function f(u) for u≥0 is given mathematically by:

$$f(u) = \frac{u^m}{\Gamma(m+1)\sigma_u^{m+1}} \exp\left\{-\frac{u}{\sigma_u}\right\}, \quad m>-1 \quad [3.67]$$

The density function for ν is given again mathematically by the following equation:

$$f(\nu) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_\nu} \exp\left\{-\frac{\nu^2}{2\sigma_\nu^2}\right\} \quad [3.68]$$

Because we assumed that u and ν are distributed independently, the joint density function of u and ν is the product of these two distributions and is written mathematically as:

$$f(u, \nu) = \frac{u^m}{\Gamma(m+1)\sigma_u^{m+1}\sqrt{2\pi}\sigma_\nu} \exp\left\{-\frac{u}{\sigma_u} - \frac{\nu^2}{2\sigma_\nu^2}\right\} \quad [3.69]$$

and so the joint density function of u and ε=ν-u is given mathematically by the following equation:

$$f(u,\varepsilon) = \frac{u^m}{\Gamma(m+1)\sigma_u^{m+1}\sqrt{2\pi}\sigma_\nu} \exp\left\{-\frac{u}{\sigma_u} - \frac{(u+\varepsilon)^2}{2\sigma_\nu^2}\right\} \quad [3.70]$$

So, the marginal density function of ε is given mathematically by the following equation:

$$f(\varepsilon) = \int_0^\infty f(u,\varepsilon)du = \frac{\sigma_v^m}{\Gamma(m+1)\sigma_u^{m+1}\sqrt{2\pi}} \exp\left\{\frac{\varepsilon}{\sigma_u} + \frac{\sigma_v^2}{2\sigma_u^2}\right\} \int_w^\infty (t-u)^m \exp\left\{-\frac{t^2}{2}\right\} dt \quad [3.71]$$

where w = $(\varepsilon/\sigma_v) + (\sigma_v/\sigma_u)$.

However, this marginal density function contains an integral term that poses problems in the estimation of the density function. Beckers and Hammond (1987) proposed a closed-form expression for this marginal density function that does not restrict m to integer values. More accurately, they showed that f(ε) can be written mathematically as:

$$f(\varepsilon) = \frac{1}{\Gamma(m+1)\sigma_u^{m+1}\sqrt{2\pi}} \exp\left\{-\frac{\varepsilon^2}{2\sigma_v^2}\right\} \int_0^\infty u^m \exp\left\{-\frac{u}{\sigma_u} - \frac{u\varepsilon}{\sigma_v^2} - \frac{u^2}{2\sigma_v^2}\right\} du \quad [3.72]$$

where the integral term:

$$\int_0^\infty u^m \exp\left\{-\frac{u}{\sigma_u} - \frac{u\varepsilon}{\sigma_v^2} - \frac{u^2}{2\sigma_v^2}\right\} du = \mathrm{J}(\mathrm{m}, \sigma_u, \sigma_v, \varepsilon) \quad [3.73]$$

now has a known closed-form expression.

As in the previous models, we must find and maximize the log likelihood function in order to estimate the parameters appeared in the model. The log likelihood function for a sample of I producers corresponding to the f(ε) is written mathematically as:

$$\ln L = c - I \ln \Gamma(\mathrm{m}+1) - (\mathrm{m}+1)\, I \ln \sigma_u + I\left(\frac{\sigma_v^2}{2\sigma_u^2}\right) +$$
$$\sum_i \frac{\varepsilon_i}{\sigma_u} + \sum_i \ln \Phi\left[-\frac{\left(\varepsilon_i + \sigma_v^2/\sigma_u\right)}{\sigma_v}\right] + \sum_i \ln h\left(m, \varepsilon_i\right), \quad \text{c : constant } [3.74]$$

where h(m, ε_i) = $E\left[z^m / z > 0, \varepsilon_i\right]$ and $z \approx N\left[-\left(\varepsilon_i + \sigma_v^2/\sigma_u\right), \sigma_v^2\right]$.

According to the methodology applied in the previously described models, we must estimate the conditional distribution of f(u/ε) in order to obtain estimates of technical efficiency of each producer in the sample. The conditional distribution of f(u/ε) is written mathematically as:

$$f(u/\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{u^m}{J(m, \sigma_u, \sigma_v, \varepsilon)} \exp\left\{-\frac{u}{\sigma_u} - \frac{u\varepsilon}{\sigma_v^2} - \frac{u^2}{2\sigma_v^2}\right\} \quad [3.75]$$

with mean:

$$\mathrm{E}\left(u_i / \varepsilon_i\right) = \frac{h\left(m+1, \varepsilon_i\right)}{h\left(m, \varepsilon_i\right)} \quad [3.76]$$

Finally, as in previous models, we must substitute either $\mathrm{E}\left(u_i / \varepsilon_i\right)$ or the mode in the equation:

$$TE_i = \exp\left\{-\hat{u}_i\right\} \quad [3.77]$$

in order to obtain estimates of technical efficiency for each producer in the sample.

All the above described models are assumed that each producer in the sample produce only one output. But this case is rarely met in real economic world. The producers at most cases are producing many outputs. In these cases researchers either weigh the outputs according to their contribution on total production of each producer or use the input distance functions with above one output variables. However, the input distance functions are not by definition in an econometrically estimable form. In order to put these distance functions in the form of an econometric model we use the fact that they are linearly homogenous in the inputs. So, we can normalize the input distance function on each arbitrarily chosen of the (all possible) inputs (e.g x_1). The input distance function is written mathematically as:

$$x_1 D_I\left(x_2 / x_1, x_3 / x_1, \ldots., x_N / x_1, y\right) TI = 1 \quad [3.78]$$

where TI is the technical inefficiency index with 0≤TI≤1 and with D_I (y,x) in most applications taking the translog form. This is written mathematically as:

$$0 = \ln x_1 + \ln D_I\left(x_2 / x_1, x_3 / x_1, \ldots., x_N / x_1, y\right) + v + \ln\left[\exp(-u)\right] \quad [3.79]$$

So, the technical inefficiency is obtained by the relation TI= exp(-u) for each producer in the sample.

3.4.1.2 Panel data models

All the above described models that estimate technical efficiency, are concerned with cross-sectional data. Some statistical problems concerning the adoption of the above cross-sectional models will be resolved if panel data are available. One of these statistical problems is the assumption required by the maximum likelihood technique that the technical inefficiency error component is independent of the regressors. However, in practice we rarely meet such situations. Always, the technical inefficiency component is correlated with the input variables the producer is selecting. The other problem is the inability of the JLMS technique to produce consistent estimates of technical efficiency for each producer in the sample. This occurs since the variance of the conditional mean or the conditional mode of (u/ε) for each individual producer does not go to zero as the size of the cross section increases.

Panel data techniques avoid these statistical limitations because conventional panel data estimation techniques that measure technical efficiency are not based on strong distributional assumptions as cross-sectional models do. This is true because repeated observations on a sample of producers can serve as a substitute for strong distributional assumptions. Also, it is true that not all panel data estimation techniques require the assumption of independence of the technical inefficiency error component from the regressors. Again repeated observations on a sample of producers can serve as a substitute for the independence assumption. Finally, since adding more observations on each producer generates information not provided by adding more producers to a cross-section, the technical efficiency of each producer in the sample can be estimated consistently as $T \rightarrow +\infty$, T being the number of observations on each producer. So, repeated observations on a sample of producers resolve the inconsistency problem with the JLMS technique.

Before starting to describe the panel data methods, we must make some assumptions for these models. We assume that we have observations on I producers(i=1,…,I), through T time periods (t=1,…,T). This means that the panels are assumed to be balanced, because each producer is observed T times. However, unbalanced panels, in which producer I is observed $T_i \leq$T times, with not all T_i equal, can be estimated by each of the panel data models we will show below. For simplicity, we again assume that the production frontier takes the Cobb-Douglas form. Also, we must discriminate the models according to the time-variability of the technical efficiency.

A Cobb-Douglas production frontier with time-invariant technical efficiency is written mathematically as:

$$\ln y_{it} = \beta_0 + \sum_n \beta_n \ln x_{nit} + v_{it} - u_i \quad [3.80]$$

where v_{it} represents random statistical noise and $u_i \geq 0$ represents technical inefficiency.

The simplest panel data model is a fixed-effects model. This model assumes additionally that the v_{it} are iid $(0, \sigma_v^2)$ and are uncorrelated with the regressors. No distributional assumption on the u_i is making, allowing the u_i to be correlated with the regressors or with the v_{it}. The u_i are treated as fixed (i.e., non-random) effects and they become producer-specific intercept parameters to be estimated along with the β_n s. In this case, the previous Cobb-Douglas production frontier is written mathematically as:

$$\ln y_{it} = \beta_{0i} + \sum_n \beta_n \ln x_{nit} + v_{it} \quad [3.81]$$

where the $\beta_{0i} = (\beta_o - u_i)$ are producer specific intercepts.

The model can be estimated by applying the OLS method. Estimation is accomplished in any of the three equivalent ways (Kumbhakar and Lovell, 2000):

- By suppressing β_o and estimating I producer-specific intercepts.
- By retaining β_o and estimating I-1 producer-specific intercepts.
- By applying the within transformation, in which all data are expressed in terms of deviations from producer means and the I intercepts are recovered as means of producer residuals (each of these variants is referred as least squares with dummy variables, LSDV for short).

After estimation, we employ the following normalization:

$$\hat{\beta}_o = \max_i \left\{ \hat{\beta}_{0i} \right\} \quad [3.82]$$

and the u_i are estimated mathematically from:

$\hat{u}_i = \hat{\beta}_o - \hat{\beta}_{0i}$ (ensuring that $\hat{u}_i \geq 0$).

As in the cross sectional models, producer-specific estimates of technical efficiency for each producer in the sample are given mathematically by:

$$TE_i = \exp\left\{ -\hat{u}_i \right\} \quad [3.83]$$

with the LSDV estimates of the β_n s and β_{0i} being consistent as either I $\rightarrow +\infty$ or T $\rightarrow +\infty$.

On the other hand, the random-effects model assumes now that u_i term is randomly distributed with constant mean and variance, but is assumed to be uncorrelated with the regressors and with the ν_{it}. Also as in the fixed-effects model, we assume that the ν_{it} has zero expected mean and constant variance. The previous Cobb-Douglas production frontier is written mathematically now as:

$$\ln y_{it} = \left[\beta_0 - \mathrm{E}(u_i) \right] + \sum_n \beta_n \ln x_{nit} + \nu_{it} - \left[u_i - E(u_i) \right] \quad [3.84] \text{ or}$$

$$\ln y_{it} = \beta_0^* + \sum_n \beta_n \ln x_{nit} + \nu_{it} - u_i^* \quad [3.85]$$

This random-effects model can be estimated by the standard two-step generalized least squares method (GLS). So, in the first step OLS is used to obtain estimates of all parameters. In the second step the intercept and the β'parameters are reestimated using feasible GLS. After the β_0^* and the $\beta_n s$ have been estimated using feasible GLS, the u_i^* can be estimated from the residuals by the following equation:

$$\hat{u}_i^* = \frac{1}{T} \sum_t \left(\ln y_{it} - \hat{\beta}_0^* - \sum_n \beta_n \, \mathrm{l\hat{n}} \, x_{nit} \right) \quad [3.86]$$

After this, estimates of the u_i s are obtained by means of the normalization and are written mathematically as:

$$\hat{u}_i = \max_i \{\hat{u}_i^*\} - \hat{u}_i^* \quad [3.87]$$

Finally, the technical efficiency of each producer in the sample is obtained by substituting $\hat{u}_i$ in the following relationship:

$$TE_i = \exp\{-\hat{u}_i\} \quad [3.88]$$

where the producing estimates are consistent as both I→+∞ and T→+∞.

However, Cornwell, Schmidt, and Sickles (CSS) (1990) and Kumbhakar (1990) proposed a stochastic production frontier panel data model but with time-varying technical efficiency. Assuming the Cobb-Douglas form, this model is written mathematically as:

$$\ln\ y_{it} = \beta_{ot} + \sum_n \beta_n \ln x_{nit} + v_{it} - u_{it} \quad [3.89] \text{ or}$$

$$\ln\ y_{it} = \beta_{it} + \sum_n \beta_n \ln x_{nit} + v_{it} \quad [3.90]$$

where $\beta_{it} = \beta_{ot} - u_{it}$.

But with an IxT panel it was not possible to estimate all the intercepts and the slope parameters in the above model. So the authors proposed the following quadratic specification:

$$\beta_{it} = \Omega_{i1} + \Omega_{i2} t + \Omega_{i3} t^2 \quad [3.91]$$

in order to reduce the number of the intercept parameters. It is also important to note that this specification allows technical efficiency to vary through time but in a different manner for each producer.

CSS in their estimations suggested both a fixed-effect and a random-effects model. In both cases, estimation of the technical efficiency of each producer in the sample is given mathematically by:

$$TE_{it} = \exp\{-\hat{u}_{it}\} \quad [3.92]$$

where $\hat{u}_{it} = \hat{\beta}_{ot} - \hat{\beta}_{it}$.

3.4.2 Estimation of cost efficiency

The standard against which cost efficiency is estimated is the cost frontier, and we adopt an input-orientation approach to the estimation of cost efficiency. The estimation methods are at a high level the same as those described above for the technical efficiency, but with some differences describing below. Whereas the estimation of technical efficiency requires information on input use and output produced, the estimation of cost efficiency requires information on input prices, output quantities, and total expenditure on the inputs used. Some models for estimating cost efficiency may require additional information for input quantities or input cost share equations. Also, the estimation of a cost frontier can be accomplished in cases in which producers produce multiple outputs, whereas estimation of a production frontier requires that producers produce a single output. In multiple output cases, the estimation of output-oriented technical efficiency is achieved by estimating an output distance function, while the estimation of input-oriented technical efficiency is achieved by estimating an input distance function. The estimation of technical efficiency does not require the imposition of a behavioral objective on producers, whereas the estimation of cost efficiency does. Finally, the technical efficiency cannot be decomposed while the cost efficiency can be decomposed into the input-oriented technical efficiency and the input allocative efficiency components.

3.4.2.1 Cross-sectional models

For these models cross-sectional data on the prices of the inputs employed, the quantities of output produced, and total expenditures are required for each of the I producers in the sample. The deterministic cost frontier is written mathematically as:

$$E_i \geq c(y_i, w_{i,} \beta) \quad \text{i=1,…,I} \quad [3.93]$$

where $E_i = \sum_n w_{ni} x_{ni}$ is the expenditure incurred by producer i, and x and y are the vector of the N inputs used and the M outputs produced respectively. So, cost efficiency is written mathematically as:

$$CE_i = \frac{c(y_i, w_i, \beta)}{E_i} \quad [3.94]$$

and defines cost efficiency as the ratio of minimum feasible cost to observed expenditures. CE_i is always ≤1 with taking the price 1 only for producers on the frontier. Goal programming, corrected OLS, and modified OLS have all been used in bibliography to estimate deterministic cost frontiers.

A stochastic cost frontier can be written mathematically as:

$$E_i \geq c(y_i, w_i, \beta)\exp\{v_i\} \quad [3.95]$$

where the right part of this inequality is the stochastic cost frontier with $c(y_i, w_i, \beta)$ to be the deterministic part of the stochastic cost frontier common to all producers and $\exp\{v_i\}$ to be a producer-specific random part. In this case the cost efficiency is written mathematically as:

$$CE_i = \frac{c(y_i, w_i, \beta)\exp\{v_i\}}{E_I} \quad [3.96]$$

which defines cost efficiency as the ratio of minimum cost attainable to observed expenditure. As in the deterministic case, the stochastic cost efficiency takes values between zero and one.

In bibliography, usually the deterministic kernel $c(y_i, w_i, \beta)$ for the single output cases takes the log-linear Cobb-Douglas form. So, the general form of the stochastic cost frontier described above can be written mathematically as:

$$\ln E_i \geq \beta_o + \beta_y \ln y_i + \sum_n \beta_n \ln w_{ni} + \varepsilon_i \quad [3.97] \text{ or}$$

$$\ln E_i = \beta_o + \beta_y \ln y_i + \sum_n \beta_n \ln w_{ni} + v_i + u_i \quad [3.98]$$

where v_i is the two-sided random noise component and u_i is the non-negative cost inefficiency component of the composed error term ε_i. However, since a cost frontier must be linear homogenous in input prices [$c(y_i, \lambda w_i, \beta) = \lambda c(y_i, w_i, \beta)$, λ>0], the above stochastic cost frontier must be reformulated by normalizing the function by one of the input prices. We choose randomly the w_{ki} and we have:

$$\ln \frac{E_i}{w_{ki}} = \beta_o + \beta_y \ln y_i + \sum_{n \neq k} \beta_n \ln\left(\frac{w_{ni}}{w_{ki}}\right) + v_i + u_i \quad [3.99]$$

where $w_{ki} \neq 0$ is the price of the k-th input selected randomly. In this case, the general mathematic equation for estimating cost efficiency described above takes the following form:

$$CE_i = \exp\{-\hat{u}_i\} \quad \text{i=1,…,I} \quad [3.100]$$

It is obvious that the stochastic cost frontier model described above is structurally indistinguishable from the stochastic production frontier model described in section 3.4.1.1. In the existing literature concerning the measurement of cost efficiency, the same distributional assumptions can be made for the error components as those made in the estimation of the technical efficiency above. In most cases, maximum likelihood techniques are employed to obtain estimates of β and the parameters of the two-error components. At the second phase, the JLMS decomposition can be used to separate noise from cost inefficiency in the residuals. Finally, the estimated cost inefficiency component can be substituted into $CE_i = \exp\{-\hat{u}_i\}$ relationship in order to obtain producer-specific estimates of cost efficiency.

Below we will illustrate the use of maximum-likelihood method for estimating the stochastic Cobb-Douglas cost frontier described analytically above. We first need to adopt the following distributional assumptions:

- $v_i \sim \text{iid } N(0, \sigma_v^2)$

- u_i ~ iid $N^+(0,\sigma_u^2)$
- v_i and u_i are distributed independently of each other, and of the regressors.

The density function of the u is given by:

$$f(u) = \frac{2}{\sqrt{2\pi}}\frac{1}{\sigma_u}\exp\left\{-\frac{u^2}{2\sigma_u^2}\right\} \quad [3.101]$$

while the density function of ν is given by:

$$f(v) = \frac{1}{\sqrt{2\pi}}\frac{1}{\sigma_v}\exp\left\{-\frac{v^2}{2\sigma_v^2}\right\} \quad [3.102]$$

The marginal density function of ε= ν+u is written mathematically as:

$$f(\varepsilon) = \int_0^\infty f(u,\varepsilon)du = \int_0^\infty \frac{2}{2\pi\sigma_u\sigma_v}\exp\left\{\frac{-u^2}{2\sigma_u^2} - \frac{(\varepsilon-u)^2}{2\sigma_v^2}\right\}du = \frac{2}{\sigma}\phi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right) \quad [3.103]$$

where $\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}, \lambda = \frac{\sigma_u}{\sigma_v}$, and $\Phi(.)$ and $\phi(.)$ are the standard normal cumulative distribution and density functions respectively.

Using the above mathematical form for f(ε), the log-likelihood function for a sample of I producers is written mathematically as:

$$\ln L = c - I\ln\sigma + \sum_i \ln\Phi\left(\frac{\varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_i \varepsilon_i^2 \qquad \text{c: constant} \quad [3.104]$$

In order to obtain maximum likelihood estimates of all parameters in the stochastic cost frontier equation, we must maximize the above log-likelihood function with respect to those parameters. As for technical efficiency, we must extract the information that ε_i contains on u_i in order to obtain consistent estimates of the cost efficiency for each producer in the sample. This is possible by taking the conditional distribution of u_i given ε_i and applying the JLMS procedure described in the previous sections. So, the conditional distribution of u given ε is written mathematically as:

$$f(u/\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi}\sigma_*}\exp\left\{-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right\} / \left[1-\Phi\left(\frac{-\mu_*}{\sigma_*}\right)\right] \quad [3.105]$$

where $\mu_* = \varepsilon\sigma_u^2/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$. Since f(u/ε) is normally distributed, either the mean:

$$E(u_i / \varepsilon_i) = \sigma_* \left[\frac{\phi(\varepsilon_i \lambda / \sigma)}{1 - \Phi\left(-\varepsilon_i \lambda / \sigma\right)} + \left(\frac{\varepsilon_i \lambda}{\sigma} \right) \right] \quad [3.106]$$

or the mode:

$$\mathrm{M}(u_i / \varepsilon_\iota) = \varepsilon_i \left(\frac{\sigma_u^2}{\sigma^2} \right) \text{ for } \varepsilon_i \geq 0 \text{ and zero otherwise}$$

can serve as a point estimator for u_i. Finally, once point estimates of u_i are obtained, estimates of the cost efficiency of each producer in the sample can be obtained by putting either this mean or mode in $CE_i = \exp\{-\hat{u}_i\}$ equation. It is also possible to adapt the Battese and Coelli (1988) point estimator for estimating cost efficiency for each producer in the sample. So we have:

$$CE_i = E(\exp\{-u_i\} / \varepsilon_i) = \left[\frac{1 - \Phi(\sigma_* - \mu_{*i} / \sigma_*)}{1 - \Phi(-\mu_{*i} / \sigma_*} \right] \exp\left\{ -\mu_{*i} + \frac{1}{2}\sigma_*^2 \right\} \quad [3.107]$$

Next, estimates of the cost efficiency of each producer in the sample can be obtained by putting this relationship in $CE_i = \exp\{-\hat{u}_i\}$ equation. The point estimators of cost efficiency obtained by the Battese and Coelli (1988) method and the JLMS method described above are different of each other. However, regardless of which method is used, the estimates of cost efficiency are inconsistent because the variation associated with the distribution of (u_i / ε_i) is independent of i.

In multiple-output cases, it is possible to estimate a cost frontier and to obtain producer-specific estimates of cost efficiency, by following the procedures analyzed in the single-output cases. Nothing changes, except for the functional form of the cost frontier. The deterministic kernel $c(y_i, w_i, \beta)$ of the multiple-output cost frontier at most cases in bibliography takes the log-quadratic translog functional form. This form was first introduced by Christensen, Jorgenson, and Lau (1971) and it is flexible in the sense that it provides a second-order approximation to any well-behaved underlying cost frontier at the mean of the data (Kumbhakar and Lovell, 2000). The stochastic cost frontier can be written analytically as:

$$\begin{aligned} \ln E_i = {} & \beta_o + \sum_m \alpha_m \ln y_{mi} + \sum_n \beta_n \ln w_{ni} + \frac{1}{2} \sum_m \sum_j \alpha_{mj} \ln y_{mi} \ln y_{ji} + \\ & + \frac{1}{2} \sum_n \sum_k \beta_{nk} \ln w_{ni} \ln w_{ki} + \sum_n \sum_m \gamma_{nm} \ln w_{ni} \ln y_{mi} + v_i + u_i \quad [3.108] \end{aligned}$$

where Young's theorem requires that $\alpha_{nk} = \alpha_{kn}$ and $\beta_{mj} = \beta_{jm}$, and the homogeneity of degree +1 in input prices requires the imposition of the additional following restrictions:

- $\sum_n \beta_n = 1$

- $\sum_n \beta_{nk} = 0, \forall k.$
- $\sum_n \gamma_{nm} = 0, \forall m.$

Here, the one-sided error component u_i now captures the composite cost of input-oriented technical inefficiency and input allocative inefficiency. However, in these multiple-output models, multicollinearity among the regressors is likely to lead to imprecise estimates of many parameters in the models. Thus, the benefit of flexibility in the multiple-output models can be offset by the cost of statistically insignificant parameter estimates (Kumbhakar and Lovell, 2000).

In many cases, some of the inputs used by the producers are fixed, perhaps by contractual agreements. In these cases, the interest shifts from the cost frontier to the variable cost frontier because producers seek to minimize the variable cost. We assume that each of the i=1,2,…,I producers use a vector of variable inputs $x_i = (x_{1i},...,x_{Ni})$ >0, available at prices $w_i = (w_{1i},...,w_{Ni})$ >0, and a vector of fixed inputs $z_i = (z_{1i},...,z_{Qi})$ >, to produce a single output y_i >0. So, the producers at these cases incur variable expense $VE_i = \sum_n w_{ni} x_{ni}$. For simplicity, we assume that the variable cost frontier takes the translog functional form, and we have:

$$\ln VE_i = \beta_o + \beta_y \ln y_i + \sum_n \alpha_n \ln w_{ni} + \sum_q \beta_q \ln z_{qi} + \frac{1}{2}\beta_{yy}(\ln y_i)^2 + \frac{1}{2}\sum_n\sum_k \alpha_{nk} \ln w_{ni} \ln w_{ki}$$
$$+\frac{1}{2}\sum_q\sum_r \beta_{qr} \ln z_{qi} \ln z_{ri} + \sum_n\sum \gamma_{nq} \ln w_{ni} \ln z_{qi} + \sum_n \alpha_{yn} \ln y_i \ln w_{ni}$$
$$+\sum_q \beta_{yq} \ln y_i \ln z_{qi} + v_i + u_i \qquad [3.109]$$

where v_i depicts the effects of the statistical noise and u_i reflects the cost of inefficiency in the allocation of the variable inputs of each producer. Here, if independence assumptions are maintained and if distributional assumption is imposed on u_i (e.g., half normal), the variable cost frontier can be estimated by the maximum likelihood method. The processes are the same as those developed in the estimation of the stochastic frontier both for the single-output and multiple output case above. So, it is not indispensable to repeat the details here again.

3.4.2.2 Panel data models for estimating cost efficiency

As we mentioned and in the description of the cross-sectional production frontiers, the fundamental problem in estimating cost efficiency with cross-sectional models is that in a single cross-section we observe each producer only once. So, this fact severely limits the confidence we have in our technical or cost efficiency estimations (Kumbhakar and Lovell, 2000). Moreover, the estimation of a cross-sectional cost frontier by the maximum-likelihood method and the subsequent decomposition of the residual into cost inefficiency and statistical noise, both rest heavily on strong distributional assumptions on each error component. The assumption that the cost inefficiency error component is independent of the regressors is always not valid in practice. Also, the JLMS method can be applied to the estimation of cost efficiency, but the estimator is not consistent as I→+∞ (Kumbhakar and Lovell, 2000). All the above problems with the cross-sectional models can be avoided by using panel data.

The procedures that are followed for the estimation of the stochastic cost frontiers in the presence of panel data are identical with those developed for the estimation of stochastic production frontier models. We assume that we have a panel of I producers for T time periods[9]. We also assume that cost efficiency is time-invariant and that the deterministic kernel of the stochastic cost frontier takes the single-output Cobb-Douglas form. So, the stochastic cost frontier is written mathematically as:

$$\ln E_{it} = \beta_o + \beta_y \ln y_{it} + \sum_n \beta_n \ln w_{nit} + v_{it} + u_i \quad [3.110]$$

where v_{it} represents random statistical noise and $u_i \geq 0$ represents the time-invariant cost inefficiency. Finally, the constraint $\sum_n \beta_n = 1$ ensures homogeneity of degree +1 of the cost frontier in input prices (w_i).

The above stochastic cost frontier can be estimated with three different procedures. First, we rearrange the stochastic cost frontier as:

$$\ln E_{it} = \beta_{oi} + \beta_y \ln y_{it} + \sum_n \beta_n \ln w_{nit} + v_{it} \quad [3.111]$$

where $\beta_{oi} = \beta_o + u_i$. If we assume that the v_{it} are iid $(0, \sigma_v^2)$ and are uncorrelated with the regressors and if we make no distributional or independence assumptions on the u_i, the rearranged stochastic cost frontier can be estimated by the LSDV fixed-effects approach. After estimation, the cost frontier intercept is estimated as $\hat{\beta}_o = \min_i \{\hat{\beta}_{oi}\}$ and the u_i are estimated from $\hat{u}_i = \hat{\beta}_{oi} - \hat{\beta}_o \geq 0$. Finally, producer-specific estimates of cost efficiency are obtained from the following equation:

$$CE_i = \exp\{-\hat{u}_i\} \quad [3.112]$$

with estimates being consistent as I→+∞ and T→+∞.

Secondly, we also can rearrange the above stochastic cost frontier as follows:

$$\ln E_{it} = \beta_o^* + \beta_y \ln y_{it} + \sum_n \beta_n \ln w_{nit} + v_{it} + u_i^* \quad [3.113]$$

where $\beta_o^* = \beta_o + E(u_i)$ and $E(u_i^*) = E[u_i - E(u_i)] = 0$. Assuming that the u_i are randomly distributed with constant mean and variance, but are uncorrelated with the v_{it} and with the regressors, and assuming that the v_{it} have zero expected mean and constant variance, we can incorporate time-invariant regressors into the model and use a random-effects approach in order to estimate the above rearranged stochastic cost

[9] The panel of the data may be balanced or unbalanced.

frontier. This frontier can be estimated by the GLS method. After estimation of the stochastic cost frontier, an estimate of u_i^* is obtained from the regression residuals by means of $\hat{u}_i^* = (1/T)\sum_t \left(\ln E_{it} - \hat{\beta}_o^* - \hat{\beta}_y \ln y_{it} - \sum_n \hat{\beta}_n \ln w_{nit} \right)$, from which we obtain $\hat{u}_i = \hat{u}_i^* - \min_i \{\hat{u}_i^*\} \geq 0$. Finally, producer-specific estimates of cost efficiency are obtained from the following equation:

$CE_i = \exp\{-\hat{u}_i\}$ [3.114]

with estimates being consistent as I→+∞ and T→+∞.

Finally, if we adopt the following assumptions concerning the error components in the above stochastic cost frontier model:

- $\nu_{it} \sim$ iid $N(0,\sigma_v^2)$
- $u_i \sim$ iid $N^+(0,\sigma_u^2)$
- ν_{it} and u_i are distributed independently of each other, and of the regressors.

we can employ maximum likelihood techniques for estimating the parameter appeared in this stochastic cost frontier. The log-likelihood function for a sample of I producers, each observed for T periods of time, is written mathematically as:

$$\ln L = c - \frac{I(T-1)}{2}\ln\sigma_v^2 - \frac{I}{2}\ln(\sigma_v^2 + T\sigma_u^2) + \sum_i \ln\left[1 - \Phi\left(-\frac{\mu_{i*}}{\sigma_*}\right)\right] -$$

$$-\left(\frac{\varepsilon'\varepsilon}{2\sigma_v^2}\right) + \frac{1}{2}\sum_i \left(\frac{\mu_{i*}}{\sigma_*}\right)^2 \quad [3.115]$$

where $\mu_{i*} = T\sigma_u^2\bar{\varepsilon}_i / \left(\sigma_v^2 + T\sigma_u^2\right)$, $\varepsilon_i = v_i + u_i$, and $\sigma_*^2 = \sigma_u^2\sigma_v^2 / \left(\sigma_v^2 + \mathrm{T}\sigma_u^2\right)$. So, this log likelihood function can be maximized with respect to the parameter appeared in this to obtain maximum likelihood estimates of $\beta, \sigma_v^2, and \sigma_u^2$.

The conditional distribution of (u/ε) is written mathematically as:

$$f(u/\varepsilon) = \frac{1}{(2\pi)^{1/2}\sigma_*[1 - \Phi(-\mu_*/\sigma_*)]}\exp\left\{-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right\} \quad [3.116]$$

Because this density function is distributed as $N^+(\mu_*, \sigma_*^2)$, either the mean:

$$\mathrm{E}(u_i/\varepsilon_i) = \mu_{i*} + \sigma_*\left[\frac{\phi(-\mu_{i*}/\sigma_*)}{1 - \Phi(-\mu_{i*}/\sigma_*)}\right] \quad [3.117]$$

or the mode $\mathrm{M}(u_i/\varepsilon_i) = \mu_{i*}$ for $\varepsilon_i \geq 0$ and 0 otherwise. These two estimators are consistent as T→+∞ (Kumbhakar and Lovell, 2000). Finally, either of these is substituted into equation $CE_i = \exp\{-\hat{u}_i\}$ to obtain producer specific estimates of cost efficiency for each producer in the sample.

3.4.3 Estimation of revenue efficiency

The standard against which revenue efficiency is estimated is provided by the revenue frontier, and we adopt an output-oriented approach to the estimation of revenue efficiency. As we saw above, the estimation of cost efficiency requires information on input prices, output quantities, and total expenditures on the inputs used. On the other hand, the estimation of revenue efficiency requires information on output prices, input quantities, and total revenues obtained by the outputs produced by each insurer. Finally, the estimation of a revenue frontier can be accomplice in situations where producers produce multiple outputs, whereas estimation of a production frontier requires that producers produce a single output.

3.4.3.1 Cross-sectional models

The deterministic revenue frontier is written mathematically as:

$$R_i \leq r(x_i, p_{i,} \beta) \quad \text{i=1,…,I} \quad [3.118]$$

where $R_i = \sum_m p_{mi} y_{mi}$, is the revenues collected by the producer i, y is the vector of the M output produced by the producer i, p is a vector of output prices faced by producer i, $r(x_i, p_i, \beta)$ is the revenue frontier common to all producers, and β is a vector of technology parameters to be estimated. The revenue efficiency of producer i is written mathematically as:

$$RE_i = \frac{R_i}{r(x_i, p_i, \beta)} \quad [3.119]$$

which defines revenue efficiency as the ratio of actual revenue for each producer to maximum revenue of all producers in the sample. However, the above revenue frontier is deterministic and so the entire difference of observed revenues over maximum feasible revenues is attributed absolutely to revenue inefficiency. But such a formulation ignores the fact that revenues may be affected by random shocks not under the control of producers. So, a stochastic revenue frontier can be written mathematically as:

$$R_i \leq r(x_i, p_{i,} \beta) \exp\{v_i\} \quad [3.120]$$

If the revenue frontier is specified as being stochastic, the appropriate measure of revenue efficiency becomes now:

$$RE_i = \frac{R_i}{r(x_i, p_i, \beta) \exp\{v_i\}} \quad [3.121]$$

Finally, as with the other types of efficiency, the revenue efficiency takes values between zero and one. Producers having revenue efficiency equal to 1 are characterized revenue efficient.

For simplicity in presentation, we assume that the deterministic kernel $r(x_i, p_i, \beta)$ of the single-output revenue frontier takes the log-linear Cobb-Douglas functional form. Then the stochastic revenue frontier is written mathematically as:

$$\ln R_i = \beta_o + \beta_x \ln x_i + \sum_m \beta_m \ln p_{mi} + v_i - u_i \quad [3.122]$$

where v_i is the two-sided random noise component and u_i is the revenue inefficiency component of the composed error term $\varepsilon_i = v_i - u_i$. The revenue function must be homogeneous of degree one in output prices. This is accomplished by normalizing the function by one of the output prices. Choosing randomly p_k as the normalizing price and appending the two-part error structure, the above stochastic revenue frontier function becomes:

$$\ln(R_i / p_{ki}) = \beta_o + \beta_x \ln x_i + \sum_m \beta_m \ln(p_{mi} / p_{ki}) + v_i - u_i \quad [3.123]$$

Using the above equation for estimating stochastic revenue efficiency, a measure of the revenue efficiency for each insurer in the sample is given mathematically as:

$$RE_i = \exp\{-\hat{u}_i\} \quad [3.124]$$

In order to estimate the stochastic Cobb-Douglas revenue frontier with the use of the maximum likelihood method, we make the following distributional assumptions:

- $v_i \sim$ iid $N(0, \sigma_v^2)$
- $u_i \sim$ iid $N^+(0, \sigma_u^2)$
- v_i and u_i are distributed independently of each other, and of the regressors.

The density function of the u is given by:

$$f(u) = \frac{2}{\sqrt{2\pi}} \frac{1}{\sigma_u} \exp\left\{-\frac{u^2}{2\sigma_u^2}\right\} \quad [3.125]$$

while the density function of v is given by:

$$f(v) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma_v} \exp\left\{-\frac{v^2}{2\sigma_v^2}\right\} \quad [3.126]$$

Since $\varepsilon = v - u$ the joint density function for u and ε is written mathematically as:

$$f(u, \varepsilon) = \frac{2}{2\pi\sigma_u\sigma_v}\exp\left\{-\frac{u^2}{2\sigma_u^2}-\frac{(\varepsilon+u)^2}{2\sigma_v^2}\right\} \quad [3.127]$$

The marginal density function of ε is obtained by integrating u out of f (u, ε), which will give the following mathematic equation:

$$f(\varepsilon) = \int_0^\infty f(u,\varepsilon)du = \frac{2}{\sigma}\varphi\left(\frac{\varepsilon}{\sigma}\right)\Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right) \quad [3.128]$$

where $\sigma = \left(\sigma_u^2+\sigma_v^2\right)^{1/2}$, $\lambda=\frac{\sigma_u}{\sigma_v}$, and Φ(·) and φ (·) are the standard normal cumulative distribution and density functions respectively.

According to the MLE method, we must estimate the log likelihood function for a sample of I producers. Using the marginal density function of ε, the log likelihood function is written mathematically as:

$$\ln L = c - \mathrm{I}\ln\sigma + \sum_i \ln\Phi\left(-\frac{\varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2\sigma^2}\sum_i \varepsilon_i^2 \quad [3.129]$$

where c is a constant.

Next, this log likelihood function can be maximized with respect to the parameters to obtain maximum likelihood estimates of all parameters we need. The revenue efficiency for each producer in the sample is estimated by extracting the information that ε_i contains on u_i. According to the JLMS procedure, the conditional distribution is written mathematically as:

$$f(u/\varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\pi}\sigma_*}\exp\left\{-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right\}/\left[1-\Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right] \quad [3.130]$$

where $\mu_* = -\varepsilon\sigma_u^2/\sigma^2$ and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$.

Since f(u/ε) is distributed as $N^+\left(\mu_{*,}\sigma_*^2\right)$, either the mean or the mode of this distribution can serve as a point estimator for u_i. They are given respectively by:

$$E\left(u_i/\varepsilon_i\right) = \sigma_*\left[\frac{\varphi\left(\varepsilon_i\lambda/\sigma\right)}{1-\Phi\left(\varepsilon_i\lambda/\sigma\right)} - \left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right]$$

and

$$\mathrm{M}\left(u_i / \varepsilon_i\right) = -\varepsilon_i \left(\frac{\sigma_u^2}{\sigma^2}\right) \text{if } \varepsilon_i \leq 0 \text{ or } \mathrm{M}\left(u_i / \varepsilon_i\right) = 0 \text{ otherwise.}$$

Finally, once point estimates of u_i are obtained, estimates of revenue efficiency for each producer in the sample can be obtained by substituting either this mean or this mode in equation $RE_i = \exp\{-\hat{u}_i\}$.

For multi-output cases, if we assume that the deterministic kernel $r(x_i, p_i, \beta)$ takes the log-quadratic translog functional form, then the stochastic revenue frontier can be written as:

$$\ln R_i = \beta_o + \sum_n \alpha_n \ln x_{ni} + \sum_m \beta_m \ln p_{mi} + \frac{1}{2}\sum_n \sum_j \alpha_{nj} \ln x_{ni} \ln x_{ji} + \\ + \frac{1}{2}\sum_m \sum_k \beta_{mk} \ln p_{mi} \ln p_{ki} + \sum_m \sum_k \gamma_{mk} \ln p_{mi} \ln p_{ki} + v_i - u_i \quad [3.131]$$

The process that must be followed for estimating the parameters and the revenue inefficiency is the same as in Cobb-Douglas stochastic revenue frontier. Only the functional form of the frontier is now different. Finally, it is important to note that the above revenue function must be homogenous of degree +1 in output prices.

Finally, an alternative or non-standard approach for estimating revenue efficiency has been applied to the existing literature (e.g. Berger and Mester, 1997). According to this approach, producers take input and output quantities as given and they influence revenues by varying output prices. The revenue frontier in these cases takes the following form:

$$R = R(y, w, u, \upsilon) \quad [3.132]$$

where again u represents revenue inefficiency and υ denotes a random error component. It is important to note that this alternative revenue specification contains the same set of independent variables as the cost frontier specification. The only difference concerns the fact that revenues replace costs as the dependent variable. The estimation approaches are the same as the approaches used in the conventional stochastic cost frontier framework. Finally, alternative revenue specifications are suitable for situations where the output markets are not perfectly competitive and the producers have some market power in determining the output prices.

3.4.3.2 Panel data models

As in other types of efficiency, we assume that we have observations on a panel of I producers through T time periods. For simplicity, we assume that the deterministic kernel of the stochastic revenue frontier takes the single-output Cobb-Douglas form[10]. Finally, we assume that the revenue efficiency is time-invariant. So, the revenue frontier model for panel data is expressed mathematically as:

[10] The extension to multiple-outputs and to flexible functional forms (e.g. translog) is straightforward.

$$\ln R_{it} = \beta_o + \beta_x \ln x_{it} + \sum_m \beta_m \ln p_{mit} + v_{it} - u_i \quad [3.133]$$

where v_{it} represents random statistical noise and u_i represents time-invariant revenue inefficiency. The fact that $\sum_m \beta_m$ =1 ensures homogeneity of degree +1 of revenue frontier in output prices.

Maximum likelihood techniques can be applied for estimating the parameters appeared in the above revenue frontier and the revenue efficiency for each producer in the sample. However, we must assume the following distributional assumptions:

- v_{it} ~ iid $N(0,\sigma_v^2)$
- u_i ~ iid $N^+(0,\sigma_u^2)$
- v_{it} and u_i are distributed independently of each other, and of the regressors.

The log-likelihood function for a sample of I producers, each observed for T periods of time, is written mathematically as:

$$\ln L = c - \frac{I(T-1)}{2}\ln\sigma_v^2 - \frac{I}{2}\ln(\sigma_v^2 + T\sigma_u^2) + \sum_i \ln\left[1 - \Phi\left(-\frac{\mu_{i*}}{\sigma_*}\right)\right] -$$

$$-\left(\frac{\varepsilon'\varepsilon}{2\sigma_v^2}\right) + \frac{1}{2}\sum_i\left(\frac{\mu_{i*}}{\sigma_*}\right)^2 \quad [3.134]$$

where $\mu_{i*} = -(T\sigma_u^2\bar{\varepsilon}_i)/\left(\sigma_v^2 + T\sigma_u^2\right)$, $\varepsilon_i = v_i - u_i$, and $\sigma_*^2 = \sigma_u^2\sigma_v^2/\left(\sigma_v^2 + \mathrm{T}\sigma_u^2\right)$. This log-likelihood function can be maximized with respect to the parameters to obtain maximum likelihood estimates $\beta, \sigma_v^2, and \sigma_u^2$.

The conditional distribution of (u/ε) is written mathematically as:

$$f(u/\varepsilon) = \frac{1}{(2\pi)^{1/2}\sigma_*\left[1 - \Phi(-\mu_*/\sigma_*\right]}\exp\left\{-\frac{(u-\mu_*)^2}{2\sigma_*^2}\right\} \quad [3.135]$$

Because this density function is distributed as $N^+(\mu_*, \sigma_*^2)$, either the mean:

$$\mathrm{E}(u_i/\varepsilon_i) = \mu_{i*} + \sigma_*\left[\frac{\phi(-\mu_{i*}/\sigma_*)}{1 - \Phi(-\mu_{i*}/\sigma_*)}\right] \quad [3.136]$$

or the mode $\mathrm{M}(u_i/\varepsilon_i) = \mu_{i*}$ for $\varepsilon_i \geq 0$ and 0 otherwise. These two estimators are consistent as T→+∞ (Kumbhakar and Lovell, 2000). Finally, either of these is substituted into equation $CE_i = \exp\{-\hat{u}_i\}$ to obtain producer specific estimates of revenue efficiency for each producer in the sample.

3.4.4 Estimation of profit efficiency

Some producers may have profit maximization as an ultimate objective for their operations. This objective is achieved by both minimizing costs and maximizing revenues. In this case the assumption is that producers face exogenously determined input and output prices and attempt to allocate inputs (allocative efficiency) and outputs in order to maximize profit. Accordingly, both inputs and output quantities are determined endogenously. So, they now have to decide not only how much of various inputs to use (cost minimization), but also how much of various outputs to produce, and the number of the decision variables increases from N to M+N.

3.4.4.1 Cross-sectional models

First, we will describe the primal production frontier approach. In this approach the production frontier and the first-order conditions for variable profit maximizations are used to estimate the parameters of the model as well as the magnitudes of technical and allocative inefficiencies and variable profit inefficiency. Here, we are treating variable inputs as endogenous but not the quasi-fixed inputs because in profit maximizing environments technical inefficiency is probably correlated with input use, resulting in inconsistent parameter estimates when a single-equation production frontier model is used (Kumbhakar and Lovell, 2000).

The production frontier is written in general form as:

$$y = f(x, z, \beta)\exp\{-u\} \quad [3.137]$$

where $y \geq 0$ is the scalar output, $x=(x_1,\ldots,x_N) \geq 0$ is a vector of variable inputs, $z=(z_1,..,z_Q) \geq 0$ is a vector of quasi-fixed inputs, $u \geq 0$ is is output-oriented technical inefficiency, and $f(x,z,\beta)$ is the deterministic kernel of a stochastic production frontier. For producers maximizing variable profit conditional on u, the first-order conditions are written mathematically as:

$$f_n(x, z, \beta)\exp\{-u\} = \frac{w_n}{p}\exp\{-\xi_n\} \quad [3.138]$$

where $f_n(x, z, \beta) = \partial f(x, z, \beta) / \partial x_n$ [11], $\frac{w_n}{p}$ are the normalized variable inputs prices, $w = (w_1, \ldots, w_N) > 0$ is an input price vector and $p > 0$ is the scalar output price. Finally, ξ_n are representing allocative inefficiency for each insurer in the sample.

We initially assume that the production frontier takes the Cobb-Douglas form. The production frontier and the first-order conditions for variable profit maximization are written in logarithmic form as:

[11] ∂ represents the first partial derivative.

$$\ln y = \beta_o + \sum_n \beta_n \ln x_n + \sum_q \gamma_q \ln z_q + v - u \quad [3.139]$$

$$\ln x_n = \beta_o + \ln\beta_n + \sum_k \beta_k \ln x_k + \sum_q \gamma_q \ln z_q - \ln\frac{w_n}{p} - u + \xi_n\ , \ \text{n=1,…,N} \quad [3.140]$$

respectively. v is the stochastic noise error component associated with the production frontier.

The above system consisting of the production frontier and the first-order profit maximization conditions can be estimated with the maximum likelihood method. We make the following distributional assumptions on the error components:

- $v \sim$ iid $N(0,\sigma_v^2)$.
- u ~ iid $N^+(0,\sigma_u^2)$.
- $\xi = (\xi_1,...,\xi_N)'$ ~iid N(0,Σ).
- The elements of ξ are distributed independently of v and u, and v and u are distributed independently of one another.

The respective log-likelihood function for a sample of I producers can be written mathematically as:

$$\ln L = c - \frac{I}{2}\ln\sigma_v^2 - \frac{I}{2}\ln\sigma_u^2 - \frac{I}{2}\ln|\Sigma| + \frac{I}{2}\ln\sigma^2 - \frac{1}{2}\sum_i \alpha_i$$

$$+ \sum_i \ln\Phi\left(-\frac{\mu_i}{\sigma}\right) + \frac{I}{2}\ln(1-r) \quad [3.141]$$

where c is a constant, $\alpha_i = \left[\Xi_i^2/\sigma_v^2 + (b_i)'\sum^{-1}(b_i) - \sigma^2(\Xi_i/\sigma_v^2 + \iota'\sum^{-1}b_i)^2\right]$, $\sigma^2 = \left[1/\sigma_v^2 + 1/\sigma_u^2 + \iota'\sum^{-1}\iota\right]^{-1}$, $\mu_i = \left[\sigma^2(\Xi_i/\sigma_v^2 + \iota'\sum^{-1}b_i)\right]$, $\Xi_i = -u_i + v_i$, and $b_i = -\iota u_i + \xi_i$, ι being an $N\times 1$ vector of ones, and the last term is the Jacobian of the transformation from $(\xi_i, b_{1i},....,b_{Ni})$ to $(\ln y_i, \ln x_{1i},..., \ln x_{Ni})$ (Kumbhakar and Lovell, 2000).

The maximization of the log-likelihood function will give consistent and efficient estimates of all technology and efficiency parameters appeared in the above system of equations. The technical inefficiency for each producer in the sample can be estimated from either the conditional mean or the conditional mode of u_i given (ξ_i, b_i') (Kumbhakar and Lovell, 2000). The conditional mean is given mathematically by:

$$E(u_i/\xi_i, b_i') = \mu_i + \sigma\frac{\phi(\mu_i/\sigma)}{\Phi(\mu_i/\sigma)}$$

and the conditional mode by:

$M(u_i/\xi_i, b_i') = \mu_i$ if μ_i >0 and 0 otherwise, where φ(·) and Φ(·) are the density and cumulative distribution functions of a standard normal variable. Producer-specific estimates of allocative inefficiencies ξ_{ni} can be obtained by subtracting the estimates of either the conditional mean or the conditional mode from the residuals of the variable profit maximization equation written in logarithmic form.

There is also the dual variable profit frontier approach in existing literature. The output oriented technical inefficiency and the allocative inefficiency are modeled as in the primal production frontier approach described above. Taking in account these assumptions, the dual variable frontier is written mathematically as (Kumbhakar and Lovell, 2000):

$$v\pi = v\pi(pe^{-u}, w^s, z, \beta,) = v\pi(p, w, z, \beta)h(p, w, z, u, \beta, \xi) \quad [3.142]$$

where $w^s = (w_1^s, ..., w_N^s) = (w_1 \exp\{-\xi_1\}, ..., w_N \exp\{-\xi_N\})$, $v\pi(pe^{-u}, w^s, z, \beta)$ is the maximum variable profit in the presence of both types of inefficiency, $v\pi(p, w, z, \beta)$ is the maximum variable profit in the absence of types of inefficiency, and $h(p, w, z, u, \beta, \xi) = v\pi(pe^{-u}, w^s, z, \beta) / v\pi(p, w, z, \beta) \leq 1$ expressing the variable profit loss due to inefficiency. Under homogeneity of $h(p, w, z, u, \beta, \xi)$, it follows that $h(p, w, z, u, \beta, \xi) = h_1(p, w, z, u, \beta)h_2(p, w, z, \beta, \xi)$. At these cases the profit inefficiency $h(p, w, z, u, \beta, \xi)$ can be decomposed into the product of its technical and allocative inefficiency components. We assume that the production function takes the Cobb-Douglas form. The dual normalized variable profit frontier is written as:

$$\ln \frac{v\pi}{p} = \ln\left[\frac{v\pi(p, w, z, \beta)}{p}\right] + \ln v\pi_u + \ln v\pi_\xi + \ln v\pi_v \quad [3.143]$$

where

$$\ln \frac{v\pi(p, w, z, \beta)}{p} = \frac{1}{1-r}\beta_o + \frac{1}{1-r}\sum_n \beta_n \ln(w_n / p) + \frac{1}{1-r}\sum_q \gamma_q \ln z_q + \ln(1-r) \quad [3.144]$$

is the normalized variable profit in the presence of technical and allocative efficiency (Kumbhakar and Lovell, 2000). The component $\ln v\pi_u$ represents the impact of technical inefficiency on the normalized variable profit, the $\ln v\pi_\xi$ represents the impact of allocative inefficiency on the normalized variable profit, the $\ln v\pi_v$ represents the impact of the statistical noise on the normalized variable profit, and $r = \sum_n \beta_n$ <1 (Kumbhakar and Lovell, 2000).

We can observe that the above described normalized variable profit frontier can be rewritten as:

$$\ln \frac{v\pi}{p} = \delta_o + \sum_n \delta_n \ln \frac{w_n}{p} + \sum_q \delta_q \ln z_q + v_\pi + u_\pi \quad [3.145]$$

where δ_o is a constant, $\delta_n = -(1/1-r)\beta_n \forall n$, $\delta_q = [1/(1-r)]\gamma_q \forall q$, $v_\pi = [1/(1-r)]v$, and $u_\pi = [\ln \pi_u + \ln \pi_\xi] \leq 0$ which represents the overall normalized variable profit inefficiency. However, this equation is structurally similar to the stochastic production frontier model in the primal production frontier approach described above. So, the MLE techniques are used for estimating the parameters and the JLMS decomposition for taking producer-specific estimates of the overall normalized variable profit inefficiency (Kumbhakar and Lovell, 2000).

For multi-output cases, we use the output-oriented distance functions for estimating technical, allocative, and profit inefficiencies. In this case if we assume that producers are allocative efficient, then the producer's profit maximization problem is written as (Kumbhakar and Lovell, 2000):

$$\max_{y,x} \{p^T y - w^T x : D_o(x, ye^u \beta) = 1\} \quad [3.146]$$

and the first-order profit maximization conditions as:

$$\frac{w_n}{p_m e^{-u}} = -\frac{\partial D_o(x, ye^u, \beta)/\partial x_n}{\partial D_o(x, ye^u, \beta)/\partial y_m e^u} \quad [3.147]$$

where y is a vector of M outputs marketed at prices $p=(p_1, \ldots, p_M)$, x is a vector of N inputs purchased at prices $w=(w_1, \ldots, w_N)$. The $u \geq 0$ is the output-oriented technical inefficiency and β is a vector of parameters to be estimated. The above system of equations can be solved for $y_m(pe^{-u}, w, \beta)\forall m$ and $x_n(pe^{-u}, w, \beta)\forall n$ which are the output-supply and input-demand equations that maximize profit in the presence of technical inefficiency respectively (Kumbhakar and Lovell, 2000). However, in practice, these systems are rarely solved easily because many statistical problems can occur. For more details one can see the work of Kumbhakar and Lovell (2000).

3.4.4.2 Panel data models

Before describing the models, we must make an explicit assumption about the time behavior of the technical inefficiency. We assume that the technical inefficiency for each firm in the sample is invariant over time and that the production frontier takes the Cobb-Douglas form. With this qualification and according to the primal production frontier approach, the system of the production frontier and the first-order variable profit conditions is written in logarithmic form as:

$$\ln y_t = \beta_o + \sum_n \beta_n \ln x_{nt} + \sum_q \gamma_q \ln z_q + v_t - u \quad [3.148]$$

$$\ln x_{nt} = \beta_o + \ln \beta_n + \sum_k \beta_k \ln x_{kt} + \sum_q \gamma_q \ln z_q - \ln \frac{w_{nt}}{p_t} - u + \xi_{nt}\text{, n=1,..,N} \quad [3.149]$$

The above system consisting of the production frontier and the first-order profit maximization conditions can be estimated with the maximum likelihood method. We make the following distributional assumptions on the error components:

- $\nu \sim$ iid $N(0,\sigma_v^2)$.
- u ~ iid $N^+(0,\sigma_u^2)$.
- $\xi = (\xi_1,...,\xi_N)'$ ~iid N(0,Σ).
- The elements of ξ are distributed independently of v and u, and v and u are distributed independently of one another.

Given these distributional assumptions and assuming that we have balanced panel data for t=1,2,..,T periods for each producer, the log likelihood function can be written mathematically as:

$$\ln L = c - \frac{IT}{2}\ln\sigma_v^2 - \frac{IT}{2}\ln\sigma_u^2 - \frac{IT}{2}\ln|\Sigma| + \frac{IT}{2}\ln\sigma^2 - \frac{1}{2}\sum_i \alpha_i +$$

$$+ \sum_i \ln\Phi\left(-\frac{\mu_i}{\sigma}\right) + \frac{IT}{2}\ln(1-r) \quad [3.150]$$

where again the parameters appeared are the same as in the cross-sectional case above. The technical inefficiency for each producer in the sample can be estimated from either the conditional mean or the conditional mode of u_i given (ξ_i, b_i') (Kumbhakar 1987). The conditional mean is given mathematically by:

$$E(u_i / \xi_i, b_i') = \mu_i + \sigma\frac{\phi(\mu_i/\sigma)}{\Phi(\mu_i/\sigma)}$$

and the conditional mode by:

$M(u_i / \xi_i, b_i') = \mu_i$ if μ_i >0 and 0 otherwise,

where φ(·) and Φ(·) are the density and cumulative distribution functions of a standard normal variable. Finally, as in the cross-sectional cases, producer-specific estimates of allocative inefficiencies ξ_{nit} can be obtained by subtracting the estimates of either the conditional mean or the conditional mode from the residuals of the variable profit maximization equation written in logarithmic form.

3.4.4.3 Alternative profit frontiers

Alternative profit frontiers have first been formulated and estimated by: Berger, Cummins, Weiss (1997), Hasan and Hunter (1996), Berger and Mester (1997), Humphrey and Pulley (1997), and Lozano-Vivas (1997). Under the standard profit frontier approach, prices of inputs and outputs are exogenously determined and producers seek to maximize profit by selecting inputs and outputs under their control. The standard approach is justified for competitive markets where producers are price-takers and have no power to influence the prices of inputs and outputs.

In contrast, in some markets producers have some degree of monopoly power in their product markets and they can at some degree determine the output prices but not the inputs prices. In this case it is useful to estimate the non-standard or alternative profit frontiers by maximizing profits and taking only input prices as exogenous. The alternative approaches are suitable if there are unmeasured differences in the quality of outputs and if output prices are not accurately measured (Berger and Mester, 1997). They are estimated as single-equation models, once a functional form is assigned to the alternative profit frontier and an assumption is made concerning the error structure (Kumbhakar and Lovell, 2000).

3.4.5 Other parametric approaches

These parametric approaches assume less restrictive or no distributional assumptions for the composed error term. These approaches are the Distribution Free Approach (DFA) and the Thick Frontier Approach (TFA).

3.4.5.1 Distribution free approach

Another parametric approach is the Distribution Free Approach (DFA) first introduced by Berger (1993). Berger called his approach with this name because no specific distributional assumptions for inefficiency component are made. This method is applicable if we have panel data only. Also, it requires that the cost inefficiency component u_i is constant over time and that the random error v_{it} cancels out over the years. DFA involves estimation of the following panel-data cost equation system consisting of the cost equation and its associated input cost share equations:

$$\ln TC_{it} = \ln c(y_{it}, w_{it}, \beta^t) + v_{it} + u_i \quad [3.151]$$

$$\frac{w_{nit} x_{nit}}{TC_{it}} = s_{nit}(y_{it}, w_{it}, \beta^t) + v_{nit} \quad \text{n=2,..,N} \quad [3.152]$$

where TC is the total cost for each firm i=1,..,N in the sample, w is the vector of input prices paid from each producer. The inefficiency component is assumed that is distributed independently of the regressors. The above system of equations is estimated using SUR method a total of T times, once for each time period. For each producer in the sample, the cost equation residuals $\hat{\varepsilon}_{it} = \hat{v}_{it} + \hat{u}_i$ are averaged over time to obtain $\hat{\varepsilon}_i = (1/T)\sum_i \hat{\varepsilon}_{it} \cong \hat{u}_i$ (since random noise assumed to tend to average over time). In order to ensure that the estimated cost inefficiency is non-negative $\hat{\varepsilon}_i$ is normalized on its smallest value and we have (Kumbhakar and Lovell, 2000):

$$CE_i = \exp\{-[\hat{\varepsilon}_i - \min_i(\hat{\varepsilon}_i)]\} \quad [3.153]$$

Although the DFA does not require restrictive error distribution assumptions, it is less preferable than the SFA approach. This is mainly because it is required that cost efficiency is time invariant, a fact that become less applicable as T increases (Kumbhakar and Lovell, 2000).

3.4.5.2 Thick frontier approach

Thick frontier approach was first developed by Berger and Humphrey (1991, 1992) in order to estimate cost efficiency with less restrictive assumptions concerning the composed error terms. It can be used either with cross-sectional or panel data with equal easy. The method starts with the sorting the firms on their average costs. So, for each of the I producers in the sample, we identify if it located in the top or the bottom quartile of the average cost distribution. Producers located in the bottom quartile are considered to be relatively cost efficient as o group by construction, and together they define a thick frontier. The producers located in the top quartile as considered to be cost inefficient according to the thick frontier by construction. The next step of the TFA is the estimation of the following system of cost equations and input cost-share equations twice, once for each quartile:

$$\ln TC_i = \ln c(y_i, w_i, \beta) + v_i \quad [3.154]$$

$$\frac{w_{ni} x_{ni}}{TC_i} = s_{ni}(y_i, w_i, \beta) + v_{ni}, \quad \text{n=2,..,N} \quad [3.155]$$

Assuming that $[v_i, v'_{ni}]'$ ~N(0,Σ), the above system can be estimated using SUR method. Then average cost inefficiency for each producer in high-cost quartile is given by the rate of the difference between the predicted average costs at the mean values of (y_i, w_i) for the two quartiles to the predicted average costs at the mean values of (y_i, w_i) for the high-cost quartile.

Although TFA does not require restrictive distributional assumptions and independence assumptions on error components, it has some serious disadvantages which reduce its above described flexibility. TFA does not generate cost efficiency estimates for each producer in the sample (Kumbhakar and Lovell, 2000). It generates only one cost efficiency estimate for the hypothetical mean producer in the high-cost quartile relative to the hypothetical mean producer in the low-cost quartile (Kumbhakar and Lovell, 2000). Finally, the TFA sorts the producers in arbitrarily selected group of firms (i.e. quintiles were used instead) and so the efficiency scores will vary depending on the sorting criterion used.

3.5 Productivity measurement and decomposition

Productivity generally is the ratio of output produced to the inputs used to produce this output. Always, the productivity is confused with the efficiency because these two concepts are related in practice. This is occurred because the productivity at any time is related to the degree of efficiency with which producers employ the available production technology.

The notion of productivity is always referred as total factor productivity (TFP) in the existing literature. Total factor productivity is formally defined as an index of total quantity of outputs produced divided by an index of total inputs consumed in the production process (Fare et al., 2008). It is obvious that a productivity change occurs when the index of outputs changes at a different rate than the index of inputs does. In the early literature productivity change was calculating using index number techniques to obtain productivity indexes such as Fisher (1922) or Tornqvist (1936). In contemporary literature productivity change can be calculated using non-parametric techniques, or can be estimated using econometric techniques, as we will see below.

3.5.1 Non-parametric techniques for productivity measurement

The Malmquist index approach is the most commonly used approach for analyzing the total factor productivity change of producers over time. This is occur because its use permits the decomposition of the TFP change in its two primary components: the shift in the production frontier over time (technical change), and the shift in the producer's position relative to the production frontier (technical efficiency change). Also, the Malmquist index approach is consistent with the DEA efficiency estimation methodology and so is more preferable than the Fisher (1922) or Tornqvist (1936) approach.

Bellow, we will present the process for measuring the Malmquist total factor productivity change by adopting an input-orientation and by adopting that the underlying technology operates under variable returns to scale technology. The form of the returns to scale does not affect the overall Malmquist productivity index because it is measured by the ratio of CRS distance functions even when the underlying technology exhibits VRS (Ray and Desli, 1997). However, in the case of VRS underlying technology the TFP index is decomposed into pure technical efficiency change, pure technical change, and scale change.

Before continuing with the description of the Malmquist measurement and decomposition, it is important to consider the following figure:

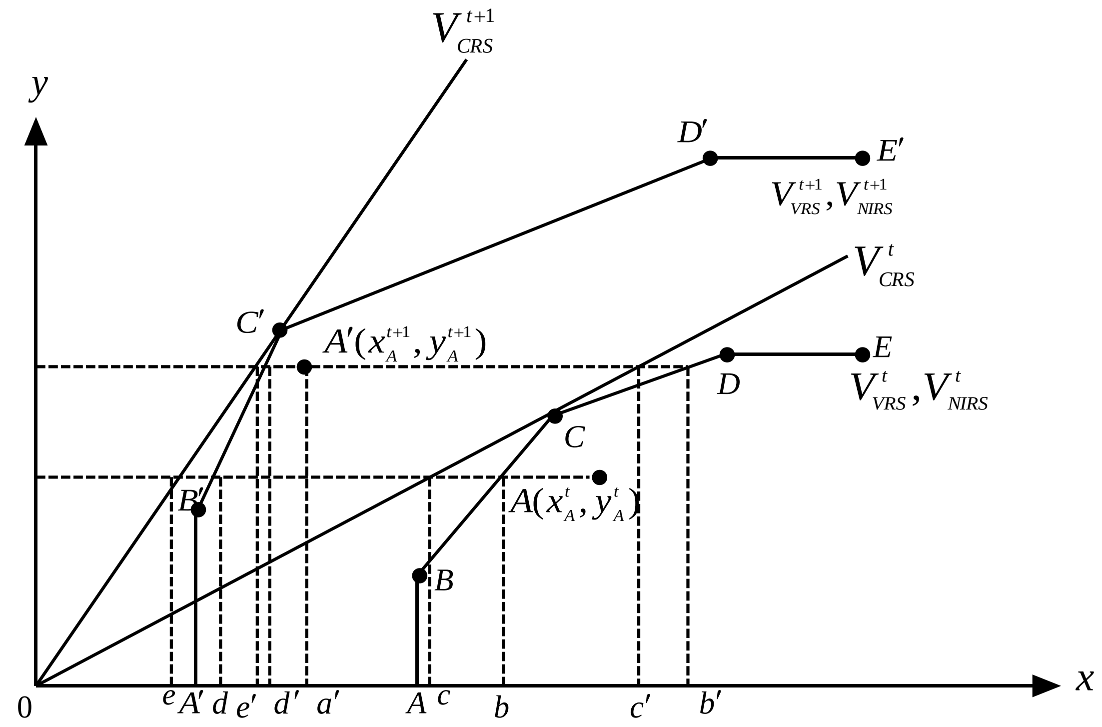

Figure 3.7. Efficiency and Productivity measurement.

This figure depicts the production frontier for a single-output (y) single-input (x) case. The lines $0V^{t}_{CRS}$ and $0V^{t+1}_{CRS}$ represent the CRS frontier in period t and t+1 respectively because of the linear relationship between input usage and output production. The frontiers labeled V^{t}_{VRS} and V^{t}_{NIRS} are variable returns to scale (VRS) and non-increasing returns to scale (NIRS) production frontiers. The lines ABCDE and $A'B'C'D'E'$ represent the VRS production frontier in period t and t+1 respectively. The lines 0CDE and 0C′D′E′ represent the NIRS frontiers for time periods t and t+1 respectively. The Malmquist TFP index is presented using input-oriented distance functions. The input distance function for producer s at time t relative to the production frontier in period p with returns to scale technology r (r= CRS or VRS) is given mathematically by:

$$D^t_r(x^p_s, y^p_s) = \sup\left\{\phi^p_s : \left(\frac{x^p_s}{\phi^p_s}, y^p_s\right) \in V^t_r(y^p_s)\right\} = \frac{1}{\inf\left\{\theta^p_s : (\theta^p_s x^p_s, y^p_s) \in V^t_r(y^p_s)\right\}} \quad [3.156]$$

where (x^p_s, y^p_s) is the input-output vector for producer s in period p=t or t+1 (Cummins and Weiss, 2012).

The Malmquist index is written relatively to the period’s t technology as:

$$M^t_{CRS} = D^t_{CRS}(x^t_A, y^t_A) / D^t_{CRS}(x^{t+1}_A, y^{t+1}_A) = \frac{0a}{0c} / \frac{0a'}{oc'} \quad [3.157]$$

while relative to the period’s t+1 technology as:

$$M_{CRS}^{t+1} = D_{CRS}^{t+1}(x_A^t, y_A^t) / D_{CRS}^{t+1}(x_A^{t+1}, y_A^{t+1}) = \frac{0a}{0e} / \frac{0a'}{0e'} \quad [3.158]$$

M_{CRS}^{t} measures productivity growth between periods t and t+1 using the period t as reference technology, while M_{CRS}^{t+1} measures productivity growth between periods t and t+1 using the period t+1 as reference technology. In existing literature, in order to avoid an arbitrary choice of reference technology, the Malmquist total factor productivity index is defined as the geometric mean of M_{CRS}^{t} and M_{CRS}^{t+1}. So we have:

$$M_{CRS}(x_A^{t+1}, y_A^{t+1}, x_A^t, y_A^t) = \left[M_{CRS}^{t} * M_{CRS}^{t+1}\right]^{1/2} \quad [3.159]$$

with the index being above one for total factor productivity growth cases and below one for total factor productivity decline cases (Cummins and Weiss, 2012). A complete decomposition of the Malmquist productivity index is given in the work of Ray and Desli (1997). They decompose the Malmquist productivity index into pure efficiency change (PEFFCH), pure technical change (TECHCH), and scale change (SCH) such as $M_{CRS}(x_A^{t+1}, y_A^{t+1}, x_A^t, y_A^t) = PEFFCH * TECHCH * SCH$.

The PEFFCH component is written, using an input-orientation, as:

$$PEFFCH = \left(\frac{D_{VRS}^{t}(x_A^t, y_A^t)}{D_{VRS}^{t+1}(x_A^{t+1}, y_A^{t+1})} \right) \quad [3.160]$$

and express the producer's distance from the VRS frontier in period t to its distance from the VRS frontier in period t+1.

The TECHCH is written as:

$$TECHCH = \left[\frac{D_{VRS}^{t+1}(x_A^{t+1}, y_A^{t+1})}{D_{VRS}^{t}(x_A^{t+1}, y_A^{t+1})} * \frac{D_{VRS}^{t+1}(x_A^t, y_A^t)}{D_{VRS}^{t}(x_A^t, y_A^t)} \right]^{1/2} \quad [3.161]$$

and express the shift in the VRS frontier between periods t and t+1 with respect to the position of each producer in the production possibility set in the two periods.

The SCH is written as:

$$SCH = \left(\frac{D_{CRS}^{t}(x_A^t, y_A^t)}{D_{VRS}^{t}(x_A^t, y_A^t)} * \frac{D_{VRS}^{t}(x_A^{t+1}, y_A^{t+1})}{D_{CRS}^{t+1}(x_A^{t+1}, y_A^{t+1})} * \frac{D_{CRS}^{t+1}(x_A^t, y_A^t)}{D_{VRS}^{t+1}(x_A^t, y_A^t)} * \frac{D_{VRS}^{t}(x_A^{t+1}, y_A^{t+1})}{D_{CRS}^{t}(x_A^{t+1}, y_A^{t+1})} \right)^{1/2} \quad [3.162]$$

where it express the ratio of the distances between the VRS and CRS frontiers in periods t and t+1 (Cummins and Weiss, 2012).

3.5.2 Parametric or econometric techniques for productivity measurement

Under these approaches the deterministic production frontier is written as a function of the technology parameter vector β and the time t which express a time trend representing a proxy for technical change. So, in contrast to the production frontiers presented above, which were functions of vector β only, the deterministic production frontier is written as:

$$y = f(x,t,\beta)\exp\{-u\} \quad [3.163]$$

where y is the scalar output vector, $f(x,t,\beta)$ is the deterministic kernel of a stochastic production frontier with technology parameter vector, x is input vector, and u≥0 is the output-oriented technical inefficiency.

According to the literature (Kumbhakar and Lovell, 2000), a primal measure of the rate of technical change is provided by:

$$\mathrm{T}\Delta = \frac{\partial \ln f(x,t,\beta)}{\partial t} \quad [3.164]$$

If TΔ takes positive values then the production frontier shifts up while if it takes negative values then the frontier shifts down.

A primal measure of the rate of change in technical efficiency is provided by:

$$\mathrm{TE}\Delta = -\frac{\partial u}{\partial t} \quad [3.165]$$

If TEΔ takes positive values then technical inefficiency declines while if it takes negative values then technical inefficiency increases through time.

In the scalar output case and if price data are available, the TFP index of productivity change is defined as the difference between the rate of change of output and the rate of change of an input quantity index (Kumbhakar and Lovell, 2000). It is written as:

$$T\dot{F}P = \dot{y} - \dot{X} = \dot{y} - \sum_n S_n \dot{x}_n \quad [3.166]$$

where the dot over the variables indicates its rate of change, $S_n = w_n x_n / E$ is the observed expenditure share of each input x_n, E is the total expenditure of each producer, and w is the input price vector for the N inputs.

According to Kumbhakar and Lovell (2000), if we differentiate the deterministic production frontier and substitute the resulting expression in the $T\dot{F}P$ expression described above, then we have:

$$T\dot{F}P = \mathrm{T}\Delta + (\varepsilon - 1)\sum_n \left(\frac{\varepsilon_n}{\varepsilon}\right)\dot{x}_n + \sum_n \left[\left(\frac{\varepsilon_n}{\varepsilon}\right) - S_n\right]\dot{x}_n + \mathrm{TE}\Delta \quad [3.167]$$

where $\varepsilon_n = \varepsilon_n(x,t,\beta) = x_n f_n(x,t,\beta)/f(x,t,\beta)$ are the elasticities of output y with respect to each of the i=1,..,N inputs. The component $\left[(\varepsilon - 1)\sum_n (\varepsilon_n/\varepsilon)\dot{x}_n\right]$ is a scale component and provides a measure of returns to scale characterizing the production frontier, the component $\left[\sum_n [(\varepsilon_n/\varepsilon) - S_n]\dot{x}_n\right]$ is the input-allocative inefficiency component, and TEΔ with TΔ as defined above.

3.6 Pros and cons of econometrics versus mathematical programming approaches

Both approaches (econometric and mathematical programming) provide measures of technical efficiency as a radial distance from the best practice frontier. However, each approach obtains efficiency scores by utilizing different techniques. In the existing literature, some researchers argue for econometric approach while others argue for the mathematical programming approach. To our opinion, none of the above approaches is superior to the others. Seemingly, both have pros and cons and the superiority of one over the other approach has been a subject of discussion and remains an unresolved issue in the literature. Below we will present the pros and cons of each approach and the suitable circumstances for applying each of the two approaches.

The most important advantage of the econometric (e.g. SFA) approaches is that the observed deviation from the frontier is attributed both to the random error and to the pure inefficiency. The primary disadvantage of the econometric approach is the use of strictly determined functional forms to estimate the frontier. However, these approaches require the adoption of specific distributional assumptions for the composed error component in order to estimate and decompose it to its inefficiency and random error components. So, the choice of an inappropriate functional form or distributional assumptions for the error terms is possible to fake the efficiency scores and the ranking of each producer in the sample as far as its individual efficiency score. Finally, the econometric approach requires relatively large samples in order to obtain consistent and accurate estimates for the parameters of the technology and the inefficiency scores.

The most important advantage of the mathematical programming approaches (e.g. DEA) is that they are non-parametric and do not restrict the production, cost, revenue, or profit function to take a particular functional form. DEA is also individual-firm based (Cummins and Weiss, 2012) since it solves the optimization problem for each decision making unit separately. While, the parametric approaches optimize over the whole sample and the estimated function is applied to all units in the sample. Also, in contrast to the parametric approaches, the DEA can be used with samples that contain a few decision making units (e.g. the branches of a bank) and can generate reliable results. Finally, beyond these properties, the non-parametric approaches have also important statistical properties. As Banker (1993) demonstrated, the DEA results are equivalent to maximum likelihood estimation results and so the non-parametric approaches are not inferior to the parametric approaches as far as their statistical properties.

CHAPTER 4

OUTPUT AND INPUT MEASUREMENT

IN THE INSURANCE SECTOR

4.1 Introduction

The accurate measurement and definition of outputs and inputs and their prices is an important assumption for estimating efficiency measures. A bad definition and measurement of the involved variables will give misleading or meaningless results. This problem is more severe in the services sector where the concept of real output is unclear, the outputs are intangible, and many prices are implicit. Insurance companies belong to the service sector and what the industry produces is not as obvious as it is for the goods sector (e.g. a computer). In the estimation of the efficiency for the insurance industry we must also define accurately the inputs because the data on the number of hours worked and the number of employees occupied are not publicly available (Cummins and Weiss, 2012). As we will see below, despite these notional difficulties researchers have devised measures for inputs, outputs, and their prices that produce economically meaningful estimates of efficiency scores.

4.2 Approaches for measuring financial services output

Insurance firms belong to the broad category of financial services firms and the outputs consist mainly of services, which are mostly unobservable. So, insurance output must be measured using proxy variables. There are three main approaches in bibliography for measuring outputs in the financial services industry: the asset (intermediation) approach, the user-cost approach, and the value added approach (Berger and Humphrey, 1992).

A financial intermediary is typically an institution that facilitates the channeling of funds between lenders and borrowers indirectly. Financial intermediaries channel funds from people who have extra money or surplus savings to those who do not have enough money to carry out a desired activity. Through the process of financial intermediation, certain assets or liabilities are transformed into different assets or liabilities. The intermediation approach treats financial firms (e.g. banks, insurance companies) as pure financial intermediaries, since they borrow funds from one set of decision makers, transform the resulting liabilities into assets, and paying out interest to cover the time value of funds used. This approach is not appropriate for measuring property-liability insurers' outputs because they provide many services in addition to financial intermediation (Cummins and Weiss, 2000, 2012). On the other hand, life insurance operations are based mainly on financial intermediation but according to Cummins and Weiss (2000, 2012) the intermediation approach is not appropriate for either property-liability or life insurers.

Hancock (1985) developed a theory of production for financial firms in which the input or output status of individual financial products can be determined empirically. The user cost of each asset is calculated as the difference between the financial intermediary's opportunity cost of capital and the holding revenues of this specific asset (Hancock 1985). The user cost of each liability is defined as the difference between its holding cost and the financial intermediary's (e.g. bank and insurance company) cost of money. When a positive user cost is attached to an asset, this will contribute to the financial firm's costs and the asset is classified as an input. When the opposite is true, the asset adds to the firms' revenue and is classified as an output. The same is true of liabilities, which can also be classified endogenously as either inputs or outputs depending on the sign of the associated user cost. This method is theoretically sound but requires data that are difficulty estimated. This specific approach is not suitable for estimating insurers' outputs because insurance policies bundle together many services that are priced implicitly (Cummins and Weiss, 2000, 2012).

The third approach for measuring output in financial services industry is the value added approach. This approach is the most commonly used in efficiency measurement literature and the most appropriate method for studying insurance firms' efficiency (Cummins and Weiss, 2000, 2012). This approach is basically derived from the micro-economic theory of the firm and is based on the theoretical premise that firms maximize profits by jointly minimizing costs and maximizing revenues. It considers all asset and liability categories to have some output characteristics rather than distinguishing inputs from outputs in a mutually exclusive way (Cummins and Weiss, 2000, 2012). The categories having significant value-added, as judged by using operating cost allocations, are determined as important outputs. The other categories are treated as unimportant outputs or inputs, depending on their characteristics (Cummins and Weiss, 2000, 2012).

4.3 Services and operations provided by insurers

Insurance outputs are intangible by nature. So, it is important to determine suitable proxies, which are highly correlated with the quantity of financial services provided, for measuring the volume of the services provided by insurers. But before describing these proxies, it is important to describe accurately these services. In the existing literature, the value-added approach identifies the following three principal services provided by insurers (Cummins and Weiss, 2000, 2012):

- Risk-pooling and risk-bearing: Insurance provides a mechanism for consumers and business entities exposed to insurable events to engage in risk reduction through pooling. Policyholders agree to contribute a small premium to a common pool held by an insurer. Insurers collect these premiums and redistribute most of them to those policyholders suffer the losses. The actuarial, underwriting, and related expenses incurred in operating the risk pool are a major component of value added in insurance. Policy holders have their net costs of risk bearing reduced using insurance contracts, because insurers hold capital in order to tackle unexpected losses and investment shocks.
- Real financial services relating to insured losses: Insurers provide a variety of real services for policyholders. Life insurers usually provide financial planning and counseling for individuals and pension and benefit plan administration for

business entities Cummins and Weiss, 2000, 2012). Property-casualty insurers provide real services such as risk surveys, recommendations regarding policy limits, and the design of coverage programs (Cummins and Weiss, 2000, 2012).

- Intermediation: Except premiums collected, insurance companies issue debt contracts (insurance policies and annuities) in order to be able to pay the claims described in their contracts. These funds are invested until policyholders withdraw them (for life insurance contracts) or are needed to pay the coverage claims. Interest credits for these investments are made directly to policyholder accounts (investment income for life insurance contracts) or received as a discount in the premiums paid to insures for compensating for the opportunity cost of the funds they held(investment income for property-liability contracts). The net interest margin between the rate of return earned on assets and the rate of return credited to policyholders represents the value-added of the intermediation function of the insurance industry.

4.4 Outputs and output prices in the insurance industry

As described above, the transfer or diversification of losses incurred is the fundamental function of the insurers. Theoretically, the value-added from the risk-pooling can be measured by the Pratt-Arrow (Arrow, 1971) concept of the insurance premium, which expresses the amount that makes an individual indifferent between purchasing insurance coverage and retaining the risk. Arrow (1971) stated accurately that an individual faced with a random outcome Y and offered the alternative of a certain income Y_0, would be willing to accept a value of Y_0 less than the mean value E(Y) of the random income. The difference between E(Y) and Y_0 is defined as insurance premium. Cummins and Weiss (2012) stated that the insurance premium, which makes the individual just indifferent between retaining and insuring the risk, is given mathematically by the following equation:

$$U(W-\mu_L-\pi)=\int U(W-L)\,f(L)dL$$

where $U(W)$ gives the utility function , W is the initial wealth of the individual, L is the loss incurred ($L\geq 0$), and f(L) is the probability of the loss distribution with mean $\mu_L = E(L)$.

Before describing the proxies representing the outputs produced by insurers, it is important to note that in the existing literature different output definitions are adopted for the life and property-liability insurers. This occurs mainly because the products offered by these two segments of the industry differ significantly. Also, insurers are obligated to report their annual statements separately for their life and property-liability activities. In many studies, the amount of premiums written was used as a proxy for the measurement of output in the insurance sector. However, this was heavily criticized by Yuengert (1993) because premiums represent price times the quantity of the output and so the amount of the output is misspecified.

For the life insurers, in most efficiency studies the approach followed by the Yuengert (1993) is used. So, incurred benefits plus addition to reserves is the proxy used for measuring the life insurance output that relates to the risk-pooling and risk-bearing functions of the life insurers. Incurred benefits represent payments received by policyholders in the current year. The additions to reserves represent the new intermediation output because the funds not used for benefit payments and general expenses are added to policy reserves (Cummins and Weiss, 2012). Another proxy used for measuring life insurers' outputs is the average invested assets because life insurers provide services in connection with funds contributed by the policyholders in previous years (Cummins and Weiss, 2012). Existing literature (Eling and Luhnen, 2010b) suggest five output variables: (a) incurred benefits and addition to reserves for the major lines of business offered by life insurers-individual life insurance, (b) individual annuities, (c) group life insurance, (d) group annuities, and (e) accident and health insurance.[12] This occurs because life insurer products differ in the types of contingent events covered and in the relative importance of the risk-pooling, intermediation, and real service components of output (Cummins and Weiss, 2012).

The price for each the five life insurance output variables described above is defined as the sum of premiums and investment income minus output for each line divided by output quantity. This is consistent with most of life insurers' efficiency studies existing in the literature. The price of the intermediation output proxied by the amount of the invested assets is usually considered as the expected rate of return on the insurer's assets. Existing literature sets the weight average of the expected debt returns and expected equity returns, weighted by the proportion of the portfolio invested in debt and stocks, as the price of the intermediation output.[13]

For property-liability insurers, the existing literature suggests the use of the present value of real losses incurred as a proxy for the risk-pooling and real services activities of these insurers. Losses incurred are the amounts of losses expected to be paid as a result of providing insurance coverage for a particular year. Some efficiency studies use premiums, but as Yuengert (1993) stated premiums are actually revenues, since premiums are the product of price and quantity and not exclusively the quantity of output. Since the timing of the loss cash flows differs by line of property-liability insurance, the existing literature uses as separate output the present values of personal lines short-tail losses, personal lines long-tail losses, commercial lines short-tail losses, and commercial lines long-tail losses, where tail refers to the length of the loss cash flow stream (Cummins and Weiss, 2012). Cash flow payout patterns are estimated from data in regulatory annual statements using a loss reserving method with Taylor separation method (Taylor, 2000) being the most preferable. Discounting is conducted by using the treasury yield curves. Finally, average real invested assets are used as a proxy for the quantity of the intermediation output for the property-liability insurers.

In the literature, the prices of the property-liability outputs are determined as:

$$p_i = \left[P_i - PV(L_i)\right] / PV(L_i)$$

where p_i is the price of output i, P_i is premium for the line i, L_i is the real losses incurred in line i, and PV is the present value operator. The price of the property-

[12] This is achievable mainly for the US market because are required to report their activities by line in their regulatory annual statements.

[13] For more detailed description of proxies used as outputs or output prices in existing literature one can see chapter 2.

liability intermediation output is defined analogously to the price of the life insurers intermediation output and so is equal to the weight average of the expected debt returns and expected equity returns, weighted by the proportion of the portfolio invested in debt and stocks.

4.5 Inputs and input prices in the insurance industry

Input determination in the insurance literature shows a common agreement as far as the inputs used for estimating efficiency[14]. Also, researchers use common inputs both for property-liability and life insurers. Usually there are three main insurance inputs in efficiency studies: labour, business services and materials, and capital. If there are data available, the labour can be further divided into agent and home-office labor because these two types of labor have different salaries. Finally, the capital can be further divided into physical, debt, and equity capital. However, it is observed that physical capital is incorporated in the business services and materials input in most of the efficiency studies.

It is observed that in most countries the physical measures of input quantities are not publicly available. In such cases we can estimate the quantity of physical inputs by dividing the appropriate insurer expense item by a corresponding price index, wage rate, or other type of deflator (Cummins and Weiss, 2012). So, for the labor input the quantity of labor is calculated by dividing the total expenditures on labor appeared in the regulatory annual statements by the wage rate. Mathematically, it is written as:

$$N_t = E_t^c / w_t^c$$

where N_t is the quantity of labor in period t, E_t^c is the current expenditure for labour in euros for period t, and w_t^c is the current hourly wage in euros for period t. Most efficiency studies use the ratio w_t^c / CPI_t as the price of labour where CPI_t is the consumer price index for period t.

In the same way, the quantity of materials and business services is calculated by dividing current expenditures on materials and business services by the materials and business services price index. So, we have:

$$Q_t = M_t^c / p_{Mt}$$

where M_t^c are the current expenditures for materials and business services in euro and p_{Mt} is the materials and business services price index. The price of the materials and business services input is defined as the ratio p_{Mt}/CPI_t. The price index for the materials and business services input is calculated as the weight average of price indices for business services from the component indices representing the various categories of the total materials and business services expenditures (Cummins and Weiss, 2012).

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[14] Eling and Luhnen (2010) stated that 61 of 95 studies reviewed use at least labour and capital as inputs.

The choice of input prices for debt and equity capital inputs is mainly determined by the data that are publicly available in the countries under investigation. The average of the beginning and end-of-year equity capital, deflated by the CPI, is used as the quantity of financial equity capital in most of the literature. The cost of equity capital is ideally expressed by the expected market return on equity capital. But this is impossible because the majority of insurers are not publicly traded. For US insurers, a usual proxy for the expected return on equity is the size adjusted capital asset pricing model expected return (Cummins and Weiss, 2012). So, the cost of equity capital for year t is calculated as the 30-day Treasury bill rate at the end of year t-1, plus the long-term (1926 to the end of year t-1) average market risk premium on large company stocks, plus the long-term (1926 to the end of year t-1) average size premium from Ibbotson Associates (Cummins and Weiss, 2012). Ibbotson Associates classifies insurers into four size categories according to their equity capital. The largest size has no size premium but for each of the smaller size categories, the Ibbotson long-term average size premium is added to the large firm expected return to give the price of equity capital (Cummins and Weiss, 2012). For non-us markets these data are unavailable and researchers use simple ratios or market indexes (e.g. Bikker and Gorter, 2011 use the total return on Amsterdam stock exchange index).

Debt capital is rarely used as an input in insurance efficiency literature. When it is used, it is measured either by borrowed funds and deposits from reinsurers or by policy reserves (Cummins and Weiss, 2012). When reserves are used as inputs, it is indispensable to be deflated by the CPI for each country. The current interest rate is used as the input price for such cases. For example, Bikker and Gorter (2011) used the one-year Dutch Treasury bill rate as the price of the debt input.

CHAPTER 5

EFFICIENCY ESTIMATION IN THE EU INSURANCE MARKET

5.1 Introduction

Efficiency estimation of the insurance sector, as we have already referred, has attracted the interest of many practitioners and researchers globally and it is shown by the plethora of published papers worldwide. The importance of efficiency measurement in insurance and more generally in the financial sector is related to the extremely extensive impact that an efficient financial sector has on the microeconomic as well as macroeconomic level of an economy. Financial systems deeply affect the allocation of financial resources, trying to find their best productive employment in the most effective way, reducing misallocation and unnecessary expenses.

The existence of a healthy and efficient insurance sector is an important condition for the wellbeing of the population and for sustainable economic growth. Individuals and enterprises everyday are confronted with a huge variety of risks such as illness, car accidents, damage to property, or interruption of productive process. However, insurance is a risk transfer mechanism that shifts some of the uncertainties from an individual or business enterprise to the insurer but with paying an amount of money (premiums). So, in the event of unfavorable but insured incidents the restoration of damages is at a large rate guaranteed. This fact contributes to the prevention of important disturbances in economic, business and social activities and ensures the smooth operation of the national economies. This role of insurance sector also contributes in encouraging innovation and trade. Many investments in new production facilities and newly founded companies would never happen if every company was required to have the necessary financial resources in order to confront the possible losses. The international trade is conducted with no special problems because the insurer takes on the possible losses if one counterpart defaults the responsibilities.

Insurance plays an additional role in the economy by providing information to individuals or corporations. The level of insurance premiums provides an indication of existing risks and of how probable is that a loss will occur. This gives companies the potential to make comparisons of the risk/return profiles of the projects, thereby ensuring that the available resources are allocated to the best available use. Due to their technical know-how and their specialized scientific staff, insurance companies also offer consultancy services advising on how to improve safety standards and a product’s quality. Especially in life insurance, policyholders are guided in how to invest their savings in order to achieve the maximum possible return.

In their role as institutional investors, insurance companies contribute to the development of a well functioned capital market due to the huge amount of assets they have to handle. Insurance companies receive premiums from the insurance contracts they sell and set them aside as provisions for the payment of future claims that will arise. They proceed by investing them in the capital markets and by withdrawing some amount when covered losses occur. So, insurance companies function as financial intermediaries that bring together savers and borrowers and contribute to the development of national economies.

For all the above reasons it is obvious that the insurance sector plays an important role in the development and the even operation of an economy. The level insurers handle wisely their resources influences this important role they perform. So, in this chapter the main objective is to measure cost, revenue and profit efficiency of the EU insurance sector. Efficiency estimation is interwoven with the performance of each insurance firm operating in the EU's financial sector. It reveals the accomplished level of successful operation and the level at which management takes the required actions. The intertemporal degradation of efficiency is a signal that motivates management team to focus in the wrong handling and to proceed in the essential structural enhancements. Regulatory authorities can base their acts and decisions on researches that measure insurance efficiency in order to enact laws and directives that foster the economic and social level of the society. The next sections describe the data and methodology used for the above mentioned target. Empirical results are cited after the description of the variables used for the efficiency estimations.

5.2 Literature review

During the last three decades, the new regulatory requirements, the increasing competition, and the recent dynamics in capital markets have all changed the business environment that insurers operate. These operational changes force insurers to develop benchmarking techniques that can be used to assist them in evaluating whether they are performing better or worse than their peers in terms of technology, scale, cost minimization, and revenue maximization. A modern class of benchmarking techniques called frontier efficiency methodologies has greatly attracted the interest of researchers. Frontier methodologies measure firm performance relative to best practice frontiers comprised of the leading firms in the industry. The insurance sector in particular has seen rapid growth in the number of studies applying frontier efficiency methodologies. Eling and Luhnen (2010) reviewed 95 studies on efficiency measurement in the insurance industry.

Existing cross-country comparisons of efficiency in the insurance industry provide valuable insights into the competitiveness of insurers in different countries. However, the number of the existing international efficiency studies is very small and the geographic coverage of them is limited to certain countries or regions. Especially, the number of the existing studies that measure efficiency in a European level is limited to the fingers of one hand. According to the existing literature, there exist striking international differences in average efficiency while efficiency in developed countries is on average higher than that in emerging markets and technical progress has increased productivity and efficiency around the world (Eling and Luhnen, 2010).

Weiss (1991b) was the first cross-country comparison of efficiency in an international level. In this paper, US and Germany had the highest productivity while Japan had the lowest one. Rai (1996), in an analogous cross-country study of 11 OECD countries found that insurers in Finland and France had the highest efficiency and firms in the United Kingdom had the lowest one. Donni and Fecher (1997) found for a sample of 15 OECD countries that average efficiency is relatively high, but varied across countries. Boonyasai et al. (2002) studied efficiency and productivity in an Asian level and found increasing productivity in Korea and Philippines due to deregulation and liberalization while liberalization had little effect on productivity in Taiwan and Thailand.

In the European insurance market, the introduction of the single European Union insurance license in 1994 raised interest concerning competitiveness and efficiency convergence among the European insurers. First, Diacon et al. (2002) found striking international differences in average efficiency using a sample of 450 companies from 15 European countries. In contrast to the existing literature finding increasing levels of efficiency over time, this paper found decreasing technical efficiency. Fenn et al. (2008) found increasing returns to scale for the majority of the European insurers in the sample, indicating that mergers and acquisitions in the European insurance market have led to efficiency gains. Taking into account the empirical studies discussed above, this thesis tries to extend the existing literature in two ways: a) We use a larger sample of European countries for the efficiency estimations and b) using the beta and sigma convergence measures for estimating insurance efficiency convergence among the European insurance markets.

5.3 Data and methodology

5.3.1 Data

Our main data source is the Orbis database. Orbis is Bureau van Dijk’s flagship data base of private and listed company information all over the world. It includes data for over 200 million companies worldwide with all information standardized for easy cross-border comparisons. Initially we consider all life and property liability insurers operating in the 28 member of EU over the period 2006-2014. The European insurance market is characterized by the existence of large multinational group of insurers selling both life and nonlife insurance services through a range of subsidiaries, which may themselves specialize in one particular product line. These groups of insurers coexist with a large number of fully independent (unaffiliated) insurance companies which may choose to specialize in life or nonlife business, or indeed, to engage in both (Fenn et al., 2008; Vencappa et al., 2013). Our Decision Making Unit (DMU) includes both these groups of insurers and the unaffiliated single insurers specialized in life or nonlife or engaged in both. Companies were included in our analysis if they had positive values for all the inputs and outputs defined below. Companies also are not required to have data for all years of the research period but insurers with less than three years of data were excluded. Thus, we have an unbalanced panel data set. Companies operating in Bulgaria, Cyprus, Estonia and Lithuania were finally excluded due to data availability for input prices defined below. After implementing these screening criteria in our initial sample we ended up in a final sample including 947 European non-life insurers operating in 24 member states with 7,936 firm-year data and 771 life insurers operating in 22 member states with 6,321 firm-year data.

There is a widespread agreement in insurance efficiency literature concerning the determination of the inputs utilized by the insurers. According to this literature, labor, business services and materials, debt capital, and equity capital are determined as inputs (Diacon et al., 2002; Eling and Luhnen, 2010a,b). However, it is common that researchers usually combine labor and business services as only operating expenses (including commissions) due to data restrictions (Fenn et al., 2008). So, in this analysis, labor (including business services and materials), debt capital, and equity capital are finally used as inputs. Ennsfellner et al. (2004) advocated for this simplification and claimed that the operating expenses should be treated as a single input in order to reduce the number of parameters that is needed to be estimated. Thus we use operating expenses to proxy both labor and business services and tackle these as a single input in the efficiency estimations.

Cummins and Weiss (2000,2012) showed in their analysis of operating expenses in the US insurance market that these are mostly labor related. They found that in both life and property-liability insurance employee salaries and commissions constitute the largest expenses they have. In this study we are based on labor to determine the price of the operating-expenses-related input factor (Eling and Luhnen, 2010a). The price of labor is determined using OECD and EUROSTAT databases and is proxied by the annual wage per year. Debt capital is proxied by total liabilities reported in the database used (Eling and Luhnen, 2010a). The price of debt capital is proxied using country specific ten-year bond rates for each year of the sample period (Fenn et al., 2008) obtained from the European Central Bank data warehouse. Equity capital is proxied by capital and surplus item reported in the Orbis database. The price of equity capital is determined using the 10-year-rolling-average of the yearly rates of total return of the country-specific MSCI stock market indices (Eling and Luhnen, 2010a) obtained from Bloomberg database. Finally, all monetary values for each year in the sample were deflated by the Harmonized European Consumer Price Index to the base year 2014 obtained from Eurostat database (Eling and Luhnen, 2010a; Fenn et al., 2008).

Despite the widespread agreement in insurance efficiency literature concerning the determination of the inputs utilized, there is an open debate concerning output selection for insurance efficiency studies. This is because insurance outputs are mostly intangible and researchers are forced to find suitable proxies for the volume of services provided by the insurers. Recently, Eling and Luhnen (2010b) reviewed 80 insurance efficiency studies that use the value added approach. In 46 of these studies output is defined as incurred benefits/losses plus additions to reserves for life and non-life insurers respectively while the in the remaining studies output is defined as net premiums written. Efficiency literature does not favor each of these two approaches and as a result there is no clear trend as to whether either of these two output proxies is more objective. Each of these two approaches has its advantages and disadvantages that we will describe below with data availability playing a crucial role in selection.

Yuengert (1993) criticized the use of premiums as output in insurance efficiency studies stating that premiums represent price times the quantity of output but not output alone. Dating back to the extensive insurance efficiency literature, the use of the incurred benefits/losses plus additions to reserves also has its drawbacks. Diacon et al. (2002) stated that this approach violates the principal output characteristics identified by Cooper et al. (2002). In this paper it is stated that more output should be preferred to less. Greene and Segal (2004) expressed their reservations stating that this proxy is not accurate since reserves change when policies age and the change in reserves measures the change in liabilities rather than the output of the selling effort. In this study we use net premiums written as an output that proxies the risk pooling/risk bearing function of insurers. We do not use incurred benefits/losses plus additions to reserves because for composite insurers in the sample the database used does not give this information separately for the life and non-life part. Also, it is unreasonable to set as output incurred benefits/losses plus additions to reserves because all insurers desire to have as less as possible incurred losses. Finally, investments are used as a second output of insurance firms and proxy the intermediation process operated by insurance firms (Eling and Luhnen, 2010b).

Table 5.1 below presents the descriptive statistics on outputs, inputs, and inputs' prices used for estimating cost, revenue, and profit efficiencies. Our statistics are moving at the same level with the average statistics presented in Gaganis et al. (2013) since we use the same database that mainly includes insurance companies featured as large and very large companies by the Bureau van Dijk’s classification. Although the inputs and outputs of the frontier function are used in natural logarithmic form, we present the mean, minimum, maximum, and standard deviations in levels in order to be more informative. All statistics are calculated on the basis of firm-level yearly observations and all the monetary values are deflated by the Harmonized CPI for the EU-28. For our sample period 2006-2014, the average European property-liability insurer has €6,87 million net premiums written and €7,54 million in investments. Investment income, captured by the investments output, compensates the losses insurers have during the underwriting process.

Table 5.1 Descriptive statistics for the European PL insurance sector.

Variable	Unit	Mean	St. Deviation	Minimum	Maximum
Labor and Business Service	Quantity	7.713,582	27.970,29	0.0	505.077
Debt Capital	Thousands €	7.867.267	46.248.931	12,0	1.060.431.000
Equity Capital	Thousands €	715.155,1	2.973.392	99,0	60.747.000
Price of Labor	Thousands €	35,50455	11,23790	3,68100	59,94600
Price of Debt Capital	%	0,037849	0,016571	0,012000	0,225000
Price of Equity Capital	%	0,098958	0,073955	0,003000	0,557000
Investments	Thousands €	7.538.400	42.146.944	829,0	709.567.631
Premiums Written	Thousands €	687.160,2	2.520.273	21,0	45.196.692,0
Operating	Thousands	267.043,8	981.191,9	10,0	17.268.090

Expenses	€				

Table 5.2 below presents the descriptive statistics on outputs, inputs, and inputs' prices for the European life insurance used for estimating cost, revenue, and profit efficiencies. For comparative purposes, all statistics are calculated on the basis of firm-level yearly observations and all the monetary values are deflated by the Harmonized CPI for the EU-28. Comparing Table 5.1 with Table 5.2 we observe the large differences in the levels of investments, premiums written, and operating expenses between life and property-liability European insurers. The average life insurance firm is much larger than the average property-liability firm.

Table 5.2 Descriptive statistics for the European Life insurance sector

Variable	Unit	Mean	St. Deviation	Minimum	Maximum
Labor and Business Service	Quantity	19.346,78	65.420,38	2,0	1.062.873
Debt Capital	Thousands €	14.703.170	55.291.360	0,0	1.060.431.000
Equity Capital	Thousands €	891.652,2	3.259.349	0.0	60.747.000
Price of Labor	Thousands €	33,62063	10,92854	3,681000	59,94600
Price of Debt Capital	%	0,037515	0,016816	0,012000	0,225000
Price of Equity Capital	%	0,102914	0,07714	0,003000	0,557000
Investments	Thousands €	14.374.913	50.972.467	4.038,076	709.567.631
Premiums Written	Thousands €	1.194.222	4.120.894	176,0	65.501.443
Operating Expenses	Thousands €	689.104,8	2.359.719	55,0	36.864.675

5.3.2 Methodology

There are two distinct approaches for estimating efficient frontiers: the parametric and non-parametric. Stochastic Frontier Analysis and Data Envelopment Analysis are the most commonly used methods for each approach respectively. In the literature there is a controversy concerning the advantages and disadvantages of each approach, with some researchers arguing for the parametric approach (e.g., Berger, 1993; Greene, 2008). The basic advantage of parametric approach in comparison with non-parametric approach is that the first allows firms to be off the frontier due to random noise as well as inefficiency and, consequently does not count purely random divergence from the frontier as inefficiency. The primary disadvantage of the parametric approach in comparison with the non-parametric approach is that it requires the adoption of a functional form in order to estimate the respective model, so the selection of an inappropriate functional form will produce unreliable results. In our case SFA was preferred than DEA because we have a multi-national sample and one has to account for country-specific differences in the national environments in which insurers operate in order to make a common European frontier meaningful. These country-specific differences were considered in the banking efficiency literature (e.g., Fiordelisi and Molyneux, 2010), but were neglected in most insurance studies that use cross-country data (Diacon et al., 2002; Fenn et al., 2008). Only Eling and Luhnen (2010) and Gaganis et al. (2013) used the Battese and Coelli (1995) model that allows for exogenous effects in a single and common frontier.

The model employed in this thesis is the one of the Battese and Coelli (1995) which permits the estimation of efficiency in a single stage while considering the impact of environmental variables on efficiency. In the general form, the cost equation can be expressed with the following form:

$$C_{it} = C(q_{it}, p_{it}; \beta) + \upsilon_{it} + u_{it} \qquad (5.1)$$

where C_{it} is the total costs of the i-th insurer in the sample in the t-th period, q_{it} is a vector of output quantities of the i-th firm in the t-th period, p_{it} is a vector of input prices of the i-th firm in the t-th period and β is the vector of unknown parameters needed to be estimated. The factor υ_{it} symbolizes the random noise component which is assumed to be independent and identically distributed, with zero mean and constant variance and independent of the u_{it}. The u_{it} represents cost inefficiency and is assumed to be independently distributed, such that u_{it} is obtained by truncation at zero point of the $N(m_{it}, \sigma_u^2)$ distribution, where the mean, m_{it}, is assumed as (e.g., Battese and Coelli 1995):

$$m_{it} = z_{it}\delta \qquad (5.2)$$

where z_{it} is a vector of variances that affect the efficiency of the i-th insurer in the t-th time period, and δ is the vector with the parameters to be estimated. The parameters of the system of equations (5.1) and (5.2) are estimated in one step using the maximum likelihood method.

For the assessment of insurers' efficiency we estimate the cost, revenue and the profit frontier using the translog functional form. Most of empirical studies in the financial institutions' efficiency literature assume the translog form followed by the flexible Fourier form. As Berger and Mester (1997) showed, these two functional forms give the same average level and dispersion of efficiency, and rank the individual firms in almost the same order. Taking it into account, we follow the translog form in order to reduce the number of parameters needed to be estimated and to increase the degree of freedom for our model estimates. The translog function in the case of the cost efficiency takes the following form:

$$\ln\left(\frac{TC_{it}}{p_{Kit}}\right) = \alpha_0 + \sum_{m=1}^{M} \alpha_{mi} \ln(q_{mit}) + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N} \alpha_{mn} \ln(q_{mit}) \ln(q_{nit}) + \sum_{k=1}^{K-1} \beta_k \ln(p_{kit}^{*}) +$$

$$+\ \frac{1}{2}\sum_{\kappa=1}^{K-1}\sum_{l=1}^{L-1}\beta_{kl}\ln(p^{*}_{kit})\ln(p^{*}_{lit})+\sum_{k=1}^{K-1}\sum_{m=1}^{M}\phi_{km}\ln(p^{*}_{kit})\ln(q_{mit})+\sum_{i=1}^{8}\rho_i T_i\ +$$

$$+\ \upsilon_{it}+u_{it} \qquad (5.3)$$

where TC_{it} are the total operating costs of insurer i at time t including marketing, underwriting, and administrative costs (Berger et al., 2000). p_{kit} are the k input prices of insurer i at time t and q_{mit} are the m outputs of insurer i at time t. T_i's are eight time dummy variables with T_i=1 (i=1,..,8) for the year 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014 respectively and zero elsewhere (2006 is excluded as a reference category). In the summations above M=N=2 representing the number of outputs produce while K=L=3 representing the number of inputs used by the insurers. In order to ensure linear homogeneity of degree one in input prices, we randomly chose one input price (p_{Ki}, the price of input equity capital in our case) and divide the dependent cost variable and all the other input prices by this input price. Thus, $p^{*}_{kit}=p_{kit}/p_{Kit}$. This is why all summations in (5.3) involving p^{*}_{kit} are over K-1 and not K. The random error υ_{it} is assumed to be distributed normally and inefficiencies u_{it} are assumed to follow a truncated normal distribution with the mean m_{it} of u_{it} varying depending on a vector of firm specific and macroeconomic variables (Gaganis et. al., 2013) as:

$$m_{it}=\delta_0+\delta_1 STOCK_{it}+\delta_2 INFL_{it}+\delta_3 GDPCH_{it} \quad (5.4)$$

where STOCK is a dummy variable taking value one when insurer i follows the stock organizational form and zero if follows the mutual. INFL is the annual rate of inflation for each firm's home country and GDPCH is the real Gross Domestic Product (GDP) growth for each firm's home country.

The parameters of the stochastic frontier model, defined by equations (5.3) and (5.4), are simultaneously estimated by the method of maximum likelihood. The Battese and Coelli (1995) model utilizes the parameterization of Battese and Corra (1977) model, which replaces σ^2_υ and σ^2_u with $\sigma^2=\sigma^2_\upsilon+\sigma^2_u$ and $\gamma=\sigma^2_u/(\sigma^2_\upsilon+\sigma^2_u)$, for the estimation of the variance parameters in the frontier model. Parameter γ takes values between zero and one. For the variables used in the inefficiency term in equation (5.4), a coefficient with a positive sign indicates a positive effect on the inefficiency component and a negative relationship with the efficiency. On the other hand, a coefficient with a negative sign indicates a negative effect on the inefficiency component and positive relationship with the efficiency.

Revenue efficiency estimation has not attracted satisfactorily the interest of the researchers despite the fact that papers estimating technical, cost, and profit efficiency are produced geometrically. In the case of the revenue frontier model, we replace the dependent variable TC in (5.3) by TR which represents total revenues. Total revenues include premium and investment income less losses and loss adjustment expenses (Berger et al., 2000; Choi and Weiss, 2005). We adopt the alternative revenue approach that takes outputs as exogenous and allows for price setting behavior by the insurers (Berger et al., 2000; Fiordelisi and Molyneux, 2010). It is assumed that insurers have enough market power that can charge different prices that reflect differences in customer convenience (e.g., one-stop shopping) or other systematic differences in product quality. All input prices and output variables adopted in the cost efficiency estimates in (5.3) remain the same and we change only the sign of the inefficiency term ($-u_{it}$). As in cost efficiency, we impose linear homogeneity restrictions of degree one in input prices by dividing the dependent variable and all input prices by the price of the input equity. The distributional assumptions concerning inefficiency term and random noise remain the same with maximum likelihood used for parameter estimates.

The standard profit maximization problem (e.g., Kumbhakar, 2006) assumes that insurance companies maximize profits by adjusting output (q's) and input (x's) quantities while taking all prices as given (i.e. fixed by competitive markets). This assumption does not fit well with the reality of the insurance sector, which has limited control over its output level (Berger and Mester, 1997; DeYoung and Hasan, 1998). Additionally, it is traditionally considered a natural monopoly sector that faces limited competition in its area (Berger and Mester, 1997; DeYoung and Hasan 1998). Maudos et al. (2002) and Kasman and Yildirim (2006) showed that in international comparisons with a diverse group of countries such as EU-28 and strong competition levels it is more suitable to estimate an alternative rather than a standard profit frontier. Thus we adopt the alternative profit efficiency's estimation approach and we replace the dependent variable TC in (5.3) by the profit before taxes (TP) as in Gaganis et al. (2013). Berger et al. (2000) used Net Income as the dependent variable but in our database this was available only for specialized insurers. All the other variables in (5.3) remain the same as well as the distributional assumption for inefficiency and random noise components of the composite error term. Finally, we change the sign of the inefficiency term ($-u_{it}$) and use the one-step Maximum Likelihood Estimation method for estimating the parameters in the profit frontier. Since some insurers in the sample exhibit negative profits (in cases of losses) we add one to the absolute value of the minimum value of TP_{it} / p_{Kit} over all the insurers in the sample. This transformation allows us to take the natural log of total profits, given that total profits can take negative values (Fiordelisi and Molyneux, 2010; Gaganis et al., 2013).

5.4 Empirical results for the European property-liability insurance sector

In this section we present the cost, revenue, and profit efficiency scores for a sample of European life and non-life insurers using a common European frontier. Cross-country comparisons of efficiency in the in the European insurance industry provide valuable insight into the competitiveness of insurers in its member states. Results of cross-country efficiency studies are of particular interest to the managers, as they can provide guidelines for their decisions regarding important topics such as areas of operational improvements, geographical expansion and optimal size of operations. In the same spirit, these international studies are of interest to the European regulators, since, among others, they provide valuable indications concerning convergence of efficiency of the European insurance markets in certain member states and analyze efficiency effects of mergers and acquisitions within and across European country borders.

Table 5.3 presents the maximum likelihood estimates of the translog cost frontier for the European PL insurance sector. The net premiums written output has the expected positive sign (0.77222) and is statistically significant at the 1% level while the investment output has a negative (-0.07676) but not a statistically significant value. Both the input prices of debt and labor and business services have the expected positive signs (0.18773 and 0.15588 respectively) and are statistically significant at the 1% level[15]. Concerning determinants of inefficiency in equation (5.4) we observe that stock insurers are less cost efficient than mutuals (0.049) but this coefficient is not statistically significant. Higher inflation increases costs and thus inflation in our results have a statistically significant and positive impact (0.53643) on cost inefficiency (thus a negative impact on efficiency), as found by Kasman and Yildirim (2006) and Eling and Schaper (2017). The effect of Gross Domestic Product Change (GDPCH) on inefficiency is positive (0.37576) and statistically significant, so we find a negative link between GDP change and efficiency as in Huang and Eling (2013) who reported that insurers in expanding markets with high growth, that present expansive demand conditions, are less inclined to control expenditure and therefore become less cost efficient.

The yearly average cost efficiency results for the property-liability insurance sector for the countries in our sample are presented in table 5.4. Cost efficiency gives a measure of how close an insurer's cost is to what a best-practice insurer's cost would be for producing the same output bundle under the same conditions. A cost efficiency score close to one (1) implies that firms are operating close to the common European frontier. The average cost efficiency scores for the 24 EU property-liability insurance markets over the whole sample period 2006-2014 is 0.836, indicating a 16.4% potential reduction in costs on average. Fenn et al. (2008) in an equivalent research for 14 EU countries found that the average cost efficiency for the property-liability sector was 0.93. This difference is possibly attributed to the larger sample we use, since Zhang and Bartles (1998) showed that the larger the sample, the lower is the average efficiency scores under the ceteris paribus hypothesis, and/or the different time period of each study. Bahloul and Bouri (2016) also estimated cost efficiency for a balanced panel of 125 non-life insurance companies of seven major European countries for the period 2002-2008 using SFA methodology. Adopting the Flexible Fourier form for the cost function, they found that their sample had an average cost efficiency of 0.692 for the whole sample period.

The aggregate results show that the cost efficiency for the firms in the EU property-liability sector remains relatively stable over the period 2006-2014 with a subtle reduction in years 2013 and 2014. Also, there are no large differences among the countries in the sample with the variation in cost efficiency between the most and the least efficient country being equal only to 0.124. To the best of our knowledge, there is no other paper that comprises so many countries belonging to the EU-28 and so the possibilities for direct comparisons are limited. Denmark (0.875), Ireland (0.872), and Luxembourg (0.868) are the three most cost efficient property-liability European

[15] The signs of these coefficients are in line with the sings of the same variables used in the paper of Gaganis et al. (2013) for estimating insurance efficiency.

insurance markets. These results are consistent with previous research since Fenn et. al. (2008) also find Denmark and Ireland to be among the most efficient European insurance markets. The lowest cost efficiency values are found for Greece (0.761), Czech Republic (0.763), and Slovakia (0.787).

As we will see below, the Greek property-liability insurance sector experienced a less severe drop in its cost efficiency than in its revenue and profit efficiency after the year 2010. This might be the effect of rationalization efforts and cost savings that these insurers accomplished in order to survive in the difficult operational conditions in Greece due to its debt crisis. In general, we notice that during the period of the US subprime crisis (2007-2009), the European property-liability insurance sector maintained stable its average cost efficiency. This result can be explained by the fact that the crisis started to exert an impact on Europe after 2009, indicating that crisis in Europe was a debt crisis (2010-2012) and not triggered by the banking sector.

The maximum likelihood estimates of the translog revenue frontier for the European PL insurance sector are presented in table 5.5. Observing the estimated coefficients of the translog revenue model, we note that both outputs (net premium written and total investments) have the expected positive sign and are statistically significant (0.40246 and 0.11885 respectively). Both the input prices of debt and labor and business services have the expected negative signs and are statistically significant at the 1% level (-0.13799 and - 0.14727 respectively). Stock insurers seem to be less revenue efficient than mutual ones (0.94778) but this coefficient is not statistically significant. Inflation in our revenue efficiency determinants has a positive and statistically significant at 5% level effect on revenue inefficiency (0.96247) as expected, since higher inflation reduces revenues (Kasman and Yildirim, 2006). Finally, GDPCH has a negative and significant at 5% level effect (-0.35997) on revenue inefficiency as expected, since the low potential for new business in developed countries might force revenue inefficient insurers to leave the market in the long run (Kasman and Yildirim, 2006).

The yearly average revenue efficiency results for the property-liability insurance sector for all the 24 EU countries in our sample are presented in table 5.6. Revenue efficiency indicates how well an insurance company operates in terms of revenue maximization relative to other insurance firms in the same period for producing the same set of outputs. To the best of our knowledge, there is no other paper measuring revenue efficiency in an EU level that includes insurers operating both in old and in new European member states. Berry-Stolzle et al. (2011) is the only study that estimated revenue efficiency for a sample of European PL insurers operating in 12 countries with the DEA methodology and found that average revenue efficiency was 0.491[16]. Klumpes (2007) also measured revenue efficiency for a sample of life and non-life insurers operating in seven European countries using DEA method. However this research was concentrated primarily on firms that were acquired during the heavy M&A period 1999-2000 and it contains no information about inter-country differences concerning revenue efficiency scores.

[16] They also found that the average cost efficiency was 0.368, which deviates largely from the average efficiency scores of the existing literature.

According to our results, revenue efficiency scores for the 24 EU property-liability industries over the sample period 2006-2014 is 0.771 indicating a 22.9% possible increase in revenues on average. The aggregate results show that the revenue efficiency for firms in the property-liability sector were highly stable over the period 2006-2014. The efficiency differences among countries are larger than the cost efficiency case with the difference between the most and least revenue efficient country being equal to 0.213. Also, these results are indicating that on average EU property-liability insurers are more cost efficient than revenue efficient. This is attributed to the fact that insurers in a competitive environment like the European financial market can cut their operating costs and become efficient in order to survive while their revenue efficiency performance depends on the existing regulation that affects the premium levels they charge and the general macroeconomic conditions under which they operate. Considering the country analysis, Slovakia (0.869), Slovenia (0.83), and Germany (0.82) are among the most revenue efficient property-liability insurance markets in EU. Ireland (0.657), Greece (0.669), and Luxembourg (0.722) are among the least revenue efficient property-liability insurance markets in EU.

The full maximum-likelihood parameter estimates for the translog profit frontier of the European PL insurance sector are presented in table 5.7. The coefficients of the output net premium written and the output of total investments are positive and statistically significant at the 1% level (0.95662 and 0.96371 respectively). The input prices of debt and labor and business services have negative and statistically significant coefficients as expected by the theory of production (-0.22883 and -0.21147 respectively. The coefficient of the dummy variable determinant for stock insurers is negative but not statistically significant (-1.28235) indicating that stock insurers are more profit efficient than the mutual ones. Inflation has a positive and statistically significant at 1% level impact on profit inefficiency (0.18749) and is as expected since inflation reduces the profits of the insurers (Eling and Schaper, 2017). The GDPCH determinant of profit inefficiency has a negative and statistically significant at 1% level effect on it (-0.10574) and is as expected by the theory since the narrow profit margins in mature countries with high GDP force profit inefficient entities to leave the market in the long run (Maudos et al., 2002).

The yearly average profit efficiency results for the property-liability insurance sector for all the 24 EU countries in our sample are presented in table 5.8. Profit efficiency indicates how well an insurance company performs in terms of profit maximization relative to other insurance firms in the same period for producing the same set of outputs. To the best of our knowledge, there is no other research measuring profit efficiency in an EU level that contains so many member-countries. Our results reveal that profit efficiency scores for the 24 EU property-liability insurance industries over the sample period 2006-2014 is 0.828 indicating a 17.2% possible increase in profits on average. Berger et al., (1997), in an analogous study for the US property-liability insurers, found that during 1981-1990 the average profit inefficiency for independent-agency insurers was 0.486 and the average inefficiency for direct writers was 0.374.

Zanghieri (2008) also estimated profit efficiency for a sample of insurers operating in 14 European countries using SFA. This paper does not state accurately the average profit efficiency during its sample period but states that the difference between the mean profit efficiency of the most profit efficient country (Switzerland) and that of the least profit efficiency one (Spain) is 48%. Jarraya and Bouri (2014) estimated the profit efficiency for 175 property-liability insurers dispersed in 9 European countries over the period 2002-2008. They found that the mean profit efficiency score for their sample was about 0.541, indicating a level of 45.9% possible improvement in profits on average. Our aggregate results show that the profit efficiency for firms in the property-liability sector was highly stable over the period 2006-2014 with subtle fluctuations from year to year. Divergence among countries' profit efficiency scores is relatively low with the difference between the most and least profit efficient country being equal to 0.239. Concerning the country analysis, Slovakia (0.915), Slovenia (0.883), and Latvia (0.88) are among the most profit efficient property-liability insurance sectors in EU. Ireland (0.676), Greece (0.685), and Portugal (0.778) are among the least profit efficient property-liability insurance markets in EU.

Table 5.3. Maximum-Likelihood Estimates of the Translog Cost Frontier for PL insurers

Deterministic Component of Stochastic Frontier Model			
Parameter	Estimate	Parameter	Estimate
α_0	15.1806***	ϕ_{11}	0.03652***
α_1	0.77222***	ϕ_{12}	-0.03536***
α_2	-0.07676	ϕ_{21}	-0.01763**
α_{11}	0.05723***	ϕ_{22}	0 .02424**
α_{12}	-0.01668***	ρ_1	-0.02681
α_{22}	-0.00345	ρ_2	0 .03845
β_1	0.18773***	ρ_3	0.13781*
β_2	0.15588***	ρ_4	0.21978**
β_{11}	0.06557***	ρ_5	0.29857**
β_{12}	-0.10487***	ρ_6	0.43278***
β_{22}	0.14237***	ρ_7	0.50446***
		ρ_8	0.54359***
Inefficient Term			
δ_0	-3.59778***		
δ_1	0.04900		
δ_2	0.53643***		
δ_3	0.37576***		
Sigma-squared	0.64510		
Gamma	0.75690		
Log-likelihood Function	1,342.65611		

***,**,* indicate significance at 1%,5%, 10% respectively.

Table 5.4. Cost efficiency scores by year and country of European Property-Liability insurers, 2006-2014

Country/year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2006-2014
Austria	0,836	0,853	0,846	0,830	0,815	0,813	0,786	0,785	0,777	0,816
Belgium	0,864	0,862	0,862	0,860	0,852	0,854	0,850	0,838	0,859	0,856
Croatia	0,842	0,856	0,875	0,893	0,850	0,821	0,861	0,800	0,668	0,830
Czech Republic	0,846	0,825	0,841	0,825	0,807	0,798	0,708	0,635	0,582	0,763
Denmark	0,879	0,877	0,873	0,872	0,868	0,850	0,884	0,888	0,885	0,875
Finland	0,878	0,863	0,852	0,840	0,838	0,828	0,846	0,861	0,869	0,853
France	0,845	0,852	0,851	0,845	0,836	0,842	0,825	0,819	0,820	0,837
Germany	0,858	0,864	0,863	0,845	0,840	0,837	0,817	0,816	0,827	0,841
Greece	0,866	0,868	0,856	0,865	0,678	0,623	0,695	0,701	0,699	0,761
Hungary	0,872	0,870	0,883	0,895	0,858	0,858	0,847	0,820	0,721	0,847
Ireland	0,860	0,863	0,874	0,881	0,885	0,898	0,877	0,862	0,851	0,872
Italy	0,829	0,838	0,828	0,834	0,829	0,852	0,846	0,838	0,819	0,835
Latvia	0,849	0,866	0,879	0,899	0,889	0,839	0,808	0,746	n.a.	0,847
Luxembourg	0,874	0,796	0,897	0,863	0,882	0,884	0,873	0,862	0,882	0,868
Malta	0,842	0,860	0,871	0,869	0,871	0,860	0,860	0,858	0,856	0,861
Netherlands	0,870	0,873	0,871	0,865	0,862	0,860	0,847	0,847	0,851	0,861
Poland	0,849	0,860	0,849	0,849	0,831	0,833	0,782	0,763	0,738	0,817
Portugal	0,823	0,837	0,834	0,824	0,832	0,879	0,882	0,838	0,793	0,838
Romania	0,881	0,865	0,841	0,884	0,834	0,812	0,848	0,775	n.a.	0,843
Slovakia	0,792	0,811	0,823	0,795	0,795	0,815	0,795	0,764	0,695	0,787
Slovenia	0,847	0,863	0,847	0,852	0,827	0,840	0,848	0,848	0,800	0,841
Spain	0,840	0,846	0,848	0,844	0,842	0,852	0,852	0,825	0,820	0,841
Sweden	0,825	0,841	0,843	0,830	0,807	0,809	0,807	0,839	0,830	0,826
United Kingdom	0,889	0,886	0,872	0,852	0,859	0,840	0,840	0,840	0,850	0,859
EU-24	0,852	0,854	0,857	0,855	0,837	0,833	0,829	0,811	0,795	0,836

Table 5.5. Maximum-Likelihood Estimates of the Translog Revenue Frontier for PL insurers

Deterministic Component of Stochastic Frontier Model			
Parameter	Estimate	Parameter	Estimate
α_0	18.5385***	ϕ_{11}	-0.08804***
α_1	0.40246***	ϕ_{12}	0.07566***
α_2	0.11885***	ϕ_{21}	0.11423***
α_{11}	0.17980***	ϕ_{22}	-0.09631***
α_{12}	-0.19952***	ρ_1	-0.12529***
α_{22}	0.21647***	ρ_2	-0.10914***
β_1	-0.13799***	ρ_3	0.03065**
β_2	-0.14727***	ρ_4	0.09986***
β_{11}	-0.00915	ρ_5	0.08111***
β_{12}	-0.05436***	ρ_6	0.30709***
β_{22}	0.12400***	ρ_7	0.34113***
		ρ_8	0.47148***
Inefficient Term			
δ_0	1.80327***		
δ_1	0.94778		
δ_2	0.96247**		
δ_3	-0.35997**		
Sigma-squared	0.54428		
Gamma	0.67477		
Log-likelihood Function	-2,275.18551		

***,**,* indicate significance at 1%,5%, 10% respectively.

Table 5.6. Revenue efficiency scores by year and country of European Property-Liability insurers, 2006-2014

Country/year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2006-2014
Austria	0,765	0,780	0,782	0,789	0,836	0,829	0,841	0,849	0,866	0,815
Belgium	0,763	0,779	0,764	0,749	0,774	0,761	0,722	0,722	0,733	0,752
Croatia	0,795	0,789	0,766	0,649	0,810	0,891	0,636	0,805	0,865	0,778
Czech Republic	0,758	0,740	0,773	0,771	0,812	0,836	0,859	0,897	0,896	0,816
Denmark	0,756	0,753	0,769	0,826	0,776	0,812	0,721	0,721	0,689	0,758
Finland	0,691	0,740	0,762	0,767	0,799	0,795	0,787	0,800	0,738	0,764
France	0,820	0,812	0,788	0,804	0,808	0,795	0,796	0,814	0,794	0,803
Germany	0,786	0,791	0,788	0,814	0,821	0,833	0,856	0,840	0,848	0,820
Greece	0,857	0,855	0,823	0,801	0,656	0,487	0,408	0,537	0,597	0,669
Hungary	0,717	0,766	0,697	0,662	0,760	0,798	0,808	0,802	0,800	0,757
Ireland	0,705	0,742	0,748	0,686	0,649	0,553	0,555	0,622	0,651	0,657
Italy	0,793	0,800	0,805	0,793	0,797	0,757	0,701	0,731	0,782	0,773
Latvia	0,794	0,809	0,787	0,766	0,743	0,815	0,804	0,846	n.a.	0,796
Luxembourg	0,749	0,738	0,663	0,709	0,713	0,705	0,743	0,714	0,764	0,722
Malta	0,802	0,796	0,768	0,781	0,782	0,827	0,841	0,853	0,806	0,806
Netherlands	0,804	0,795	0,795	0,779	0,781	0,797	0,799	0,773	0,787	0,790
Poland	0,722	0,719	0,708	0,750	0,740	0,774	0,754	0,835	0,784	0,754
Portugal	0,826	0,809	0,800	0,790	0,754	0,660	0,578	0,667	0,754	0,738
Romania	0,747	0,794	0,862	0,794	0,850	0,830	0,687	0,714	n.a.	0,785
Slovakia	0,884	0,863	0,836	0,882	0,874	0,859	0,862	0,874	0,890	0,869
Slovenia	0,848	0,829	0,829	0,819	0,864	0,850	0,798	0,788	0,841	0,830
Spain	0,817	0,810	0,814	0,790	0,782	0,778	0,784	0,807	0,774	0,795
Sweden	0,706	0,705	0,732	0,731	0,731	0,752	0,780	0,698	0,700	0,726
United Kingdom	0,709	0,714	0,746	0,768	0,739	0,773	0,788	0,748	0,686	0,741
EU-24	0,776	0,780	0,775	0,770	0,777	0,774	0,746	0,769	0,775	0,771

Table 5.7. Maximum-Likelihood Estimates of the Translog Profit Frontier for PL insurers

Deterministic Component of Stochastic Frontier Model			
Parameter	Estimate	Parameter	Estimate
α_0	41.9604***	ϕ_{11}	0.06640***
α_1	0.95662***	ϕ_{12}	-0.04063***
α_2	0.96371***	ϕ_{21}	-0.04774***
α_{11}	0.08185***	ϕ_{22}	0.03038***
α_{12}	-0.02812***	ρ_1	-0.06545**
α_{22}	0.07991***	ρ_2	-0.05847***
β_1	-0.22883***	ρ_3	0.02688
β_2	-0.21147***	ρ_4	0.07116***
β_{11}	0.10522***	ρ_5	0.05779**
β_{12}	-0.15716***	ρ_6	0.16155***
β_{22}	0.20597***	ρ_7	0.19188***
ϕ_{11}	0.06640***	ρ_8	0.21254***
Inefficient Term			
δ_0	6.68819***		
δ_1	-1.28235		
δ_2	0.18749***		
δ_3	-0.10574***		
Sigma-squared	0.5282		
Gamma	0.625		
Log-likelihood Function	-3,600.27694		

***,**,* indicate significance at 1%,5%, 10% respectively.

Table 5.8. Profit efficiency scores by year and country of European Property-Liability insurers, 2006-2014.

Country/year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2006-2014
Austria	0,831	0,851	0,860	0,840	0,887	0,893	0,896	0,901	0,908	0,874
Belgium	0,825	0,837	0,833	0,788	0,831	0,830	0,782	0,774	0,769	0,808
Croatia	0,861	0,869	0,863	0,702	0,855	0,924	0,679	0,847	0,883	0,831
Czech Republic	0,804	0,797	0,857	0,840	0,845	0,881	0,899	0,921	0,910	0,862
Denmark	0,818	0,815	0,848	0,885	0,838	0,860	0,788	0,784	0,760	0,822
Finland	0,773	0,805	0,826	0,843	0,872	0,865	0,848	0,859	0,799	0,832
France	0,872	0,864	0,848	0,848	0,858	0,853	0,855	0,865	0,839	0,856
Germany	0,849	0,858	0,862	0,862	0,875	0,893	0,907	0,895	0,895	0,877
Greece	0,910	0,910	0,895	0,860	0,729	0,493	0,335	0,489	0,540	0,685
Hungary	0,787	0,847	0,820	0,728	0,804	0,864	0,873	0,833	0,819	0,819
Ireland	0,773	0,817	0,825	0,670	0,617	0,533	0,548	0,634	0,663	0,676
Italy	0,848	0,857	0,867	0,840	0,849	0,825	0,765	0,784	0,822	0,829
Latvia	0,898	0,918	0,928	0,863	0,775	0,884	0,877	0,896	n.a.	0,880
Luxembourg	0,836	0,820	0,749	0,750	0,787	0,808	0,831	0,783	0,829	0,799
Malta	0,872	0,890	0,860	0,844	0,844	0,881	0,896	0,898	0,851	0,871
Netherlands	0,866	0,858	0,861	0,836	0,835	0,865	0,866	0,846	0,837	0,852
Poland	0,804	0,787	0,789	0,854	0,750	0,859	0,812	0,882	0,823	0,818
Portugal	0,886	0,874	0,854	0,819	0,796	0,719	0,597	0,685	0,775	0,778
Romania	0,899	0,897	0,937	0,850	0,899	0,904	0,774	0,793	n.a.	0,869
Slovakia	0,930	0,912	0,907	0,923	0,911	0,911	0,908	0,913	0,918	0,915
Slovenia	0,900	0,895	0,902	0,873	0,907	0,895	0,857	0,839	0,875	0,883
Spain	0,888	0,877	0,888	0,837	0,837	0,843	0,840	0,858	0,806	0,853
Sweden	0,756	0,767	0,803	0,778	0,763	0,836	0,847	0,763	0,740	0,784
United Kingdom	0,775	0,787	0,824	0,793	0,775	0,861	0,853	0,835	0,708	0,801
EU-24	0,844	0,850	0,854	0,822	0,822	0,833	0,797	0,816	0,808	0,828

5.5 Empirical results for the European life insurance sector

Table 5.9 shows the maximum-likelihood estimates of the cost frontier for the European life insurance sector. Both outputs (net premiums written and investments) have the expected positive signs and are statistically significant at 1% level (0.97920 and 0.92593 respectively). Input prices of debt and labor and business services have also the expected positive sign and are statistically significant at 1% level (0.13531 and 0.57771 respectively). Stock insurers appear to be more cost efficient than mutual ones since the coefficient of the STOCK dummy variable is negative in this table (-0.04899) but is not statistically significant. The inflation has a positive and statistically significant impact on cost inefficiency (thus negative on efficiency) as expected (0.89996) since higher inflation increases total costs of insurers (Kasman and Yildirim, 2006; Eling and Schaper, 2017). Finally, the effect of GDP growth on cost inefficiency is negative and statistically significant at 1% level (-0.16770), indicating that the higher the growth rate, the higher the cost efficiency of life insurers (Kasman and Yildirim, 2006).

The yearly average cost efficiency results for the European life insurance sector for the countries in our sample are presented in table 5.10. The average cost efficiency scores for the 22 EU life insurance markets[17] over the whole sample period 2006-2014 is 0.772, indicating a 22.8% potential reduction in costs on average. Fenn et. al. (2008) in an equivalent research for 14 EU countries found that the average cost efficiency for the European life insurance sector was 0.796. The difference with our average cost efficiency is insignificant and since they covered the 1995-2001, we can conclude that in general terms cost efficiency remained relatively stable. The aggregate results show that the cost efficiency for the firms in the EU life insurance sector was relatively stable over the period 2006-2014 with a small reduction in year 2012.

Considering the country ranking, Slovakia (0.869), Slovenia (0.83), and Austria (0.827) have the most cost efficient life insurance sectors in EU. Ireland (0.657), Greece (0.669), and Sweden (0.726) are among the least cost efficient life insurance markets in EU. Observing the results, it is important to point out the dramatic drop in cost efficiency of the Greek, Irish, and Portuguese life insurance sectors after the burst of the sovereign debt crisis in 2010. All these countries requested the assistance of the European support mechanism and joined in rescue programs in order to restructure their economies. Greek insurance market experienced at a greater extent the European debt crisis although in 2014 its cost efficiency slightly improved.

Studying the existing literature, it is evident that there is no research estimating revenue efficiency in a European or international level. Until the moment of writing this thesis we are not aware of such an effort to close the gap on this research issue. Most of the empirical studies measuring efficiency of financial institutions are focused on cost efficiency (Berger and Humphrey, 1997). Revenue efficiency is the mirror image of cost inefficiency, incorporating errors in the choice of output mix and

[17] In our sample, only one life insurance company operating in Latvia and one operating in Luxembourg satisfy our screening criteria. So, these two countries were left out during the estimation of efficiencies for the European life insurance sector.

the estimation techniques are essentially the same those used in cost efficiency estimations but with different data (Berger and Humphrey, 1997). Although few revenue frontier analyses concerning financial institutions have been undertaken, revenue efficiency estimates (measured by output distance functions) appear to be similar to those for cost efficiency (English et al., 1993; Elyasiani and Mehdian, 1990). This conclusion, as we will see below, is verified in our own case.

The maximum-likelihood estimates for the translog revenue frontier of the European life insurance industry are presented in table 5.11. Both outputs (net premiums written and investments) have the expected positive signs and are statistically significant at 1% level (0.18608 and 0.84677 respectively). Input prices of debt and labor and business services have also the expected negative sign and are statistically significant at 1% level (-0.12631 and -0.61207 respectively). Stock insurers appear to be less revenue efficient than mutual ones since the coefficient of the STOCK dummy variable is positive in this table (1.17263) but is not statistically significant. The inflation has a positive and statistically significant impact on revenue inefficiency (thus negative on efficiency) as expected (0.15255) since higher inflation reduces total revenues of the insurers (Kasman and Yildirim, 2006). Finally, the effect of GDP growth on revenue inefficiency is negative and statistically significant at 1% level (-0.13880), indicating that the higher the growth rate, the higher the revenue efficiency of life insurers (Kasman and Yildirim, 2006).

The yearly average revenue efficiency results for the life insurance sector for all the 22 EU countries in our sample are presented in table 5.12. According to our results, revenue efficiency scores for the 22 EU life insurance industries over the sample period 2006-2014 is 0.792 indicating a 20.8% possible increase in revenues on average. The average revenue efficiency score for the EU-22 life sector remained relatively stable during the period 2006-2014 with a subtle drop in the year 2011. Considering the country analysis, Croatia (0.953), Slovakia (0.947), and Czech Republic (0.942) are among the most revenue efficient life insurance markets in EU. Greece (0.546), Denmark (0.601), and Ireland (0.662) are among the least revenue efficient life insurance markets in EU.

We also are not aware of any study estimating profit efficiency for the European life insurers at an international base. The work of Jarraya and Bouri (2014) estimates profit efficiency for a sample smaller than ours, which comprises only European property-liability insurers. However, there exist a few studies that measure profit efficiency for banks and we will use the relevant literature as a general comparison (Berger and Mester, 1997; Humphrey and Pulley, 1997; Miller and Noulas, 1996). Berger and Humphrey (1997) found that the average profit efficiency from studies of US depository institutions was 0.64. Akhavein et al. (1997) found much lower profit efficiency for large merging US banks, 0.24 before merger and 0.34 after merger. In contrast, Miller and Noulas (1996), using a sample of large US banks, found that average profit efficiency was 0.97, with 42% of banks being fully technical efficient.

The full parameter estimates for the profit frontier of the European life insurance sector are presented in table 5.13. The effect of the first output (net premiums written) on the total profits of the European life insurers is near zero and is positive as expected (0.00936) but is not statistically significant. The effect of the second output (total investments) is also positive as expected (0.10746) and statistically important at

1% level. Both input prices of debt and labor and business services are negative (-0.70965 and -0.26653 respectively) and statistically significant at 1% level as expected. Stock insurers appear to be more profit efficient than mutual ones since the coefficient of the STOCK dummy variable is negative in this table (-1.19855) but is not statistically significant. The inflation has a positive and statistically significant impact on profit inefficiency (thus negative on efficiency) as expected (0.27134) since higher inflation reduces total profits of the insurers (Kasman and Yildirim, 2006). Finally, the effect of GDP growth on profit inefficiency is negative and statistically significant at 1% level (-0.26615), indicating that the higher the growth rate, the higher the profit efficiency of the European life insurers (Kasman and Yildirim, 2006).

The yearly average profit efficiency results for the life insurance sector for all the 24 EU countries in our sample are presented in table 5.14. Our results reveal that profit efficiency scores for the 22 EU life insurance industries over the sample period 2006-2014 is 0.811 indicating a 18.9% possible increase in profits on average. The estimated average results in the present study are very similar to those reported in Klumpes (2004) for a sample of 40 UK life insurers (average profit inefficiency is 0.131 and 0.143 for representative and independent insurers respectively). Our aggregate results show that profit efficiency for firms in the EU-22 life insurance sector declined largely especially after year 2010. This reduction is possibly due to sovereign debt crisis that hit EU after 2010. Concerning the country analysis, Slovakia (0.941), Croatia (0.939), and Austria (0.922) are among the most profit efficient life insurance markets in EU. Greece (0.549), Ireland (0.622), and Denmark (0.725) are among the least profit efficient life insurance markets in EU. As we can observe, the least revenue efficient EU life insurance markets are also the least profit efficient ones.

Table 5.9. Maximum-Likelihood Estimates of the Translog Cost Frontier for Life insurers

Deterministic Component of Stochastic Frontier Model			
Parameter	Estimate	Parameter	Estimate
α_0	9.71290***	ϕ_{11}	0.12310***
α_1	0.97920***	ϕ_{12}	-0.13506***
α_2	0.92593***	ϕ_{21}	-0.13442***
α_{11}	0.13443***	ϕ_{22}	0.15138***
α_{12}	-0.13627***	ρ_1	-0.02411
α_{22}	0.12633***	ρ_2	-0.11391**
β_1	0.13531***	ρ_3	0.24255***
β_2	0.57771***	ρ_4	0.37233***
β_{11}	0.05765**	ρ_5	0.29145***
β_{12}	-0.08192***	ρ_6	0.60160***
β_{22}	0.09247***	ρ_7	0.66078***
		ρ_8	0.90223***
Inefficient Term			
δ_0	-13.0324***		
δ_1	-0.04899		
δ_2	0.89996***		
δ_3	-0.16770***		
Sigma-squared	0.68500		
Gamma	0.61201		
Log-likelihood Function	1,136.03061		

***,**,* indicate significance at 1%,5%, 10% respectively.

Table 5.10 Cost efficiency scores by year and country of European Life insurers, 2006-2014

Country/year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2006-2014
Austria	0,765	0,780	0,782	0,789	0,836	0,829	0,841	0,849	0,866	0,827
Belgium	0,763	0,779	0,764	0,749	0,774	0,761	0,722	0,722	0,733	0,752
Croatia	0,795	0,789	0,766	0,649	0,810	0,891	0,636	0,805	0,865	0,778
Czech Republic	0,758	0,740	0,773	0,771	0,812	0,836	0,859	0,897	0,896	0,816
Denmark	0,756	0,753	0,769	0,826	0,776	0,812	0,721	0,721	0,689	0,758
Finland	0,691	0,740	0,762	0,767	0,799	0,795	0,787	0,800	0,738	0,764
France	0,820	0,812	0,788	0,804	0,808	0,795	0,796	0,814	0,794	0,803
Germany	0,786	0,791	0,788	0,814	0,821	0,833	0,856	0,840	0,848	0,820
Greece	0,857	0,855	0,823	0,801	0,656	0,487	0,408	0,537	0,597	0,669
Hungary	0,717	0,766	0,697	0,662	0,760	0,798	0,808	0,802	0,800	0,757
Ireland	0,705	0,742	0,748	0,686	0,649	0,553	0,555	0,622	0,651	0,657
Italy	0,793	0,800	0,805	0,793	0,797	0,757	0,701	0,731	0,782	0,773
Malta	0,802	0,796	0,768	0,781	0,782	0,827	0,841	0,853	0,806	0,806
Netherlands	0,804	0,795	0,795	0,779	0,781	0,797	0,799	0,773	0,787	0,790
Poland	0,722	0,719	0,708	0,750	0,740	0,774	0,754	0,835	0,784	0,754
Portugal	0,826	0,809	0,800	0,790	0,754	0,660	0,578	0,667	0,754	0,738
Romania	0,747	0,794	0,862	0,794	0,850	0,830	0,687	0,714	0,714	0,777
Slovakia	0,884	0,863	0,836	0,882	0,874	0,859	0,862	0,874	0,890	0,869
Slovenia	0,848	0,829	0,829	0,819	0,864	0,850	0,798	0,788	0,841	0,830
Spain	0,817	0,810	0,814	0,790	0,782	0,778	0,784	0,807	0,774	0,795
Sweden	0,706	0,705	0,732	0,731	0,731	0,752	0,780	0,698	0,700	0,726
United Kingdom	0,709	0,714	0,746	0,768	0,739	0,773	0,788	0,748	0,686	0,741
EU-22	0,776	0,781	0,780	0,773	0,782	0,775	0,744	0,768	0,773	0,772

Table 5.11. Maximum-Likelihood Estimates of the Translog Revenue Frontier for Life insurers

Deterministic Component of Stochastic Frontier Model			
Parameter	Estimate	Parameter	Estimate
α_0	4.80063***	ϕ_{11}	0.09968***
α_1	0.18608***	ϕ_{12}	-0.09953***
α_2	0.84677***	ϕ_{21}	-0.10252***
α_{11}	0.17390***	ϕ_{22}	0.10666***
α_{12}	-0.17967***	ρ_1	-0.13082***
α_{22}	0.18192***	ρ_2	-0.26222***
β_1	-0.12631***	ρ_3	0.02064
β_2	-0.61207***	ρ_4	0.07476***
β_{11}	0.06599***	ρ_5	-0.04228
β_{12}	-0.09204***	ρ_6	0.26326***
β_{22}	0.11812***	ρ_7	0.24876***
		ρ_8	0.35277***
Inefficient Term			
δ_0	9.27094***		
δ_1	1.17263		
δ_2	0.15225***		
δ_3	-0.13880***		
Sigma-squared	0.69732		
Gamma	0.52231		
Log-likelihood Function	-4,394.99583		

***,**,* indicate significance at 1%,5%, 10% respectively.

Table 5.12 Revenue efficiency scores by year and country of European Life insurers, 2006-2014

Country/year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2006-2014
Austria	0,890	0,889	0,882	0,892	0,891	0,888	0,890	0,885	0,881	0,888
Belgium	0,685	0,682	0,676	0,679	0,676	0,674	0,671	0,659	0,635	0,671
Croatia	0,952	0,952	0,951	0,951	0,950	0,952	0,952	0,952	0,968	0,953
Czech Republic	0,943	0,942	0,942	0,941	0,941	0,939	0,943	0,943	0,942	0,942
Denmark	0,612	0,612	0,589	0,609	0,606	0,602	0,599	0,593	0,591	0,601
Finland	0,785	0,783	0,780	0,777	0,775	0,773	0,771	0,764	0,789	0,777
France	0,851	0,843	0,838	0,840	0,835	0,833	0,832	0,836	0,834	0,838
Germany	0,888	0,888	0,886	0,885	0,884	0,883	0,882	0,880	0,878	0,884
Greece	0,599	0,595	0,570	0,571	0,513	0,458	0,506	0,502	0,600	0,546
Hungary	0,836	0,834	0,825	0,824	0,822	0,846	0,860	0,860	0,864	0,841
Ireland	0,678	0,675	0,665	0,671	0,668	0,647	0,662	0,645	0,644	0,662
Italy	0,857	0,855	0,854	0,853	0,868	0,866	0,861	0,852	0,806	0,852
Malta	0,705	0,703	0,700	0,698	0,696	0,694	0,668	0,660	0,657	0,687
Netherlands	0,757	0,755	0,741	0,746	0,751	0,749	0,747	0,733	0,746	0,747
Poland	0,883	0,882	0,860	0,858	0,861	0,860	0,859	0,865	0,918	0,872
Portugal	0,845	0,842	0,828	0,827	0,825	0,823	0,822	0,820	0,801	0,826
Romania	0,743	0,716	0,713	0,707	0,704	0,702	0,699	0,712	0,712	0,712
Slovakia	0,950	0,949	0,949	0,948	0,948	0,947	0,947	0,946	0,938	0,947
Slovenia	0,785	0,787	0,766	0,764	0,749	0,747	0,758	0,755	0,768	0,764
Spain	0,834	0,831	0,831	0,829	0,828	0,826	0,825	0,829	0,826	0,829
Sweden	0,785	0,762	0,739	0,787	0,792	0,780	0,788	0,763	0,774	0,774
United Kingdom	0,821	0,816	0,821	0,821	0,812	0,817	0,814	0,831	0,769	0,814
EU-22	0,804	0,800	0,791	0,794	0,791	0,787	0,789	0,786	0,788	0,792

Table 5.13. Maximum-Likelihood Estimates of the Translog Profit Frontier for Life insurers

Deterministic Component of Stochastic Frontier Model			
Parameter	Estimate	Parameter	Estimate
α_0	18.4887***	ϕ_{11}	0.02357***
α_1	0.00936	ϕ_{12}	-0.01305***
α_2	0.10746***	ϕ_{21}	-0.02145***
α_{11}	-0.00599***	ϕ_{22}	0.01337***
α_{12}	0.01670***	ρ_1	-0.10842***
α_{22}	-0.01301*	ρ_2	-0.13680***
β_1	-0.70965***	ρ_3	-0.09397***
β_2	-0.26653***	ρ_4	0.01103
β_{11}	0.00795***	ρ_5	-0.04893
β_{12}	-0.04966**	ρ_6	0.14965***
β_{22}	0.11376***	ρ_7	0.25241***
		ρ_8	0.82646***
Inefficient Term			
δ_0	2.09171***		
δ_1	-1.19855		
δ_2	0.27134***		
δ_3	-0.26615***		
Sigma-squared	0,71142		
Gamma	0.59971		
Log-likelihood Function	-4,044.61023		

***,**,* indicate significance at 1%,5%, 10% respectively.

Table 5.14. Profit efficiency scores by year and country of European Life insurers, 2006-2014

Country/year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2006-2014
Austria	0,965	0,958	0,951	0,941	0,930	0,917	0,900	0,882	0,858	0,922
Belgium	0,880	0,857	0,832	0,802	0,766	0,726	0,680	0,629	0,572	0,749
Croatia	0,972	0,966	0,959	0,951	0,942	0,930	0,916	0,902	0,916	0,939
Czech Republic	0,978	0,974	0,968	0,962	0,954	0,946	0,987	0,985	0,982	0,971
Denmark	0,861	0,835	0,808	0,782	0,744	0,701	0,652	0,599	0,541	0,725
Finland	0,902	0,883	0,847	0,819	0,787	0,749	0,707	0,660	0,868	0,802
France	0,924	0,909	0,894	0,875	0,852	0,825	0,793	0,755	0,712	0,838
Germany	0,950	0,940	0,929	0,915	0,899	0,880	0,875	0,831	0,800	0,891
Greece	0,753	0,711	0,671	0,617	0,552	0,484	0,439	0,372	0,339	0,549
Hungary	0,900	0,881	0,871	0,847	0,819	0,789	0,773	0,737	0,695	0,812
Ireland	0,794	0,757	0,730	0,688	0,639	0,584	0,529	0,470	0,404	0,622
Italy	0,831	0,800	0,764	0,724	0,899	0,880	0,859	0,679	0,634	0,786
Malta	0,897	0,877	0,854	0,827	0,796	0,760	0,786	0,939	0,927	0,851
Netherlands	0,884	0,863	0,838	0,812	0,774	0,736	0,694	0,660	0,608	0,763
Poland	0,949	0,939	0,918	0,903	0,884	0,862	0,837	0,823	0,835	0,883
Portugal	0,906	0,886	0,866	0,841	0,811	0,778	0,739	0,695	0,662	0,798
Romania	0,862	0,841	0,812	0,771	0,731	0,686	0,636	0,580	0,637	0,728
Slovakia	0,976	0,969	0,962	0,955	0,946	0,935	0,923	0,908	0,892	0,941
Slovenia	0,930	0,918	0,881	0,858	0,835	0,805	0,774	0,734	0,898	0,848
Spain	0,927	0,912	0,895	0,875	0,852	0,824	0,793	0,759	0,721	0,840
Sweden	0,891	0,869	0,880	0,842	0,817	0,788	0,755	0,717	0,668	0,803
United Kingdom	0,884	0,868	0,826	0,794	0,761	0,720	0,675	0,620	0,847	0,777
EU-22	0,901	0,882	0,862	0,836	0,818	0,787	0,760	0,724	0,728	0,811

5.6 Conclusions

This chapter presented the empirical results obtained by estimating the operating efficiency for the European life and non-life insurance sector. Using a large sample of 947 European non-life insurers operating in 24 member states with 7,936 firm-year data and 771 life insurers operating in 22 member states with 6,321 firm-year data for the years 2006-2014, cost, revenue, and profit efficiency scores were calculated employing Stochastic Frontier Analysis (SFA). It was found that there have been significant improvement potentials. For the non-life European insurance sector we find that the average cost, revenue and profit efficiencies for the whole period were 0.836, 0.771, and 0.828, respectively. For the life sector the respective scores were 0.772, 0.792, and 0.881, respectively. This thesis is the first integrated effort to measure revenue and profit efficiency for the European insurance industry using a large multinational sample.

The period of this study includes the years of the global financial crisis and the European debt crisis. Global financial crisis began in 2007 with a crisis in subprime mortgage market in the USA, and developed in an international banking crisis. European debt crisis is a multi-year debt crisis that has been taking place in the European Union since the end of 2009. Several Eurozone member states (Greece, Cyprus, Ireland, Portugal, and Spain) were unable to repay or refinance their government debt. Except Spain, the other four Eurozone states had to be rescued by sovereign bailout programs, which were provided jointly by the International Monetary Fund, the European Commission, and the European Central Bank. Despite these negative economic conditions, the European life and non-life insurance sector maintained its efficiency levels stable with minimal changes from year to year. Only the average profit efficiency of the European life insurance sector showed a significant drop during the period 2006-2014.

CHAPTER 6

INTEGRATION AND EFFICIENCY CONVERGENCE IN THE EU INSURANCE MARKET

6.1 Introduction

The significant financial innovation and deregulation that has occurred over the past twenty years has affected the structure and performance of financial institutions and markets. The European financial sector experienced important changes and reforms aiming to improve the integration of the national financial systems in Europe. The changes in the deregulation of financial services in the EU, the establishment of the Economic and Monetary Union and the introduction of the euro, aim in moving towards integration. Operating in this economic environment, the European insurance industry incurred a breaking step towards integration in a single insurance market by the enactment of the life and non-life Third Generation Insurance Directives implemented in 1 July 1994. These directives promoted: (a) the abolition of price and product regulations, (b) the restriction of host country supervision to solvency control, (c) the establishment of the principle of minimum harmonization, (d) the introduction of a single EU license whereby an insurer licensed in one EU country can develop activities in all EU countries without being subject to regulations by host countries, and (e) the home country control for all insurance types (Beckmann et al., 2002). The removal of these legal and administrative obstacles should foster the integration for the provision of insurance services across the EU's landscape.

The notion of financial integration is interwoven with the law of one price which states that if assets have identical risks and returns, then they should be priced identically regardless of where they are traded (Casu and Girardone, 2010). We can allege that a financial market is integrated if all its potential participants with the same relevant characteristics: (a) face a single set of rules when they decide to invest in this market, (b) have equal access to financial instruments and/or services of this market, and are treated equally when they are active in this market (Baele et al., 2004). Based on the spirit of the low of one price, several measures of financial integration were suggested in literature. Most of them were based on the cross-sectional variation of several relevant variables such as interest rate spreads or return divergences (Baele et al., 2004). However, in the most recent literature the concepts of β- convergence and σ-convergence were used to estimate the speed with which financial markets are integrating (Mamatzakis et al., 2008; Weill, 2009; Casu and Girardone, 2010). Thus, the level of convergence in a financial market is the key issue in estimating the creation of a single European insurance market via financial integration.

Financial integration creates both advantages and disadvantages concerning the efficient operation of the European economy. Conducting financial business (e.g. insurance or banking) in a unified European market should promote competition and efficiency. Improvements in the efficiency of financial intermediaries in the euro area economy should lead to the reduction of the cost of capital and to the enhancement of allocating financial resources (ECB, 2015). The increased competition shall put pressure on them to adopt new technologies, to pare operating cost in order to remain profitable and to restructure to more optimal sizes. Additionally, the insurance firms can benefit from improved regional diversification of insured risks and from the wider variety of the assets they can invest (Beckmann et al., 2002). While it is commonly accepted that deepening financial integration is beneficial on the whole, it might have negative effects since high integration levels in a particular market segment might lead to a high degree of consolidation which might hinder competition (Casu and Girardone, 2010)[18].

The level of operating efficiency in a financial market expresses the ability of its participants to exploit efficiently their available resources (e.g. capital, deposits) in order to minimize their costs and to maximize their revenues. Measuring convergence towards a European average efficiency frontier is important in the context of the single market for financial services since a satisfying level of convergence would indicate a reduction in the level of variation among the countries constituting the EU. This possible reduction in variation of efficiency level in EU in turn would be expressed as progress in the real economy since the financial institutions form the basis of an economy by bringing into contact the redundant and the deficient entities. This thesis tries to contribute to this debate by examining the impact of the EU integration on the level of the efficiency in the European life insurance industry.

6.2 Literature review on convergence

Since the preparation of the Single Market Program in Europe in the 80s, financial integration has been expected to provide gains in growth by favoring competition and efficiency on financial markets (Guiso et al., 2004). The main objective of this effort to integrate national financial markets was the convergence towards the one price law. According to this law all financial institutions (e.g. banks and insurers) should charge the same price for similar products and services. To reach this objective, convergence in cost, revenue, and profit efficiency of financial intermediaries is required as large differences in costs, revenues, and profits respectively prevent prices charged for services from converging. Efficient institutions exploit in the maximum extent their capabilities and resources in contrast with the inefficient ones creating differences in their pricing policy. Therefore, the investigation of convergence in cost, revenue, and profit efficiency of insurance companies is an indicator on the degree of the integration in the EU insurance market.

There is a vast majority literature measuring efficiency in finance industry and specifying the determinants of efficiency[19]. Despite the great abundance of papers measuring financial institutions' efficiency, the empirical evidence investigating the impact of integration on the efficiency of financial services industry is rather scarce. Among the few studies available, most have been focused on the banking European market and in most cases show cost efficiency convergence. Conversely, there is extensive literature that considers convergence with respect to interest rates. Earlier studies have provided evidence of an ongoing integration process despite persistent cross-country interest rate differences (e.g. Vajanne, 2007; ECB, 2006). Yet, the more

[18] Baele et al. (2004) showed that financial integration does not necessarily have implications for consolidation in all market segments. They stressed that while integration may lead to consolidation in an industry, there is no direct causal link between integration and consolidation.
[19] Eling and Luhnen (2010b) provided the most recent literature review for insurance industry and categorized the existing papers in ten different categories according to their aim.

recent literature provides evidence that the post 2008 financial crisis has had a profound negative effect on the convergence process of retail banking interest rates (e.g. ECB, 2011). Thus, with this research we try to shed light on the relationship that exists between integration and efficiency convergence.

Fung (2006) was the first who dealt with the convergence in pure technical and scale efficiency for the US banking holding companies. The findings showed strong evidence for "conditional convergence" which means that steady-state productivity to which a bank holding company is converging is conditional on its own level of x-efficiency. Mamatzakis et al. (2008) analyzed banking efficiency's convergence in ten new EU members for the period 1998-2003 using β- and σ-convergence criteria. Results indicate some convergence in cost efficiency across the new members, yet no convergence appears to have been achieved in terms of profit efficiency. Weill (2009) used β- and σ-convergence tests for panel data in order to investigate the convergence in banking efficiency for a sample of banks from ten EU member countries from 1994 to 2005. The results showed a process in convergence in cost efficiency between EU countries. Casu and Girardone (2010) estimated banking cost efficiency convergence in 15 EU members for the period 1997-2003. They provided supporting evidence of convergence of efficiency scores towards an EU average, but they find no evidence of an overall improvement of efficiency levels toward best practice. Matousek et al. (2015) investigated the process of banking efficiency integration in the EU15 countries and the Eurozone for the period 2005-2012 by using the Philips and Sul (2007) panel convergence methodology. Their results indicated an overall decline in efficiency and no evidence of group convergence following the financial crisis.

Although there are some papers that study efficiency and productivity in a European insurance market level (e.g. Diacon et al., 2002; Fenn et al., 2008), no one studies the integration and efficiency convergence of European insurance sector. All these papers focused on the evolution of efficiency during the sample periods while trying to determine the factors affecting efficiency levels. Mahlberg and Url (2010), although it was not their primary purpose, to the best of our knowledge are the only to use the long-run economic growth literature (β- and σ-convergence) in order to analyze convergence in efficiency and productivity for the German insurance industry. They did not follow the approach used in banking literature described above (e.g. Weill 2009; Casu and Girardone 2010). Rather they applied a formal test of convergence by adopting lower one-tailed F-tests proposed by Snedecor and Cochran (1989) for decreasing standard deviations between consecutive years ($\sigma_t < \sigma_{t-1}$) and between the first year in their sample and each following year ($\sigma_t < \sigma_{t=1992}$). Taking into account the p-values of their F-tests it was proved that the dispersion of cost efficiency scores declines over time. It is indicating σ-convergence for cost efficiency among German insurance companies while dispersion in revenue efficiency diminishes only in year 2003. Following the literature examining banking efficiency convergence, we try to put a stone in the respective insurance's efficiency convergence literature.

6.3 Convergence modeling

Convergence has been mainly modeled using time-series, cross sectional, and panel data methods with respect to economic growth models (Murinde et al., 2004). In the growth literature when the dispersion of real per capita income across a group of economies falls over time, there is σ-convergence and when the partial correlation between growth in income over time and its initial level is negative, there is β-convergence (Young et al., 2008). Thus, the notion of convergence in economics (catch-up effect) means that the poorer economies' per capita incomes tend to grow at faster rates than that of richer ones. Young et al. (2008) demonstrated that β-convergence is a necessary but not sufficient condition for σ-convergence.

The notions of β- and σ-convergence used here were originally proposed by Barro and Sala-i-Martin (1992, 1995) for measuring convergence in economic growth rates across different countries. Quah (1996) criticized the β-convergence test by stressing the fact that when countries with low initial level grow faster than those with high initial level, this can lead to a situation where the first ones overpass the latter ones, meaning the absence of convergence. Second, it was stated that β-convergence tests provide no information on the evolution of the dispersion over a sample of countries. The σ-convergence test does not suffer from these limits as it investigates the evolution of dispersion and convergence exists if dispersion diminishes over time (Quah, 1996). Thus, the σ-convergence notion captures how quickly each country's level (e.g. GDP, interest rates) is converging to the average level of the countries in the group investigated. Young et al. (2008) proved that the β- and σ-convergence measures are complementary but not excludable with β-convergence being a necessary but not a sufficient condition for σ-convergence existence. They stressed that economies can be β-converging toward each other while, at the same time random shocks are pushing them apart.

We advance the work of Casu and Girardone (2010) and Weill (2009) in order to investigate the convergence of insurance efficiency levels across the EU countries over the period of analysis. More accurately, in order to estimate the unconditional β-convergence (catch-up effect) we define the following model:

$$\Delta y_{i,t} = \alpha + \beta(\ln y_{i,t-1}) + \rho\Delta y_{i,t-1} + \varepsilon_{i,t} \qquad (6.1)$$

where i=1,2,.., and t=1,…,8; $y_{i,t}$ is the mean efficiency of the insurance market of country i at year t; $y_{i,t-1}$ is the mean efficiency of the insurance sector in country i at the year t-1. $\Delta y_{i,t} = \ln(y_{i,t}) - \ln(y_{i,t-1})$, and α, β, and ρ are the parameters needed to be estimated. Finally, $\varepsilon_{i,t}$ is assumed to be the random error term catching up the effects of the factors not included in (6.1). A negative value for the β parameter implies convergence with the higher the coefficient in relative terms the greater the tendency for convergence (Casu and Girardone, 2010).

In order to estimate the cross-section dispersion or σ-convergence, that is to estimate how quickly each country's efficiency levels are converging to the European average, we determine the following autoregressive distributed lag model (Casu and Girardone, 2010; Weill, 2009):

$$\Delta E_{it} = \alpha + \sigma E_{i,t-1} + \rho\Delta E_{i,t-1} + \varepsilon_{i,t} \qquad (6.2)$$

where $E_{i,t} = \ln(y_{i,t}) - \ln(\overline{y_t})$; $E_{i,t-1} = \ln(y_{i,t-1}) - \ln(\overline{y_{t-1}})$; $y_{i,t}$ and $y_{i,t-1}$ as defined above in (6.1); $\overline{y_t}$ and $\overline{y_{t-1}}$ are the mean efficiencies of the EU insurance market at time t and t-1 respectively; $\Delta E_{it} = E_{i,t} - E_{i,t-1}$; α, σ, and ρ are the parameters needed to be estimate. $\varepsilon_{i,t}$ is assumed to be the random error term catching up the effects in the model. The coefficient σ<0 represents the rate of convergence of $y_{i,t}$ towards $\overline{y_t}$. The larger is σ in absolute value, the faster the rate of efficiency convergence will be (Casu and Girardone, 2010).

Following Casu and Girardone (2010), we first estimate equation (6.1) without including the lagged dependent variable $\Delta y_{i,t-1}$ in the estimations needed. The equation (6.1) describing β-convergence is estimated both by pooled OLS regression and by the Generalized Method of Moments (GMM) in order to introduce dynamic behavior in the time series and cross-sectional variation (Blundell and Bond, 1998). The equation (6.2) that models σ-convergence is first estimated, as the (6.1), without the inclusion of the lagged dependent variable $\Delta E_{i,t-1}$.

6.4 Convergence results

As noted in section 6.3, a negative value for the parameter β in equation (6.1) implies convergence. The higher the coefficient in absolute terms the greater the tendency for convergence. In the same way, a negative value for the parameter σ in equation (6.2) represents the rate of convergence of each country's insurance sector average efficiency towards the European average from 2007 to 2014. The larger the σ parameter in absolute value, the faster the rate of convergence. In other words, β-convergence implies that the most efficient insurance sectors in the initial year 2008 have shown a lower improvement of efficiency than the least efficient ones while σ-convergence implies that the dispersion of the average efficiency scores between the EU insurance markets was reduced during the 2008-2014 period of study.

6.4.1 Convergence of P-L insurance sector in EU

We evaluate β-convergence for our cross-section of the 24 EU countries by estimating (6.1) first by OLS and GMM. We use OLS only as a robustness check since GMM has the advantage to introduce dynamic behavior in the time series and cross-sectional variation in equation (6.1) as it allows the existence of lagged levels of the dependent variable as regressors. Table 6.1 presents regression estimates of the cost efficiency β-convergence coefficient for the period 2008-2014. The beta coefficient is negative (-.04939) and statistically significant under the GMM estimator, thus indicating that convergence in cost efficiency has occurred across the EU-24 PL insurance sector.

Table 6.1. Beta convergence for cost efficiency for the PL European Insurers

Coefficients	Eq. (6.1) without lagged dependent variable	Eq. (6.1)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
β	.04058 (.05672)	-.00743 (.06670)	-.04939*** (.00973)

ρ	-	.14314 (.10532)	-.59760*** (.06924)
α	-.00440 (.01040)	-.01189 (.01175)	-.03335 (Fixed Parameter)
Goodness of fit			
R^2	.00311	.01428	-

***, **, * ==> Significance at 1%, 5%, 10% level.

The respective β-convergence coefficients for the revenue and profit efficiency of the PL insurance market in EU are presented in tables 6.2 and 6.3 respectively for the period 2008-2014. More accurately, the β coefficients for revenue and profit efficiency convergence are negative and statistically significant (-.60093 and-.82634 respectively) meaning that beta convergence in revenue and profit efficiency scores has occurred.

Table 6.2. Beta convergence for revenue efficiency for the PL European Insurers

Coefficients	Eq. (6.1) without lagged dependent variable	Eq. (6.1)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
β	-.20292*** (.05265)	-.24217*** (.05792)	-.60093*** (.06321)
ρ	-	.13533 (.08502)	-.96789*** (.03984)
α	-.05554*** (.01510)	-.06567*** (.01632)	-.14409 (Fixed Parameter)
Goodness of fit			
R^2	.08304	.09708	-

***, **, * ==> Significance at 1%, 5%, 10% level.

Table 6.3. Beta convergence for profit efficiency for the PL European Insurers.

Coefficients	Eq. (6.1) without lagged dependent variable	Eq. (6.1)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
β	-.18467*** (.05081)	-.21820*** (.05621)	-.82634*** (.04748)
ρ	-	.11778 (.08550)	-.28959 (Fixed Parameter)
α	-.04386*** (.01187)	-.04970*** (.01257)	-.08421*** (.00574)
Goodness of fit			
R^2	.07455	.08520	-

***, **, * ==> Significance at 1%, 5%, 10% level.

As noticed above, a coefficient $\sigma<0$ in the regression results for the equation (6.2) represents the rate of convergence of each country's average efficiency towards the European average efficiency. In other words, the σ-coefficient indicates how quickly each country's average efficiency score is converging to the respective European average efficiency score. The larger the σ in absolute terms, the faster the rate of convergence. If the σ coefficient is positive and statistically important, it is evidence of σ-divergence (Young et al., 2008). The results for σ-convergence concerning cost efficiency are reported in table 6.4. The σ coefficient is negative but it is not statistically significant. So, it cannot be alleged that sigma convergence has been achieved in the European PL insurance sector.

Table 6.4. Sigma convergence for cost efficiency for the PL European Insurers

Coefficients	Eq. (6.2) without lagged dependent variable	Eq. (6.2)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
σ	-.00101 (.05794)	-.05174 (.06752)	-.01534 (.05266)
ρ	-	.15032 (.10367)	-.97871*** (.11515)
α	-.00140 (.00294)	-.00149 (.00293)	.00550*** (.00136)
Goodness of fit			
R^2	.00003	.01274	-

***, **, * ==> Significance at 1%, 5%, 10% level.

The results for sigma convergence concerning revenue and profit efficiencies of the European PL insurance sector are presented in tables 6.5 and 6.6 respectively. The sigma coefficient for revenue and profit efficiency convergence is negative and statistically significant in both cases if we assume that OLS is used as an estimation method of equation (6.2). The respective sigma coefficient for the revenue efficiency convergence if we adopt the GMM estimation method is positive (.17483) and statistically significant indicating that convergence for revenue efficiency scores has not achieved. The sigma coefficient for the profit efficiency convergence obtained by using the GMM estimation method is positive but not statistically significant indicating that profit efficiency convergence has not been achieved.

Table 6.5. Sigma convergence for revenue efficiency for the PL European Insurers

Coefficients	Eq. (6.2) without lagged dependent variable	Eq. (6.2)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
σ	-.18492*** (.05129)	-.22807*** (.05610)	.17483*** (.05454)
ρ	-	.15567* (.08498)	-1.10243*** (.16803)
α	-.00140 (.00536)	-.00152 (.00533)	.01401 (Fixed Parameter)
Goodness of fit			
R^2	.07345	.09214	-

***, **, * ==> Significance at 1%, 5%, 10% level.

Table 6.6. Sigma convergence for profit efficiency for the PL European Insurers

Coefficients	Eq. (6.2) without lagged dependent variable	Eq. (6.2)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
σ	-.16554*** (.04972)	-.21517*** (.05456)	.07134 (.34606)
ρ	-	.18051** (.08576)	-.04476 (.63299)
α	-.00158 (.00616)	-.00174 (.00610)	-.00750 (.01652)
Goodness of fit			
R^2	.06332	.08810	-

***, **, * ==> Significance at 1%, 5%, 10% level.

6.4.2 Convergence of Life insurance sector in EU

As we noted in the previous section concerning PL insurers, a negative value for the parameter β in equation (6.1) implies convergence. The higher the coefficient in absolute terms, the greater the tendency for convergence. In the same way, a negative σ coefficient in equation (6.2) implies convergence of each country' s average efficiency towards the EU-22 average. Table 6.7 presents regression estimates of the convergence coefficient β concerning European Life Insurers' cost efficiencies for the period 2008-2014. Equation (6.1) is first estimated by OLS as a robustness check. The first column of Table 6.7 shows the results of OLS for the same equation but with excluding the lagged dependent variable. The beta coefficient is negative (-.7319) and statistically significant for each statistical level, thus indicating that convergence in cost efficiency scores has taken place in the EU-22 life insurance industry.

Table 6.7. Beta convergence for cost efficiency for the Life European Insurers

Coefficients	Eq. (6.1) without lagged dependent variable	Eq. (6.1)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
σ	-0.19928*** (0.05435)	-.24279*** (.05957)	-.73190*** (.06112)
ρ	-	.15175* (.08776)	-.21414*** (.05379)
α	-0.05482*** (0.01554)	-.06603*** (.01674)	-.19155 (Fixed Parameter)
Goodness of fit			
R^2	0.08127	.09911	-

***, **, * ==> Significance at 1%, 5%, 10% level.

Tables 6.8 and 6.9 report the results for β-convergence concerning revenue and profit efficiencies of the European Life Insurance sector for the period 2008-2014 respectively. The beta coefficient concerning revenue efficiency is negative and statistically significant (-1.83210) for the GMM estimator, thus indicating that convergence has occurred across these countries during the 2008-2014 period. This beta coefficient for revenue efficiency convergence is also negative but not statistically significant if we use OLS for the estimations. The beta coefficient concerning profit efficiency convergence is positive and statistically significant for all the three specifications of equation (6.1), as it is presented in table 6.9, indicating that convergence concerning profit efficiency has not occurred across these countries.

Table 6.8. Beta convergence for revenue efficiency for the Life European Insurers

Coefficients	Eq. (6.1) without lagged dependent variable	Eq. (6.1)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
β	-.00443 (.01415)	-.00058 (.01475)	-1.83210*** (.28619)
ρ	-	-.10640 (.11460)	.058668*** (.06261)
α	-.00340 (.00406)	-.00286 (.00410)	-0.22045*** (.0335)
Goodness of fit			
R^2	.00064	.00632	-

***, **, * ==> Significance at 1%, 5%, 10% level.

Table 6.9. Beta convergence for profit efficiency for the Life European Insurers

Coefficients	Eq. (6.1) without lagged dependent variable	Eq. (6.1)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
β	.09971*** (.02959)	.08214* (.04243)	.46257*** (.01104)
ρ	-	.09583 (.16559)	-1.4705*** (.05720)
α	-.00934 (.00818)	-.00998 (.00827)	.00202*** (.00012)
Goodness of fit			
R^2	.06953	.07159	-

***, **, * ==> Significance at 1%, 5%, 10% level.

Table 6.10 presents the results of sigma cost efficiency convergence among European life insurers for the period 2008-2014. As noted earlier, the existence of σ-convergence implies that the dispersion of the average efficiency scores between the EU insurance markets was reduced during the 2008-2014 period of study. In our case the σ coefficient is negative and statistically significant (-1.212) suggesting that the dispersion of the mean cost efficiency scores among the 22 EU countries decreased during the sample period. Tables 6.11 and 6.12 present the results for sigma convergence concerning revenue and profit efficiency of the European life insurance sector respectively. As far as revenue efficiency, the σ coefficient is negative and statistically significant (-0.0333) indicating that the dispersion of the mean revenue efficiency scores between the EU-22 countries was reduced during the 2008-2014 period. The respective σ coefficient for the profit efficiencies of the European life insurers is positive but not statistically significant (0.521) indicating that σ-convergence has not been achieved concerning profit efficiency scores.

Table 6.10. Sigma convergence for cost efficiency for the Life European Insurers

Coefficients	Eq. (6.2) without lagged dependent variable	Eq. (6.2)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
σ	-.79024*** (.04214)	-.43198*** (.04203)	-1.21182*** (.02109)
ρ	-	.55149*** (.04527)	.01013* (.00560)
α	-.01290 (.00850)	-.00362 (.00610)	.02969*** (.00446)
Goodness of fit			
R^2	.69825	.84781	-

***, **, * ==> Significance at 1%, 5%, 10% level.

Table 6.11. Sigma convergence for revenue efficiency for the Life European Insurers

Coefficients	Eq. (6.2) without lagged dependent variable	Eq. (6.2)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
σ	-.00325 (.01376)	-.00070 (.01441)	-.03336*** (.01283)
ρ	-	-.07101 (.11675)	.89031*** (.12731)
α	-.00022 (.00206)	-.00024 (.00206)	-.02746 (Fixed Parameter)
Goodness of fit			
R^2	.00037	.00281	-

***, **, * ==> Significance at 1%, 5%, 10% level.

Table 6.12. Sigma convergence for profit efficiency for the Life European Insurers.

Coefficients	Eq. (6.2) without lagged dependent variable	Eq. (6.2)	
	Pooled OLS robust	Pooled OLS robust	GMM two-step robust
σ	.13016*** (.03134)	.10735** (.04393)	.52123
ρ	-	.11868 (.15989)	-14.8363*** (.25061)
α	-.00286 (.00461)	-.00274 (.00462)	-.15832 (Fixed Parameter)
Goodness of fit			

R^2	.10192	.10519	-

***, **, * ==> Significance at 1%, 5%, 10% level.

6.5 CONCLUSIONS

In this chapter we estimated the level of the efficiency convergence in the European life and non-life insurance markets during the period 2008-2014 since the so-called Fifth Enlargement part-II completed in 2007. More accurately, we used the notion of beta and sigma convergence concerning cost, revenue, and profit efficiency in 22 and 24 life and non-life European insurance markets respectively. For the non-life European insurance sector we find evidence of beta convergence concerning cost, revenue, and profit efficiency scores but no evidence of sigma convergence. For the life European insurance markets we find evidence of beta and sigma convergence concerning cost and revenue efficiencies but no evidence of beta or sigma convergence for its profit efficiency. These results show that the harmonization of the regulatory and supervisory rules of the European insurers that has been attempted over the last three decades has led to the efficiency integration of them. But the European regulatory authorities should continue their efforts for more integration since we found no evidence of profit efficiency convergence.

To the best of our knowledge, there is no other research effort to estimate the level of beta convergence (catch up effect) and sigma convergence concerning the efficiency of the European life and non-life insurance sector. However, there are some efforts for the European banking sector that measure beta and sigma efficiency convergence in order to examine if the financial integration tried during the last three decades in Europe has eliminated the differences in the operating efficiency of the European banks (Casu and Girardone, 2010; Weill (2009). These papers provide evidence both for beta and sigma convergence concerning the cost efficiency of the European banks. For the insurance sector, although we found evidence for sigma and beta convergence, it would be interesting to undertake additional similar efforts with different samples or sample periods to confirm our results.

CHAPTER 7

SUMMARY AND CONCLUSIONS

This thesis is a response to the need for more empirical studies on estimating at which level the financial integration tried in EU has eliminate differences concerning operating efficiency in the European financial markets and especially insurance markets. The 1986 Single European Act, the 1992 Maastricht Treaty, the deregulation of the European insurance markets by the implementation of the associated European Third Generation Directives in 1994, and the introduction of the euro as a common currency in 1999 are a sample of key legislative changes occurred during the last two decades at a EU level that have contributed towards the integration of European financial markets. Especially for insurers, the implementation of the EU's Third Generation Directives on July 1, 1994 was an important step in creating conditions for the creation of a single European insurance market.

The Third Generation Directives had three key contributions to the attempt for achieving financial integration in the European insurance markets. First, the establishment of a single EU license, whereby an insurer is required to obtain only one license to operate in the EU rather than being licensed in each member country (Cummins and Rubio-Misas, 2006). Second, the principle of home country supervision, whereby an insurer is regulated only by the nation which issued its license and not by each host country where it operates (Cummins and Rubio-Misas, 2006). Finally, the abolition of substantive insurance supervision, meaning that regulation at national levels is limited to solvency control and that pricing, contracting, and other insurance operations are effectively deregulated (Cummins and Rubio-Misas, 2006).

The main objective of these efforts toward deregulation and liberalization was to increase competition in the formerly closed European insurance markets both within and among the insurance markets of the member states. This internationalization of business was expected to continue to bring pressure on insurers to increase operating efficiency. More accurately, cost, revenue, and profit efficiency were expected to increase as foreign competition forces firms to reduce cost, to increase possible revenues and to realize unused profit potentials. This increase in operating efficiency of the European insurers after the above mentioned legislative changes is expected since any deviation from the profit maximizing strategies would force inefficient firms out of the market in the long run by possible mergers and acquisitions. Consequently, with the removal of cross-border restrictions, differences in the efficiency of the insurers from different European countries should be reduced. This hypothesis was the incentive to estimate the degree of convergence of the efficiency scores in the life and non-life European insurance sector.

There is a vast empirical literature on the measurement of the efficiency in the insurance industry. Chapter 2 of this thesis describes analytically the existing literature while chapter 3 describes the existing frontier methodologies for estimating efficiency. There are two main approaches for the estimation of the efficiency: the econometric approach and the mathematical programming approach. Both approaches have their advantages and their disadvantages and there is no consensus in the field as to which method is superior. The econometric approach has the main disadvantage of using strong assumptions regarding the form of the efficient frontier. It assumes a specific functional form, such as the translog or composite cost, and therefore expects a certain underlying economic behavior, which may not be valid. Against this argument, the mathematical programming approach has the advantage of imposing less structure on the efficient frontier. However, compared to the econometric approach, it has the main disadvantage of not taking into account a random error term.

Taking these methodological differences into account, we estimated in Chapter 5 the cost, revenue, and profit efficiency for a sample of European life and non-life insurers operating in 22 and 24 European member states respectively for the period 2006-2014. In our case SFA was preferred to DEA because we have a multi-national sample and one has to account for country-specific differences in order to make a common European frontier meaningful. These country-specific differences were considered in the banking efficiency literature (e.g., Fiordelisi and Molyneux, 2010), but were neglected in most insurance studies that use cross-country data (Diacon et al., 2002; Fenn et al., 2008). Only Eling and Luhnen (2010a) and Gaganis et al., (2013) used the Battese and Coelli (1995) model that allows for exogenous effects in a single and common frontier. The model employed in this thesis is the one of the Battese and Coelli (1995) which permits the estimation of efficiency in a single stage while considering the impact of environmental variables on efficiency.

In Chapter 5 we provide inefficiency estimates for cost, revenue, and profit at a European level based on a flexible stochastic frontier. It is the first organized effort to measure revenue efficiency in a European level. There are only a few papers that measure cost efficiency for the European insurers (e.g. Diacon et al., 2002; Fenn et al., 2008) and only one paper of Jarraya and Bouri (2014) that estimates profit efficiency in a European level. For the non-life European insurance sector we find that the average cost, revenue and profit efficiencies for the whole period were 0.836, 0.771, and 0.828 respectively. For the life sector the respective scores are 0.772, 0.792, and 0.881 respectively. It is evident that despite the efficiency improvements after the deregulation process in the last three decades (Eling and Luhnen, 2010b), there are margins for cost reductions and for revenue and profit improvements for the European life and non-life insurance market.

The period of this study includes the years of the global financial crisis and the European debt crisis. Global financial crisis began in 2007 with a crisis in subprime mortgage market in the USA, and developed in an international banking crisis. European debt crisis is a multi-year debt crisis that has been taking place in the European Union since the end of 2009. Several Eurozone member states (Greece, Cyprus, Ireland, Portugal, and Spain) were unable to repay or refinance their government debt. Except Spain, the other four Eurozone states had to be rescued by sovereign bailout programs, which were provided jointly by the International Monetary Fund, the European Commission, and the European Central Bank. Despite these negative economic conditions, the European life and non-life insurance sector maintained its efficiency levels stable with minimal changes from year to year. Only the average profit efficiency of the European life insurance sector showed a significant drop during the period 2006-2014.

The non-life insurance sectors in the member states that entered in sovereign bailout programs (Greece, Ireland, and Portugal) kept their average cost efficiency relative stable during the debt financial crisis while their average revenue and profit efficiencies showed an important drop after the burst of the European sovereign debt crisis. This fact probably is attributed to the efforts of these companies' management team to cut their cost in order to survive in the inhospitable economic environment formed after the burst of the debt crisis. In these above mentioned countries, the life insurance sector showed a semantic drop in its cost efficiency and profit efficiency. Concerning revenue efficiency, only Greek and Irish life insurance sectors presented an important drop in it while the Portuguese life insurance sector maintained its revenue efficiency level stable during the debt crisis hit European financial market.

Examining the determinants affecting efficiency, we found no statistically significant evidence of efficiency differences between stock and mutually organized European insurers although some studies find that stock insurers are more efficient than mutuals, confirming the expense preference hypothesis (e.g. Cummins et al., 1999a). However, other studies have found mutuals more efficient than stocks (e.g. Diacon et al., 2002). We also found a negative and statistically significant relationship between inflation and cost, revenue, and profit efficiency as expected since higher inflation increases costs and reduces revenues and profits of the financial institutions (e.g. Kasman and Yildirim, 2006). Also, we found a positive and statistically significant relationship among revenue and profit efficiencies and GDP change as many other works in the financial institutions literature since the revenue and profit margins are limited in high developed markets and thus inefficient players are absorbed from efficient ones (e.g. Kasman and Yildirim, 2006 ; Maudos et al., 2002). Finally, we found a negative relationship between cost efficiency and GDP change for the European property-liability insurers while this relationship is positive for the European life insurers. This is consistent with many other works (e.g. Huang and Eling, 2013) although some other find positive evidence (e.g. Maudos et al., 2002) since under expansive demand conditions in expanding markets, financial institutions are less inclined to control expenditure and therefore become less cost efficient.

In Chapter 6 of this thesis, we estimated the level of the efficiency convergence in the European life and non-life insurance markets during the period 2008-2014 since the so-called Fifth Enlargement part-II completed in 2007. While quantification of the extent to which European financial markets have achieved integration, in the sense of the complete elimination of the barriers to cross-border activity, remains an imprecise matter, several indicators are available. Dermine (2006) summarizes evidence based on three criteria: i) the extent to which the law of one price is applicable for the financial services produced; ii) the volume of cross-border financial services that are provided in each member state; and iii) the market share of foreign financial institutions in each member state.

We use the notion of beta and sigma convergence concerning cost, revenue, and profit efficiency in 22 and 24 life and non-life European insurance markets respectively. The beta and sigma convergence estimations are based on the law of one price that mentioned above. Beta convergence implies that countries with lower initial levels (i.e. efficiency in year 2008) of efficiency for our period would have shown faster efficiency growth than countries with higher initial levels (i.e. efficiency in year 2008) of efficiency. Sigma convergence means that the dispersion of the mean efficiency scores among the European member states would be reduced during our period of study. For the non-life European insurance sector we find evidence of beta convergence concerning cost, revenue, and profit efficiency scores but no evidence of sigma convergence. For the life European insurance markets we find evidence of beta and sigma convergence concerning cost and revenue efficiencies but no evidence of beta or sigma convergence for its profit efficiency. Although it is the first effort to estimate efficiency convergence for the European insurance market, we can claim that the efforts for the harmonization of regulatory and supervisory policies as well as the mechanisms for coordination of macroeconomic policies of the national authorities that took place in the European Monetary Union, have achieved efficiency convergence in the European insurance market although these efforts must continue for achieving convergence concerning profit efficiency.

This thesis contributes to the existing body of knowledge concerning European insurance's sector efficiency as well as its efficiency convergence after three decades of deregulation and liberalization efforts toward the creation of a theoretically common European insurance market. This research has identified a gap in the literature on insurance efficiency estimation, which has not been empirically addressed in previous studies. To the best of our knowledge, this thesis is one of the first studies to investigate the cost, revenue, and profit efficiency convergence in the European life and non-life insurance markets using a large and very recent sample. All the contributions of this thesis are summarized in the following paragraph.

Our analysis, one of the first to include a very large sample of countries and firms, extends the existing literature in several important aspects. First, we provide inefficiency estimates for cost, revenue, and profit functions at a European level based on a flexible stochastic frontier. Indeed, it is the first attempt to measure revenue efficiency for life and non-life European insurers in a European context. Second, we consider the level of convergence of the European life and non-life insurance industry by estimating β-convergence and σ-convergence. To our knowledge, no other study has examined the convergence of the European insurance industry. Third, unlike articles measuring banking efficiency convergence by estimating efficiency with DEA or with the classical SFA methods, this thesis uses the Battese and Coelli (1995) model for the efficiency estimations. This model has the advantage to permit the estimation of efficiency in a single stage while accounting for the impact of environmental variables (e.g. inflation). So, the measurement of β-convergence and σ-convergence concerning efficiency is more accurate than the respective convergence measures that derived by using the DEA or the classical SFA for the efficiency estimations. Finally, by the time this thesis is written it is the only study that uses the most recent data in its efficiency estimations.

First, the present study focuses on the estimation of operating efficiency for a sample of European life and non-life insurers operating in 22 and 24 European member states respectively. Although our initial design was to include in our sample insurance companies from all the 28 member states of the EU, data availability forced us to revise our initial target. Our average efficiency results and the estimated level of beta and sigma convergence concerning operating efficiency might be affected if we were able to gain access to insurance data operating in countries that are excluded from our final sample. So, we cannot draw conclusions concerning average operating efficiency and its level of convergence for the whole of the EU-28 member countries.

Second, only the notion of beta and sigma convergence is used for estimating the level of convergence concerning efficiency of the European life and non-life sector. Phillips and Sul (2007) developed a new convergence panel methodology based on a time-varying assumption which allows for both common and individual heterogeneity over time. This method verifies whether the European insurance markets are converging concerning their efficiency scores and if so, it can analyze the speed of convergence. It also includes a club convergence algorithm which detects possible clusters of convergence (Phillips and Sul, 2007). This approach together with the results of the sigma and beta convergence tests might give us a better picture of the degree of convergence and the respective achieved financial integration in the European insurance sector. However, we have no approach to the relative software and its needed algorithm.

Finally, as it mentioned in Chapter 5, our main source of information is the Orbis database which draws data for insurance companies from the specialized A.M Best database that contains financial information for approximately 5.300 insurers in Europe. However, our database has not access to all of these corporations. The majority of our sample consists of very large and large insurance companies. Another sample that includes more companies might enable us to draw more full conclusions concerning the average efficiency and the level of beta and sigma convergence. So, the non-availability of these data does not allow us to categorize our sample in large, medium and small insurers and to estimate average efficiency scores and convergence levels for each category separately.

This thesis concludes by putting forward a number of further research suggestions to complement and perhaps to go further this existing work. These suggestions stem from the empirical findings and the research limitations of this thesis. There are several prospective areas for future research which will be described immediately below.

First, future research could test the robustness of this thesis's results by conducting sensitivity analysis and employing different output definitions, data from different sources, and different measures of efficiency. In this thesis the SFA method was preferred against the DEA since we have an international data sample and the model of Battese and Coelli (1995) allows for taking into account the country-specific environmental factors (e.g. GDP, Inflation) in the estimation of the efficiency scorers. The DEA method estimates the efficiency scores in an cross-sectional basis for each year in the sample and takes only into account the inputs used, the outputs produced and their prices. However, it can be used as a robustness check for our results.

Second, it is commonly accepted in efficiency literature that the modern frontier efficiency methodologies have become the state-of-the-art in measuring the performance of the financial institutions or other decision making units. Despite the widespread interest in efficiency research, only a few attempts to measure the linkage between efficiency and market value performance are existing (Cummins and Xie, 2009; Gaganis et. al., 2013). Cummins and Xie (2009) estimated the market-value response to acquisitions and divestitures in the US insurance market using a standard market model event study and found significant positive abnormal returns around announcement dates. Gaganis et al. (2013) found a positive and statistically important relationship between profit efficiency and market adjusted stock returns for a sample of international insurers. Another possible work in this field in a European level might further advanced the existing literature.

Third, a further step for future research would be to examine in more detail, using multiple regression analysis, the determinants of the efficiency scores. As we noted in the previous chapters, the majority of the existing insurance efficiency literature estimates only cost efficiency and tries to find its possible determinants. To the best of our knowledge, there is no research concerning the estimation of revenue efficiency in the European insurance sector and only a few studies estimate profit efficiency in the European insurance sector (e.g. Jarraya and Bouri, 2014). A further examination of the determinants of revenue and profit efficiency would be valuable to ascertain the factors affecting the operating efficiency of the European insurance sector. Such factors could involve national economic conditions, culture, differences in fiscal and legal systems, and differences in tax systems and may be significant barriers to the integration of the European insurance industry. This future research avenue may enlighten industry regulators in a possible future reform of the European regulatory system.

REFERENCES

1) Afriat, S., 1972. Efficiency Estimation of Production Functions. International Economic Review 13, 568–598.
2) Aigner, D. J., and S.-F. Chu, 1968. On Estimating the Industry Production Function. American Economic Review 58 (4), 826–39.
3) Aigner, D. J., Lovell, C. A. K., Schmidt P., 1977. Formulation and estimation of stochastic frontier production functions models. Journal of Econometrics 6(1), 21–37.
4) Aigner, D. J., Schmidt P., 1979. Specification and Estimation of Frontier Production, Profit and Cost Functions. Journal of Econometrics 13(1), 121–147.
5) Akhavein, J.D., Berger, A.N., Humphrey, D.B., 1997. The effects of megamergers on efficiency and prices: Evidence from a bank profit function. Review of Industrial Organization 12 (1997), 95-130.
6) Arrow, K., 1971. Essays in the Theory of Risk Bearing. Chicago, IL.
7) Badunenko, O., Grechanyuk, B., Talavera, O., 2006. Development under Regulation: The Way of the Ukrainian Insurance Market. Discussion Papers of DIW Berlin 644, DIW Berlin, German Institute for Economic Research.
8) Baele L., Ferrando A., Hordahl P., Krylova E., Monnet C., 2004. Measuring Financial Integration in the Euro Area. European Central Bank Occasional Paper 14.
9) Bahloul, W., Bouri, A., 2016. The Efficiency of the European Non-Life Insurance: CEO Power, Macroeconomic, and Market Characteristics Impact. International Journal of Financial Studies 4 (4), 1-13.
10) Banker, Rajiv D., 1993. Maximum Likelihood, Consistency and Data Envelopment Analysis: A Statistical Foundation. Management Science 39, 1265-1273.
11) Barro R.J., Sala-i-Martin., 1992. Convergence. The Journal of Political Economy 100 (2), 223-251.
12) Barro R.J., Sala-i-Martin., 1995. Economic Growth. McGraw Hill, New York.
13) Barros, P., Barroso, N., Borges, M. R., 2005. Evaluating the Efficiency and Productivity of Insurance Companies with a Malmquist Index: A Case Study for Portugal. Geneva Papers on Risk and Insurance 30(2), 244–267.
14) Barros, P., Obijiaku, E. L., 2007. Technical Efficiency of Nigerian Insurance Companies. Department of Economics, Institute for Economics and Business Administration (ISEG), Technical University of Lisbon. Working Papers No. 18.
15) Battese, G., and T. Coelli, 1988. Prediction of Firm-level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data. Journal of Econometrics 38, 387–399.
16) Battese, G., Coelli, T., 1995. A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. Empirical Economics 20 (2), 325-332.
17) Battese, G.E., Corra, G.S., 1977. Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia. Australian Journal of Agricultural Economics 21 (3), 169-179.
18) Beckers, D., and C., Hammond, 1987. A Tractable Likelihood Function for the Normal-Gamma Stochastic Frontier Model. Economics Letters 24, 33–38.

19) Beckmann R., Eppendorfer C., Neimke M., 2002. Financial Integration within the European Union: Towards a Single Market for Insurance. Ruhr University Working Paper, Bochum.
20) Berger, A. N., 1993. Distribution-Free Estimates of Efficiency of in the U.S. Banking Industry and Tests of the Standard Distributional Assumptions. Journal of Productivity Analysis 4(3), 261–292.
21) Berger, A. N., Cummins, J. D., Weiss, M. A., 1997. The Coexistence of Multiple Distribution Systems for Financial Services: The Case of Property-Liability Insurance. Journal of Business 70(4), 515–546.
22) Berger, A. N., Cummins, J. D., Weiss, M. A., Zi, H., 2000. Conglomeration Versus Strategic Focus: Evidence from the Insurance Industry. Journal of Financial Intermediation 9(4), 323–362.
23) Berger, A. N., Humphrey, D. B., 1991. The Dominance of Inefficiencies Over Scale and Product Mix Economies in Banking. Journal of Monetary Economics 28(1), 117–148.
24) Berger, A. N., Humphrey, D. B., 1992. Measurement and Efficiency Issues in Commercial Banking. In: Griliches, Z., ed., Output Measurement in the Service Sectors, Vol. 56, National Bureau of Economic Research, Studies in Income and Wealth, University of Chicago Press, Chicago, IL.
25) Berger, A. N., Humphrey, D. B., 1997. Efficiency of Financial Institutions: International Survey and Directions for Future Research. European Journal of Operational Research 98(2), 175–212.
26) Berger, A., and L. Mester, 1997. Inside the Black Box: What Explains Differences in Efficiencies of Financial Institutions? Journal of Banking and Finance 21, 895–947.
27) Berry-Stolzle, T., Weiss, M., Wende, S., 2011. Market Structure, Efficiency, and Performance in the European Property-Liability Insurance Industry. Working Paper, University of Georgia.
28) Bertoni F., Croce A., 2011. The Productivity of European Life Insurers: Best-Practice Adoption vs. Innovation. The Geneva Papers, 36 (2011), 165-185.
29) Biener C., Eling M., Wirfs J-H., 2016. The Determinants of Efficiency and Productivity in the Swiss Insurance Industry. European Journal of Operational Research 248 (2016), 703-714.
30) Biener, C., Eling, M., 2012. Organization and Efficiency in the International Insurance Industry: A Cross-Frontier Analysis. European Journal of Operational Research, 221 (2012), 454-468.
31) Bikker J., Gorter J., 2011. Restructuring of the Dutch Nonlife Insurance Industry: Consolidation, Organizational Form, and Focus. The Journal of Risk and Insurance 78 (1), 163-184.
32) Bikker, A., Gorter, J., 2011. Restructuring of the Dutch Nonlife Insurance Industry: Consolidation, Organizational Form, and Focus. Journal of Risk and Insurance 78 (1), 163-184.
33) Bikker, J. A., van Leuvensteijn, M., 2008. Competition and Efficiency in the Dutch Life Insurance Industry. Applied Economics 40 (16), 2063-2084.
34) Blundell R., Bond S.R., 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. Journal of Econometrics 87 (1), 115-143.
35) Boonyasai, T., Grace, M. F., Skipper, Jr., H. D., 2002. The Effect of Liberalization and Deregulation on Life Insurer Efficiency. Working Paper No. 02-2, Center for Risk Management and Insurance Research, Georgia State University.

36) Brockett, P. L., Chang, R. C., Rousseau, J. J., Semple, J. H., Yang, C, 2004b. A Comparison of HMO Efficiencies as a Function of Provider Autonomy. Journal of Risk and Insurance 71(1), 1–19.
37) Brockett, P. L., Cooper, W. W., Golden, L. L., Rousseau, J. J., Wang, Y., 2005. Financial Intermediary versus Production Approach to Efficiency of Marketing Distribution Systems and Organizational Structure of Insurance Companies. Journal of Risk and Insurance 72(3), 393–412.
38) Brockett, P. L., Cooper, W. W., Golden, L. L., Rousseau, J. J., Wang, Y., 1998. DEA Evaluations of the Efficiency of Organizational Forms and Distribution Systems in the US Property and Liability Insurance Industry. International Journal of Systems Science 29(11), 1235–1247.
39) Brockett, P. L., Cooper, W. W., Golden, L. L., Rousseau, J. J., Wang, Y., 2004a. Evaluating Solvency Versus Efficiency Performance and Different Forms of Organization and Marketing in US Property-Liability Insurance Companies. European Journal of Operational Research 154(2), 492–514.
40) Casu B., Girardone C., 2010. Integration and Efficiency in EU Banking Markets. Omega (38), 260-267.
41) Charnes, A., Cooper, W. W., Rhodes, E., 1978. Measuring the Efficiency of Decision Making Units. European Journal of Operational Research 2(6), 429–444.
42) Choi, P. B., Weiss, M. A., 2005. An Empirical Investigation of Market Structure, Efficiency, and Performance in Property-Liability Insurance. Journal of Risk and Insurance 72(4), 635–673.
43) Choi, P. B., Weiss, M. A., 2008. State Regulation and the Structure, Conduct, Efficiency and Performance of US Auto Insurers. Journal of Banking and Finance 32(1), 134–156.
44) Christensen, L. R.,D.W. Jorgenson, L.J. Lau., 1971. Conjugate the Transcendental Logarithmic Production Function. Econometrica 39, 255-256.
45) Cooper, W. W., Seiford, L. M., Tone, K., 2007. Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software. Springer, Boston, MA.
46) Cooper, W.W., L. M. Seiford, and K. Tone, 2000. Data Envelopment Analysis. Boston: Kluwer Academic Publishers.
47) Cornwell, C., P. Schmidt, and R. Sickles, 1990. Production Frontiers with Cross Sectional and Time Series Variation in Efficiency Levels. Journal of Econometrics, 46, 185–200.
48) Cummins, J. D., Dionne, G., Gagné, R., Nouira, A., 2009. Efficiency of Insurance Firms with Endogenous Risk Management and Financial Intermediation Activities. Journal of Productivity Analysis 32(2), 145-159.
49) Cummins, J. D., Nini, G. P., 2002. Optimal Capital Utilization by Financial Firms: Evidence from the Property-Liability Insurance Industry. Journal of Financial Services Research 21(1–2), 15–53.
50) Cummins, J. D., Rubio-Misas, M., 2006. Deregulation, Consolidation, and Efficiency: Evidence from the Spanish Insurance Industry. Journal of Money, Credit, and Banking 38(2), 323–355.
51) Cummins, J. D., Rubio-Misas, M., Zi, H., 2004. The Effect of Organizational Structure on Efficiency: Evidence from the Spanish Insurance Industry. Journal of Banking and Finance 28(12), 3113–3150.

52) Cummins, J. D., Tennyson, S., Weiss, M. A., 1999a. Consolidation and Efficiency in the US Life Insurance Industry. Journal of Banking and Finance 23(2–4), 325–357.
53) Cummins, J. D., Turchetti, G., Weiss, M. A., 1996. Productivity and Technical Efficiency in the Italian Insurance Industry. Working Paper, Wharton Financial Institutions Center, University of Pennsylvania, PA.
54) Cummins, J. D., Weiss, M. A., 1993. Measuring Cost Efficiency in the Property-Liability Insurance Industry. Journal of Banking and Finance 17(2–3), 463–481.
55) Cummins, J. D., Weiss, M. A., 2000. Analyzing Firm Performance in the Insurance Industry Using Frontier Efficiency Methods. In: Dionne, G., ed., Handbook of Insurance Economics. Kluwer Academic Publishers, Boston, MA.
56) Cummins, J. D., Weiss, M. A., 2012. Analyzing Firm Performance in the Insurance Industry Using Frontier Efficiency Methods. In: Dionne, G., ed., Handbook of Insurance Economics. Kluwer Academic Publishers, Boston, MA. Second Edition.
57) Cummins, J. D., Weiss, M. A., Zi, H., 1999b. Organizational Form and Efficiency: The Coexistence of Stock and Mutual Property-Liability Insurers. Management Science 45(9), 1254–1269.
58) Cummins, J. D., Weiss, M. A., Zi, H., 2010. Economics of Scope in Financial Services: A DEA Efficiency Analysis of the US Insurance Industry. Journal of Banking and Finance 34(7), 1525–1539.
59) Cummins, J. D., Xie, X., 2008. Mergers and Acquisitions in the US Property-Liability Insurance Industry: Productivity and Efficiency Effects. Journal of Banking and Finance 32(1), 30–55.
60) Cummins, J. D., Zi, H., 1998. Comparison of Frontier Efficiency Methods: An Application to the U.S. Life Insurance Industry. Journal of Productivity Analysis 10(2), 131–152.
61) Davutyan, N., Klumpes, P. J. M., 2008. Consolidation and Efficiency in the Major European Insurance Markets: A Non Discretionary Inputs Approach. Working Paper.
62) Debreu, G., 1951. The Coefficient of Resource Utilization. Econometrica 19 (3), 273-292.
63) Delhausse, B., Fecher, F., Pestieau, P., 1995. Measuring Productive Performance in the Non-Life Insurance Industry: The Case of French and Belgian Markets. Tijdschrift voor Economie en Management 40(1), 47–69.
64) Deprins, D., L. Simar, and H. Tulkens 1984. “Measuring Labor-Efficiency in Post Offices,” in M. Marchand, P. Pestieau, and H. Tulkens, eds., The Performance of Public Enterprises: Concepts and Measurement. Amsterdam, North-Holland.
65) Deprins, E., Simar, L., Tulkens, H., 1984. Measuring Labor Efficiency in Post Offices. In: Marchand, M., Pestieau, P., Tulkens, H., eds., The Performance of Public Enterprises: Concepts and Measurement. North Holland, Amsterdam.
66) Dermine, J., 2006. European Banking Integration: Don’t Put the Cart Before the Horse. Financial Institutions, Markets, and Money 15 (3), 57-106.
67) DeYoung R., Hasan I., 1998. The Performance of de Novo Commercial Banks: a Profit Efficiency Approach. Journal of Banking and Finance 22 (5), 565-587.

68) Diacon, S. R., 2001. The Efficiency of UK General Insurance Companies. Working Paper, Centre for Risk & Insurance Studies, University of Nottingham.
69) Diacon, S. R., Starkey, K., O'Brien, C., 2002. Size and Efficiency in European Long-Term Insurance Companies: An International Comparison. Geneva Papers on Risk and Insurance 27(3), 444–466.
70) Diboky, F., Ubl, E., 2007. Ownership and Efficiency in the German Life Insurance Market: A DEA Bootstrap Approach. Working Paper, University of Vienna.
71) Doff, R., 2011. Risk Management for Insurers. Risk Control, Economic Capital, and Solvency II. Risk Books Publications, 2011. Second Edition.
72) Donni, O., Fecher, F., 1997. Efficiency and Productivity of the Insurance Industry in the OECD Countries. Geneva Papers on Risk and Insurance 22, 523–535.
73) Eling, M., Huang, W., 2013. An Efficiency Comparison of the Non-Life Insurance Industry in the BRIC Countries. European Journal of Operational Research 226(3) 577-591.
74) Eling, M., Luhnen, M. 2010a. Efficiency in the International Insurance Industry: A Cross-country Comparison. Journal of Banking and Finance 34 (7), 1497-1509.
75) Eling, M., Luhnen, M. 2010b. Frontier Efficiency Methodologies to Measure Performance in the Insurance Industry: Overview, Systemization, and Recent Developments. The Geneva Papers on Risk and Insurance 35 (2), 217–265.
76) Eling, M., Schaper, P., 2017. Under pressure: how the business environment affects productivity and efficiency of European life insurance companies. European Journal of Operational Research 258 (2017), 1082-1094.
77) Elyasiani, E., Mehdian, S.M., 1990. Efficiency in the commercial banking industry. A production frontier approach. Applied Economics 22 (1990), 539-551.
78) English, M., Grosskopf, S., Hayes, K., Yaisawamg, S., 1993. Output allocative and technical efficiency of banks. Journal of Banking and Finance 17 (1993), 349-366.
79) Ennsfellner, K. C., Lewis, D., Anderson, R. I., 2004. Production Efficiency in the Austrian Insurance Industry: A Bayesian Examination. Journal of Risk and Insurance 71(1), 135–159.
80) Erhemjamts, O., Leverty, J. T., 2007. The Demise of the Mutual Organizational Form: An Investigation of the Life Insurance Industry. Working Paper.
81) European Central Bank (ECB), 2010. Financial Integration in Europe. April Report.
82) European Central Bank (ECB), 2011. Financial Integration in Europe. April Report.
83) European Central Bank (ECB), 2015. Financial Integration in Europe. April Report.
84) European Central Bank, 2006. Differences in MFI Interest Rates across Euro Area Countries. September Report.
85) Färe, R., and Grosskopf, S. (2004) New directions: Efficiency and productivity, Kluwer academic Publishers.

86) Fare, R., Grosskopf, S., Weber, W., 2004. The Effect of Risk-Based Capital Requirements on Profit Efficiency in Banking. Applied Economics 36 (15), 1731-1743.
87) Färe, Rolf, Shawna Grosskopf, Dimitris Margaritis, 2008. "Efficiency and Productivity: Malmquist and More," in H.O. Fried, C.A.K. Lovell, and S.S. Schmidt, eds,. The Measurement of Productive Efficiency and Productivity Growth. Oxford University Press, New York.
88) Farrell, M. J., 1957. The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Series A, General 120 (3), 253–82.
89) Fecher, F., Kessler, D., Perelman, S., Pestieau, P., 1993. Productive Performance in the French Insurance Industry. Journal of Productivity Analysis 4(1–2), 77–93.
90) Fecher, F., Perelman, S., Pestieau, P., 1991. Scale Economics and Performance in the French Insurance Industry. Geneva Papers on Risk and Insurance 16, 315–326.
91) Fenn, P., Vencappa, D., Diacon, S., Klumpes, P., O'Brien, C., 2008. Market Structure and the Efficiency of European Insurance Companies: A Stochastic Frontier Analysis. Journal of Banking and Finance 32(1), 86–100.
92) Fiordelisi, F., Molyneux, P., 2010. The Determinants of Shareholder Value in European Banking. Journal of Banking and Finance 34 (6), 1189-1200.
93) Fisher, I. (1922). The Making of Index Numbers. Boston, Houghton-Mifflin.
94) Fried, H., Lovell, C., Schmidt, S., 2008. The Measurement of Productive Efficiency and Productivity Growth. Oxford University Press, New York.
95) Fuentes, H., Grifell-Tatjé, E., Perelman, S., 2001. A Parametric Distance Function Approach for Malmquist Productivity Index Estimation. Journal of Productivity Analysis 15(2), 79–94.
96) Fuentes, H., Grifell-Tatjé, E., Perelman, S., 2005. Product Specialization, Efficiency and Productivity Change in the Spanish Insurance Industry. Working Paper, Université de Liège.
97) Fukuyama, H., 1997. Investigating Productive Efficiency and Productivity Changes of Japanese Life Insurance Companies. Pacific-Basin Finance Journal 5(4), 482–509.
98) Fukuyama, H., Weber, W. L., 2001. Efficiency and Productivity Change of Non-Life Insurance Companies in Japan. Pacific Economic Review 6(1), 129–146.
99) Fung M., 2006. Scale Economies, x-Efficiency, and Convergence of Productivity among Bank Holding Companies. Journal of Banking and Finance 30 (10), 2857-2874.
100) Gaganis, C., Hasan, I., Pasiouras, F., 2013. Efficiency and Stock Returns: Evidence from the Insurance Industry. Journal of Productivity Analysis 40 (3), 429-442.
101) Gardner, L. A., Grace, M. F., 1993. X-Efficiency in the US Life Insurance Industry. Journal of Banking and Finance 17(2–3), 497–510.
102) Greene, W. H., Segal, D., 2004. Profitability and Efficiency in the U.S. Life Insurance Industry. Journal of Productivity Analysis 21(3), 229–247.
103) Greene, W., 1980a. Maximum Likelihood Estimation of Econometric Frontier Functions. Journal of Econometrics 13, 27–56.
104) Greene, W., 1980b. On the Estimation of a Flexible Frontier Production Model, Journal of Econometrics 3, 101–115.

105) Greene, W., 1990. A Gamma Distributed Stochastic Frontier Model. Journal of Econometrics 46, 141–163.
106) Greene, W., 2008. “The Econometric Approach to Efficiency Analysis” in Fried, H., Lovell, C., Schmidt, S., 2008 eds., The Measurement of Productive Efficiency and Productivity Growth. Oxford University Press, New York.
107) Guiso L., Jappeli T., Padula M., Pagano M., 2004. Financial Market Integration and Economic Growth in the EU. Economic Policy, 524-527.
108) Hancock, D., 1985. The Financial Firm: Production with Monetary and Non-Monetary Goods. Journal of Political Economy 93 (5), 859-880.
109) Hao, J. C. J., 2007. Efficiency Test on Taiwan’s Life Insurance Industry Using X-Efficiency Approach. Information and Management Sciences 18(1), 37–48.
110) Hao, J. C. J., Chou, L. Y., 2005. The Estimation of Efficiency for Life Insurance Industry: The Case in Taiwan. Journal of Asian Economics 16(5), 847–860.
111) Hardwick, P., 1997. Measuring Cost Inefficiency in the UK Life Insurance Industry. Applied Financial Economics 7(1), 37–44.
112) Hardwick, P., Adams, M., Zou, H., 2004. Corporate Governance and Cost Efficiency in the United Kingdom Life Insurance Industry. Working Paper.
113) Harrington, S., Niehaus, G., 2004. Risk Management and Insurance. McGraw-Hill Publications, 2004. Second Edition.
114) Hasan, I., W. C., Hunter 1996. Efficiency of Japanese Multinational Banks in the US. Research in Finance 14, Greenwich, CT: JAI Press, 157-173.
115) He E., Sommer D., Xie X., 2011. The Impact of CEO Turnover on Property-Liability Insurer Performance. The Journal of Risk and Insurance, 78 (3), 583-608.
116) Hirao, Y., Inoue, T., 2004. On the Cost Structure of the Japanese Property-Casualty Insurance Industry. Journal of Risk and Insurance 71(3), 501–530.
117) Hsu W-Y., Petchsakulwong P., 2010. The Impact of Corporate Governance on the Efficiency Performance of the Thai Non-Life Insurance Industry. The Geneva Papers 35 (2010), 528-549.
118) Huang L-Y., Lai G., McNamara M., Wang J, 2011. Corporate Governance and Efficiency: Evidence from U.S Property-Liability Insurance Industry. Journal of Risk and Insurance 78 (3), 519-550.
119) Huang, W., 2007. Efficiency in the China Insurance Industry: 1999–2004. Working Paper. Wuhan University, University of Toronto.
120) Humphrey, D., and L. Pulley, 1997. Banks’ Responses to Deregulation: Profits, Technology and Efficiency. Journal of Money, Credit and Banking 29 73–93.
121) Hussels, S., Ward, D. R., 2006. The Impact of Deregulation on the German and UK Life Insurance Markets: An Analysis of Efficiency and Productivity Between 1991–2002. Working Paper, Cranfield Research Paper Series (4).
122) Hwang, S. N., Kao, C., 2008. Efficiency Decomposition in Two-Stage Data Envelopment Analysis: An Application to Non-Life Insurance Companies in Taiwan. European Journal of Operational Research 185(1),418–429.

123) Jarraya B., Bouri A., 2014. Optimal Production Plan and Profit Efficiency in European Non-Life Insurance Companies. Procedia Economics and Finance 13 (2014), 69-81.
124) Jeng, V., Lai, G. C., 2005. Ownership Structure, Agency Costs, Specialization, and Efficiency: Analysis of Keiretsu and Independent Insurers in the Japanese Nonlife Insurance Industry. Journal of Risk and Insurance 72(1), 105–158.
125) Jeng, V., Lai, G. C., McNamara, M. J., 2007. Efficiency and Demutualization: Evidence from the U.S. Life Insurance Industry in the 1980s and 1990s. Journal of Risk and Insurance 74(3), 683–711.
126) Jondrow, J., Lovell, K., Materov, I., and Schmidt P., 1982. On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model. Journal of Econometrics 19, 233–238.
127) Kasman A., Yildirim C., 2006. Cost and Profit Efficiencies in Transition Banking: the Case of New EU Members. Applied Economics 38 (9), 1079-1090.
128) Klumpes P., Schuermann S., 2011. Corporate, Product, and Distribution Strategies in the European Life Insurance Industry. The Geneva Papers 36 (2011), 50-75.
129) Klumpes, P. J. M., 2004. Performance Benchmarking in Financial Services: Evidence from the UK Life Insurance Industry. Journal of Business 77(2), 257–274.
130) Klumpes, P. J. M., 2007. Consolidation and Efficiency in the Major European Insurance Markets. Working Paper, Imperial College, London.
131) Koopmans, T. C., 1951. "An Analysis of Production as an Efficient Combination of Activities," in T. C. Koopmans, ed., Activity Analysis of Production and Allocation. Cowles Commission for Research in Economics Monograph No. 13. New York, John Wiley and Sons.
132) Kumbhakar, S. 2006. Specification and Estimation of Nonstandard Profit Functions. Empirical Economics 31 (1), 243–260.
133) Kumbhakar, S. C., Lovell, C. A. K., 2000. Stochastic Frontier Analysis. Cambridge University Press.
134) Kumbhakar, S., 1990. Production Frontiers and Panel Data, and Time Varying Technical Inefficiency. Journal of Econometrics 46, 201–211.
135) Leverty, T. J., Grace, M. F., 2008. Issues in Measuring the Efficiency of Property-Liability Insurers. Working Paper.
136) Leverty, T., Lin, Y., Zhou, H., 2004. Firm Performance in the Chinese Insurance Industry. Working Paper. Georgia State University.
137) Lozano-Vivas, A., 1997. Profit Efficiency for Spanish Savings Banks. European Journal of Operational Research 98, 381–394.
138) Luhnen, M. 2008. Determinants of Efficiency and Productivity in German Property-Liability Insuracne: Evidence for 1995–2006. Working Paper, University of St. Gallen.
139) Mahlberg B., Url T., 2010. Single Market Effects on Productivity in the German Insurance Industry. Journal of Banking and Finance 34 (7), 1540-1548.
140) Mahlberg, B., Url, T., 2000. The Transition to the Single Market in the German Insurance Industry. Working Paper, Austrian Institute of Economic Research.

141) Mahlberg, B., Url, T., 2003. Effects of the Single Market on the Austrian Insurance Industry. Empirical Economics 28(4), 823–838.
142) Mamatzakis E., Staikouras C., Koutsomanoli-Filippaki A., 2008. Bank Efficiency in the New European Union Member States: Is There Convergence? International Review of Financial Analysis 17 (2008), 1156-1172.
143) Matousek R., Rughoo A., Sarantis N., Assaf A.G., 2015. Bank Performance and Convergence during the Financial Crisis: Evidence from the 'Old' European Union and Eurozone. Journal of Banking and Finance 52 (March 2015), 208-216.
144) Maudos J., Pastor M., Perez F., Quesada J., 2002. Cost and Profit Efficiency in European banks. Journal of International Financial Markets, Institutions and Money 12 (1), 33-58.
145) Meador, J. W., Ryan, Jr., H. E., Schellhorn, C. D., 2000. Product Focus Versus Diversification: Estimates of XEfficiency for the US Life Insurance Industry. Working Paper, Wharton Financial Institutions Center, University of Pennsylvania.
146) Meeusen,W., and J. Van den Broeck, 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. International Economic Review 18 (2), 435–44.
147) Miller, S.M., Noulas, A.G., 1996. The technical efficiency of large bank production. Journal of Banking and Finance 20 (1996), 495-509.
148) Murinde V., Agung J., Mullineux A., 2004. Patterns of Corporate Financing and Financial System Convergence in Europe. Review of International Economics 12 (4), 693-705.
149) Nektarios M., Barros C-P., 2010. A Malmquist Index for the Greek Insurance Industry. The Geneva Papers 35 (2010), 309-324.
150) Noulas, A. G., Hatzigayios, T., Lazaridis, J., Lyroudi, K., 2001. Non-Parametric Production Frontier Approach to the Study of Efficiency of Non-Life Insurance Companies in Greece. Journal of Financial Management and Analysis 14(1), 19–26.
151) Pestana-Barros, C., Nektarios, M., Assaf, A., 2010. Efficiency in the Greek Insurance Industry. European Journal of Operational Research 205 (2010), 431-436.
152) Pestana-Barros, C., Wanke, P., 2014. Insurance Companies in Mozambique: A Two-Stage DEA and Neural Networks on Efficiency and Capacity Slacks. Applied Economics 46 (29), 3591-3600.
153) Pestana-Barros, C., Wanke, P., 2017. Technology Gaps and Capacity Issues in African Insurance Companies: Selected Country Evidence. Journal of International Development 29 (2017), 117-133.
154) Phillips P.C.B., Sul D., 2007. Transition Modelling and Econometric Convergence Tests. Econometrica 75 (6), 1771-1855.
155) Pulley, L. B., Braunstein, Y., 1992. A Composite Cost Function for Multiproduct Firms with an Application to Economies of Scope in Banking. Review of Economics and Statistics 74(2), 221–230.
156) Qiu, S., Chen, B., 2006. Efficiencies of Life Insurers in China—An Application of Data Envelopment Analysis. Working Paper.
157) Quah D., 1996. Empirics for Economic Growth and Convergence. European Economic Review 40 (6), 1353-1376.

158) Rai, A., 1996. Cost Efficiency of International Insurance Firms. Journal of Financial Services Research 10(3), 213–233.
159) Ray, S., 2004. Data Envelopment Analysis: Theory and Techniques for Economics and Operations Research. Cambridge University Press, New York.
160) Ray, Subhash and E., Desli, 1997. Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries: Comment. American Economic Review 87, 1033-1039.
161) Rees, R., Kessner, E., Klemperer, P., Matutes, C., 1999. Regulation and Efficiency in European Insurance Markets. Economic Policy 14(29), 363–397.
162) Richmond, J., 1974. Estimating the Efficiency of Production. International Economic Review 15, 515–521.
163) Rousseau, J. J., and J. Semple, 1995, Two-Person Ratio Efficiency Games. Management Science 41 (3), 435-441.
164) Ryan, Jr., H. E., Schellhorn, C. D., 2000. Life Insurer Cost Efficiency Before and After Implementation of the NAIC Risk-Based Capital Standards. Journal of Insurance Regulation 18(3), 362–384.
165) Saunders, A., Cornett, M-M., 2008. Financial Institutions Management: A Risk Management Approach. McGraw-Hill Publications, 2008. Sixth Edition.
166) Shephard, R. W., 1953. Cost and Production Functions. Princeton, NJ. Princeton University Press.
167) Shephard, R. W., 1970. Theory of Cost and Production Functions. Princeton, NJ: Princeton University Press.
168) Simar L., Wilson P., 2007. Estimation and Inference in Two-Stage, Semi-Parametric Models of Production Processes. Journal of Econometrics 136(1), 31–64.
169) Snedecor G.W., Cochran W.G., 1989. Statistical Methods. Iowa State University Press, Ames.
170) Stevenson, R., 1980. Likelihood Functions for Generalized Stochastic Frontier Estimation. Journal of Econometrics 13, 58–66.
171) Talat Afza, Jam-E-Kausar, 2008. Technical Efficiency of Non-life Insurance Companies in Pakistan. COMSATS Institute of Information Technology Working Paper. Lahore, Pakistan.
172) Taylor, G., 2000. Loss Reserving. An Actuarial Perspective. Springer Publications.
173) Toivanen, O., 1997. Economies of Scale and Scope in the Finnish Non-Life Insurance Industry. Journal of Banking and Finance 21(6), 759–779.
174) Tone, K., Sahoo, B. K., 2005. Evaluating Cost Efficiency and Returns to Scale in the Life Insurance Corporation of India Using Data Envelopment Analysis. Socio-Economic Planning Sciences 39(4), 261–285.
175) Tornqvist, L. (1936). The Bank of Finland's Consumption Price Index. Bank of Finland Monthly Bulletin 10, 1–8.
176) Trainar, P., 2001. The Role of Insurance in Ensuring Financial Market Liquidity. The Geneva Papers on Risk and Insurance 26 (3), 346-359.
177) Trigo Gamarra, L., 2008. The Effects of Liberalization and Deregulation on the Performance of Financial Institutions: The Case of the German Life Insurance Market. Working Paper, University of Rostock.
178) Trigo Gamarra, L., Growitsch, C., 2008. Single- versus Multi-Channel Distribution Strategies in the German Life Insurance Market: A Cost and

Profit Efficiency Analysis. Thünen-Series of Applied Economic Theory. Working Paper No. 81, University of Rostock.
179) Turchetti, G., Daraio, C., 2004. How Deregulation Shapes Market Structure and Industry Efficiency: The Case of the Italian Motor Insurance Industry. The Geneva Papers on Risk and Insurance - Issues and Practice29(2), 202–218.
180) Vajanne L., 2007. Integration in Euro Area Retail Banking Markets-Convergence of Credit Interest Rates. Bank of Finland Research Discussion Papers, no. 27.
181) Vaughan, E., Vaughan, T., 2008. Fundamentals of Risk and Insurance. John Wiley and Sons Publications, 2008. Tenth Edition.
182) Vencappa, D., Fenn, P., Diacon, S., 2008. Parametric Decomposition of Total Factor Productivity Growth in the European Insurance Industry: Evidence from Life and Non-Life Companies. Working Paper.
183) Vencappa, D., Fenn, P., Diacon, S., 2013. Productivity Growth in the European Insurance Industry: Evidence from Life and Non-Life Companies. International Journal of the Economics of Business 20 (2), 281-305.
184) Wagenvoort, R., Schure, P., 1999. The Recursive Thick Frontier Approach to Estimating Efficiency. European Investment Bank Working Paper. Economic and Financial Report 1999/02.
185) Ward, D., 2002. The Costs of Distribution in the UK Life Insurance Market. Applied Economics 34(15), 1959–1968.
186) Weill L., 2009. Convergence in Banking Efficiency across European Countries. Journal of International Financial Markets, Institutions and Money 19 (2009), 818-833.
187) Weiss, M. A., 1991. Efficiency in the Property-Liability Insurance Industry. Journal of Risk and Insurance 58(3), 452–479.
188) Weiss, M. A., 1991b. International P/L Insurance Output, Input, and Productivity Comparisons. Geneva Papers on Risk and Insurance Theory 16(2), 179–200.
189) Wende, S., Berry-Stölzle, T. R., Lai, G. L., 2008. The Effect of Regulation on Comparative Advantages of Different Organizational Forms: Evidence from the German Property-Liability Insurance Industry. Working Paper, University of Cologne.
190) Winsten, C. B., 1957. Discussion of Mr. Farrell's Paper. Journal of the Royal Statistical Society Series A, General 120 (3), 282–84.
191) Worthington, A. C., Hurley, E. V., 2002. Cost Efficiency in Australian General Insurers: A Non-Parametric Approach. British Accounting Review 34(2), 89–108.
192) Wu, D., Yang, Z., Vela, S., Liang, L., 2007. Simultaneous Analysis of Production and Investment Performance of Canadian Life and Health Insurance Companies Using Data Envelopment Analysis. Computers & Operations Research 34(1), 180–198.
193) Xie X., Lu W., Reising J., Stohs M-H., 2011. Demutualization, Control, and Efficiency in the U.S Life Insurance Industry. The Geneva Papers, 36 (2011), 197-225.
194) Xie, X., 2010. Are Publicly Held Firms Less Efficient? Evidence from the US Property-Liability Insurance Industry. Journal of Banking and Finance 34(7), 1549–1563.

195) Yang, Z., 2006. A Two-Stage DEA Model to Evaluate the Overall Performance of Canadian Life and Health Insurance Companies and Computer. Mathematical and Computer Modeling 43(7–8), 910–919.

196) Yao, S., Han, Z., Feng, G., 2007. On the Technical Efficiency of China's Insurance Industry after WTO Accession. China Economic Review 18(1), 66–86.

197) Young A., Higgins M., Levy D., 2008. Sigma Convergence versus Beta Convergence: Evidence from U.S Country-Level Data. Journal of Money, Credit, and Banking 40 (5), 1083-1093.

198) Young, A., Higgins, M., Levy, D., 2008. Sigma Convergence versus Beta Convergence: Evidence from U.S. County-Level Data. Journal of Money, Credit and Banking 40 (5), 1083-1093.

199) Yuan, Y., Phillips, R. D., 2008. Financial Integration and Scope Efficiency in U.S. Financial Services Post Gramm-Leach-Bliley. Working Paper.

200) Yuengert, A. M., 1993. The Measurement of Efficiency in Life Insurance: Estimates of a Mixed Normal-Gamma Error Model. Journal of Banking and Finance 17(2–3), 483–496.

201) Zanghieri, P., 2008. Efficiency of European Insurance Companies: Do Local Factors Matter? Working Paper, Association of Italian Insurers, Rome.

202) Zhang, Y., Bartles, R., 1998. The Effect of Sample Size on the Mean Efficiency in DEA With an Application to Electricity Distribution in Australia, Sweden, and New Zealand. Journal of Productivity Analysis 9 (3), 187-204.