VILNIUS UNIVERSITY

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FRONTIER METHODS FOR ANALYSIS OF THE PRODUCTIVE EFFICIENCY AND TOTAL FACTOR PRODUCTIVITY: LITHUANIAN AGRICULTURE AFTER ACCESSION TO THE EUROPEAN UNION

Doctoral Dissertation

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VILNIAUS UNIVERSITETAS

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RIBINIAI METODAI GAMYBINIO EFEKTYVUMO IR BENDROJO PRODUKTYVUMO ANALIZEI: LIETUVOS ŽEMĖS ŪKIO SEKTORIUS PO ĮSTOJIMO Į EUROPOS SĄJUNGĄ

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Abstract

The research aims to develop an integrated framework for measurement and analysis the productive efficiency of Lithuanian family farms and identify the related implications for efficiency improvement. The proposed framework is mainly based on the non-parametric frontier methods. Object of the research is Lithuanian family farms reporting to the Farm Accountancy Data Network. The research features both empirical and theoretical novelty in that it develops some new techniques for efficiency analysis and employs them to analyse the performance of Lithuanian family farms.

The efficiency analysis rests on the neoclassical production theory. The research is mainly based on the non-parametric technique, viz. DEA. The latter technique is implemented by the means of the linear programming. The robust production frontiers are estimated via the bootstrapping and Monte Carlo simulations. The uncertainty is dealt with by the means of the fuzzy numbers. The program (i. e. farming type) efficiency is assessed by utilising the MEA methodology along with the meta-frontier approach. The TFP changes are measured by employing the TFP indices, which are based on the DEA models. The results are analysed by the means of the regression models (truncated regression, panel models) and multivariate statistical methods (namely cluster analysis and multiple correspondence analysis).

Anotacija

Tyrimo tikslas – pasiūlius integruotą Lietuvos ūkininkų ūkių gamybinio efektyvumo matavimo ir analizės metodiką, numatyti atitinkamas žemės ūkio efektyvumo didinimo kryptis. Pasiūlyta metodika remiasi neparametriniais ribiniais metodais. Tikslui pasiekti keliami šie uždaviniai: 1) pristatyti efektyvumo analizės praktiką ir mokslinio tyrimo metodiką; 2) pasiūlyti žemės ūkio efektyvumo analizei tinkamus metodus; 3) įvertinti Lietuvos ūkininkų ūkių veiklos efektyvumą taikant neparametrinius metodus; 4) atlikti technologijos, būdingos nagrinėjamam sektoriui, ir jos pokyčių analizę; 5) kiekybiškai įvertinti efektyvumo ir produktyvumo veiksnių poveikį.

Efektyvumo analizė remiasi neoklasikine gamybos teorija. Tyrimui daugiausia naudojamas neparametrinis metodas, t. y. duomenų apgaubties analizė (DEA). Pastarasis metodas įgyvendinamas tiesinio programavimo modelių pagalba. Nuokrypiams atsparios gamybos ribos įvertinamos taikant saviranką ir Monte Karlo simuliaciją. Siekiant atsižvelgti į neapibrėžtumą, taikoma neraiškiųjų skaičių teorija. Programinis (ūkininkavimo tipų) efektyvumas vertinamas taikant daugiakryptę efektyvumo analizę (MEA) ir meta-ribos požiūrį. Bendrojo produktyvumo pokyčių analizė remiasi bendrojo produktyvumo indeksais, kurie apskaičiuojami DEA pagalba. Gautieji rezultatai yra analizuojami taikant regresijos modelius (nupjauta regresija, panelinė regresija), daugiamatės statistikos metodais (sankaupų analizė, dauginė atitikties analizė).

Contents

Abbreviations

BCC –	Banker, R. D., Charnes, A., Cooper, W. W.
CAP –	Common Agricultural Policy
CCR –	Charnes, A., Cooper, W. W., Rhodes, E.
CRS –	Constant Returns to Scale
DEA –	Data Envelopment Analysis
DMU –	Decision Making Unit
DRS –	Decreasing Returns to Scale
EC –	Efficiency Change
EU –	European Union
FADN –	Farm Accountancy Data Network
IRS –	Increasing Returns to Scale
NIRS –	Non-increasing Returns to Scale
SFA –	Stochastic Frontier Analysis
TC –	Technical Change
TE –	Technical Efficiency
TFP –	Total Factor Productivity
VRS –	Variable Returns to Scale

Acknowledgments

I should like to extend my gratitude to Dr Romualdas Valkauskas and Dr Irena Kriščiukaitienė, who guided my research and supported me in a very special way. I am also indebted to Dr Algirdas Bartkus, who supervised my MSc research, which has become a part of the thesis. Sincere thanks go to Prof. Jens Leth Hougaard, Prof. Mette Asmild, and Prof. Kristof De Witte, who worked with me during research visits.

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INTRODUCTION

The foremost goal of any economic research is to ensure the proper allocation of resources and thus achieve social and economic welfare (Latruffe, 2010). In order to identify the most promising practice one needs to employ respective methodology. Performance management aims at identifying and spreading the best practices within an organization, sector, or the whole economy. The relative performance evaluation—benchmarking—is the systematic comparison of one production entity (decision making unit) against other entities (Bogetoft, Otto, 2011). Indeed, benchmarking is an important issue for both private and public decision makers to ensure the sustainable change. Due to Jack and Boone (2009) benchmarking can create motivation for change; provide a vision for what an organization can look like after change; provide data, evidence, and success stories for inspiring change; identify best practices for how to manage change; and create a baseline or yardstick by which to evaluate the impact of earlier changes.

Reasonable strategic decision making requires an integrated assessment of the regulated sector. The agricultural sector is related to voluminous public support as well as regulations. The application of benchmarking, thus, becomes especially important when fostering sustainable agricultural development. Furthermore, productive efficiency gains might result into lower costs as well as greater profit margins for the producer and better prices for the participants in the agricultural supply chain (Samarajeewa et al., 2012). Nauges et al. (2011) presented the following factors stressing the need for research into agricultural efficiency. First, agricultural producers typically own land and live on their farms, therefore the standard assumption that only efficient producers are to maintain their market activity usually does not hold in agriculture; moreover, suchlike adjustments would result in various social problems. Second, it is policy interventions—education, training, and extension programmes—that should increase the efficiency. Third, policy issues relating to farm structure are of high importance across many regions.

In order to perform appropriate benchmarking it is necessary to fathom the terms of effectiveness, efficiency, and productivity. One can evaluate effectiveness when certain utility or objective function is defined (Bogetoft, Otto, 2011). In the real life, however, this is not the case and the ideal behaviour can be described only by analysing the actual data, i. e. by the means of benchmarking. Finally, productivity means the ability to convert inputs to outputs. There can be a distinction made between total factor productivity (Solow, 1957) and partial (single factor) productivity. The productivity growth is a source of a non-inflatory growth and thus should be encouraged by a means of benchmarking and efficiency management.

It is due to Alvarez and Arias (2004) and Gorton and Davidova (2004) that frontier techniques are the most widely applied methods for efficiency measurement in agriculture. Indeed, the frontier methods can be grouped into parametric and non-parametric ones. For instance, Aysan et al. (2011) employed stochastic frontier analysis for assessment of the Turkish banking sector. Rasmussen (2011) employed the same method for analysis of the Danish farms. Chou et al. (2012) employed stochastic frontier analysis to measure performance of the IT capital goods sectors across OECD countries. Zhan (2012) analysed the properties of different stochastic frontier specifications. Aristovnik (2012) utilized the non-parametric technique, namely data envelopment analysis, to analyse the efficiency of R&D expenditures in some European Union Member States. Bojnec and Latruffe (2011) as well as Davidova and Latruffe (2007) applied data envelopment analysis to assess the performance of Slovenian and Czech farms, respectively. Bilgin et al. (2012) attempted to research into the Chinese firm performance by the means of the deterministic Cobb-Douglas frontier. Latruffe et al. (2004) applied both stochastic frontier analysis and data envelopment analysis to analyse the technical efficiency of the Polish farms. Rahman and Salim (2013) employed the Fare-Primont index to analyse the TFP growth in the Bangladesh agriculture.

Topicality of the research. Family farming has been reinvigorating in Lithuania since early 1990s when the collective farming system was deconstructed. Since then the Lithuanian farming system has undergone many economic, structural, and institutional reforms. Year 2004 marks the accession to the European Union (EU) which is related to the Common Agricultural Policy. The Lithuanian farming system, however, is not fully developed yet. In terms of the utilized agricultural area, the average Lithuanian farm expanded from 9.2 ha up to 13.7 ha during 2003–2010, whereas the total utilized agricultural area increased by some 10% and the number of agricultural holdings decreased by 27% from 272 thousand down to less than 200 thousand (Statistics Lithuania, 2014). Indeed, the number of the smallest farms has decreased and these adjustments lead to a farm structure which is similar to that of the European countries. There is, however, a substantial area of state-owned or abandoned land which can be employed for the agricultural activities in the future. Therefore it is important to analyse the farming efficiency which might impact a number of factors influencing farmers' decisions.

Research problem. The research is motivated by both importance of efficiency measurement and lack of suchlike studies in the Lithuanian context. Lithuanian farming system is still underperforming if compared to the western standards. Thus, it is important to identify certain types of farming which are the forerunners or laggards in terms of operation efficiency. Furthermore, both public and private investments are needed in the agricultural sector to improve its efficiency and productivity (OECD, FAO, 2011). To be specific, some 2.287 billion EUR were assigned under the Lithuanian Rural Development Programme for 2007–2013. The appropriate allocation of such investments, however, requires a decision support system based on multi–objective optimization. Consequently, it is important to develop benchmarking frameworks and integrate them into the processes of the strategic management. The forthcoming programming period of 2014–2020 together with the new Rural Development Programme will certainly require suchlike management decisions. Up to now, only a handful of studies attempted to analyse the farming efficiency in Lithuania (Rimkuvienė et al., 2010, Douarin, Latruffe, 2011; Baležentis, Baležentis, 2011, 2013; Baležentis, Kriščiukaitienė, 2012a). Moreover, these papers were focused on diachronic analysis or different farming types were analysed by employing single–period data. Another issue to be tackled is post–efficiency analysis. Indeed, the uncertainties associated with the agricultural production data do also require appropriate techniques for efficiency estimation.

The research **aims** to develop an integrated framework for measurement and analysis the productive efficiency of Lithuanian family farms and identify the related implications for efficiency improvement. The proposed framework is mainly based on the non-parametric frontier methods. The following **tasks** are, therefore, set: (i) to present the research methodology for efficiency analysis, (ii) to develop the appropriate techniques for analysis of the agricultural efficiency; (iii) to estimate the technical efficiency of Lithuanian family farms by the means of the non-parametric techniques, (iv) to analyse the underlying technology as well as its shifts, and (v) to quantify the impact of the efficiency and productivity change effects. **Object** of the research is Lithuanian family farms reporting to the Farm Accountancy Data Network.

Novelty of the research. The research features both empirical and theoretical novelty in that it develops some new techniques for efficiency analysis and employs them to analyse the performance of Lithuanian family farms. Specifically, the hybrid method DEA-MULTIMOORA is introduced to analyse the TFP changes with respect to multiple criteria. In addition, the fuzzy FDH method based on α-cuts is suggested to tackle the uncertainty associated with the production data. The MEA method is extended to the meta-frontier analysis. Considering the empirical novelty, the research develops and employs a systematic framework for the analysis of the agricultural sector in terms of the efficiency and TFP measures. The research thus estimates the technical, allocative, and cost efficiency of Lithuanian family farms. A variety of TFP indices, viz. Malmquist, Hicks-Moorsteen, Färe-Primont, Malmquist-Luenberger indices, are employed to estimate the TFP change as well as bias of the production frontier. The factors driving the change in the analysed variables are also identified by employing regression and multivariate statistics. Furthermore, the optimal farm size is estimated by the means of DEA. Noteworthy, these measures have not been estimated for Lithuanian family farms ever before. The results of the research provide certain insights into the causes and sources of (in)efficiency prevailing among Lithuanian family farms. Suchlike information can be used to facilitate a reasonable decision making, especially at the macro level.

Practical value. The research estimates the level of efficiency for different farming types along with the determinants of efficiency. Therefore, it is possible to identify the causes of inefficiency prevailing among Lithuanian family farms. Suchlike knowledge thus is beneficial for decision makers and farmers themselves in order to better understand the ways efficiency can be improved. Analysis of the most productive scale size is particularly important for land market regulation, which limits the maximal land area per farm. The methodologies proposed in the research can also be employed in other instances of economic analysis and thus contribute to reasonable managerial decision making.

Research methodology. The efficiency analysis rests on the neoclassical production theory. The research is mainly based on the non-parametric technique, viz. DEA. The latter technique is implemented by the means of the linear programming. The robust production frontiers are estimated via the bootstrapping and Monte Carlo simulations. The uncertainty is dealt with by the means of the fuzzy numbers. The program (i. e. farming type) efficiency is assessed by utilising the MEA methodology along with the meta-frontier approach. The TFP changes are measured by employing the TFP indices, which are based on the DEA models. The results are analysed by the means of the regression models (truncated regression, panel models) and multivariate statistical methods (namely cluster analysis and multiple correspondence analysis).

The study is therefore **structured** as follows. Section 1 presents the preliminaries for efficiency analysis along with general trends prevailing in Lithuanian agriculture. Section 2 presents methodology of the research. Section 3 focuses on the performance of Lithuanian family farms. The latter section also attempts to present the position of agricultural sector among other sectors of Lithuanian economy. In order to account for uncertainties in the data, the technical efficiency is further analysed by the means of the simulation-based methodology (bootstrapped DEA, robust frontiers, double bootstrap, conditional measures) and fuzzy FDH. Section 4 is dedicated to analysis of the total factor productivity change in Lithuanian family farms. Section 5 aims to analyse the underlying productive technology of Lithuanian family farms. Therefore, the technical change is analysed with respect to change in the input productivity. Another important issue to be addressed is that of the optimal farm size (i. e. returns to scale). Section 6 employs the extended data set to check the impact of increase in the time span upon results of the analysis. Finally, Section 7 discusses limitations of the research.

Propositions defended:

1. The changes in the total factor productivity are to be analysed in terms of 1) level of efficiency; 2) dynamics in the total factor productivity, 3) level of variance. Therefore, a hybrid multi-criteria decision making methodology—DEA-MULTIMOORA—is proposed.
2. It is the uncertainty of the performance and accountancy of Lithuanian agricultural sector (as well as those of other Central and Eastern European countries) that makes the use of fuzzy logics and probabilistic (stochastic) methodologies relevant when analysing agricultural efficiency. Accordingly, a fuzzy efficiency estimation model is proposed.
3. Even though a vibrant growth of the crop farming has been observed in Lithuania, the livestock farms appeared to be more efficient. The public support, thus, should be aligned with respect to the trends of different

farming types. Indeed, the mixed farming should receive an additional financial and technological support to increase their productivity.

4. The farm size limitations currently imposed in Lithuania are not likely to render deadweight losses, however, the issues related to corporate farming still need to be analysed.

Approbation of the research results. The main findings of the research have been presented in 19 scientific articles, 8 of which are indexed in the *Web of Science* data base. A scientific study has also been prepared. The results have also been presented at 6 international or national conferences. In addition, a research visit to Maastricht university was carried out on 2014 01 26 – 2014 02 16 (supervisor Dr Kristof De Witte).

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2. 15th International Scientific Conference *Economic Science for Rural Development 2014*, Jelgava, Latvia, 2014 04 24–25.
3. International Scientific – Practical Conference *Innovative Solutions in Economics and Management Science and Studies*, Akademija, Lithuania, 2014 06 19–20.
4. 20th Conference of the International Federation of Operational Research Societies, Barcelona, Spain, 2014 07 13–18.

5. Scientific Conference *Jaunieji mokslininkai – žemės ūkio pažangai*, Lietuvos mokslų akademija, 2013 11 21.
6. Scientific Seminar V*adybinė ekonomika: gamybinis efektyvumas ir ribinių metodų taikymas*, LAEI, 2013 11 20.
7. Scientific Conference *Mokslo ir verslo dermė*, Vilniaus kooperacijos kolegija, 2014 05 29.

Vita

Tomas Baležentis graduated from Vilnius University in 2011 and was awarded the degree of BSc in Economics. In 2013, he was awarded MSc in Economics (magna cum laude) by Vilnius University. He was enrolled as a PhD student at Vilnius University Faculty of Economics in 2013.

Tomas Baležentis worked as a senior specialist at the Training Centre of the Ministry of Finance during 2009–2010. Since 2011, he has been a researcher at the Lithuanian Institute of Agrarian Economics.

Tomas Baležentis has received the following awards: student scientific paper award (2011) from the Lithuanian Academy of Sciences, President of the Republic of Lithuania A. Brazauskas scholarship for 2012–2013, PhD Scholarship for Academic Achievements (Research Council of Lithuania), 2014.

The author has published over 30 publications indexed in the *Web of Science* data base and another 30 in other international data bases. In addition, he has co-authored three scientific studies.

1. PRELIMINARIES FOR THE EFFICIENCY ANALYSIS

This part of the thesis is to present the preliminaries for efficiency analysis. In particular, Section 1.1 focuses on literature review. The following Section 1.2 presents the key concepts of efficiency analysis based on the neoclassical methodology. Finally, Section 1.3 discusses the key techniques for estimation of the efficiency measures. Finally, Section 1.4 attempts to present the general trends prevailing in Lithuanian agriculture.

1. 1. State-of-the-art of the agricultural efficiency research

This section presents a literature survey on efficiency analyses in agriculture. The first sub-section tackles the foreign literature, whereas the second one focuses on the Lithuanian researches.

As Henningsen (2009) put it, the agricultural efficiency is interrelated with labour intensity, farm structure, technology and investment, managerial skills, and profitability. The very efficiency thus can be considered as a measure of productivity and profitability. The farm structure impacts technology, labour intensity, and managerial skills given larger farms tend to accumulate respective resources to a higher extent. The labour intensity and labour opportunity costs are reciprocally related to the investments into advanced technologies. Management skills also influence both labour intensity and investments into technology. The aforementioned factors affect the profitability, whereas the profitability, in turn, determines farmers' decisions on staying in the sector or distributing their working time across various economic sectors. The productive efficiency, therefore, needs to be measured and analysed in terms of multiple interrelated variables and dimensions. Furthermore, the performance management aims at identifying and spreading the best practices within an organization, sector, or the whole economy. The relative performance evaluation—benchmarking—is the systematic comparison of one production entity (decision making unit) against other entities (Bogetoft, Otto 2011). Indeed, benchmarking is an important issue for both private and public decision makers to ensure the sustainable change. Due to Jack and Boone (2009) benchmarking can create motivation for change; provide a vision for what an organization can look like after change; provide data, evidence, and success stories for inspiring change; identify best practices for how to manage change; and create a baseline or yardstick by which to evaluate the impact of earlier changes.

The general framework for efficiency analysis is presented in Figure 1.1. First, input, output, and price data are needed to estimate various types of efficiency by the means of frontier models. Second, the obtained efficiency estimates are treated as dependent variables for econometric model aimed at explaining the underlying causes of (in)efficiency. The latter model requires a set of explanatory variables—regressors—identifying certain sources of (in)efficiency. Particularly, these variables can be objective and subjective ones. Objective data may come from the same source as the data for the frontier model, namely databases, measurements etc. As for subjective data, they may be obtained by the means of questionnaire survey (see, for instance, Douarin and Latruffe, 2011).

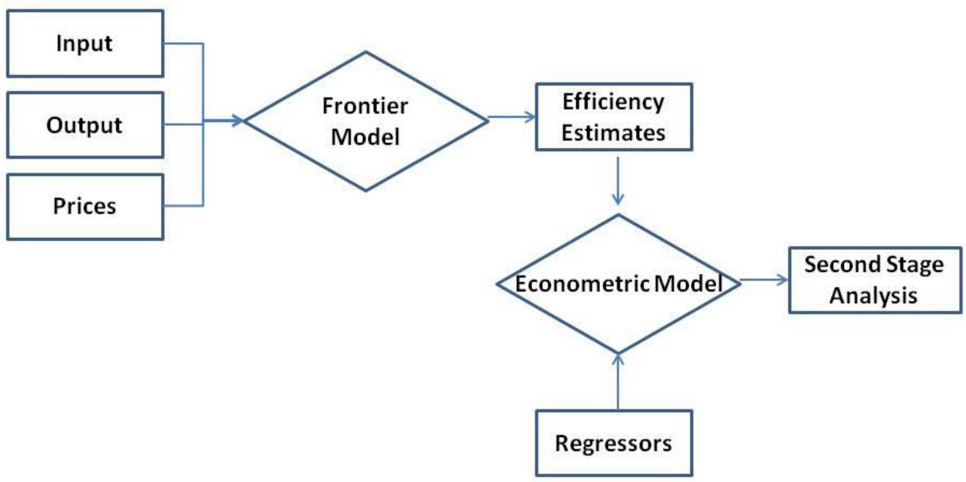


Fig. 1.1. The conceptual framework for the frontier-based benchmarking.

Indeed, the frontier models of the agricultural efficiency anlaysis usually involve the following variables:

1. *Inputs* – usually these are the quantities of the intermediate products (working capital as it is treated by the neoclassical economic thought) and factors of production (fixed capital along with labour force). Intermediate consumption comprises feed, fertilizers, seed as well as other inputs transformed throughout the production process. Production factors (land, labour etc.) might be partially affected by the production process and embodied in the produce, yet they remain essentially unchanged for further use. It is often possible, though, to transform the quantities of fixed capital (stock variables) into monetary terms (flow variables) by assuming depreciation or considering the relevant price data.
2. *Outputs* – the quantities of produce. The preferred measures in agricultural efficiency analyses are those physical quantities (e. g. weight in tonnes). However, the agricultural producers often feature diversity in their products thus it might be impossible to include all those quantities because of the curse of dimensionality. Furthermore, some quantities would be equal to zero. Therefore, the implicit output quantities (output value deflated by respective price indices) are often used in the analyses.
3. *Input prices* allow estimating production cost and thus the allocative efficiency. This information results in the cost efficiency.
4. *Output prices* allow estimating production revenue and the output allocative efficiency. As a result, one can estimate the revenue efficiency. If both the input and output price data are available, the profit efficiency can be analysed.
5. *Environmental variables* (in the narrow sense) define the impact a production process causes upon its environment. These are usually the side effects of a production process. Inclusion of these variables enables to re-define the production function and thus the concept of

efficiency. In order to account for the side (environmental) effects, the undesirable outputs (e. g. greenhouse gas emission) are usually included in the frontier models. However, the environmental variables can include Czekaj (2013) included the area of permanent grassland or agri-environmental payments as desirable outputs.

The second stage (post-efficiency) analysis enables to identify specific factors influencing efficiency as well to quantify their impact. Therefore appropriate strategic management decisions can be offered, whereas the existing ones may undergo a thorough analysis. The contextual variables can also be referred to as the environmental variables even they do not necessarily deal with the environmental issues in the narrow sense.

The key elements of a benchmarking framework, namely frontier and econometric models, might be chosen from a set of various possible instruments. As it was discussed in the preceding section, the frontier models can be grouped into parametric and non-parametric ones with SFA and DEA representing these groups. The econometric model for second stage analysis can be, for instance, a logit or Tobit model, whereas panel data might be analysed by the means of fixed or random effects models. Combinations of these options create certain patterns for efficiency research. We have thus performed a scientometric analysis aimed at identifying the current trends of frontier benchmarking in agriculture.

1. 1. 1. Foreign literature survey

The scientometric analysis is based on data retrieved from the globally renowned database *Web of Science* (Thomson Reuters) which is usually employed for suchlike analyses (Zavadskas et al., 2011). The aim of the scientometric research was to analyse the dynamics in number of citable items, namely articles, reviews, proceedings etc., related to the frontier efficiency measurement in agriculture. The research covers the period of 1990–2012 (as of March 2012).

The initial query was defined by setting publication topic equal to: (frontier OR stochastic frontier analysis OR data envelopment analysis) AND (agriculture OR farming). The latter query should identify the extent of manifestation of frontier measures across the current scientific sources. Of course, some papers are omitted thanks to usage of acronyms. As a result, the query returned 1011 publications. The number of released publications has been growing throughout the analysed period and exceeded 140 publications per annum in 2013 (Figure 1.2). Meanwhile, the number of citations has also been increasing and reached 13121 citations (9946 without self-citation) until 2012 with over 2000 citations per annum in 2013 (Figure 1.3). Frontier-based efficiency measurements in agriculture, therefore, can be considered as a rather prospective and expanding research area.

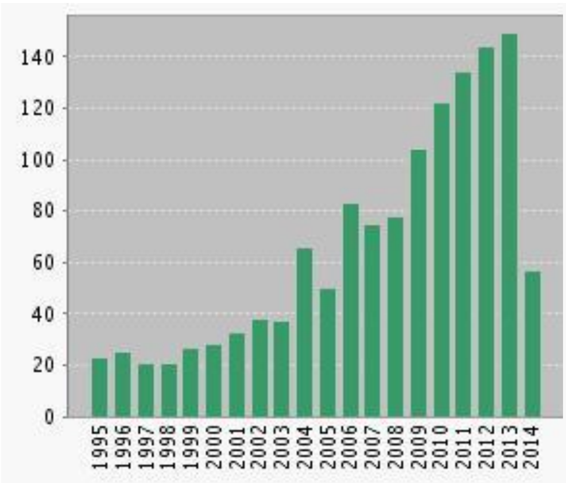


Fig. 1.2. Published items in each year.
Source: Thomson Reuters.

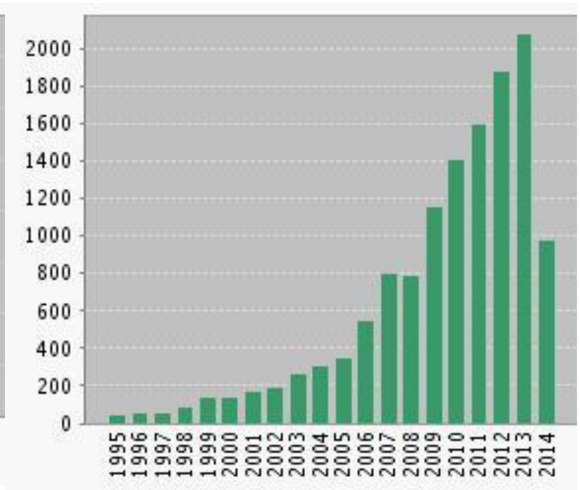


Fig. 1.3. Citations in each year.
Source: Thomson Reuters.

Table 1.1 presents the main journals which constitute the basis for dissemination of the agricultural efficiency research results. The presented list implies that journals covering the areas of both agricultural economics and applied economics tend to publish these studies.

Table 1.1. The main journals featuring publications on agricultural efficiency, 1990–2014.

No.	Source Titles	Record Count	% of the total number
1.	Agricultural Economics	53	5.2
2.	Journal of Productivity Analysis	32	3.2
3.	American Journal of Agricultural Economics	29	2.9
4.	Applied Economics	27	2.7
5.	Journal of Agricultural Economics	22	2.2
6.	Agricultural Systems	20	2.0
7.	European Review of Agricultural Economics	18	1.8
8.	Ecological Economics	14	1.4
9.	African Journal of Agricultural Research	13	1.3
10.	Journal of Dairy Science	13	1.3

Queries on applications of SFA and DEA returned similar results, namely 272 and 230 publications, respectively. Therefore both of these methods are equally important for agricultural research. Meanwhile, the respective queries on application of the econometric instruments for second–stage analysis suggested Tobit regression being the most popular method (37 publications), whereas fixed effects (13 publications), random effects (7 publications), and logit (4 publications) models remained behind.

We will review some recent studies on frontier measures of agricultural efficiency in order to reveal the concrete manifestations of frontier efficiency measurement as well as second stage analysis. Latruffe et al. (2004) analysed the efficiency of crop and livestock farming in Poland by the means of SFA and DEA. SFA analysis was carried out by employing efficiency effects model

(Battese, Coelli, 1995) relating the observed inefficiencies with a pre-defined set of efficiency variables. Thus, the second stage analysis can be implemented simultaneously with estimation of the SFA model. The DEA analysis, however, was supplemented by the second stage analysis, namely Tobit regression. The Cobb-Douglas production function was employed for SFA to regress the total output in value against utilized agricultural area (UAA) as a land factor, annual work units (AWU) as a labour factor, depreciation plus interests as a capital factor, and intermediate consumption as a variable factor. The following variables were chosen as the determinants of inefficiency: total output, share of hired labour, degree of market integration (i. e. the ratio of total revenue over total output), soil quality index, and farmer's age. The Tobit model for DEA included variables defining ratios between certain inputs as well as the inefficiency determinants from SFA model.

Bojnec and Latruffe (2008) analysed performance of the Slovenian farms by the means of both DEA and SFA. The allocative and economic efficiencies were also estimated. The cluster analysis was employed to classify the analysed farming types into relatively homogeneous groups, however there was no second state analysis performed. Later on, efficiency was related to the farm structure (Bojnec, Latruffe, 2011). Akinbode et al. (2011) employed the same SFA with efficiency effects model for estimation of technical efficiency. Moreover, the cost function was specified to estimate allocative and economic efficiency. The variation in the latter two efficiencies was explained by employing Tobit model. The same methodological framework was implemented by Samarajeewa et al. (2012) to analyse beef cow/calf farming in Canada. Lambarraa and Kallas (2010) implemented efficiency effects SFA model when estimating impact of Less Favoured Area (LFA) payments on farming efficiency. The two production functions therefore were defined for farms receiving LFA payments and for those not receiving payments. The random effect Tobit model was employed for the whole sample with an additional dummy variable identifying absorption of these payments.

The study of Asmild and Hougaard (2006) focuses on efficiency of Danish pig farms from the ecological and economic viewpoints. The directional DEA was applied to estimate the efficiency and possible improvements. Kuosmanen and Kuosmanen (2009) analysed technical efficiency of Finnish dairy farms with respect to environmental impact. Indeed, the concept of sustainable value included the surplus of nitrogen into account. Rasmussen (2011) employed the input distance function to estimate efficiency of the Danish pig, dairy, and crop farms. These functions were also used to estimate the optimal operation scale for respective farming type. Nauges et al. (2011) presented the state-contingent stochastic production function to assess land distribution under different plant species regarding the weather conditions (i. e. states).

A meta-regression analysis[1] including 167 farm level technical efficiency studies of developing and developed countries was undertaken by Bravo-Ureta et al. (2006). The econometric results implied lower TE scores are obtained by employing SFA as opposed to those obtained by DEA. In addition, deterministic parametric models are also likely to populate lower efficiency scores if compared to SFA. Production functions (the primal approach) were estimated most frequently. The study showed that animal farming features higher TE if compared to crop farming. It was also concluded that farming in Western Europe and Oceania is likely to feature higher levels of TE. Indeed, a negative relationship between subsidies and efficiency is omnipresent across the European countries according to the meta-analysis by Minviel and Latruffe (2014).

There have been some studies to agricultural efficiency carried out in the CEE countries. Gorton and Davidova (2004) presented a survey of the relevant studies. Brümmer (2001) employed data envelopment analysis (DEA) and stochastic frontier analysis (SFA) with efficiency effects model to analyse the efficiency of Slovenian farms. Later on, Bojnec and Latruffe (2011, 2013)

[1] A meta-regression analysis is based on results of the previous (econometric) researches. In this particular case the obtained mean efficiency scores were related to certain variables describing the environment of respective farming systems.

analysed the relationships between size and efficiency of Slovenian farms. Bojnec and Fertő (2013) employed SFA to analyse the relationships between efficiency and off-farm income. Latruffe et al. (2004, 2005) employed the bootstrapped DEA along with the SFA to estimate the efficiency of the Polish farms. Balcombe et al. (2008) analysed the determinants of the total factor productivity change in Polish farms. Davidova and Latruffe (2007) related the Czech farm efficiency to the financial indicators. Latruffe et al. (2008) utilised the double bootstrapping methodology to assess the Czech farm efficiency. Chaplin et al. (2004) analysed the efficiency of Polish, Czech, and Hungarian farms. Latruffe et al. (2012) compared the Hungarian and French farm performance by the means of DEA and meta-frontier approach. Baležentis and Kriščiukaitienė (2013) analysed the determinants of Lithuanian family farms' efficiency by the means of the Tobit model, whereas Baležentis et al. (2014) employed the bootstrapped DEA and the non-parametric regression for the latter purpose.

1. 1. 2. Lithuanian literature survey

Productive efficiency of agricultural sector is extensively analysed across the Central and East European states where agriculture is relatively important economic activity if compared to the western states (Gorton and Davidova, 2004). The Lithuanian agricultural sector, though, received less attention in the latter scientific area. Moreover, those few examples employed non-parametric methods, whereas parametric methods (e. g. stochastic frontier analysis) remain underused. The remaining part of this section overviews earlier papers which analysed efficiency of the Lithuanian agricultural sector by the means of frontier measures, namely DEA.

The paper by Rimkuvienė et al. (2010) also addressed the farming efficiency by performing an international comparison on a basis of DEA and free disposal hull—the two non-parametric methods. This study also discussed the differences between terms efficiency and effectiveness which are often misused in Lithuanian scientific works. The research covered years 2004–2008 and some 174 observations (aggregates) for EU and non-EU states. Input- and output-oriented DEA models yielded efficiency scores of 43.2 and 41.4%, respectively. In addition the effectiveness of capital and intermediate consumption was observed in Lithuania.

Baležentis and Baležentis (2011) followed the similar framework for international comparison. However, the latter study employed not only DEA but also multi-criteria decision making method MULTIMOORA. The agricultural efficiency was assessed with respect to the three ratios, namely crop output (EUR) per ha, livestock output (EUR) per LSU, and farm net value added (EUR) per AWU. Therefore, the land, livestock, and labour productivity were estimated. According to the DEA efficiency scores, Lithuania and Latvia reached the efficiency of 52 and 54%, whereas Estonia and Poland that of 58%. The high value of slacks in crop output (land productivity) and the net value added per AWU (labour productivity) for the three Baltic States indicated the necessity of qualitative and quantitative changes to be implemented here.

It was Douarin and Latruffe (2011) who offered the single foreign contribution to the DEA-based efficiency analysis of Lithuanian agriculture. The aim of that study was to estimate the farming efficiency and possible outcomes of the incentives provided by EU Single Area Payments. Moreover, this study was based on micro- rather than aggregate data. Thus, farm efficiency estimation was followed by questionnaire survey which tried to identify the farmers' behaviour, namely decisions to expand their farms or stay in the farming sector, as a result of public support distribution. The research showed that 1) larger farms operated more efficiently, 2) subsidies were related to lower efficiency scores. The Heckman model was employed to quantify the impact of various factors on farmers' decisions to stay in farming or expand the farm. It was concluded that the overall farming efficiency should decrease, for lower efficiency farms were about to expand and thus increase competition in the land market.

Baležentis and Kriščiukaitienė (2012) also analysed performance of the Lithuanian family farms on a basis of FADN aggregates. The DEA was employed for the analysis. As a result, slack analysis revealed that low land productivity, returns on assets, and intermediate consumption productivity are the most important sources of the inefficiency, in that order. Low land productivity is especially important for specialised cereals and general field cropping. Therefore, the incentives for crop structure adjustment should be imposed in order to increase land productivity. The highest mean values of return on assets slacks were observed for specialist cereal farming and general field cropping.

The carried out analysis suggests that frontier benchmarking in agriculture is a robustly developing branch of science. To be specific, the number of publications released per year on frontier benchmarking in agriculture has increased sixfold since early 1990s. Indeed, both data envelopment analysis and stochastic frontier analysis are equally important instruments for estimating productive efficiency. It is the tobit model that can be considered as the most popular method for the second stage analysis.

The Lithuanian agricultural sector, however, is not sufficiently analysed by the means of the frontier techniques. The Lithuanian agricultural sector still facing the consequences of post-communist transformations should be analysed by employing the discussed two-stage frontier benchmarking framework in order to fathom the underlying trends in productivity, efficiency, and farming decisions. In addition, the parametric techniques should be involved in the analysis. The discussed methods and research frameworks would certainly increase the effectiveness of the strategic management decisions.

1. 2. Definitions and measures of efficiency

Instead of defining the efficiency as the ratio between outputs and inputs, we can describe it as a distance between the quantity of input and output, and the quantity of input and output that defines a frontier, the best possible frontier for a firm in its cluster (Daraio, Simar, 2007a).

The very term of efficiency was initially defined by Koopmans (1951). Koopmans offered the following definition of an efficient decision making unit (DMU): *A DMU is fully efficient if and only if it is not possible to improve any input or output without worsening some other input or output*. Due to similarity to the definition of Pareto efficiency, the former is called Pareto–Koopmans Efficiency. Such a definition enabled to distinguish efficient and inefficient DMUs, however it did not offer a measure to quantify the level of inefficiency specific to a certain DMU.

Thus Debreu (1951) discussed the question of resource utilization and introduced the measure of productive efficiency, namely coefficient of resource utilization. Debreu's measure is a radial measure of technical efficiency. Radial measures focus on the maximum feasible equiproportionate reduction in all variable inputs for an input-conserving orientation, or the maximum feasible equiproportionate expansion of all outputs for an output-augmenting orientation (Daraio, Simar, 2007a; Fried et al., 2008).

Finally, Farrell (1957) summarized works of Debreu (1951) and Koopmans (1951) thus offering frontier analysis of efficiency and describing two types of *economic efficiency*, namely *technical efficiency* and *allocative efficiency* (indeed, a different terminology was used at that time). It is worth to note, that the seminal paper of Farrell (1957) was dedicated to analysis of agricultural production in the United States. The concept of technical efficiency is defined as the capacity and willingness to produce the maximum possible output from a given bundle of inputs and technology, whereas the allocative efficiency reflects the ability of a DMU to use the inputs in optimal proportions, considering respective marginal costs (Kalirajan, Shand, 2002).

However, Farrell (1957) noted that price information is rather hard to tackle in a proper way, thus technical efficiency became a primal measure of the productive efficiency.

Besides, the two other types of efficiency can be defined, viz. scale and structural efficiency. Scale efficiency measures the extent to which outputs increase due to increase in input. Farrell (1957) and later Charnes, Cooper and Rhodes (1978) employed the most restrictive constant returns to scale (CRS) assumption. The latter assumption was relaxed by Banker, Charnes and Cooper (1984), who also pointed out that scale efficiency is related to variable returns to scale (VRS) efficiency (pure technical efficiency) and CRS technical efficiency. The structural efficiency is an industry level concept describing the structure and performance of certain sector which is determined by performance of its firms. Indeed, one sector can be structurally efficient than another in case its firms are operating closer to the efficiency frontier. For instance, one can define hypothetic average values for several sector and compute efficiency scores for them thus assessing differences in structural efficiency across these sectors.

In order to relate the Debreu–Farrell measures to the Koopmans definition, and to relate both to the structure of production technology, it is useful to introduce some notation and terminology (Fried et al., 2008). Let producers use inputs $x = (x_1, x_2, ..., x_m) \in \Re_+^m$ to produce outputs $y = (y_1, y_2, ..., y_n) \in \Re_+^n$. Production technology then can be defined in terms of the production set:

$$T = \{(x, y) | x \text{ can produce } y\}. \quad (1.1)$$

Thus, Koopmans efficiency holds for an input-output bundle $(x, y) \in T$ if, and only if, $(x', y') \notin T$ for $(-x', y') \geq (-x, y)$.

Technology set can also be represented by input requirement and output correspondence sets, respectively:

$$I(y) = \{x | (x, y) \in T\}, \quad (1.2)$$

$$O(x) = \{y | (x, y) \in T\}. \tag{1.3}$$

The isoquants or efficient boundaries of the sections of T can be defined in radial terms as follows (Farrell, 1957). Every $y \in \Re^n_+$ has an input isoquant:

$$isoI(y) = \{x | x \in I(y), \lambda x \notin I(y), \lambda < 1\}. \tag{1.4}$$

Similarly, every $x \in \Re^m_+$ has an output isoquant (transformation curve):

$$isoO(x) = \{y | y \in O(x), \lambda y \notin O(x), \lambda > 1\}. \tag{1.5}$$

In addition, DMUs might be operating on the efficiency frontier defined by Eqs. 1.4–1.5, albeit still use more inputs to produce the same output if compared to another efficient DMU. In this case the former DMU experiences a slack in inputs. The following subsets of the boundaries $I(y)$ and $O(x)$ describe Pareto-Koopmans efficient firms:

$$effI(y) = \{x | x \in I(y), x' \notin I(y), \forall x' \le x, x' \ne x\}, \tag{1.6}$$

$$effO(x) = \{y | y \in O(x), y' \notin O(x), \forall y' \ge y, y' \ne y\}. \tag{1.7}$$

Note that $effI(y) \subseteq isoI(y) \subseteq I(y)$ and $effO(x) \subseteq isoO(x) \subseteq O(x)$.

There are two types of efficiency measures, namely Shepard distance function, and Farrell efficiency measure. These functions yield the distance between an observation and the efficiency frontier. Shepard (1953) defined the following input distance function:

$$D_I(x, y) = \max\{\lambda | (x/\lambda, y) \in I(y)\}. \tag{1.8}$$

Here $D_I(x, y) \ge 1$ for all $x \in I(y)$, and $D_I(x, y) = 1$ for $x \in isoI(y)$. The Farrell input-oriented measure of efficiency can be expressed as:

$$TE_I(x, y) = \min\{\theta | (\theta x, y) \in I(y)\}. \tag{1.9}$$

Comparing Eqs. 1.8 and 1.9 we arrive at the following relation:

$$TE_I(x, y) = 1/D_I(x, y), \tag{1.10}$$

with $TE_I(x, y) \le 1$ for $x \in I(y)$, and $TE_I(x, y) = 1$ for $x \in isoI(y)$.

Similarly, the following equations hold for the output-oriented measure:

$$D_O(x, y) = \min\{\lambda | (x, y/\lambda) \in O(x)\}, \tag{1.11}$$

$$TE_O(x,y) = \max\{\phi | (x, \phi y) \in O(x)\}, \tag{1.12}$$

$$TE_O(x,y) = 1/D_O(x,y), \tag{1.13}$$

where $TE_O(x,y) \geq 1$ for $y \in O(x)$, and $TE_O(x,y) = 1$ for $y \in isoO(x)$.

Note that the Farrell measures, TE_I and TE_O, are homogeneous of degree –1 in inputs and outputs, respectively; whereas the Shepard measures, D_I and D_O, are homogeneous of degree +1 in inputs and outputs, respectively.

Figure 1.4 depicts the two efficiency measurement approaches discussed above, namely input- and output-oriented. Initial input-output bundle (x_0, y_0) is projected into efficiency frontier T by (i) reducing inputs and thus achieving an efficient point $(\theta x_0, y_0)$ or (ii) augmenting outputs and thus achieving an efficient point $(x_0, \phi y_0)$. Noteworthy, Figure 1.4 presents a production frontier, for output quantity is related to input quantity there. In case the two input (output) quantities were related, one would have an isoquant (a transformation curve) as well as the implicit assumption of constant returns to scale.

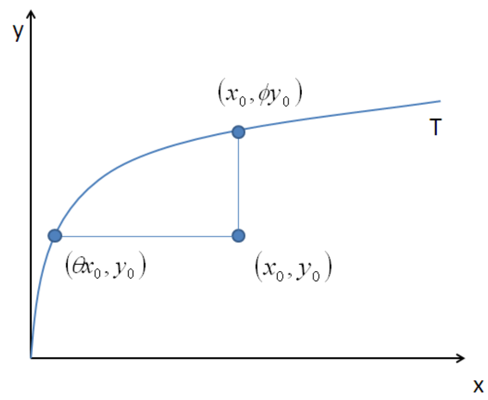


Fig. 1.4. Technical efficiency measurement in terms of the Farrell measures.

Besides the discussed non-directional efficiency measures there exists a class of directional efficiency measures. Whereas the former methods analyse equiproportional scaling of either inputs or outputs, the directional measures consider both of these alterations simultaneously.

One of the initial suggestions of the directional efficiency measurement is the graph hyperbolic measure of technical efficiency:

$$TE_G = \min\{\alpha | (\alpha x, y/\alpha) \in T\}. \tag{1.14}$$

By simultaneously reducing inputs and expanding outputs with α>0 we move the initial point (x_0, y_0) along the hyperbolic curve (the dashed line in Figure 1.5) until it reaches the efficiency frontier at the point $(\alpha x_0, y_0 / \alpha)$.

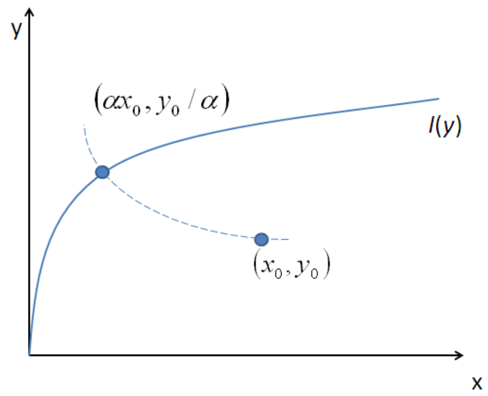


Fig. 1.5. The graph efficiency measure.

The graph efficiency measure, however, is seldom employed due to the non-linearities involved (Bogetoft, Otto, 2011).

The previously discussed Shepard measures of efficiency can be generalized into the directional technology distance function (Färe et al., 2008). In this case direction of improvement can be considered as a vector rather than a scalar (as in case of Shepard and Farrell measures of efficiency). Thus, let $g = (g_x, g_y)$ be a direction vector with $g_x \in \Re_+^m$ and $g_y \in \Re_+^n$ and introduce the excess function:

$$E_D(x, y; g_x, g_y) = \max\{\beta | (x_0 - \beta g_x, y_0 + \beta g_y) \in T\}. \tag{1.15}$$

Figure 1.6 illustrates this function.

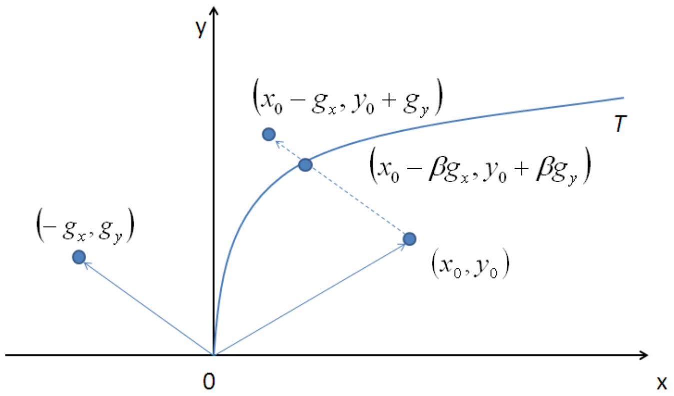


Fig. 1.6. The directional technology distance function.

Technology is denoted by *T*, whereas the directional vector *g* is in the fourth quadrant indicating that the inputs are to be contracted and outputs augmented simultaneously. To be specific, inputs are scaled down by g_x, whereas outputs are increased by g_y. Thus the directional vector is transformed into $(-g_x, g_y)$ and added to the initial point (x_0, y_0). Addition of the two vectors means defining a parallelogram, the vertex whereof is given by $(x_0 - g_x, y_0 + g_y)$. Therefore, one will put the initial point on the efficiency frontier by maximizing β. By setting $(g_x, g_y) = (x, 0)$ and $(g_x, g_y) = (0, y)$ we would arrive at the input- and output-oriented distance functions, respectively. In addition one may choose $(g_x, g_y) = (x, y)$, $(g_x, g_y) = (\bar{x}, \bar{y})$, $(g_x, g_y) = (1,1)$, or optimize (g_x, g_y) to minimize distance to frontier technology.

As it was already said, Farrell (1957) defined the two types of efficiency, which are known as technical and economic efficiency. The technical efficiency and its measures were described above. The economic efficiency is divided into cost, revenue and profit efficiency. For each of the three measures, a respective frontier is established. Here we focus solely on cost efficiency. However, revenue efficiency is a straightforward modification of the cost efficiency.

Assume that producers face input prices $w = (w_1, w_2, ..., w_m) \in \Re^m_{++}$ and seek to minimize cost. Thus, a minimum cost function—cost frontier—is defined as:

$$c(y,w) = \min_x \{ w^T x | D_I(x,y) \geq 1 \}. \tag{1.16}$$

Then a measure of cost efficiency (CE) is defined as the ratio of the minimum cost to the actual cost:

$$CE(x,y,w) = c(y,w) / w^T x. \tag{1.17}$$

A measure of input-allocative efficiency AE_I is obtained by employing Eqs. 1.17 and 1.9:

$$AE_I(x,y,w) = CE(x,y,w) / TE_I(x,y). \tag{1.18}$$

Thus, cost efficiency can be expressed as a product of technical efficiency and cost allocative efficiency. Figure 1.7 depicts these measures.

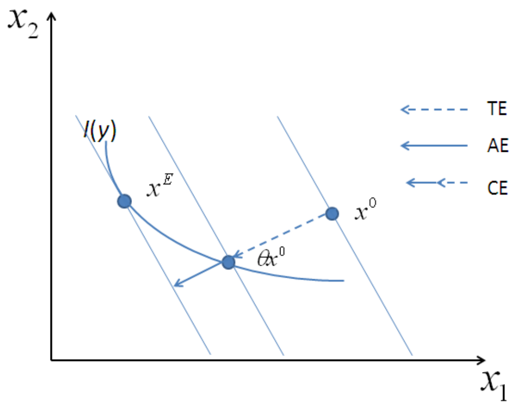


Fig. 1.7. The concept of cost efficiency.

The three lines in Figure 1.7 represent respective isocosts, namely $w^T x^E$, $w^T \theta x^0$, and $w^T x^0$ for points x^E, θx^0, and x^0, in that order. Here the efficient point x^E minimizes cost and thus defines the cost frontier $c(y,w) = w^T x^E$. The cost efficiency of the point x^0 is then given by ratio $c(y,w)/w^T x^0 = w^T x^E / w^T x^0$ (cf. Eq. 1.17). The cost efficiency of x^0 can be further decomposed into technical efficiency $\theta^0 = \theta^0 x^0 / x^0 = w^T(\theta^0 x^0) / w^T x^0$ and allocative efficiency determined by the ratio $w^T x^E / w^T(\theta^0 x^0)$.

1. 3. Frontier models for efficiency analysis

Indeed, there are many techniques to establish an efficiency frontier (i. e. an instance of representation of the underlying technology). First, these can be broken down into parametric and non-parametric methods (Murillo-Zamorano, 2004). Second, frontier techniques can be either deterministic or stochastic (Kuosmanen, Kortelainen, 2012). Third, frontier techniques can be either axiomatic or non-axiomatic (Afriat, 1972). Fourth, frontiers can be either average-practice or best-practice (Kuosmanen, Kuosmanen, 2009).

The parametric frontier methods rely on econometric inference and aims at estimating parameters for pre-defined exact production functions. These parameters may refer, for instance, to the relative importance of different cost drivers or to parameters in the possibly random noise and efficiency distributions (Bogetoft, Otto, 2011). The parametric frontier methods can be further classified into deterministic and stochastic ones. The two deterministic frontier models, namely Ordinary Least Squares (OLS) and Corrected Ordinary Least Squares (COLS), attribute the distance between an observation and the efficiency frontier to statistical noise or inefficiency, respectively. The stochastic parametric method—Stochastic Frontier Analysis (SFA)—explains the gap between an observation and the efficiency frontier in terms of both inefficiency and random errors.

On the other side, non-parametric frontier methods usually aim at establishing an empirical production frontier. Specifically, the empirical production frontier (surface) is defined by enveloping linearly independent points (observations) and does not require subjective specification of the functional form. Therefore the non-parametric models are easier to be implemented. It is the deterministic non-parametric frontier methods that do not allow statistical noise and thus explains the whole distance between the observation and production frontier by inefficiency. Data Envelopment Analysis (DEA) and Free Disposable Hull (FDH) are the two widely renowned non-parametric deterministic models. The stochastic non-parametric methods account for the statistical noise by correcting the initial observations and, thus, the efficiency frontiers. Bootstrapped DEA, chance-constrained (stochastic) DEA, stochastic semi-non-parametric envelopment of data (STONED) can be given as the examples of the latter class of the frontier methods.

The following Figure 1.8 depicts the differences between some of the discussed methods. As one can note, the parametric methods (OLS, COLS, SFA) define continuous frontiers, whereas non-parametric model DEA offers a piece-wise approximation thereof. FDH would result in a non-convex frontier. To be precise, the DEA frontier is not completely devoid of assumptions on its functional form. Indeed, it is considered to be locally linear one. Given DEA and FDH frontiers are defined empirically, they do include at least one observation, which is then considered as an efficient one. The same applies for the COLS frontier. In case of the OLS and SFA frontiers, no observations are considered to be fully efficient.

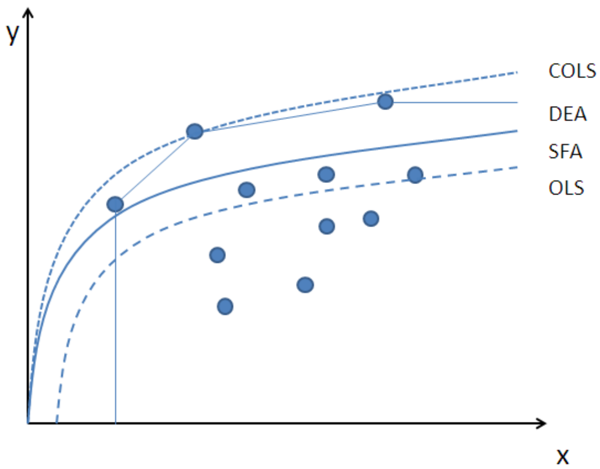


Fig. 1.8. Parametric and non-parametric frontier models.

COLS frontier is based on the OLS one and shifted by a constant equal to the maximal error term so that the resulting error term would satisfy $e \geq 0$. SFA assumes certain distribution of random error as well as inefficiency terms and thus defines an intermediary frontier.

Indeed, SFA and DEA are the two seminal methods for, respectively, parametric and non-parametric analysis. These methods are to be discussed throughout the remaining part of the section.

1. 3. 1. Data Envelopment Analysis

DEA specifies the efficiency frontier with respect to the two assumptions, namely free disposability and convexity. The assumption of the free disposability means that we can dispose of unwanted inputs and outputs. First, if we can produce a certain quantity of outputs with a given quantity of input, then we can also produce the same quantity of outputs with more inputs. Second, if a given quantity of inputs can produce a given quantity of outputs, then the same input can also be used to produce less output (Bogetoft, Otto, 2011). By combining these two assumptions we arrive at the free disposability of inputs and outputs. The technology related to free disposability assumption is called the free disposable hull. Assume there are $k = 1,2,...,K$ firms each possessing a certain input-output bundle (x^k, y^k), then the free disposable hull is defined as

$$T = \left\{(x, y) \in \Re_+^m \times \Re_+^n \middle| \exists k \in \{1,2,...,K\} : x \geq x^k, y \leq y^k \right\}. \qquad (1.19)$$

An graphic interpretation of the free disposable hull is presented in Figure 1.9.

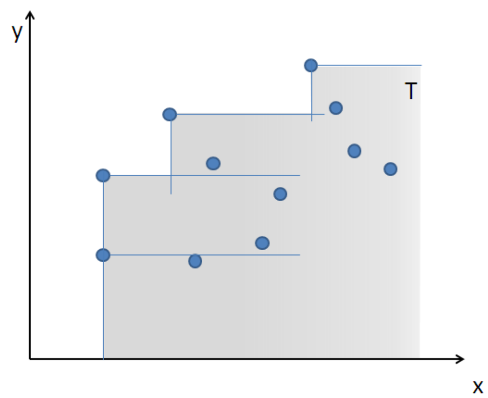


Fig. 1.9. Free disposable hull.

The convexity assumption implies that any linear combination of the feasible production plans (x^k, y^k) is also feasible. The convex VRS technology set is defined in the following way:

$$T = \left\{(x, y) \middle| x = \sum_{k=1}^{K} \lambda^k x^k, y = \sum_{k=1}^{K} \lambda^k y^k, \sum_{k=1}^{K} \lambda^k = 1, \lambda^k \geq 0, k = 1,2,...,K \right\}. \qquad (1.20)$$

By combining assumptions of the free disposability, VRS, and convexity (cf. Eqs. 19 and 20) the following technology set is obtained:

$$T = \left\{(x, y) \middle| x \geq \sum_{k=1}^{K} \lambda^k x^k, y \leq \sum_{k=1}^{K} \lambda^k y^k, \sum_{k=1}^{K} \lambda^k = 1, \lambda^k \geq 0, k = 1,2,...,K \right\}. \qquad (1.21)$$

The latter technology set includes all points that can be considered as feasible ones under assumption of either convexity or free disposability (Figure 1.7).

DEA is a nonparametric method of measuring the efficiency of a decision–making unit (DMU) such as a firm or a public–sector agency (Ray, 2004).

The modern version of DEA originated in studies of A. Charnes, W. W. Cooper and E. Rhodes (Charnes et al., 1978, 1981). Hence, these DEA models are called CCR models. Initially, the fractional form of DEA was offered. However, this model was transformed into input– and output–oriented multiplier models, which could be solved by means of the linear programming (LP). In addition, the dual CCR model (i. e. envelopment program) can be described for each of the primal programs (Cooper et al., 2007; Ramanathan, 2003).

Unlike many traditional analysis tools, DEA does not require to gather information about prices of materials or produced goods, thus making it suitable for evaluating both private– and public–sector efficiency. Suppose that there are $k = 1,2,...,K$ DMUs, each producing $j = 1,2,...,n$ outputs from $i = 1,2,...,m$ inputs. Hence, the *t*–th DMU ($t = 1,2,...,K$) exhibits input–oriented Farrell technical efficiency θ_t, whereas input–oriented Shepard technical efficiency is a reciprocal number and $\theta_t = 1/\lambda_t$. The input–oriented technical efficiency θ_t may be obtained by solving the following multiplier DEA program:

$$\min_{\theta_t, \lambda_k} \theta_t \qquad (1.22)$$

$$\text{s. t.}$$
$$\sum_{k=1}^{K} \lambda_k x_i^k \le \theta_t x_i^t, \quad i = 1,2,\dots,m;$$
$$\sum_{k=1}^{K} \lambda_k y_j^k \ge y_j^t, \quad j = 1,2,\dots,n;$$
$$\lambda_k \ge 0, \quad k = 1,2,\dots,K;$$
$$\theta_t \text{ unrestricted.}$$

Meanwhile, the output–oriented technical efficiency ϕ_t may be obtained by solving the following multiplier DEA program:

$$\max_{\phi_t, \lambda_k} \phi_t$$
$$\text{s. t.}$$
$$\sum_{k=1}^{K} \lambda_k x_i^k \le x_i^t, \quad i = 1,2,\dots,m;$$
$$\sum_{k=1}^{K} \lambda_k y_j^k \ge \phi_t y_j^t, \quad j = 1,2,\dots,n; \tag{1.23}$$
$$\lambda_k \ge 0, \quad k = 1,2,\dots,K;$$
$$\phi_k \text{ unrestricted.}$$

In Eqs. 1.22 and 1.23, coefficients λ_k are weights of peer DMUs. Noteworthy, this model presumes existing constant returns to scale (CRS), which is rather arbitrary condition. CRS indicates that the manufacturer is able to scale the inputs and outputs linearly without increasing or decreasing efficiency (Ramanathan, 2003).

Whereas the CRS constraint was considered over–restrictive, the BCC (Banker, Charnes, and Cooper) model was introduced (Banker et al., 1984). The CRS presumption was overridden by introducing a convexity constraint $\sum_{k=1}^{K} \lambda_k = 1$, which enabled to tackle the variable returns to scale (VRS). The BBC model, hence, can be written by supplementing Eqs. 1.22 and 1.23 with a convexity constraint $\sum_{k=1}^{K} \lambda_k = 1$.

The best achievable input can therefore be calculated by multiplying actual input by technical efficiency of certain DMU (cf. Eq. 1.22). On the other hand, the best achievable output is obtained by multiplying the actual output by the output-oriented technical efficiency, where technical efficiency scores are obtained by the virtue of Eq. 1.23. The difference between the actual output and the potential one is called the radial slack. Let us consider point (x^1, y^1) in Figure 1.10. We can note that the latter point is projected onto the efficiency frontier by reducing input x^1 to θx^1 (radial movement); however output still needs to be improved by the non-radial movement from y^1 to y^E.

In addition it is possible to ascertain whether a DMU operates under increasing returns to scale (IRS), CRS, or decreasing returns to scale (DRS). CCR measures gross technical efficiency (TE) and hence resembles both TE and scale efficiency (SE); whereas BCC represents pure TE. As a result, pure SE can be obtained by dividing CCR TE by BCC TE. Noteworthy, technical efficiency describes the efficiency in converting inputs to outputs, while scale efficiency recognizes that economy of scale cannot be attained at all scales of production (Ramanathan, 2003).

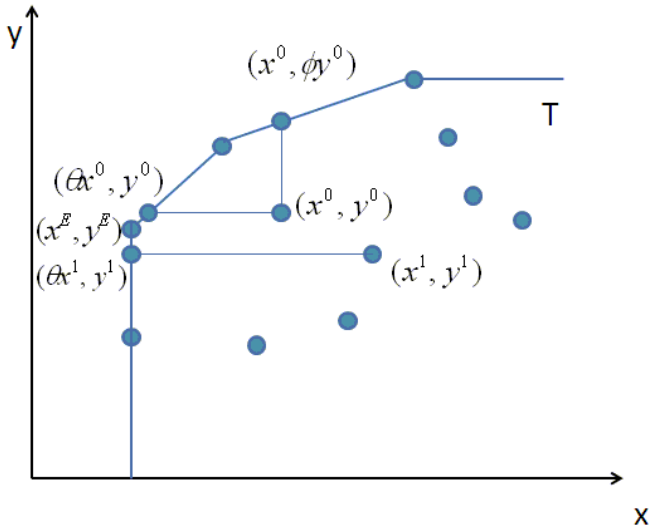


Fig. 1.10. Data envelopment analysis model.

DEA is considered as an axiomatic approach for it satisfies the axioms of convexity, free disposability, and minimal extrapolation (Afriat, 1972). The axiom of minimal extrapolation implies that the observed data are enveloped by a frontier which features the minimal distance between itself and the data.

As a result, the underlying production is given as $y_t^* = f(x^t) = \max\left\{ y \mid y = \sum_{k=1}^{K} \lambda_k y^k, x^t \geq \sum_{k=1}^{K} \lambda_k x^k, \sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0 \right\}$.

It is due to Thanassoulis et al. (2008) that the cost efficiency is obtained by the virtue of the following linear cost minimization model:

$$\begin{aligned} & \min_{\lambda_k, x_i} c(y,w) = \sum_{i=1}^{m} w_i^t x_i \\ & \text{s. t.} \\ & \sum_{k=1}^{K} \lambda_k x_i^k \leq x_i, \quad i = 1,2,...,m \\ & \sum_{k=1}^{K} \lambda_k y_j^k \geq y_j^t, \quad j = 1,2,...,n \end{aligned} \tag{1.24}$$

,

where w_i^t are the input prices for the *t*–th DMU. Indeed, this model yields the minimum cost which is the input for Eq. 1.17

Recently, many improvements to DEA have been offered (Shetty, Pakkala, 2010; Zerafat Angiz et al., 2010; Wang et al., 2009) which mainly focus on imposing peer weight restrictions and thus making DEA a more robust instrument for ranking of the DMUs. Moreover, bootstrapping techniques might be employed to estimate confidence intervals for the efficiency scores (Wilson, 2008; Odeck, 2009).

1. 3. 2. Stochastic Frontier Analysis

SFA is a parametric method for efficiency measurement. In its simplest form, it allows to define the production frontier for one output and multiple inputs technology. Further modifications, however, enable to relax this restriction. Unlike OLS and COLS, SFA models take into account both the efficiency term *u* and the error term *v*. The base model proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) then can be presented in the following manner:

$$y^k = f(x^k) TE_k e^{v_k}. \tag{1.25}$$

The base model after a log transformation becomes

$$\begin{aligned} &y^k = f(x^k, \beta) + v^k - u^k \\ &v^k \sim N(0, \sigma_v^2), u^k \sim N_+(0, \sigma_u^2) \end{aligned}, \tag{1.26}$$

where N_+ denotes half-normal distribution truncated at the zero point. Greene (2008) presented a variety of possible distribution functions, namely truncated normal, exponential, and gamma. The Maximum Likelihood method is employed to estimate parameters *β*, *u*, and *v*. The firm-specific technical efficiency is computed as follows: $TE_k = \exp(-u)$.

As one can note, a disturbance term in Eq. 1.26 consists of an inefficiency measure, *u*, and a random error, *v*, with the former being independently identically distributed truncated normal (half-normal) variable and the latter one being independently identically distributed normal variable. Therefore we cannot use OLS to decompose the disturbance term. The maximum likelihood method[2] is therefore applied.

First, we need the likelihood function describing the SFA model (Eq. 1.26). The density function for the error term, *v*, of a certain observation is the normal distribution (Bogetoft, Otto, 2011):

$$\varphi_v(v) = \frac{1}{\sqrt{2\pi\sigma_v^2}} \exp\left(-\frac{1}{2} \frac{v^2}{\sigma_v^2} \right), \tag{1.27}$$

---

[2] The method of maximum likelihood (ML) can be applied for the following linear model (Maddala, 2001):

$$y_i = \alpha + \beta x_i + u_i \quad u_i \sim iidN(0, \sigma^2),$$

where y_i are independently and normally distributed with respective means $\alpha + \beta x_i$ and a common variance σ^2. The joint density of the observations, therefore, is

$$f(y_1, y_2, ..., y_n) = \prod_{i=1}^{n} \left(\frac{1}{2\pi\sigma^2} \right)^{1/2} \exp\left[-\frac{1}{2\sigma^2}(y_i - \alpha - \beta x_i)^2 \right].$$

In case the parameters *β* are fixed, we have a density function. In case, we have a set of observations and analyse a density function in terms of parameters $(\alpha, \beta, \sigma^2)$ the latter is called a likelihood function and denoted by $L(\alpha, \beta, \sigma^2)$. The essence of the ML method is to choose these parameters so that they maximize this likelihood function. Commonly it is more convenient to maximize the logarithm of the likelihood function:

$$\ln L = \sum_{i=1}^{n} \left(-\frac{1}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}(y_i - \alpha - \beta x_i)^2 \right).$$

where σ_v^2 is the variance of *v*. The inefficiency term, *u*, follows the half–normal distribution truncated at zero:

$$\varphi_u(u) = \begin{cases} \dfrac{2}{\sqrt{2\pi\sigma_u^2}} \exp\left(-\dfrac{1}{2}\dfrac{u^2}{\sigma_u^2}\right) & \text{for } u \geq 0 \\ 0 & \text{for } u < 0 \end{cases}, \tag{1.28}$$

here the extra 2-factor is introduced to maintain the total mass of the half-normal distribution equal to unity, i. e. $\int_{-\infty}^{+\infty} \varphi_u(u)du = 1$.

Having a set of observations (x, y), one cannot directly calculate the *v* and *u* terms. Indeed, it is possible to calculate the total error term $\varepsilon = v - u = y - f(x, \beta)$. The distribution of ε, thus, is the convolution of distributions of *v* and *–u*:

$$\varphi_\varepsilon(\varepsilon) = \int_{-\infty}^{+\infty} \varphi_u(u)\varphi_v(\varepsilon + u)du = \int_0^{+\infty} \varphi_u(u)\varphi_v(\varepsilon + u)du \,. \tag{1.29}$$

After setting

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 , \tag{1.30}$$

$$\lambda = \sqrt{\sigma_u^2 / \sigma_v^2} \,, \tag{1.31}$$

and combining Eqs. 1.27–1.29 we get

$$\varphi_\varepsilon(\varepsilon) = \frac{\sqrt{2}}{\sqrt{\pi\sigma^2}} \Phi\left(-\frac{\lambda\varepsilon}{\sqrt{\sigma^2}}\right) \exp\left(-\frac{1}{2}\frac{\varepsilon^2}{\sigma^2}\right), \tag{1.32}$$

with Φ being the distribution function of the standard normal distribution with zero mean, and variance of unity, i. e. $\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{1}{2}t^2} dt$. When the parameter λ is 0, there is no effect from differences in efficiency and when it gets larger, the larger part of the whole disturbance term is attributed to variation in efficiency. The logged density function gets the following form:

$$\ln \varphi_\varepsilon(\varepsilon) = -\frac{1}{2}\ln\left(\frac{\pi}{2}\right) - \frac{1}{2}\ln \sigma^2 + \ln \Phi\left(-\frac{\lambda\varepsilon}{\sqrt{\sigma^2}}\right) - \frac{1}{2}\frac{\varepsilon^2}{\sigma^2} \,. \tag{1.33}$$

In case we have *K* observations, the joint density function becomes

$$\varphi(\varepsilon_1, \varepsilon_2, ..., \varepsilon_K) = \prod_{k=1}^{K} \varphi_\varepsilon(\varepsilon_k) \,, \tag{1.34}$$

and the logarithm of the joint density function is then given by

$$\ln \varphi(\varepsilon_1, \varepsilon_2, ..., \varepsilon_K) = \sum_{k=1}^{K} \varphi_\varepsilon(\varepsilon_k)$$
$$= -\frac{K}{2}\ln\left(\frac{\pi}{2}\right) - \frac{K}{2}\ln\sigma^2 + \sum_{k=1}^{K}\ln\Phi\left(-\frac{\lambda\varepsilon_k}{\sqrt{\sigma^2}}\right) - \frac{1}{2\sigma^2}\sum_{k=1}^{K}\varepsilon_k^2 . \quad (1.35)$$

By taking into account that the error term ε_k depends on the vector of parameters, β, we can rearrange Eq. 1.35 into the following log likelihood function:

$$l(\beta, \sigma^2, \lambda) = \ln \varphi_e(\varepsilon_1(\beta), \varepsilon_2(\beta), ..., \varepsilon_K(\beta); \sigma^2, \lambda)$$
$$= \ln \varphi_e(y_1 - f(x_1, \beta), y_2 - f(x_2, \beta), ..., y_K - f(x_K, \beta); \sigma^2, \lambda)$$
$$= -\frac{K}{2}\ln\left(\frac{\pi}{2}\right) - \frac{K}{2}\ln\sigma^2 + \sum_{k=1}^{K}\ln\Phi\left(-\frac{\lambda(y_k - f(x_k, \beta))}{\sqrt{\sigma^2}}\right) - \frac{1}{2\sigma^2}\sum_{k=1}^{K}(y_k - f(x_k, \beta))^2$$
$$. \quad (1.36)$$

The function $l(\beta, \sigma^2, \lambda)$ is the log-likelihood function which depends on the parameters β, σ^2, λ and on the observed data $(x_1, y_1), ..., (x_K, y_K)$. Thus, the maximum of the log-likelihood function is found by equating every element of its gradient to zero. The existing non-linearity, however, does not allow achieving a closed-form solution. Therefore, an iterative optimization algorithm, namely Newton's method, is employed to estimate the parameters.

The two functional forms are usually employed for SFA, viz. Cobb–Douglas (Cobb, Douglas, 1928) and Translog (Christensen et al., 1971, 1973). The logged Cobb–Douglas production function has the following form:

$$\ln y_k = \ln \beta_0 + \sum\nolimits_{i=1}^{m} \beta_i \ln x_i^k + v^k - u^k . \quad (1.37)$$

Translog (Transcendental Logarithmic Production Function) is a generalization of the Cobb–Douglas function:

$$\ln y_k = \beta_0 + \sum\nolimits_{i=1}^{m} \beta_i \ln x_i^k + \frac{1}{2}\sum\nolimits_{i=1}^{m}\sum\nolimits_{l=1}^{m} \beta_{il} \ln x_i^k \ln x_l^k + v^k - u^k . \quad (1.38)$$

As one can note, production functions defined by Eqs. 1.37–1.38 can tackle single–output technology only. To measure the productive efficiency and analyse the production technology, we can employ the Shepard distance functions (cf. Eqs. 1.8 and 1.11). Given both $D_I(x, y)$ and $D_O(x, y)$ are homogeneous of degree +1 in x and y, respectively, the following equations hold:

$$D_I^k(x^k, y^k) = x_m^k D_I^k\left(\frac{x^k}{x_m^k}, y^k\right), \tag{1.39}$$

$$D_O^k(x^k, y^k) = y_n^k D_O^k\left(x^k, \frac{y^k}{y_n^k}\right). \tag{1.40}$$

By logging both sides of Eqs. 1.39–1.40 and substituting $-\ln D_I^k = -\ln D_O^k = -u^k$, where u^k is the inefficiency term of the k-th DMU, we have:

$$\ln\left(\frac{1}{x_m^k}\right) = \ln D_I^k\left(\frac{x^k}{x_m^k}, y^k\right) - u^k, \tag{1.41}$$

$$\ln\left(\frac{1}{y_n^k}\right) = \ln D_O^k\left(x^k, \frac{y^k}{y_n^k}\right) - u^k. \tag{1.42}$$

The latter two equations can be evaluated by adding the error term v^k and specifying a SFA model. A translog function might be employed to approximate the input and output distance functions. By choosing (arbitrarily) certain input x_m we normalize the input vector and thus define a homogeneous translog input distance function:

$$\begin{aligned}\ln\left(\frac{1}{x_m^k}\right) = {} & a_0 + \sum_{i=1}^{m-1} a_i \ln\frac{x_i^k}{x_m^k} + \sum_{j=1}^{n} b_j \ln y_j^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{l=1}^{m-1}\alpha_{il} \ln\frac{x_i^k}{x_m^k}\ln\frac{x_l^k}{x_m^k} \\ & + \frac{1}{2}\sum_{j=1}^{n}\sum_{p=1}^{n}\beta_{jp} \ln y_j^k \ln y_p^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{j=1}^{n}\gamma_{ij} \ln\frac{x_i^k}{x_m^k}\ln y_j^k + v^k - u^k.\end{aligned} \tag{1.43}$$

Similarly, a translog output distance function is defined in the following way:

$$\begin{aligned}\ln\left(\frac{1}{y_n^k}\right) = {} & a_0 + \sum_{i=1}^{m} a_i \ln x_i^k + \sum_{j=1}^{n-1} b_j \ln\frac{y_j^k}{y_n^k} + \frac{1}{2}\sum_{i=1}^{m}\sum_{l=1}^{m}\alpha_{il} \ln x_i^k \ln x_l^k \\ & + \frac{1}{2}\sum_{j=1}^{n-1}\sum_{p=1}^{n-1}\beta_{jp} \ln\frac{y_j^k}{y_n^k}\ln\frac{y_p^k}{y_n^k} + \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n-1}\gamma_{ij} \ln x_i^k \ln\frac{y_j^k}{y_n^k} + v^k - u^k\end{aligned}. \tag{1.44}$$

Equations 1.43 and 1.44 imply that we only need to estimate a_1, a_2, ..., a_{m-1} and b_1, b_2, ..., b_{n-1}, respectively, whereas $a_m = 1 - \sum_{i=1}^{m-1} a_i$ and $b_n = 1 - \sum_{j=1}^{n-1} b_n$.

The similar computations are valid for the cost frontier. For instance, Greene (2008) presents the specification of a multiple–output translog cost function. After imposing its homogeneity it has the following form:

$$\ln\frac{C_k}{w_m} = \alpha_0 + \sum_{i=1}^{m-1}\alpha_i \ln\frac{w_i^k}{w_m^k} + \sum_{j=1}^{n}\beta_j \ln y_j^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{l=1}^{m-1}\gamma_{il}\ln\frac{w_i^k}{w_m^k}\ln\frac{w_l^k}{w_m^k} + \frac{1}{2}\sum_{j=1}^{n}\sum_{p=1}^{n}\delta_{jp}\ln y_j^k \ln y_p^k + \frac{1}{2}\sum_{i=1}^{m-1}\sum_{j=1}^{n}\phi_{ij}\ln\frac{w_i^k}{w_m^k}\ln y_j^k + v^k + u^k, \quad (1.45)$$

where C_k is the observed costs for the k-th DMU and w_i^k denotes price of the i-th input for the k-th DMU. Note that inefficiency term, u^k, increases the value of cost function. Accordingly, special treatment of these functions is needed when employing statistical packages (e. g. package *frontier* in *R*).

1. 4. Agriculture in Lithuania

For historical reasons, the agricultural sector still faces the consequences of the previous collectivization (Gorton and Davidova, 2004). Since Lithuania joined the EU in 2004 they have been subject to the regulations of the Common Agricultural Policy and the Lithuanian agricultural sector has undergone substantial transformation. Therefore in the present study we choose to consider input efficiency since our focus will be on the efficiency in the utilization of various input factors. Considering the utilization of specific input factors enables individual farmers to better target efficiency improving strategies as well as planners to better design efficiency improving policies.

The economic crisis stressed the importance to look for efficiency gains in the agricultural sector. As it is the case in all Central and East European (CEE) countries, the agricultural sector constitutes an important part of the Lithuanian economy. Eurostat (2014) reports that the share of the gross domestic product (GDP) generated in the latter sector decreased from 4% in 2004 down to 2.3% in 2009; however it rebounded to 3.2% in 2011 (in current prices). To compare, the respective figures for the 27 European Union (EU) Member States (EU-27) are 1.8%, 1.3%, and 1.5%. As for the “old” EU

Member States (EU-15), these figures are even lower, viz. 1.6%, 1.2%, and 1.3%. The same pattern is revealed by considering the structure of employment: the share of employees working the agricultural sector is 15% back in 2004, whereas it subsequently decreased to 8.3% in 2008 and further down to 7.7% in 2011. Meanwhile, the EU-27 featured the shares of 5.8%, 5%, and 4.9%, respectively. Considering the EU-15, the corresponding figures are 3.2%, 2.8%, and 2.8%. Thus, the Lithuanian agricultural sector still plays a relatively more important role in the Lithuanian economy as it is the case in the economically advanced EU Member States. Even though the outcomes of the economic transition are evident, agriculture will remain both an economically and socially important activity in Lithuania.

In addition, the Lithuanian agricultural sector faces certain transformations due to the historical context prevailing in the CEE countries. Specifically, the collectivization and de-collectivization rendered distortions of the factor markets, which, in turn, have been shaping farmers' decisions to a certain extent. Another important factor of the agricultural development in Lithuania is the European integration processes. Lithuania acceded to the EU in 2004 and thus became a subject to the Common Agricultural Policy. As a result, the farm structure has been changing in terms of both land area and farming type. The aforementioned circumstances stress the need for researches into efficiency of the Lithuanian farms. Indeed, these researches would enable to identify the main reasons of inefficiency and possible paths for development.

The issues of agricultural efficiency are of particular importance in Lithuania, which, like other post-communist Central and East European states, has a relatively large agricultural sector and, to some extent, still faces the consequences of collectivization (Gorton, Davidova, 2004). In Lithuania, the process of de-collectivization began in 1989 and reached its peak in 1992–1993. Since then the Lithuanian agricultural sector has undergone a profound transformation. Lithuania acceded to the EU in 2004. Consequently, the Lithuanian agricultural sector became subject to the regulations of the

Common Agricultural Policy. As of 2004–2009, the rural population constituted one third of the total population of Lithuania. The share of agricultural and related activities in gross value added accounted for some 4% in 2004 but went down to 2.3% in 2009 (Statistics Lithuania, 2010). Over the same period, the share of employees engaged in agricultural and related activities also dropped, from 15.2% to 8.3%.

Gross agricultural production amounted to some 4.6 billion Litas (1.3 billion Euros) in 2004, whereas it decreased during years 2006 and 2009. A value of 5.7 billion Litas (1.65 billion Euros) was observed in 2009. Family farms account for the most significant share of agricultural production; 75% in 2004 and 71% in 2009 (Statistics Lithuania, 2010). Thus, family farms are the key suppliers of agricultural production in Lithuania.

The agricultural census of 2010 indicated certain changes in Lithuanian farm structure. Specifically, both the number and area of small farms (up to 100 ha) decreased between 2003 and 2010, whereas indicators for large farms (over 100 ha) increased during the same period. As Statistics Lithuania (2012) reports, the number of large farms grew from 2.1 thousand in 2003 up to 3.8 thousand in 2010, an increase of 81%. The land area owned by large farms consequently increased to 74%. The relative importance of large farms increased at an even more rapid pace. In 2003, large farms occupied some 26% of all utilized agricultural area (i.e. 2.49 million ha), whereas by 2010 these farms had increased their land share to 42% of the utilized agricultural area, which itself had also increased (to 2.74 million ha). Those developments led to an increase in the average farm size from 9.3 ha to 13.8 ha throughout 2003–2010 (Department …, 2005; Statistics Lithuania, 2012). Indeed, these trends can be perceived as an adjustment toward the farm structure typical of developed EU member states. Therefore, one can expect further expansion of large farms given that agricultural policy will not impose additional incentives for small farms. In addition, a significant amount of existing abandoned land provides large farms with opportunities for further expansion. As of 2010, there were approximately 500 thousand ha of abandoned land in Lithuania

(Kuliešis et al., 2011). It is thus important to estimate the possible effect of these developments on the technical efficiency of the Lithuanian agricultural sector.

Furthermore, a decline in livestock farming is evident in Lithuania. The share of the crop output to the gross agricultural output increased from 50% in 2004 to 56% in 2009 (Statistics Lithuania, 2010). This increase was especially significant among family farms, where the share of the crop output increased from 55% to 65% throughout the same period. However, the agricultural enterprises themselves virtually did not change their production structure. Noteworthy, dairy is the main branch of livestock farming in Lithuania. Significant changes in the relative prices of livestock production fuelled the transition from livestock farming toward crop farming.

We can observe a general trend of farmers shifting from livestock to crop farming. From 2004 to 2011, the share of crop output to the gross agricultural output increased from 50% to 59% for the sector in general and from 55% to 65% amongst the family farms (Statistics Lithuania, 2012). This indicates that family farms are switching from livestock to crop farming at a faster pace than the sector in general.

2. RESEARCH METHODOLOGY

This section describes the techniques employed to address the tasks of the research. Indeed, we present techniques for estimation of the efficiency scores and efficiency effects, TFP indices, and techniques for analysis of the productive technology. The general framework of the research is depicted in Fig. 2.1.

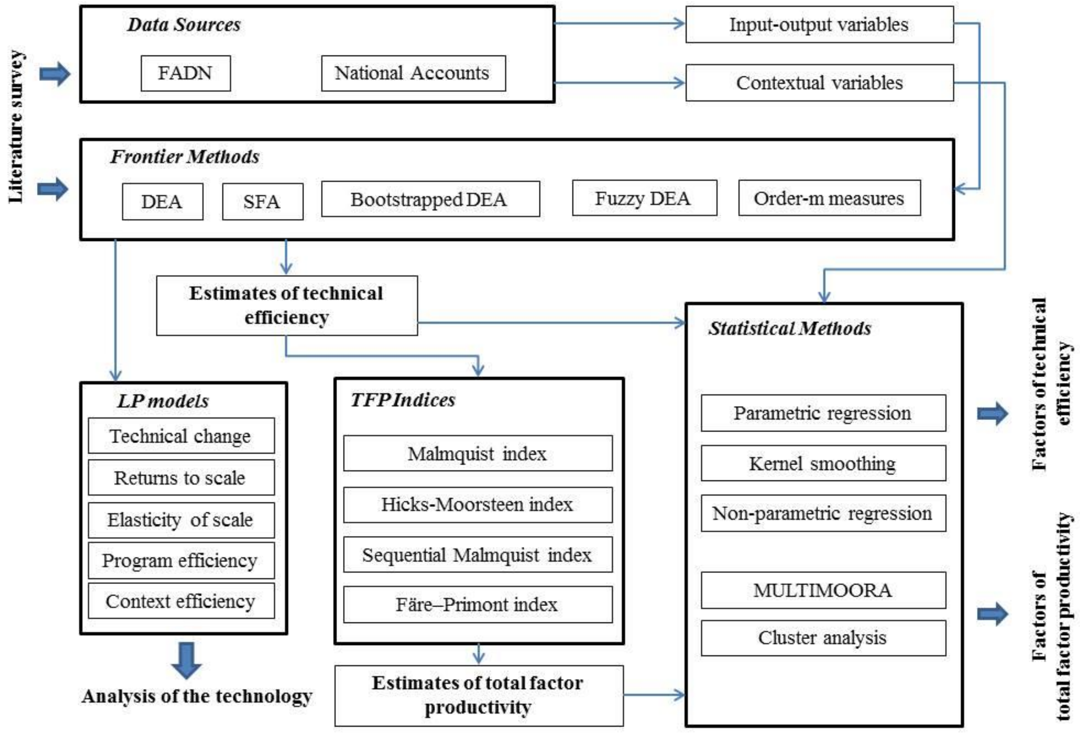


Fig. 2.1. Framework of the research.

Noteworthy, the following methodologies are introduced by the author:

- A hybrid methodology for TFP and efficiency analysis, DEA-MULTIMOORA (Baležentis et al., 2013);
- non-parametric analysis of efficiency effects with assumption of separability (Baležentis et al., 2014);
- fuzzy FDH (Hougaard, Baležentis, 2014) for analysis of uncertain data;
- program MEA for analysis of managerial and program efficiency.

2. 1. Estimation of technical efficiency and its determinants

This sub-section presents the main methods used for estimation of the productive efficiency as well the second stage analysis. In particular, we focus on the following issues: 1) bootstrapped DEA, 2) partial frontiers, 3) fuzzy FDH, 4) second stage analysis.

Productivity is considered as the key factor for competitiveness in the long run (European Commission, 2011). Indeed, it also guarantees non-inflatory growth and thus provides a momentum for increase in real income. It is due to Latruffe (2010) that measures of competitiveness can be broadly classified into neoclassical ones and strategic management ones. The neoclassical approach analyses competitiveness from the viewpoint of international trade flows, whereas the strategic management theories focus on the specific factors of competitiveness. These factors encompass, for instance, profitability, productivity, and efficiency. It is, therefore, important to analyse the trends in productivity and efficiency in order to make reasonable strategic management decisions. Furthermore, this study will focus on the strategic management approach rather than neoclassical one.

Frontier techniques are those most suitable for efficiency and productivity analysis (Murillo-Zamorano, 2004; Margono et al., 2011; Bogetoft, Otto, 2011; Bojnec, Latruffe, 2011; Atici, Ulucan 2011; Hajiagha et al., 2013). These methods can be grouped into parametric and nonparametric as well as into deterministic and stochastic ones. This study employs a deterministic non-parametric method, data envelopment analysis, which requires no a priori specification of the functional form of the underlying production function[3]. Furthermore, productivity indices are employed to analyse the changes in productivity. The two seminal methods are usually employed, namely Malmquist and Luenberger productivity indices (Ippoliti, Falavigna, 2012; Tohidi et al., 2012).

[3] Indeed, the production function is implicitly assumed to be a locally linear one.

On the other hand, efficiency can be analysed at various levels, namely at the firm, sector, and nation level. The assessment of inter-sectoral patterns of efficiency provides a rationale for strategic management for both private and public decision makers. Indeed, the comparison of efficiency across different sector of Lithuanian economy has been analysed by the means of financial ratios (Baležentis et al., 2012). Therefore, there is a need for further studies on the area. This thesis aims to analyse the productive efficiency across different sectors of Lithuanian economy by the means of the Malmquist productivity index. It is worth to be noted, that the latter method has not been applied for analysis of the Lithuanian economy.

Hybrid method DEA-MULTIMOORA. The economic researches often involve multiple conflicting objectives and criteria (Zavadskas, Turskis, 2011). In our case, we have different efficiency and productivity change indicators. Accordingly the multi-criteria decision making method MULTIMOORA (Brauers, Zavadskas, 2006; 2010, 2011) is employed to summarize these indicators and provide an integrated ranking of the economic sectors. Such a ranking provides some insights regarding possible success in competition for resources among the economic sectors.

Graph DEA and rank-sum test. Agricultural census of 2010 indicated certain changes in the Lithuanian farm structure. Specifically, both the number and the area of small farms (up to 100 ha) had decreased in between 2003 and 2010, whereas respective indicators for large farms (over 100 ha) had increased during the same period (cf. Section 1.4). It is thus important to estimate the possible effect of these developments on the technical efficiency of the Lithuanian agricultural sector. The graph DEA and the rank–sum test were employed to test the relationships between efficiency and farm expansion variables. The *R* programming language and package *Benchmarking* (Bogetoft, Otto, 2011) were employed to implement the graph DEA model.

Henningsen and Kumbhakar (2009) pointed out that farm-level data for Central and Eastern Europe often feature statistical noise, owing to both internal and external factors. Internal factors encompass farmers' and consulting services' willingness and ability to report the true figures associated with inputs and outputs involved in the production process. For instance, tax policies or gaps in methodologies could lead to biased farm-level data. As for the external factors, these are related to ongoing shifts in farm structure and factor markets, which, in turn, were fuelled by integration into the Common Market. The purely deterministic DEA, therefore, might not ensure robust analysis. As a remedy to this problem, we opted to employ bootstrapped DEA, which mitigates the underlying bias to a certain extent.

Bootstrapped DEA was introduced by Simar and Wilson (1998b, 2000a, 2000b). Assaf and Matawie (2010) employed bootstrapped DEA to assess the efficiency of health care foodservice facilities. Aldea and Ciobanu (2011) and Aldea et al. (2012) used bootstrapped DEA to analyse renewable energy production efficiency across EU Member States. Halkos and Tzeremes (2012) used it in their analysis of the Greek renewable energy sector. Noteworthy, the Lithuanian agricultural sector has not yet been analysed by means of bootstrapped DEA. Analysis of efficiency can be carried out by visualizing the densities of the efficiency scores (Simar, Zelenyuk, 2006; Mugera, Langemeier, 2011). Fuzzy clustering is used to identify efficiency change paths. Finally, non-parametric regression is employed to reveal underlying relationships between the efficiency scores and the determinants of inefficiency.

Robust frontiers. The analyses of efficiency and productivity usually rest on the estimation of the production frontier. The production frontier can be estimated via either the parametric or non-parametric methods or combinations thereof. The non-parametric techniques are appealing ones due to the fact that they do not need the explicit assumptions on the functional form of the underlying production function and still enable to impose certain axioms in regards to the latter function (Afriat, 1972).

The deterministic non-parametric methods, though, feature some caveats. Given the data generating process (DGP) of the observed production set is unknown, the underlying production set also remains unknown.

Therefore, the efficiency scores based on the observed data—which constitute a single realization of the underlying DGP—might be biased due to outliers. As a remedy to the latter shortcoming, the statistical theory could be employed to construct the random production frontiers. The chance constrained DEA seek to tackle the statistical noise which affects all the observations (Land et al., 1993; Huang, Li, 2001). Another remedy to the uncertainty in the efficiency analysis is the partial frontier measures (Daraio, Simar, 2007a).

The partial frontiers (also referred to as the robust frontiers) were introduced by Cazals et al. (2002). The idea was to benchmark an observation not against all the observations dominating it but rather against a randomly drawn sample of these. This type of frontier was named the order–*m* frontier. The latter methodology has been extended by introducing the conditional measures enabling to analyse the impact of the environmental variables on the efficiency scores (Daraio, Simar, 2005, 2007a, 2007b). Wheelock and Wilson (2003) introduced the Malmquist productivity index based on the partial frontiers. Simar and Vanhems (2013) presented the directional distance functions in the environment of the partial frontiers. The order–*m* frontiers have been employed in the sectors of healthcare (Pilyavsky, Staat, 2008) and finance (Abdelsalam et al., 2013) among others.

In spite of the importance of the efficiency analysis and the shortcomings of the conventional efficiency measures, efficiency of the Lithuanian agricultural sector—like that of the other ones—has not been analysed by the means of the partial frontiers. Indeed, the Lithuanian agricultural sector has been analysed by the means of the bootstrapped Data Envelopment Analysis (Baležentis, Kriščiukaitienė, 2012b). However, the latter method offers rather poor means for the analysis of sensitivity. Therefore, there is a need for further analyses of performance of the Lithuanian family farms and agricultural sector in general. The simulation–based methodology is of particular importance in the latter context.

On the other hand, the order–α frontiers were introduced to define the benchmark by rather setting the probability of dominance, α. It was Aragon et al. (2005) who introduced the concept of the order–α frontiers in a (partially) univariate framework. Daouia and Simar (2007) further developed the latter concept by allowing for the multivariate analysis. Wheelock and Wilson (2008) offered an unconditional measure of the α–efficiency.

Fuzzy FDH. In practice, though, the results of DEA studies are often subject to considerable uncertainties. There are at least two main reasons for that:

First, the data that are used are typically connected with some level of uncertainty. This may not only be a result of stochastic measurement errors but also be caused by more systematic differences in data registration (for instance if units are compared across different countries or if units are compared across different time periods). In some countries data uncertainties are also caused by lack of tradition for data collection and thereby strong varying data quality with partly missing or estimated data etc.

Second, the DEA methodology is very sensitive to such data uncertainties since the methods are non-parametric and based on extreme observations (undominated observations). Thus, flawed data distorts the estimated efficient frontier of the production possibility set, which plays the role as benchmark for all other observations.

These problems are well-recognized in the DEA-literature and dealt with in many different ways (Liu et al., 2013). One such way is to express data uncertainties through the use of fuzzy numbers instead of usual crisp data. Data sets consisting of fuzzy numbers can then be incorporated into the DEA framework as demonstrated in the, by now, substantial strand of literature on fuzzy DEA, see e.g., the recent survey in Hatami-Marbini et al. (2011).

In this study, we suggest yet another approach particularly related to a variant of the DEA model called the FDH-method, see e.g. Deprins et al. (1984), Tulkens (1993). The FDH-method is basically DEA without the assumption of convexity (of the technology). As such it builds on a minimal set of assumptions concerning the underlying production technology. While theoretically convenient, the convexity assumption is often questionable in practice.

We suggest a specific method (Hougaard, Baležentis, 2014) for fuzzy production data which mimics the FDH-method for crisp data. For each α-level fuzzy data (in the form of fuzzy numbers) take the form of intervals. Our main idea is to rank such intervals using probabilities for having either the lowest or the highest value among a given set of intervals under the assumption that values are uniformly distributed over the range of each interval. Using these probabilities we define a dominance relation between production units as well as max and min operators over intervals. This enables us to mimic exactly the way (Farrell's radial technical) efficiencies are determined in the crisp FDH-model. The final fuzzy efficiency score combines the interval scores of each α-level set.

Our approach has the advantage to alternative approaches that all involved computations are quite simple. In this way we avoid, for instance, the use of fuzzy programming techniques. Moreover, our approach is quite flexible in the sense that it allows the analyst (and/or decision maker) to engage in an iterative decision process through changes in the various parameters of the method.

We illustrate the suggested fuzzy FDH-method using a data set on Lithuanian family farms where significant variation in data can be found for the same farm over several time periods. One reason for this can be stochastic events like changing weather conditions but other types of data uncertainties may be present as well. We therefore model data uncertainty by triangular fuzzy numbers where the value of a given variable for the year in question can be modelled as the kernel and the support is made up by respectively the minimal and maximal observation for that variable over the total time span.

Second-stage analysis. Efficiency analysis is often followed by second-stage analysis to estimate the impact of certain efficiency determinants. Suchlike inference might be useful for understanding of the underlying trends of efficiency and, thus, reasonable policy making. The second-stage analysis can be based on various techniques (Hoff, 2007; Bogetoft, Otto, 2011). In principle, the two frameworks can be defined for DEA-based efficiency scores. In semi-parametric frameworks, the DEA scores are regressed on explanatory variables by employing models of limited dependent variables. In fully non-parametric frameworks, non-parametric regression is used in the second stage analysis. The non-parametric framework under the assumption of separability among explanatory variables and production frontier was described by Daraio and Simar (2005), whereas that under no assumption of separability is presented in this thesis (cf. Section 3.3)

Initially, the ordinary least squares (OLS) regression was considered as a primal tool for post-efficiency analysis. The latter method is attractive in that its coefficients are easy to interpret. However, it is obvious that efficiency scores are bounded to certain intervals which depend on both the type and the orientation of the distance functions. Consequently, the censored regression (tobit model) emerged as a remedy. Later on, however, Simar and Wilson (2007) argued that the censored regression models suffer from certain drawbacks. First, the underlying data generating process does not generate censored variables. Indeed, it is the finite sampling that causes efficiency estimates concentrated around unity. Second, censored model's errors are serially correlated. Therefore they suggested using truncated regression alongside bootstrapping (Efron, Tibshirani, 1993) in order to avoid the serial correlation. The proposed methodology is thus referred to as the double bootstrapping.

The double bootstrap procedure was implemented in analyses dedicated for various economic sectors (Assaf, Agbola, 2011; Alexander et al., 2010; Afonso, Aubyn, 2006). Though, there are few examples of application of the double bootstrap methodology for the researches of agricultural efficiency. Latruffe et al. (2008) analysed the performance of Czech farms, both private and corporate ones. Balcombe et al. (2008) employed the double bootstrap methodology to identify the determinants of efficiency in Bangladesh rice farming. Olson and Vu (2009) utilised single and double bootstrap procedures to analyse farm household efficiency.

The conditional measures of efficiency are developed for a univariate framework by Cazals et al. (2002) and for a multivariate framework by Daraio and Simar (2005). Conditional measures estimate efficiencies without assuming that the environmental variables affect only the distribution of the efficiency scores, but do not alter the very production frontier (i.e. the separability condition does not hold). By comparing like with likes the operational environment is immediately included in the efficiency estimates.

The environment a certain observation operates in can be described by a vector of environmental variables, $Z = z \in \mathbb{R}^r$. The joint probability function of dominance can then be extended as $H_{XY|Z}(x, y) = \Pr(X \le x, Y \ge y \mid Z = z)$. The environmental variables can be both discrete and continuous. As suggested by De Witte and Kortelainen (2013), the kernel of Aitchison and Aitken (1976) can be used for unordered discrete variables, whereas that of Li and Racine (2007) – for ordered discrete variables. Hall et al. (2004) and Li and Racine (2008) presented the least squares cross validation method for bandwidth selection.

The influence of the environmental variables upon the efficiency scores can be quantified by computing the ratios of the conditional measures over the unconditional ones: $Q^z = \frac{\hat{\lambda}_{m,K}(x, y \mid z)}{\hat{\lambda}_{m,K}(x, y)}$. In a fully non-parametric framework, one than specify a non-parametric model to relate the ratios, Q_k^z, to the environmental variables, z_k: $Q_z^k = f(z_k) + \epsilon_k$ for $k = 1, 2, \ldots, K$ (De Witte and Kortelainen, 2013).

2. 2. Total factor productivity indices

A production frontier can move inwards or outwards from the origin point depending on the technological development underlying the observed productive system. Thus, one needs to measure not only efficiency, but also the total factor productivity (TFP) change which tackles both firm-specific catch-up and system-wide technical change. For the latter purpose, the productivity indices are usually employed (Caves et al., 1982). These can be Malmquist, Luenberger, Hicks–Moorsteen, Färe–Primont etc.

Efficiency measures can be employed to construct various productivity indices, which, in turn, can be further decomposed into certain terms describing the different factors on productivity change (Bojnec, Latruffe, 2009, 2011). One of the most elaborated measures for efficiency is data envelopment analysis (DEA), see, for instance, studies by Murillo-Zamorano (2004), Knežević et al. (2011), Borůvková and Kuncová (2012), Votápková and Žák (2013), Zelenyuk (2012). Accordingly, various studies employed DEA for efficiency and productivity analysis in agriculture (Alvares, Arias, 2004; Gorton, Davidova, 2004; Douarin, Latruffe, 2011; Bojnec, Latruffe, 2011). However, efficiency estimates are not enough to identify the underlying trends of productivity. Therefore, the productivity indices are employed to measure changes in the total factor productivity (Mahlberg et al., 2011; Sufian, 2011).

Specifically, the three types of TFP indices are commonly utilized to estimate the dynamics of the total factor productivity viz. (i) Malmquist index, (ii) Hicks–Moorsteen index, and (iii) Luenberger index (Färe et al., 2008). The Malmquist productivity index relies on multiplicative relations and usually is either input- or output-oriented. The Hicks–Moosteen index is based on input and output modification. The Luenberger productivity index (Luenberger, 1992; Chambers et al., 1996) is based on additive decomposition and directional distance function.

Moreover, Tulkens and Vanden Eeckaut (1995) defined the three types of technologies underlying the TFP indices, namely (i) contemporaneous, (ii) sequential, and (iii) intertemporal technologies. This study also employs the sequential Malmquist–Luenberger productivity index (Oh, Heshmati, 2010), which is more robust as outliers have lesser effect on the shape of the production possibility set. Furthermore, no technical regress is allowed which might be true in the agricultural sector assuming that farmers do not lose their knowledge.

Färe et al. (2008) firstly describe productivity as the ratio of output *y* over input *x*. Thereafter, the productivity can be measured by employing the output distance function of Shepard (1953):

$$D_o^t(x, y) = \min\{\theta : (x, y/\theta) \in T^t\}, \tag{2.1}$$

where T^t stands for the technology set (production possibility set) of the period *t*. This function is equal to unity if and only if certain input and output set belongs to production possibility frontier.

The Malmquist productivity index (Malmquist, 1953) can be employed to estimate TFP changes of single firm over two periods (or *vice versa*), across two production modes, strategies, locations etc. In this study we shall focus on output–oriented Malmquist productivity index and apply it to measure period–wise changes in TFP. The output–oriented Malmquist productivity index due to Caves et al. (1982) is defined as

$$M_o = \left(M_o^0 \cdot M_o^1\right)^{1/2} = \left(\frac{D_o^0\left(x^1, y^1\right)}{D_o^0\left(x^0, y^0\right)} \frac{D_o^1\left(x^1, y^1\right)}{D_o^1\left(x^0, y^0\right)}\right)^{1/2}, \tag{2.2}$$

with indexes 0 and 1 representing respective periods. The two terms in brackets follows the structure of Fisher's index. Consequently a number of studies (Färe et al., 1992, 1994; Ray, Desli, 1997; Simar, Wilson, 1998a; Wheelock, Wilson, 1999) attempted to decompose the latter index into different terms each explaining certain factors of productivity shifts. Specifically, Färe et al. (1992) decomposed productivity change into efficiency change (EC or catching up) and technical change (TC or shifts in the frontier):

$$M_o = EC \cdot TC, \tag{2.3}$$

where

$$EC = D_o^1\left(x^1, y^1\right) / D_o^0\left(x^0, y^0\right), \tag{2.4}$$

and

$$TC = \left(\frac{D_o^0\left(x^1, y^1\right)}{D_o^1\left(x^1, y^1\right)} \frac{D_o^0\left(x^0, y^0\right)}{D_o^1\left(x^0, y^0\right)}\right)^{1/2}. \tag{2.5}$$

EC measures the relative technical efficiency change. The index becomes greater than unity in case the firm approaches frontier of the current technology. TC indicates whether the technology has progressed and thus moved further away from the observed point. In case of technological progress, the TC becomes greater than unity; and that virtually means that more can be produced using fewer resources. Given the Malmquist productivity index measures TFP growth, improvement in productivity will be indicated by values greater than unity, whereas regress – by that below unity.

An important issue associated with the decomposition a la Färe et al. (1992) is that of returns to scale. In this case Eqs. 2.1–2.5 represent distance functions relying on the assumption of the constant returns to scale (CRS) rather than variable returns to scale (VRS). As a result the efficiency change component, *EC*, catches both the pure technical efficiency change and scale change. The latter two terms were defined by Färe et al. (1994) who offered the decomposition of the Malmquist productivity index under assumption of VRS. Indeed, macro-level studies do often assume the underlying production technology as a CRS technology.

Färe et al. (1994), for instance, further decomposed the EC term, i. e. the global efficiency change, into the two components, viz. pure technical efficiency change (PEC) and scale efficiency change (SEC):

$$M_o = EC \cdot TC \equiv PEC \cdot SEC \cdot TC . \tag{2.6}$$

The latter two components measure the performance of a firm in terms of both variable returns to scale (VRS) and CRS technologies. Specifically, the PEC component is obtained by considering the change in pure technical efficiency (i. e. VRS efficiency), whereas the SEC component relies on distance from both CRS and VRS frontiers:

$$M_o = \underbrace{\frac{D_{ov}^1\left(x^1, y^1\right)}{D_{ov}^0\left(x^0, y^0\right)}}_{PEC} \cdot \underbrace{\left(\frac{D_{oc}^1\left(x^1, y^1\right) / D_{ov}^1\left(x^1, y^1\right)}{D_{oc}^0\left(x^0, y^0\right) / D_{ov}^0\left(x^0, y^0\right)}\right)}_{SEC} \cdot \underbrace{\left(\frac{D_{oc}^0\left(x^1, y^1\right)}{D_{oc}^1\left(x^1, y^1\right)} \frac{D_{oc}^0\left(x^0, y^0\right)}{D_{oc}^1\left(x^0, y^0\right)}\right)^{1/2}}_{TC}, \tag{2.7}$$

where $PEC > 1$ indicates catch-up of a certain DMU in terms of pure technical efficiency, $PEC = 1$ indicates no change, and $PEC < 1$ indicates a negative catch-up effect; $SEC > 1$ indicates that a DMU gets closer to its optimal scale of operation, $SEC = 1$ indicates no change in scale efficiency, and $SEC < 1$ implies that that a DMU moves further from the optimal scale. As one can note, the TC component in Eq. 2.7 is the same as that in Eq. 2.5.

In case a certain DMU keeps its efficiency at the same level throughout the two periods under consideration, the CRS frontier remains unchanged and the only change is the shift in the VRS frontier, the TC component will not identify these developments. As a remedy to this shortcoming, an additional decomposition of the Malmquist productivity index was offered by Simar and Wilson (1998a). Whereas the EC component was further decomposed by Färe et al. (1994), Simar and Wilson (1998a) introduced a decomposition of the TC term into the pure technology change (PTC) and changes in scale of the technology (STC). Therefore, the Malmquist productivity index can be decomposed into the four components:

$$M_o = EC \cdot TC \equiv PEC \cdot SEC \cdot PTC \cdot STC. \tag{2.8}$$

The latter two terms refer to VRS and both VRS and CRS technologies, respectively. Indeed, these computations follow the spirit of the EC decomposition offered by Färe et al. (1994). The following computations then lead to estimation of the Malmquist productivity index (Simar, Wilson, 1998a):

$$M_o = \underbrace{\frac{D_{ov}^1\left(x^1, y^1\right)}{D_{ov}^0\left(x^0, y^0\right)}}_{PEC} \cdot \underbrace{\left(\frac{D_{oc}^1\left(x^1, y^1\right) / D_{ov}^1\left(x^1, y^1\right)}{D_{oc}^0\left(x^0, y^0\right) / D_{ov}^0\left(x^0, y^0\right)} \right)}_{SEC}$$

$$\cdot \underbrace{\left(\frac{D_{ov}^0\left(x^1, y^1\right)}{D_{ov}^1\left(x^1, y^1\right)} \frac{D_{ov}^0\left(x^0, y^0\right)}{D_{ov}^1\left(x^0, y^0\right)} \right)^{1/2}}_{PTC} \quad , \qquad (2.9)$$

$$\cdot \underbrace{\left(\frac{D_{oc}^0\left(x^1, y^1\right) / D_{ov}^0\left(x^1, y^1\right)}{D_{oc}^1\left(x^1, y^1\right) / D_{ov}^1\left(x^1, y^1\right)} \frac{D_{oc}^0\left(x^0, y^0\right) / D_{ov}^0\left(x^0, y^0\right)}{D_{oc}^1\left(x^0, y^0\right) / D_{ov}^1\left(x^0, y^0\right)} \right)^{1/2}}_{STC}$$

where PEC and SEC feature the same interpretations as in Eq. 2.7; $PTC > 1$ means that the VRS frontier moves outwards due to a technical progress, $PTC = 1$ implies no change, and $PTC < 1$ indicates an inward movement of the VRS frontier associated with a technological regress; $STC > 1$ suggests that the underlying technology increases its curvature and approaches VRS; $STC = 1$ means that the technology exhibits no change in its shape, and $STC < 1$ implies a flattening of the technology and a movement towards CRS.

The Malmquist productivity index can be estimated by the means of the distance functions based either on parametric (e. g. stochastic frontier analysis) or non-parametric (e. g. data envelopment analysis) estimates. The generic non-parametric methods do not account for the statistical noise. Therefore, the bootstrapping approach was offered by Simar & Wilson (1998b, 2000) for the data envelopment analysis (DEA) and the Malmquist productivity indices (Simar & Wilson, 1999). Wilson (2008) did also develop the *FEAR* package to facilitate these computations.

The latter methodology has been widely employed for the productivity analyses. As for agriculture and fisheries, Hoff (2006) analysed the fishing activity by the means of the bootstrapped Malmquist indices; Odeck (2009) applied the bootstrapped Malmquist indices to the Norwegian grain industry; Balcombe, Davidova & Latruffe (2008) researched into the productivity of the Polish family farms, whereas Rezitis, Tsiboukas & Tsoukalas (2009) focused on the Greek livestock farms. The remaining sectors were also analysed by the means of the bootstrapped Malmquist indices. For instance, Perelman & Serebrisky (2012) analysed the efficiency and productivity of the Latin American airports. Jaraitė & Di Maria (2012) employed the bootstrapped Malmquist indices for analysis of power generation in the European Union. Horta et al. (2013) analysed the performance of the construction industry. Arjomandi, Valadkhani & Harvie (2011) utilized the bootstrapped Malmquist indices for analysis of the Iranian banking sector. Zhou, Ang & Han (2010) employed the bootstrapped Malmquist indices for the analysis of carbon emissions with weak disposability.

This study applies the bootstrapped Malmquist productivity index to a sample of the Lithuanian family farms in order to estimate the dynamics of the total factor productivity there. Furthermore, the multiple correspondence analysis is employed to visualize the underlying patterns of the total factor productivity change. Indeed, the bootstrapped Malmquist indices have not been applied to the Lithuanian agricultural sector up to now.

In case the confidence interval obtained by the virtue of bootstrapping does not include the unity, one can conclude that the change in the Malmquist productivity index is significant at the significance level of α. The same routine can be generalized for the components of the Malmquist productivity index, i. e. $EC_o^k, TC_o^k, PEC_o^k, SEC_o^k, PTC_o^k, STC_o^k$.

Sequential Malmquist–Luenberger productivity index. The contemporaneous efficiency measure, $E_\tau(\mathbf{x},\mathbf{y};\mathbf{g}_\mathbf{x},\mathbf{g}_\mathbf{y}) = \max\left\{\beta \middle| \left(\mathbf{x}-\beta\mathbf{g}_\mathbf{x}, \mathbf{y}+\beta\mathbf{g}_\mathbf{y}\right) \in T(\tau)\right\}$, τ={$t$, t+1}, can be employed to construct the contemporaneous Malmquist–Luenberger productivity index and thus quantify the change in total factor productivity between the two periods, t and t+1, in the following manner (Chung et al., 1997):

$$ML^s = \frac{1+E_s(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_s(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})}, \quad (2.10)$$

where s={t, t+1}. In order to avoid the arbitrary choice of the base period, τ, a geometric mean of the two consecutive contemporaneous is used as a measure of change in total factor productivity: $ML^{t,t+1} = (ML^t \cdot ML^{t+1})^{1/2}$. It is due to Chung et al. (1997) that the Malmquist–Luenberger index can be decomposed into the two terms representing technical and efficiency change, respectively.

Similarly, the sequential Malmquist–Luenberger productivity index is defined by utilizing the sequential efficiency measure, $E_\tau^q(\mathbf{x},\mathbf{y};\mathbf{g}_\mathbf{x},\mathbf{g}_\mathbf{y}) = \max\left\{\beta \middle| \left(\mathbf{x}-\beta\mathbf{g}_\mathbf{x}, \mathbf{y}+\beta\mathbf{g}_\mathbf{y}\right) \in T_q(\tau)\right\}$, s={t, t+1}, and sequential production possibility sets:

$$SML^\tau = \frac{1+E_s^q(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_s^q(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})}. \quad (2.11)$$

The sequential Malmquist–Luenberger productivity index depends on its base period. Therefore, a geometric mean of the two indices is used:

$$SML^{t,t+1} = \left(\frac{1+E_t^q(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_t^q(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})} \cdot \frac{1+E_{t+1}^q(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_{t+1}^q(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})}\right)^{1/2}. \quad (2.12)$$

The geometric mean form of the Luenberger–Malmquist productivity index can be decomposed into the two components as follows:

$$\begin{aligned} SML^{t,t+1} &= \frac{1+E_t^q(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_{t+1}^q(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})} \\ &\quad \cdot \left(\frac{1+E_{t+1}^q(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_t^q(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)} \cdot \frac{1+E_{t+1}^q(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})}{1+E_t^q(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})}\right)^{1/2} \\ &= EC^{t,t+1} \cdot TC^{t,t+1} \end{aligned}, \quad (2.13)$$

where efficiency change, $EC^{t,t+1}$, measures the movement of a certain DMU towards the production frontier (catch-up) in between time periods t and t+1; and technical change, $TC^{t,t+1}$, measures the sift of the production frontier in between the two time periods. In case there has been an increase (decrease) in the productivity, $SML^{t,t+1}$ becomes greater (lesser) than unity. If there have been no changes in productivity between the two periods, then $SML^{t,t+1} = 1$. Note that all of the directional distance functions employed in Eqs. 2.11–2.13 assume a constant returns to scale (CRS) technology.

In case $EC^{t,t+1}$ is greater than unity, a DMU is said to have improved its efficiency in terms of respective sequential frontier, i. e. it experienced a catching-up movement in between time periods t and t+1. On the contrary, the $EC^{t,t+1}$ component lesser than unity indicates a DMU specific with a divergence from the production frontier throughout the time.

The technical change is captured by $TC^{t,t+1}$. Given we are dealing with the sequential production possibility sets, $TC^{t,t+1}$ can be equal to unity in case of no shifts in production frontier or greater than unity in case of technical progress. As Oh and Heshmati (2010) pointed out, both the DMUs-innovators and those DMUs surrounded by the innovators exhibit $TC^{t,t+1} > 1$.

The two terms of the Malmquist productivity index—efficiency change and technical change—were already presented in the study of Färe et al. (1992). As it was already mentioned, that decomposition assumed a CRS technology and omitted the scale efficiency from analysis. Indeed, one might be interested in scale efficiency when analysing micro data. Later on, Färe et al. (1994) suggested a decomposition of the Malmquist productivity index under assumption of variable returns to scale (VRS). In the spirit of Färe et al. (1994), we can now assume the VRS technology and thus further decompose the efficiency term into pure technical efficiency change and scale efficiency change:

$$
\begin{aligned}
SML^{t,t+1} &= \underbrace{\left(\frac{1+E_t^{q,v}(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_{t+1}^{q,v}(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})} \right)}_{PEC^{t,t+1}} \cdot \underbrace{\left(\frac{1+E_t^{q}(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_t^{q,v}(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)} \Bigg/ \frac{1+E_{t+1}^{q}(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})}{1+E_{t+1}^{q,v}(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})} \right)}_{SEC^{t,t+1}} \\
&\cdot \left(\frac{1+E_{t+1}^{q}(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)}{1+E_t^{q}(\mathbf{x}^t,\mathbf{y}^t;\mathbf{g}_\mathbf{x}^t,\mathbf{g}_\mathbf{y}^t)} \cdot \frac{1+E_{t+1}^{q}(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})}{1+E_t^{q}(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1})} \right)^{1/2} \\
&= EC^{t,t+1} \cdot TC^{t,t+1}
\end{aligned}
\quad , \quad (2.14)
$$

where $PEC^{t,t+1}$ is the pure efficiency change and $SEC^{t,t+1}$ is the scale efficiency change in between time periods t and t+1; superscript v denotes the VRS directional distance functions. Obviously, $PEC^{t,t+1} > 1$ indicates an increase in pure technical efficiency, whereas $SEC^{t,t+1} > 1$ indicates scale efficiency gains.

The directional distance functions for Eqs. 2.13–2.14 can be estimated in a non-parametric deterministic way by employing data envelopment analysis (DEA).

A Hicks–Moorsteen (or Malmquist TFP) productivity index for the base period t is defined as the ratio of a Malmquist output quantity index at the base period t and a Malmquist input quantity index at the base period t (Kerstens et al., 2010):

$$HM_{T(t)}\left((x^t, y^t),(x^{t+1}, y^{t+1})\right) = \frac{E^O_{T(t)}(x^t, y^t) \big/ E^O_{T(t)}(x^t, y^{t+1})}{E^I_{T(t)}(x^t, y^t) \big/ E^I_{T(t)}(x^{t+1}, y^t)}, \tag{2.15}$$

where $E^O_{T(t)}$ and $E^I_{T(t)}$ are, respectively, output- and input- oriented Farrell measures of efficiency (cf. the TE terms in Eqs. 1.9 and 1.12). Obviously, $y^t < y^{t+1}$ entails $E^O_{T(t)}(x^t, y^t) > E^O_{T(t)}(x^t, y^{t+1})$ and thus the numerator in Eq. 2.15 becomes greater than unity. Similarly, $x^{t+1} < x^t$ makes $E^I_{T(t)}(x^t, y^t) > E^I_{T(t)}(x^{t+1}, y^t)$ and thus the denominator in Eq. 2.15 becomes lesser than unity. Therefore Hicks–Moorsteen index exceeding (less than) unity indicates productivity gain (loss).

The decomposition of the Hicks–Moorsteen index, however, is a rather complicated issue. Although Bjurek (1994, 1996) stated that the latter index can be decomposed in the similar way as the Malmquist index he did not present an explicit formulation of this procedure. Later on, Lovell (2003) described the general framework for decomposition of the Hicks–Moorsteen index and noted that is suffers from double accounting and a lack of economic interpretability. However, Lovell (2003) did offer the two ways to improve the decomposition by (i) partially orienting it or (ii) rearranging the terms of decomposition. Following the first approach one can decompose the Hicks–Moorsteen index with a base period t in the following way:

$$\begin{aligned} HM_{T(t)}\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = {} & \Delta TE_O\left(x^t, y^t, x^{t+1}, y^{t+1}\right) \cdot \Delta T_O\left(x^{t+1}, y^{t+1}\right) \cdot \\ & \cdot \Delta S^t\left(x^t, y^t, \mu x^t, \nu x^t\right) \cdot \Delta OM^t\left(x^t, y^{t+1}, \nu y^t\right) \cdot, \\ & \cdot \Delta IM^t\left(y^t, x^{t+1}, \mu x^t\right) \end{aligned} \tag{2.16}$$

where $HM_{T(t)}\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \dfrac{D^O_{T(t)}(x^t, y^{t+1}) / D^O_{T(t)}(x^t, y^t)}{D^I_{T(t)}(x^{t+1}, y^t) / D^I_{T(t)}(x^t, y^t)}$ is the total factor productivity index with $D^I_{T(\tau)}$ and $D^O_{T(\tau)}$ being the Shepard efficiency measures (cf. Eqs. 1.8 and 1.11, respectively) for $\tau = \{t, t+1\}$.

The two output-oriented terms ΔTE_O and ΔT_O in Eq. 2.16 measure efficiency change and technical change, respectively. They are obtained in the following way:

$$\Delta TE_O(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D^O_{T(t+1)}(x^{t+1}, y^{t+1})}{D^O_{T(t)}(x^t, y^t)}, \tag{2.17}$$

$$\Delta T_O(x^{t+1}, y^{t+1}) = \frac{D^O_{T(t+1)}(x^{t+1}, y^{t+1})}{D^O_{T(t)}(x^t, y^t)}. \tag{2.18}$$

The product of the remaining three terms, namely the scale effect (ΔS^t), the output mix effect (ΔOM^t), and input mix effect (ΔIM^t), constitutes the activity effect (Lovell, 2003). The latter three terms are computed in Kerstens et al. (2010). This study, therefore, utilizes the Hicks–Moorsteen TFP index (Bjurek, 1994; Lovell, 2003; Epure, Prior, 2007) and DEA to measure TFP changes in Lithuanian family farms and decompose these changes into separate effects.

Färe-Primont index approach. Recently, O'Donnell (2011b) developed the package DPIN which facilitates the computations of the latter indices. Rahman and Salim (2013) and Khan et al. (2014) employed the Färe-Primont index for analysis of the agricultural productivity and efficiency. Productivity is generally defined as a ratio of output over input (Färe et al., 2008). However, this principle becomes a more complex one in the presence of multi-input and/or multi-output technology. Let there be *K* decision making units (DMUs) observed during *T* time periods with each using inputs $\mathbf{x}^t_k = \left(x^t_{1k}, x^t_{2k}, \ldots, x^t_{mk}\right)'$ and producing outputs $\mathbf{y}^t_k = \left(y^t_{1k}, y^t_{2k}, \ldots, y^t_{nk}\right)'$, where $k = 1, 2, \ldots, K$ is a DMU index, $t = 1, 2, \ldots, T$ denotes a respective time period, and *m* and *n* are the numbers of inputs and outputs respectively. As O'Donnell

(2008, 2012) put it, the total factor productivity (TFP)[4] of a DMU is then defined as $TFP_{kt} = Y_{kt} / X_{kt}$, where $Y_{kt} \equiv Y(\mathbf{y}_k^t)$ is an aggregate output, $X_{kt} \equiv X(\mathbf{x}_k^t)$ is an aggregate input, and $Y(\cdot)$ and $X(\cdot)$ are non-negative non-decreasing linearly-homogeneous aggregator functions respectively. One can further compute the index comparing the TFP of DMU *k* in period *t* with the TFP of DMU *l* in period *s*:

$$TFP_{ls,kt} = \frac{TFP_{kt}}{TFP_{ls}} = \frac{Y_{kt} / X_{kt}}{Y_{ls} / X_{ls}} = \frac{Y_{kt} / Y_{ls}}{X_{kt} / X_{ls}} = \frac{Y_{ls,kt}}{X_{ls,kt}}, \tag{2.19}$$

where $Y_{ls,kt} \equiv Y_{kt} / Y_{ls}$ and $X_{ls,kt} \equiv X_{kt} / X_{ls}$ are output and input quantity indices respectively. Indeed, Eq. 2.19 measures the growth in TFP as a measure of output growth divided by a measure of input growth (O'Donnell, 2011a).

The change in TFP defined in terms of by Eq. 2.19 can be further analysed by decomposing it into certain terms describing efficiency and productivity changes. It was O'Donnell (2008) who argued that a TFP index can be decomposed into the two terms describing TFP efficiency (TFPE) change and technology change (TC). Specifically, the TFPE measures the difference between an observed TFP and maximal TFP related to the underlying technology. In case of DMU *k* in period *t* we have:

$$TFPE_{kt} = TFP_{kt} / TFP_t^*, \tag{2.20}$$

where $TFP_t^* = \max_k TFP_{kt}$ denotes the maximal TFP possible for period *t*. Similarly, the following equation holds for DMU *l* in period *s*:

$$TFPE_{ls} = TFP_{ls} / TFP_s^*. \tag{2.21}$$

Thus, the change in TFPE catches the change in DMU's performance (efficiency change – EC), whereas the TC accounts for change in the maximal TFP. The TFP change (cf. Eq. 2.19) then decomposes as:

$$TFP_{ls,kt} = \frac{TFP_{kt}}{TFP_{ls}} = \underbrace{\left(\frac{TFP_t^*}{TFP_s^*}\right)}_{TC}\underbrace{\left(\frac{TFPE_{kt}}{TFPE_{ls}}\right)}_{EC}. \tag{2.22}$$

[4] Indeed, one can also use the term multi-factor productivity instead of TFP. This might be more relevant in the sense that an analysis might not cover *all* factors of production.

The EC term in Eq. 2.22 can be further decomposed into measures of scale efficiency change (SEC) and mix efficiency change (MEC). The concept of the mix efficiency was introduced by O'Donnell (2008). Whereas scale efficiency is related to economies of scale, mix efficiency is related to economies of scope. The difference between allocative efficiency and mix efficiency lies in the fact that the former is a value concept (i. e. cost, revenue, profit), and the latter one is a productivity (quantity) concept. All in all, mix efficiency indicates possible improvement in productivity due to changes in input structure.

The following Fig. 2.2 depicts the concept of the mix efficiency in the input space (in the presence of two inputs). The curve passing through points B, R, and U is an input isoquant, i. e. an efficient frontier. An isocost is based on input prices, whereas the dashed lines going through points A, B, R, and U are iso-aggregate-input lines. Specifically, they were established by the virtue of the simple linear aggregation function $X_{kt} = \alpha_1 x_{1k}^t + \alpha_2 x_{2k}^t$, where $\alpha_1 \geq 0$ and $\alpha_2 \geq 0$. The slope of an iso-aggregate-input line thus becomes $-\alpha_1 / \alpha_2$ and intercept varies depending on the aggregate input quantity in between X_{kt} / α_2 and $\hat{X}_{kt} / \alpha_2$. The DMU operating at point A could move towards point B in case it managed to reduce its input consumption securing the same level of output and holding input structure constant; as a result the aggregate input would fall from X_{kt} down to $\bar{X}_{kt}$. Minimisation of costs without any restrictions on input mix results in a movement from B to R and subsequent decrease in aggregate input from $\bar{X}_{kt}$ to $\breve{X}_{kt}$. Minimisation of the aggregate input without constraints on the input mix entails a movement from B to U and a decrease in aggregate input from $\bar{X}_{kt}$ to $\widehat{X}_{kt}$. The following measures of efficiency can be defined in terms of Fig. 2.2:

$$ITE_{kt} = \bar{X}_{kt} / X_{kt}, \tag{2.23}$$

$$AE_{kt} = \breve{X}_{kt} / \bar{X}_{kt}, \tag{2.24}$$

$$IME_{kt} = \hat{X}_{kt} / \bar{X}_{kt}. \tag{2.25}$$

Indeed, Eq. 2.23 defines an input-oriented measure of the technical efficiency (Farrell, 1957), Eq. 2.24 stands for a measure of the allocative efficiency (Färe, Grosskopf, 1990; Thanassoulis et al., 2008), and Eq. 2.25 defines an input-oriented measure of the mix efficiency (O'Donnell, 2008).

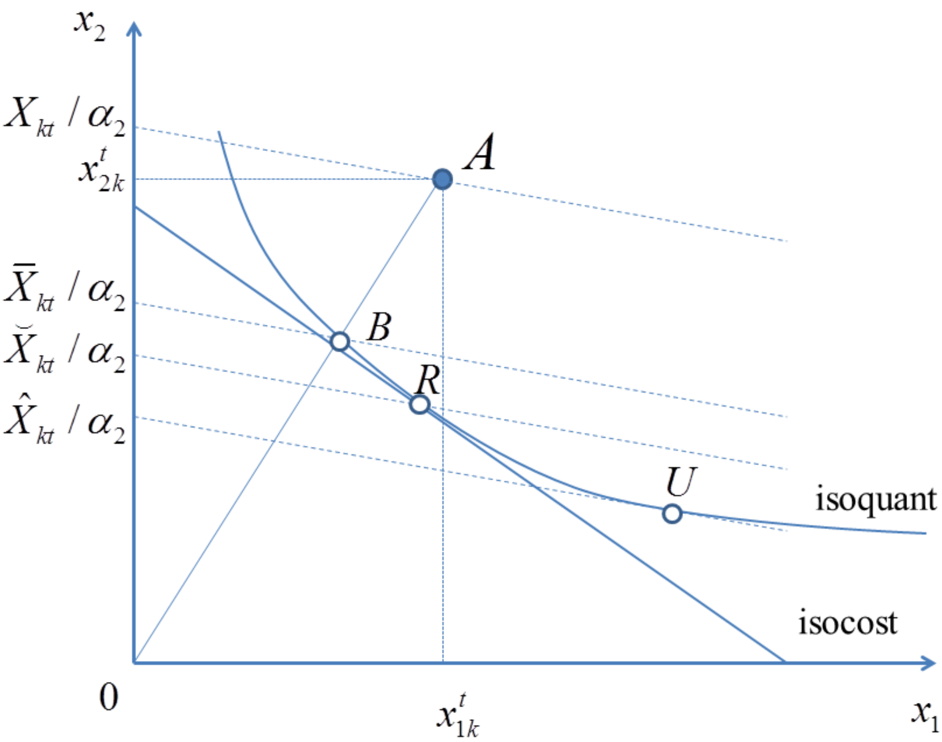


Fig. 2.2. The concept of mix efficiency (O'Donnell, 2011a).

The measures of TFP and efficiency can be further depicted in an input-output space (Fig. 2.3). The points A, R, and U come from Fig. 2.2 and denote the observed production plan, technically efficient production plan with mix restrictions, and technically efficient production plan without mix restrictions respectively. The curve passing through points B and D is a mix-restricted frontier, whereas that passing through points E and U is an unrestricted frontier. The rays passing through each point are associated with respective TFP levels. The Farrell (1957) input-oriented measure of efficiency can thus be described in terms of the TFP change: $ITE_{kt} = TFP_A / TFP_B \equiv TFP_{BA}$. Similarly, the mix efficiency measure defined by O'Donnell (2008) can be given as $IME_{kt} = TFP_B / TFP_U \equiv TFP_{UB}$. The input-oriented scale efficiency measure, ISE, compares TFP at the efficient point B to the highest one under the same input-mix at point D:

$$ISE_{kt} = \frac{Y_{kt} / \bar{X}_{kt}}{\tilde{Y}_{kt} / \tilde{X}_{kt}}. \tag{2.26}$$

The residual mix efficiency, RME, measures the difference between the maximal TFP for the unrestricted frontier (point E) and TFP at the scale-efficient point D:

$$RME_{kt} = \frac{\tilde{Y}_{kt} / \tilde{X}_{kt}}{TFP_t^*}. \tag{2.27}$$

The input-oriented scale-mix efficiency, ISME, encompasses ISE and RME and thus compares the maximal TFP at point E to that at the scale-efficient point D:

$$ISME_{kt} = \frac{Y_{kt} / \bar{X}_{kt}}{TFP_t^*}. \tag{2.28}$$

Further details on these measures can be found in O'Donnell (2008).

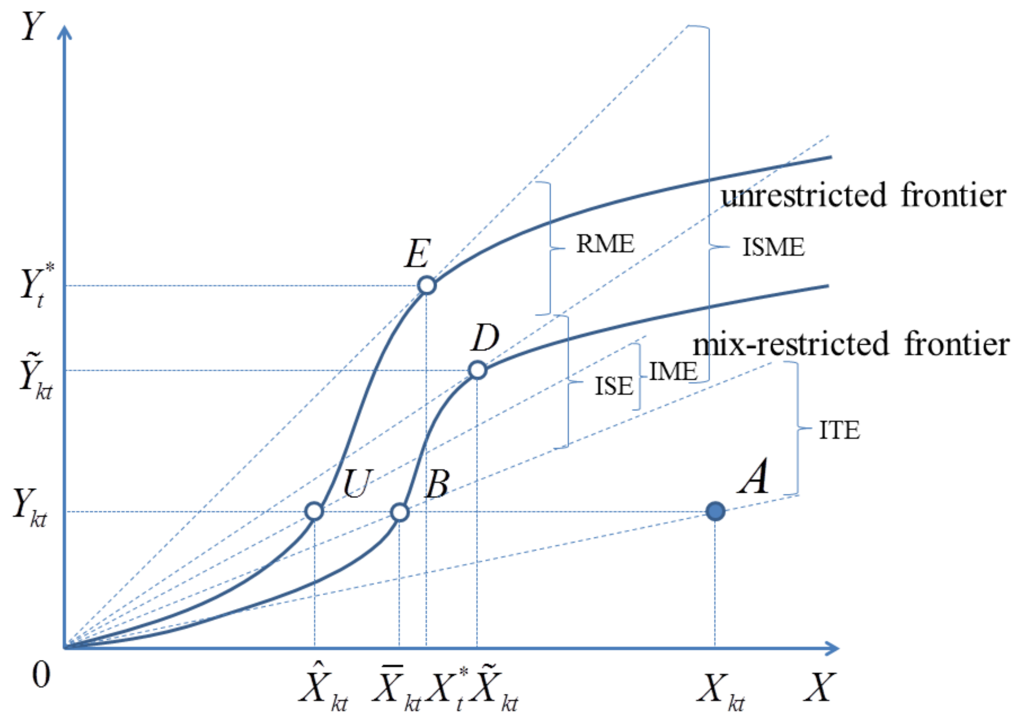


Fig. 2.3. The input-oriented measures of technical, scale and mix efficiency (O'Donnell, 2011a).

The TFP efficiency, TFPE, can therefore be decomposed into several terms: $TFPE_{kt} = ITE_{kt} \times ISME_{kt} = ITE_{kt} \times ISE_{kt} \times RME_{kt}$. In an input-oriented framework, the TFP index given by Eqs. 2.19 and 2.22 can also be decomposed in the following way:

$$TFP_{ls,kt} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{ITE_{kt}}{ITE_{ls}}\right)\left(\frac{ISME_{kt}}{ISME_{ls}}\right) = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{ITE_{kt}}{ITE_{ls}}\right)\left(\frac{ISE_{kt}}{ISE_{ls}}\right)\left(\frac{RME_{kt}}{RME_{ls}}\right). \quad (2.29)$$

An analogous decomposition is available for the output orientation (O'Donnell, 2011a). The components defined in Eq. 2.29 can be estimated by employing linear programming models and package *DPIN*. The routine for estimation of the Färe-Primont indices is further discussed by O'Donnell (2011a).

2. 3. Analysis of the productive technology

In this research, the following features of the underlying productive technologies are considered: 1) nature of the technical change specific to a technology, 2) prevailing returns to scale, 3) managerial and program efficiency, 4) context efficiency.

The biased technical change was analysed across various economic sectors and management levels by the means of the bias-corrected Malmquist indices (Färe et al., 1997). Weber and Domazlicky (1999) focused on TFP growth in US manufacturing across the states. Managi and Karemera (2004) analysed the US agricultural sector. Kumar (2006) analysed the performance of manufacturing across Indian states. Barros et al. (2009) attempted to research into productivity of the Japanese credit banks. Barros and Weber (2009) focused at the airport productivity change. Assaf and Barros (2011) employed the bias-corrected Malmquist index to measure the performance of the hotel chains. Barros et al. (2012) analysed the productivity of Brazilian seaports. It was Briec and Peypoch (2007) who offered the concept of parallel neutrality and developed the bias-corrected Luenberger productivity indices. These measures were employed in a number of researches on TFP growth (Barros et al., 2011; Briec et al., 2011; Peypoch, Sbai, 2011).

Färe et al. (1997) introduced the further decomposition of the Malmquist productivity index as a remedy to the biased technological change (Weber, Domazlicky, 1999; Assaf, Barros, 2011). Specifically, the TC component was decomposed into the three terms with each of them describing output–biased technical change (OBTC), input–biased technical change (IBTC), and the magnitude of technological change (MTC):

$$OBTC = \left(\frac{D_I^t\left(x^{t+1}, y^{t+1}\right)}{D_I^{t+1}\left(x^{t+1}, y^{t+1}\right)} \frac{D_I^{t+1}\left(x^{t+1}, y^{t}\right)}{D_I^{t}\left(x^{t+1}, y^{t}\right)} \right)^{1/2}, \tag{2.30}$$

$$IBTC = \left(\frac{D_I^{t+1}\left(x^{t}, y^{t}\right)}{D_I^{t}\left(x^{t}, y^{t}\right)} \frac{D_I^{t}\left(x^{t+1}, y^{t}\right)}{D_I^{t+1}\left(x^{t+1}, y^{t}\right)} \right)^{1/2}, \tag{2.31}$$

$$MTC = \frac{D_I^t\left(x^{t}, y^{t}\right)}{D_I^{t+1}\left(x^{t}, y^{t}\right)}, \tag{2.32}$$

where $TC = OBTC \cdot IBTC \cdot MTC$.

Increase in the MRTS of x_1 for x_2 in between periods t and $t+1$ would entail $\left(x_2 / x_1\right)_t < \left(x_2 / x_1\right)_{t+1}$. These changes, coupled with an increasing productivity ($IBTC < 1$), would imply that the observed technical change is an x_2–consuming and x_1–saving one. On the other hand, an increasing MRTS and a decreasing productivity ($IBTC > 1$) would indicate movement towards an x_2–saving and x_1–consuming technology. The Hicks-neutral technical change is observed when $IBTC = 1$. The following Table 2.1 summarizes the discussed patterns of the input–biased technology change.

Table 2.1. Input–biased technology change.

	$IBTC > 1$	$IBTC < 1$	$IBTC = 1$
$\left(x_i / x_q\right)_t < \left(x_i / x_q\right)_{t+1}$	x_q–using, x_i–saving	x_i–using, x_q–saving	Neutral
$\left(x_i / x_q\right)_t > \left(x_i / x_q\right)_{t+1}$	x_i–using, x_q–saving	x_q–using, x_i–saving	

In case the number of output or inputs is reduced to one, the term *OBTC* or *IBTC*, respectively, equals unity. All in all, the discussed measures enable one to fathom the underlying technical change in terms of changes in the structure of input-output bundle. Specifically, the technical change can be identified as Hicks' neutral, or Hicks' factor-saving (-consuming). By facilitating the pairwise comparisons, one can analyse the substitution between the production factors evolved in between the two time periods and its effect on the TFP.

Returns to scale and scale elasticity constitute a fundamental issue for the economic analysis and performance management. Specifically, the analysis of the prevailing returns to scale enables to describe the structure of a certain sector in terms of scale efficiency. Accordingly, various studies attempted to estimate the underlying returns to scale (Growitsch et al., 2009; Atici, Podinovski, 2012). Indeed, the regulated economic sectors feature a particular need for suchlike analyses.

Agricultural sectors are relatively more important in the Central and East European countries than in the Western countries given the differences in economic structure prevailing there. Therefore, the researches of agricultural efficiency are of particular importance in suchlike countries (van Zyl et al., 1996; Gorton, Davidova, 2004; Kirner, Kratochvil, 2006). Indeed, farm size and farm structure do often constitute the key foci of the economic researches thanks to the land reform and farm restructuring there. The scale efficiency size is therefore a measure of interest as well as the most productive scale. The latter measures enable to determine whether a farm operates at increasing, constant, and decreasing return to scale. However, the issues of farm size were analysed across the whole world. Townsend et al. (1998), Luik et al. (2009), and Mugera and Langemeier (2011) applied data envelopment analysis to analyse the returns to scale and size of the agricultural producers. Alvarez and Arias (2004) employed the fixed-effects frontier and the translog supply function to relate the technical efficiency to the farm size.

The data envelopment analysis (DEA) enables to determine whether a decision making unit (DMU) operates at the optimal scale size. This can be implemented by estimating the scale efficiency which, in turn, is a ratio between CRS efficiency scores and VRS efficiency scores. DMUs operating at the most productive scale size (MPSS) would be attributed with scale efficiency values of unity, whereas the remaining ones would feature scale efficiency scores lower than unity. However, this measure does not give any information regarding the direction of the prospective changes in scale size for the scale-inefficient DMUs. Accordingly, the two approaches prevail allowing for a more detailed analysis of returns to scale (RTS) by the means of DEA (Førsund, Hjalmarsson, 2004; Zschille, 2014): The qualitative approach (Färe et al., 1983; Färe and Grosskopf, 1985; Grosskopf, 1986; Tone, 1996) enables to determine whether a DMU operates under increasing returns to scale (IRS), CRS, or decreasing returns to scale (DRS). The quantitative approach further enables to quantify scale elasticity in DEA. The latter analysis can be further employed in an indirect or a direct approach. The indirect approach was introduced by Banker and Thrall (1992) and utilized by Førsund and Hjalmarsson (2004), Førsund et al. (2007), Podinovski et al. (2009), Zschille (2014). The direct approach was followed by Krivonozhko et al. (2004), Førsund et al. (2007). In the sequel we will focus on the qualitative approach which classifies the farms in terms of the regions of RTS they operate in.

Thiele and Brodersen (1999) analysed the performance of the West and East German farms with respect to returns to scale. Latruffe et al. (2005) focused on the Polish farms while analysing the technical and scale efficiencies. Vasiliev et al. (2008) conducted a similar analysis on the Estonian grain farms. The Lithuanian agricultural sector, though, has not been sufficiently analysed in terms of optimal farm size and returns to scale. Kriščiukaitienė et al. (2007) employed the linear programming methodology to model the optimal farm size in terms of technological and economic variables. The latter study was based on a hypothetic farm data. Jurkėnaitė (2012) analysed the viability of certain farming types in terms of various financial indicators.

The elasticity of scale can be estimated once the production frontier is established for a technology of interest. Data envelopment analysis (DEA) constitutes a proper tool for analysis of the scale elasticity (Soleimani-Damaneh et al., 2009). Therefore, we follow an axiomatic non-parametric deterministic approach. Axiomatic approach implies that the axioms of the free disposability, convexity, and minimal extrapolation (Afriat, 1972) are respected. Non-parametric approach implies that there are no assumptions on the distribution of the error terms. However, the DEA implicitly assumes the piecewise-linear functional form of the underlying production function. Finally, deterministic approach means that the whole error term is assumed to arise due to inefficiency.

Program and managerial efficiency. In this section we shall first briefly recall the MEA approach developed in Bogetoft and Hougaard (1999) and subsequently in Asmild et al. (2003). MEA will also be compared to standard DEA. We then move on to reconsider the program efficiency approach of Charnes et al (1981) related to DEA and show how this can be reformulated along the lines of MEA. The advantage of the latter is improved information due to a disaggregation into input specific efficiency scores as well as an improved underlying benchmark selection.

Consider a set of farms using multiple inputs to produce multiple outputs $y = (y_1, y_2, ..., y_n) \in \Re_+^n$. The common underlying technology:

$$T = \{(x, y) | x \text{ can produce } y\}. \tag{2.33}$$

can be represented by input requirement sets:

$$I(y) = \{x | (x, y) \in T\}. \tag{2.34}$$

and the standard Farrell input-oriented index of technical efficiency used in DEA to assign an efficiency score to each farm, can be defined as:

$$E_I^F(x, y) = \min\{\theta | (\theta x, y) \in I(y)\}. \tag{2.35}$$

The Farrell efficiency score, E^F, implicitly concerns the distance between the observation at hand (x, y) and its projection onto an isoquant in the direction of the origin. Figure 2.4 presents a graphical interpretation of this measure: The initial point, x_0, is projected onto the isoquant describing the technology T at the point $S^F = \theta x^0$. The Farrell efficiency measure, θ, is then obtained as the ratio $0S^F / 0x^0$. Clearly, an efficient production plan (here a farm) is assigned efficiency score $E_I^F = 1$ while inefficient farms are assigned scores $E_I^F < 1$.

The implicit selection of the benchmark does not depend on the potential improvements in input consumption (in our case we have $x_1^0 - x_1^*$ and $x_2^0 - x_2^*$). Thus, the inputs are uniformly scaled down by a common factor θ. Obviously, suchlike scaling is not proportional to improvement potentials. As argued in Bogetoft and Hougaard (1999) it is compelling to select a benchmark proportional to improvements potentials. They also suggest an efficiency index which relates to such a benchmark selection that was later used in connection with the linear programs of DEA to produce a procedure dubbed Multi-directional Efficiency Analysis (MEA), in Asmild et al (2003). In Figure 2.4 below the benchmark selection of MEA is illustrated compared to the traditional Farrell approach.

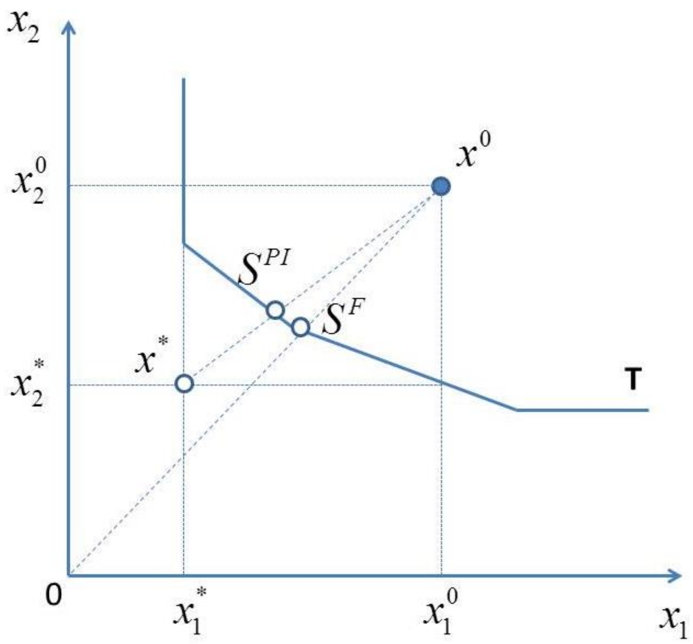


Fig. 2.4. DEA and MEA efficiency scores.

Contrary to the conventional DEA model, where the reference production plan is established in an implicit manner as described above, MEA facilitates efficiency measurement based on the ideal reference plan, $x^* = (x_1^*, x_2^*, ..., x_m^*)$, and the benchmark plan, S^{PI}. The ideal reference plan depends on the observed plan, *x*, and is defined as

$$x_i^*(x) = \min\left(\bar{x}_i \in \Re \mid \left(x_1, x_2, ..., x_{i-1}, \bar{x}_i, x_{i+1}, ..., x_m\right) \in I(y)\right),\ \forall i = 1, 2, ..., m. \quad (2.36)$$

That is, the ideal reference plan consists of the minimal input requirements for each input obtained independently in terms of the given technology. Note that x^* is generally infeasible. The benchmark plan, S^{PI}, is then found as the largest possible reduction of *x* in the direction of x^x. Indeed, the reductions are made in proportion to the input specific excesses given by $(x - x^*(x))_{i=1,2,...,m}$. In case *x* is an efficient plan, we have $x = x^*(x)$ and all the excesses are equal to zero. This entails $x = S^{PI}$ and all the input specific MEA scores become zero.

The ideal reference plan for an input-oriented model is found by solving the *m* linear programming problems (Asmild et al., 2003):

$$\begin{aligned}
&\min_{\bar{x}_i, \lambda_k} \bar{x}_i \\
&\text{s. t.} \\
&\sum_{k=1}^{K} \lambda_k x_i^k \leq \bar{x}_i \ , \\
&\sum_{k=1}^{K} \lambda_k x_{(-i)}^k \leq x_{(-i)}^t, \quad (-i) = 1, 2, ..., i-1, i+1, ..., m; \\
&\sum_{k=1}^{K} \lambda_k y_j^k \geq y_j^t, \quad j = 1, 2, ..., n; \\
&\sum_{k=1}^{K} \lambda_k = 1, \\
&\lambda_k \geq 0, \quad k = 1, 2, ..., K,
\end{aligned} \tag{2.37}$$

where $\sum_{k=1}^{K} \lambda_k = 1$ is a variable returns to scale (VRS) constraint. Thus, a solution yielded by Eq. 2.37 (λ^*, x^*) further serve as coordinates of the ideal reference plan: $x^* = (x_1^*, x_2^*, ..., x_3^*)$. Assuming that $x \neq x^*$, consider the following linear programming problem:

$$\begin{aligned}
&\max_{\beta, \lambda_k} \beta \\
&\text{s. t.} \\
&\sum_{k=1}^{K} \lambda_k x_i^k \leq x_i^t - \beta\left(x_i^t - x_i^*\right), \quad i = 1, 2, ..., , m; \\
&\sum_{k=1}^{K} \lambda_k y_j^k \geq y_j^t, \quad j = 1, 2, ..., n; \\
&\sum_{k=1}^{K} \lambda_k = 1, \\
&\lambda_k \geq 0, \quad k = 1, 2, ..., K,
\end{aligned} \tag{2.38}$$

where $\sum_{k=1}^{K} \lambda_k = 1$ is a variable returns to scale constraint. Eq. 2.38 entails a solution, (λ^*, β^*). We shall here be more concerned with the disaggregated input specific efficiency scores of MEA for particular farms (x^0, y^0) defined as $\left(\frac{\beta^*(x_i^0 - x_i^*)}{x_i^0} \right)_{i=1,\ldots,m}$.

The sample of DMUs under analysis can often be decomposed into homogeneous sub-samples, which are engaged in the same field of activity but are likely to have different production frontiers. Thereafter, we refer these sub-samples to as programs. The program specificities imply that their production frontiers will be differently related to the pooled frontier of the total sample.

Charnes et al. (1981) proposed a framework to distinguish between managerial efficiency and the program efficiency: First, efficiency scores (in terms of managerial efficiency) are estimated for each observation within a sub-sample relative to the sub-samples (programs) own frontier. Second, the observed inputs are adjusted so that the managerial inefficiency is removed and all farms are projected onto their efficient sub-sample frontier. Third, the efficient frontiers of each program are then compared to the pooled frontier of the entire sample. Thus, one can identify the program-specific efficiency constraints. Indeed, Charnes et al. (1981) investigated the efficiency of two education programs in US using DEA to determine of efficiency scores involved.

We will pick up on the approach of Charnes et al. but with the important difference that we will use the MEA efficiency scores rather than the DEA scores to estimate both managerial and program efficiency. As in case of the standard application of DEA we argue that the implicit benchmark selection of MEA is more compelling and its disaggregation into input specific efficiency scores provides further insights into the underlying technological differences between sub-samples.

The MEA model (Eqs. 2.37–2.38) is applied in both stages of process, that is both when individual observations are compared to their sub-sample specific frontier and when the program frontier (adjusted for managerial inefficiency) is compared to the pooled frontier of the entire sample. Figure 2.5 illustrates the concept of the program efficiency MEA with two programs defined by respective sub-sample technologies, T_1 and T_2.

As it was already discussed in the preceding section, suchlike projection consists of the two steps, namely (i) determination of the Stage 1 ideal reference plan, x^*, by the virtue of Eq. 2.37 and (ii) Stage 1 benchmark selection, $S^{PI,1}$, which is facilitated by considering Eq. 2.38. Let the coordinates of the Stage 1 benchmark selection be denoted in the following way: $S^{PI,1}=\left(x_1^{PI,1},x_2^{PI,1},...,x_m^{PI,1}\right)$. The input-specific managerial efficiency can thus be evaluated by computing respective ratios:

$$b_i^M=\frac{x_i}{x_i^{PI,1}},\ i=1,2,...,m, \tag{2.39}$$

where $b_i^M=1$ indicates an efficient utilization of the *i*-th input in terms of the managerial efficiency. Note that the sub-index for DMUs is removed from the previously discussed notations for sake of brevity.

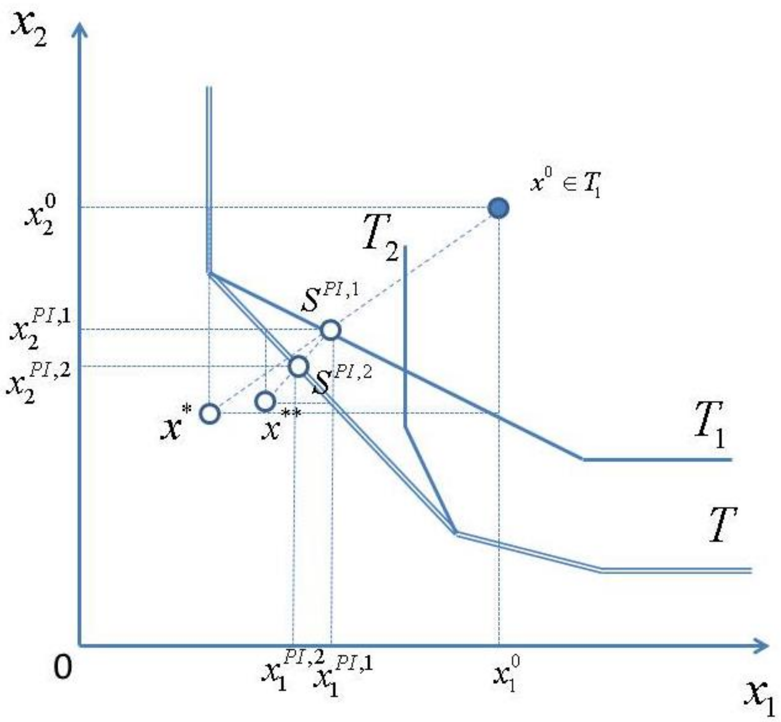


Fig. 2.5. The two-stage model MEA for the assessment of managerial and program efficiency.

Given Stage 2 focuses on program efficiency, all the observations are projected onto their respective program frontiers. That is, we further analyse the production plans $(S^{PI,1},y)$. The observed production plans (x^0,y), though, serve as those describing the pooled production frontier, *T*. Similarly, the projection of $(S^{PI,1}, y)$ on the pooled frontier consists of the two steps, namely (i) determination of the Stage 2 ideal reference plan, x^{**}, by the virtue of Eq. 2.37 and (ii) Stage 2 benchmark selection, $S^{PI,2}$, which is facilitated by considering Eq. 2.38. Let the coordinates of the Stage 2 benchmark selection be denoted in the following way: $S^{PI,2} = \left(x_1^{PI,2}, x_2^{PI,2}, ..., x_m^{PI,2}\right)$. The input-specific program efficiency can thus be evaluated by computing respective ratios:

$$b_i^P = \frac{x_i^{PI,1}}{x_i^{PI,2}}, \; i = 1, 2, ..., m, \tag{2.40}$$

where $b_i^P = 1$ indicates an efficient utilization of the ***i***-th input in terms of the program efficiency. Note that the sub-index for DMUs is removed from the previously discussed notations for sake of brevity.

The two-stage MEA methodology thus allows one to evaluate the managerial and program efficiency in terms of separate inputs. Indeed, this technique can be adapted to input-output or output oriented models in a straightforward manner. The software package *Benchmarking* (Bogetoft, Otto, 2011) was employed for the analysis.

Context-dependent assessment of efficiency. Depending on the assumptions on returns to scale, the efficient frontier is defined by considering observations which are the most productive ones, whether locally or globally. As a result, the analysis depends on the observations used as a yardstick. In case of DEA, the efficiency scores attributed to the inefficient observations will not be affected by changes in other inefficient observations, albeit changes in the efficient ones will render respective alterations in the overall ranking. Thus, it is possible to alter the efficiency scores by changing the reference set (i. e. efficiency frontier).

Another peculiarity of the DEA is associated with the distribution of the efficiency scores. As Ulucan and Atici (2010) pointed out, the proportion of (extremely) inefficient observations is often inflated due to exogenous factors or different activities certain decision making units (DMUs) are engaged in. As a result, the targets for input consumption or output production become meaningless. Furthermore, the consumer choice theory also stipulates that consumers usually choose a product amongst those belonging to a certain sub-group (determined by the product positioning) of the products. By generalizing this idea to efficiency analysis one can conclude that performance of a DMU might be low in terms of the entire sample, albeit sufficient in its environment.

The context-dependent DEA, therefore, becomes particularly appealing in that the observations are stratified with respect to their levels of efficiency. The latter instance of stratification enables one to draw more reasonable recommendations regarding performance improvements. The context-dependent DEA was introduced by Seiford and Zhu (Seiford, Zhu, 2003; Zhu, 2003). The latter approach relied on the radial measures. Later on, the slack-based context-development DEA was developed (Morita et al., 2005; Morita, Zhu, 2007; Cheng et al., 2010). The context-dependent DEA has also been extended with the ratio DEA (Wei et al., 2012) and cross-efficiency measures (Lim, 2012).

The concept of progress is visualized in Fig. 2.6. The observations define the first-level efficiency frontier, i. e. $l = 1$. The observations belonging to the latter frontier, E^1, are then removed from the reference set and the new frontier is established. After iteratively removing the efficient observations, analysis ends up when no inefficient observations are included in the reference set. In this instance, there are four levels of efficiency. As one can note, the progress scores for the original observation, (x_t, y_t), can be measured against each level of efficiency, up to the third degree in total. Meanwhile, the attractiveness scores for that particular observations cannot be computed given it is already located at the lowest level of efficiency.

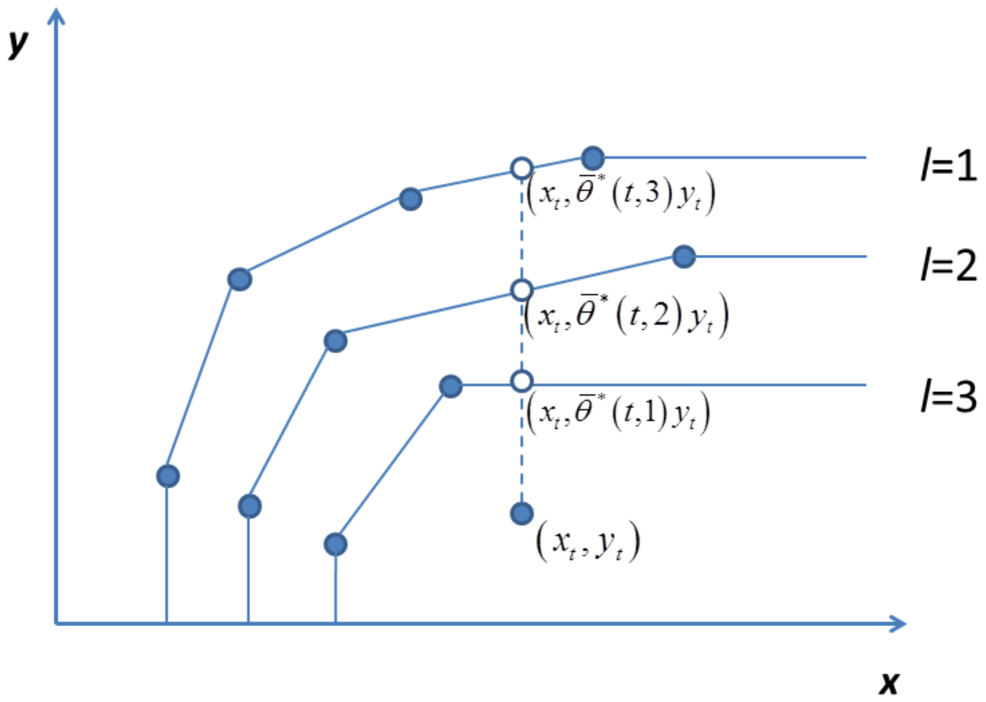


Fig. 2.6. The measurement of progress in the context-dependent DEA model.

As Seiford and Zhu (2003) pointed out, the observations can be grouped into the four groups with respect to the attractiveness and progress scores. Highly attractive observations can feature either low progress (LH) or high progress (HH). Little attractive observations can also feature either low progress (LL) or high progress (HL). The LH-type observations can therefore be considered as the most desirable ones, for they are quite efficient and maintain higher distance from the dominated observations. On the other hand, the HL-type observations are least desirable, given they are peculiar with low efficiency and low distance from the dominated observations.

This research employs the context-dependent DEA to Lithuanian family farms. In particular, the analysis focuses on the three farming types, viz. crop, livestock, and mixed farming.

2. 4. Data used

Farm Accountancy Data Network. The technical and scale efficiency was assessed in terms of the input and output indicators commonly employed for agricultural productivity analyses (Bojnec, Latruffe 2008, 2011; Douarin, Latruffe 2011). More specifically, the utilized agricultural area (UAA) in hectares was chosen as land input variable, annual work units (AWU) – as labour input variable, intermediate consumption in Litas was used as a variable of the variable costs, and total assets in Litas as a capital factor. On the other hand, the three output indicators represent crop, livestock, and other outputs in Litas, respectively. Indeed, the three output indicators enable to tackle the heterogeneity of production technology across different farms.

The cost efficiency was estimated by defining respective prices for each of the four inputs described earlier. The land price was obtained from the Eurostat and assumed to be uniform for all farms during the same period. The labour price is the average salary in agricultural sector from Statistics Lithuania. The price of capital is depreciation plus interests per one Litas of assets. Meanwhile, the intermediate consumption is directly considered as a part of total costs.

The data for 200 farms selected from the FADN sample cover the period of 2004–2009. Thus a balanced panel of 1200 observations is employed for analysis. The analysed sample covers relatively large farms (mean UAA – 244 ha). As for labour force, the average was 3.6 AWU.

In order to quantify the factors influencing the agricultural productivity, we employed the following indicators for the second–stage analysis. Total output was used to identify relationship between farm size and efficiency. Soil index was used to check whether it significantly influences productivity. Farmer's age was used to test the linkage between demographic processes and efficiency. The dummy variable for organic farming was introduced to explore the performance of the organic farms. The share of crop output in the total output was used to ascertain whether either the crop or livestock farming is more efficient in Lithuania. The ratio of production subsidies to the total output was employed to estimate the effect of support payments, whereas the ratio of subsidies for equipment to the total output was defined to identify the impact of capital investments. The time trend (*Time*) was used to assess whether a general increase in efficiency scores was observed throughout the research period. UAA in hectares (*UAA*) was used as a proxy for farm size. A ratio of assets to labour force in AWU (*Assets/AWU*) was used to capture the degree of sufficiency of the capital. The share of the crop output in the total output (*Crop*) was employed as a measure of farm specialisation. Finally, the ratio of production subsidies[5] to the total output (*Subsidies*) was included in the model to account for the accumulated public support. Note that the first three variables were mean-scaled in order to ensure a faster convergence of the maximum likelihood model.

National Accounts. The part of research regarding the performance of Lithuanian agriculture as an economic sector (cf. Section 3.1) relies on National Accounts data provided by Statistics Lithuania (2014). We used the aggregates for 35 economic activities (NACE 2 classification), see Table A1 for details. The data cover the period of 2000–2010. The gross value added generated in certain sector was chosen as the output variable, whereas intermediate consumption, remuneration, and fixed capital consumption were treated as inputs. The latter three indicators enable to tackle the total factor productivity and thus are usually employed for productivity analysis (Piesse, Thirtle, 2000). The FEAR package (Wilson, 2008) was employed for the analysis.

[5] For 2007-2013, production subsidies comprise subsidies under Pillar I and Pilar II Axis 2, whereas investment subsidies are distributed according to Axis 1 of Pillar II.

3. THE TRENDS IN EFFICIENCY OF LITHUANIAN AGRICULTURE

Section 3.1 presents the dynamics of efficiency and TFP of Lithuanian agricultural sector. Sections 3.2–3.7 focus on the performance of Lithuanian family farms. Therefore we assess the relationship between farm size change and efficiency. Further on, the determinants of the technical, allocative, and economic (cost) efficiency are analysed. In order to account for uncertainties in the data, the technical efficiency is further analysed by the means of the simulation-based methodology (bootstrapped DEA, robust frontiers, double bootstrap, conditional measures) and fuzzy FDH.

3. 1. Efficiency and total factor productivity of Lithuanian agricultural sector

The VRS technical efficiency scores[6] were estimated by employing the output oriented DEA model as described in Section 1.3.1. The following Fig. 3.1 presents these estimates for years 2000 and 2010. The weighted average was obtained by weighting the efficiency scores by the value added generated in the respective sector during the base year. As the results suggest, the mean efficiency increased from 0.79 in 2000 up to 0.85 in 2010. These efficiency scores imply that there was a 21% gap in output for 2000 which decreased to 15% in 2010 given technological frontier of those periods. Note that the contemporaneous technological frontier is defined by the efficient DMUs viz. economic sectors, and these gaps are therefore incomparable in absolute terms. The application of Malmquist index will enable to identify the shifts of the efficiency frontier. As one can note, the four sectors remained operating on the efficiency frontier during 2000–2010: pharmaceutical products (C21), wholesale and retail trade (G), real estate activities (L), and education (P).

[6] Please note that the VRS assumption is relaxed for the Malmquist productivity index, see Section 2.2 for more details.

As in 2000, the whole manufacturing sector (activities C22 to C33) and utility services (D and E) exhibited the lowest values of technical efficiency ranging between 0.32 and 0.49. Most of these sectors, however, experienced the steepest increase in efficiency amounting to some 50% of the initial efficiency scores and thus graduated the group of the worst performing sectors. Meanwhile the most significant decrease in efficiency was observed for the primary sector (A and B). This indicates the need for modernization in these sectors. Anyway, it may also be related to the overall transformation of the economy. Scientific research and development (M72) was specific with particularly high decrease in efficiency probably caused by rising compensations for employees.

The Malmquist index given by Eqs. 2.3-2.5 was employed to examine the productivity changes across different economic sectors. Initially, we estimated the shift in productivity between years 2000 and 2010 (Fig. 3.2). As one can note, the most significant increase in productivity was observed for pharmaceutical (C21) and chemical (C20) production. Indeed, these industries were positively affected by the investments and market enlargement following the accession to the European Union. Similar trends were also exhibited in sectors of electronics (C26), machinery (C28), and transport equipment (C29, C30). Although the scientific research sector (M72) was specific with the decreased efficiency score, it enjoyed an increase in productivity. At the other end of spectrum, the two primary sectors (A and B) demonstrated a tremendous decrease in productivity. Specifically, the agricultural sector was specific with decrease of 40%, whereas mining and quarrying with that of some 23%. Publishing industry (J58–J60) was also experiencing the decreasing productivity: the Malmquist index for that sector suggested that productivity there dropped by some 28% thanks to decreasing sectoral efficiency. Indeed, cancellation of value-added tax exemptions might have caused the efficiency decrease in the latter sector.

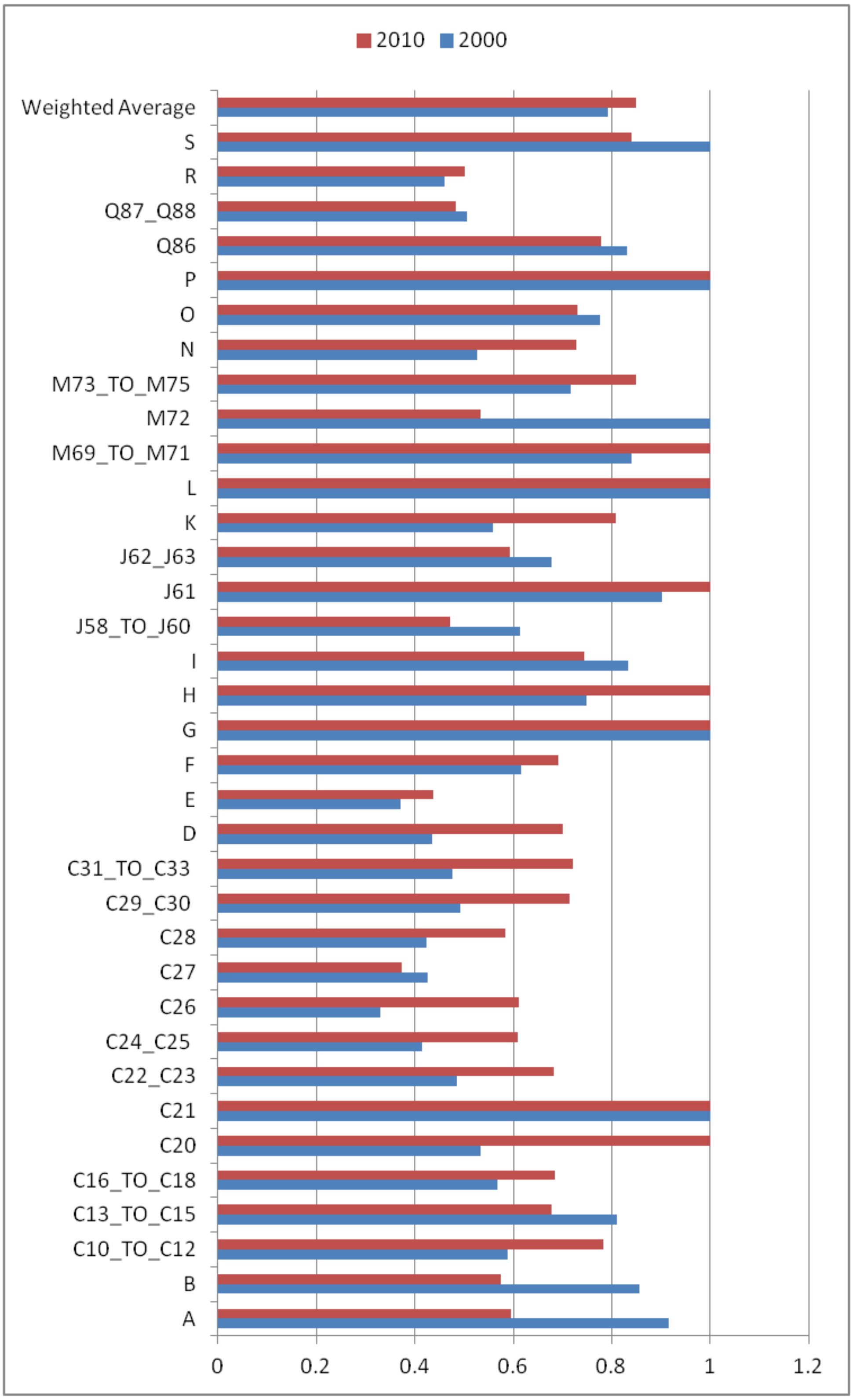


Fig. 3.1. Technical efficiency scores across economic sectors, 2000 and 2010.

Note: see Table A1 in Annex A for abbreviations.

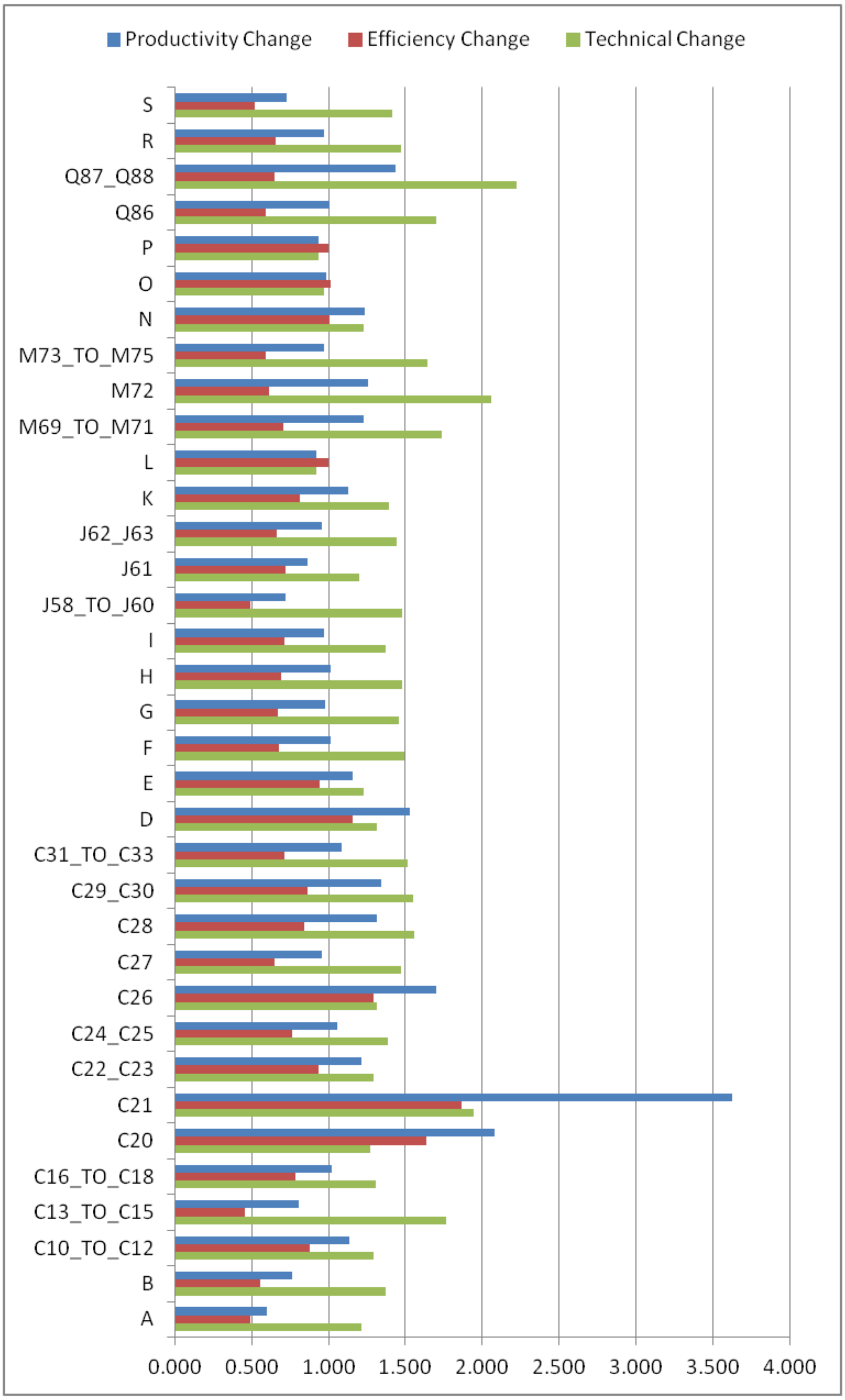


Fig. 3.2. Malmquist productivity index across economic sectors, 2010 compared to 2000.

Note: see Table A1 for abbreviations.

The decomposition of the Malmquist index enables to identify the underlying reasons in productivity change. As Fig. 3.2 suggests, the increase in productivity of the pharmaceutical sector was driven by both inner innovation (efficiency change) and shift in the production frontier (technology change). As for chemical sector, these two factors have a positive effect, however catch-up effect was stronger. In general, the technology effect was positive for all sectors with exception of public administration (O) and education (P) which were subject to a negative shift in the efficiency frontier (i. e. the reference sector exhibited higher efficiency in 2010).

In addition, the Malmquist productivity indices were computed for each period of the two subsequent years between 2000 and 2010. The results indicate that the total factor productivity had been decreasing during 2003-2006 and has been recovering since 2008 (Fig. 3.3). The analysis of the cumulative change in the total factor productivity implies that the productivity has never been decreased below the level of 2000 and had reached its peak in 2007 when the accumulated growth since 2000 reached some 6%. As for the whole period of 2000–2010, the accumulated growth rate was some 4%. Furthermore, the cumulative change in total factor productivity has never been below the value unity what indicates that the Lithuanian economy was rather persistent throughout the economic downturns.

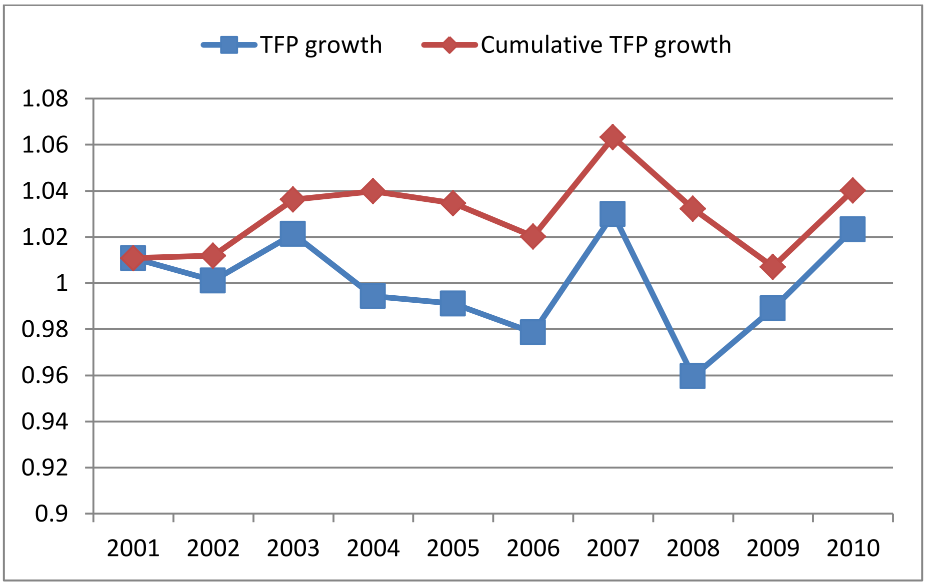


Fig. 3.3. Changes in the mean total factor productivity (TFP) during 2000–2010.

In order to better understand the driving forces of change in total factor productivity, the mean values of the Malmquist components are depicted in Fig. 3.4. As one can note, the overall productivity (i. e. shifts in the production frontier) were generally downwards until 2005 and has been following an opposite trend afterwards. Meanwhile, the catch-up effect exhibited an inverse movement: firm-specific increase in productivity had been increasing until 2005 and decreasing ever since. The results imply that the recent economic downturn negatively affected the firm-specific innovations, whereas the overall productivity of the economy has increased possibly due to appropriate managerial decisions. The reported results also imply that efficiency and changes in productivity varied across the economic sectors throughout 2000–2010.

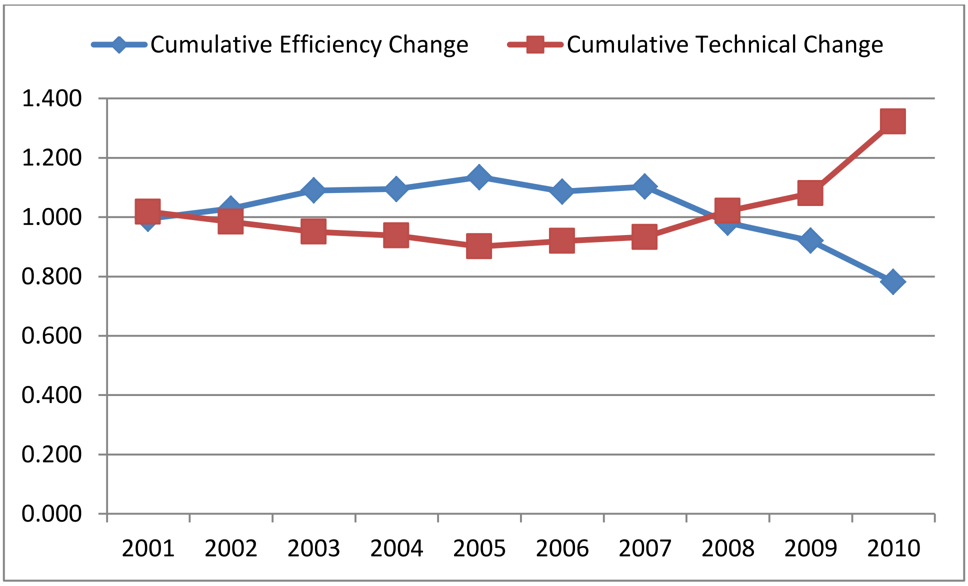


Fig. 3.4. Decomposition of the Malmquist productivity index for 2000–2010.

Steep increases in productivity, however, do not necessarily mean that a certain sector is operating efficiently in relative terms. One thus needs to take into account the level of efficiency as well as productivity changes when performing a robust comparison. Furthermore, these indicators and indices are time–variant and thus might fluctuate in a wider or tighter range. Indeed, higher variation of these indicators is associated with higher risk and uncertainty in respective economic sectors. To cap it all, there is a dichotomy between efficiency and productivity as well as between mean values and variation of the analysed criteria. The multi-criteria decision making method MULTIMOORA will therefore be employed to simultaneously consider these criteria identifying different objectives:

1. the mean technical efficiency score for 2000–2010 (to be maximized);
2. coefficient of variation of the technical efficiency scores (to be minimized);
3. the mean change in total factor productivity for 2000–2010 (to be maximized);
4. coefficient of variation of change in total factor productivity (to be minimized).

The presented set of indicators has the following implications. First, a sector specific with high values of technical efficiency might be experiencing decreasing total factor productivity and thus require certain managerial and institutional measures to be taken. Second, a sector exhibiting increasing total factor productivity might still remain an inefficient one. Third, a high variance in these indicators indicates high volatility of performance and should also attract certain attention. The initial data are given in Table A2.

The analysed alternatives, i. e. economic sectors, were ranked by the MULTIMOORA method as reported by Brauers and Zavadskas (2010). Table 3.1 presents the results.

The results indicate that the best performing sectors in terms of efficiency and productivity were those of wholesale and retail trade, real estate activities, education, hospitality, health, telecommunications, transport, legal services, accounting, advertising. Therefore, the services sector seems to be that most developed in Lithuania. Indeed, some of them, viz. education, hospitality, and health sectors, can prevail by providing services for foreign visitors and thus generating substantial revenues. Meanwhile, transport, legal services, accounting, and advertising sectors rely both on local and international customers. Finally, real estate, telecommunications, and trade sectors are mainly focused on domestic market and thus on the development of the remaining economic sectors in Lithuania.

Table 3.1. Ranks of the economic sectors provided by the MULTIMOORA.

Economic sector	Ratio System	Reference Point	Multiplicative Form	**Final Rank (MULTIMOORA)**
G	1	1	1	**1**
L	2	2	2	**2**
P	3	5	3	**3**
I	4	4	5	**4**
Q86	5	3	6	**5**
J61	6	7	7	**6**
M73_TO_M75	8	8	8	**7**
H	7	12	9	**8**
O	9	6	10	**9**
M69_TO_M71	10	11	11	**10**
C21	11	29	4	**11**
E	12	9	12	**12**
C16_TO_C18	13	10	14	**13**
C10_TO_C12	14	15	16	**14**
C31_TO_C33	15	16	13	**15**
F	16	21	15	**16**
J58_TO_J60	17	13	18	**17**
N	18	14	17	**18**
B	19	20	19	**19**
C13_TO_C15	20	25	20	**20**
C24_C25	21	19	21	**21**
C28	22	18	23	**22**
D	23	24	22	**23**
R	24	17	26	**24**
C29_C30	25	28	24	**25**
C22_C23	26	26	25	**26**
S	27	23	27	**27**
J62_J63	29	22	28	**28**
C27	28	30	29	**29**
A	30	27	30	**30**
Q87_Q88	31	31	31	**31**
C26	32	32	35	**32**
C20	33	34	33	**33**
K	34	33	34	**34**
M72	35	35	32	**35**

The manufacturing sector followed the services. Pharmaceutical, wood, food, and furniture production exhibited the best performance amidst the manufacturing activities. Indeed, these sectors received substantial foreign investments and thus modernized their production technologies. Therefore, these sectors can be considered as those constituting the core of the Lithuanian economy. The construction sector was also attributed with rather high rank. The textile, metallurgy, machinery, transport equipment, and rubber industry operated less efficiently. Accordingly, certain fiscal and institutional measures should be considered to improve the situation in the latter sectors.

The multi–criteria analysis also suggested that the worst performing sectors were those of IT services, electrical equipment, agriculture, computer products, and electrical equipment. IT–related industries are likely to face the competition of the developing countries. Finally, financial and insurance activities as well as scientific research (R&D) were placed at the very bottom. Indeed, the last two sectors were peculiar with rather high volatility of the efficiency indicators. As for the financial sector, these findings are almost imminent in the presence of the economic downturn. However, R&D sector should be appropriately supported in order to create a basis for prospective activities. As European Commission (2011) reported, the Lithuanian knowledge-intensive business sectors, namely IT and R&D, are specific with one of the largest backward dependence on the imported materials among the EU Member States. Therefore, this dependence should be reduced in order to maintain efficiency as well as competitiveness.

The following Fig. 3.5 exhibits a steep decrease in efficiency of the agricultural sector during 2005–2009. Meanwhile, the weighted average for the whole economy fluctuated around 0.85. The efficiency of the agricultural sector fell to somewhere below 0.5 in 2009 and thus reaching its minimum. However, this indicator did increase in 2010 up to 0.6. The decrease of 2005–2009 can mainly be related to an increased capital consumption which, in turn, gained momentum after Lithuania acceded to the EU and the Lithuanian agricultural sector received significant financial support under various schemes. Nevertheless, the economic crisis of 2008–2009 had a relatively lower impact upon the agricultural sector if compared to the remaining ones. Given the TE score for the agricultural sector approached 0.6 (Shepard measure) in 2010, it should increase its output by a factor of 1/0.6=1.66 (Farrell measure) in order to approach the efficiency frontier.

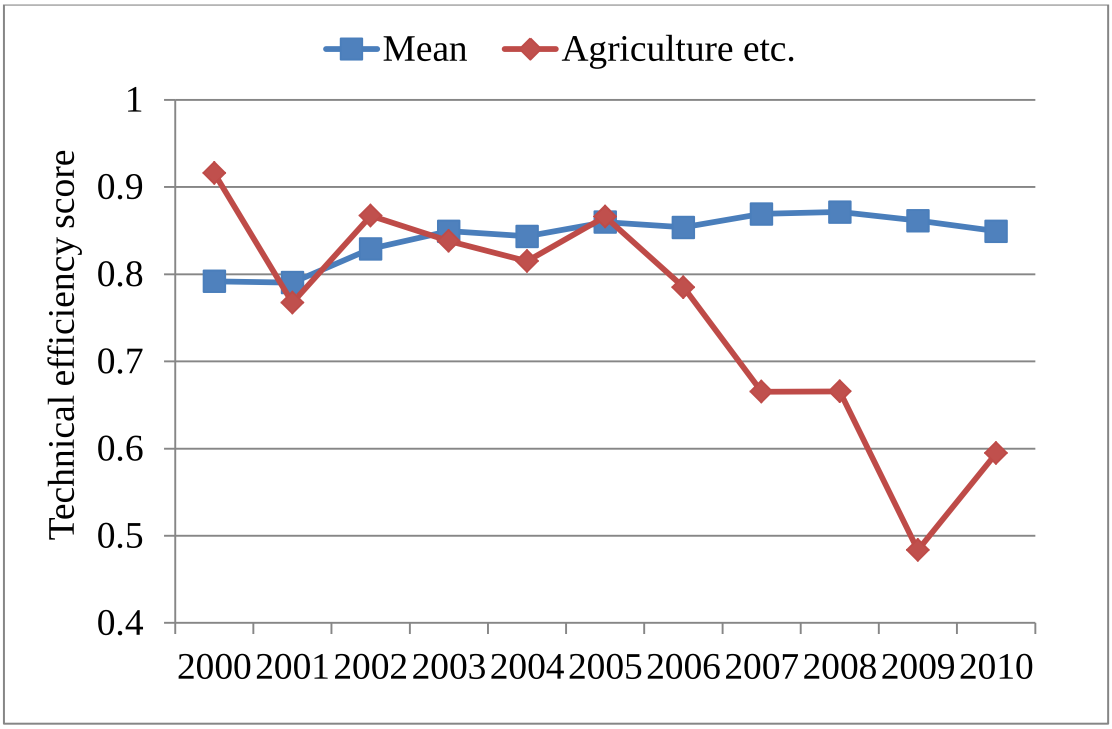


Fig. 3.5. Technical efficiency scores for the whole economy (Mean) and agricultural sector (Agriculture etc.), 2000–2010

TFP can increase not only because of increasing efficiency, but also due to movements of the production frontier. The total change in TFP is presented in Fig. 3.6. As one can note, it follows the similar pattern as Fig. 3.5. Although the TFP used to move upwards during certain periods, the cumulative TFP change remained negative for the agricultural sector and indicated that TFP had decreased by some 40% during 2000–2010. Meanwhile, the weighted average TFP change for the whole economy indicated TFP increase of some 4%.

The changes in TFP can be decomposed in the spirit of Eq. 2.3 into the two terms, TC and EC. Fig. 3.7 exhibits the results of this decomposition for the whole economy (as the weighted average) and the agricultural sector. It is obvious, that a negative TC—an inward movement of the production frontier—was observed for both the agricultural sector and the whole economy until 2004. Ever since, TC has been positive indicating technological progress.

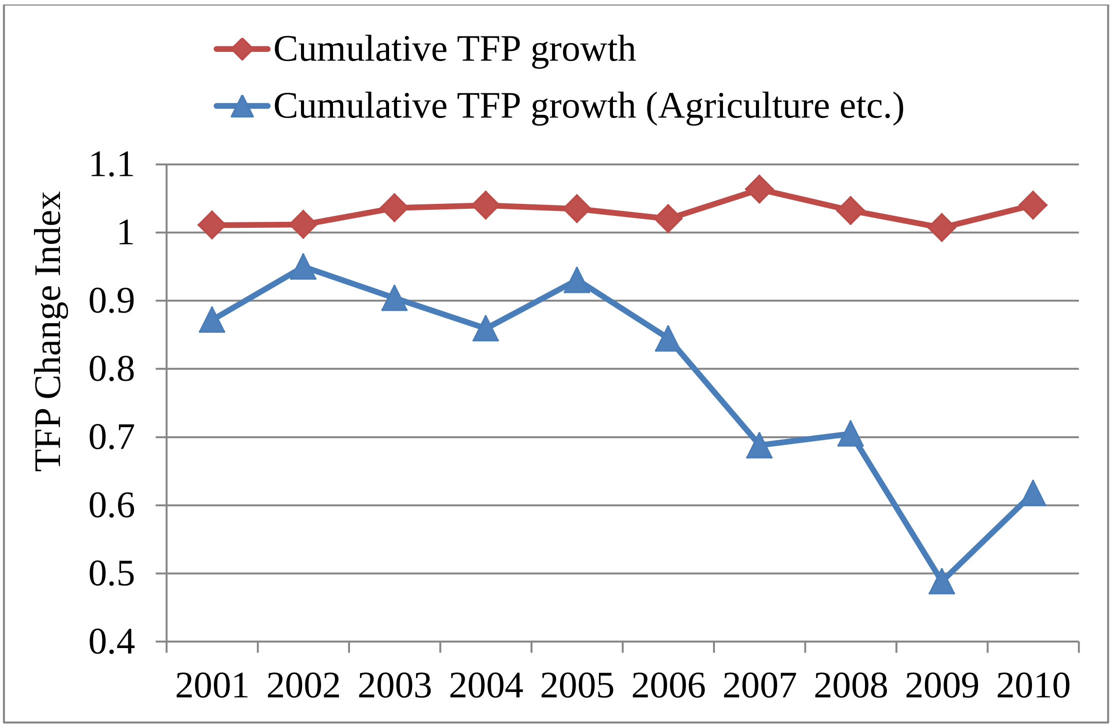


Fig. 3.6. TFP change in the whole economy (Mean) and agricultural sector (Agriculture etc.), 2000–2010.

Once again, it might the integration with the EU that encouraged technological and market developments. The agricultural sector, though, has not gained much from these processes yet in terms of efficiency and productivity. On the other hand, the high-technology and trade services cannot be directly compared to the agricultural sector due to different value added chains and technologies.

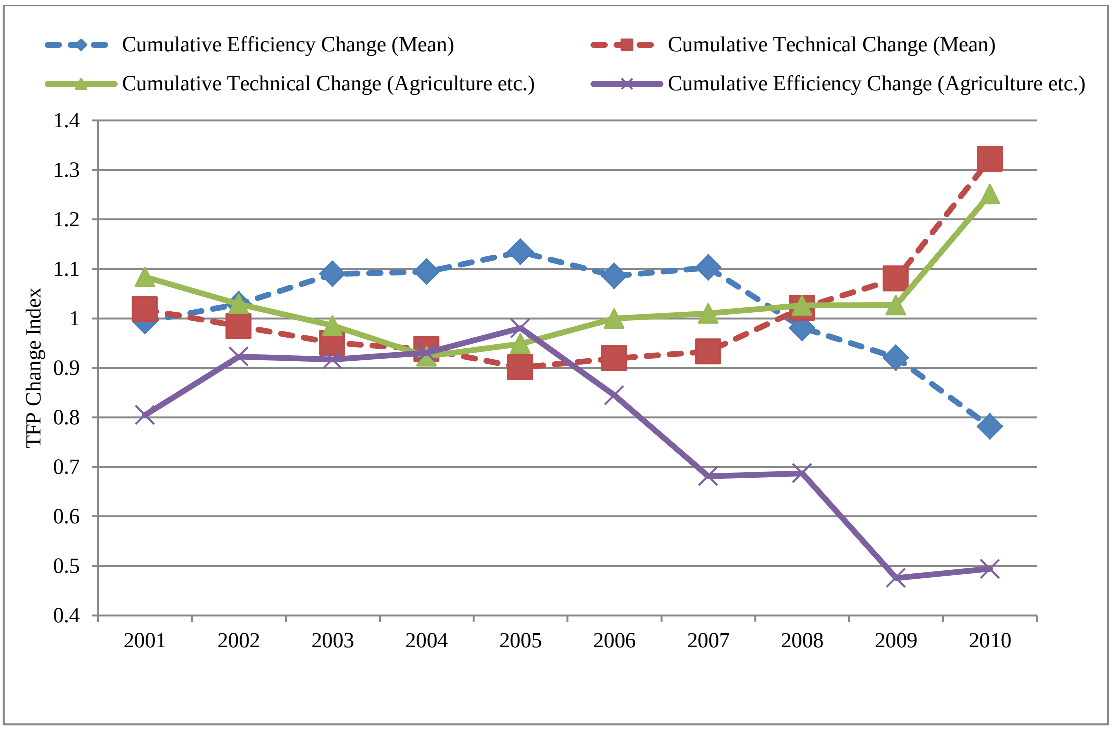


Fig. 3.7. Decomposition of the TFP change in the whole economy (Mean) and agricultural sector (Agriculture etc.), 2000–2010

The presented set of indicators has the following implications. First, a sector specific with high values of technical efficiency might be experiencing decreasing total factor productivity and thus require certain managerial and institutional measures to be taken. Second, a sector exhibiting increasing total factor productivity might still remain an inefficient one. Third, a high variance in these indicators indicates high volatility of performance and should also attract certain attention. The analysis showed that the agricultural sector was the 30th among the 35 economic sectors under analysis. This finding implies that the agricultural sector might not be attractive for investors and entrepreneurs in the long run.

To conclude, a multi–criteria framework for estimation of productive efficiency across economic sectors has been developed. Noteworthy, the further researches could focus on international comparisons based on growth accounting databases like EU KLEMS (O'Mahony, Timmer, 2009) and the World Input-Output Database (Timmer, 2012). Indeed, suchlike analyses would enable to identify the possible development paths for Lithuanian agriculture.

3. 2. Technical efficiency and expansion of Lithuanian family farms

The relative farming efficiency (i. e. technical efficiency) was estimated by the graph DEA method during 2004–2009 (Table 3.2). Table 3.2 also presents the dynamics in the farm size described by European Size Units (ESU, a standard gross margin of EUR 1200) and UAA.

Table 3.2. Productive efficiency and mean farm size of Lithuanian family farms (*N*=200), 2004–2009.

Year	Technical Efficiency	Farm size (ESU)		Farm size (UAA in ha)	
		Mean	Change	Mean	Change
2004	0.817	34.05		202.1	
2005	0.774	38.25	4.20	226.4	24.3
2006	0.720	49.12	10.86	248.0	21.6
2007	0.827	60.91	11.79	254.9	6.8
2008	0.823	61.31	0.40	265.4	10.6
2009	0.732	66.08	4.77	270.2	4.8
Mean	0.782	51.62	6.40	244.5	13.6

The observed technical efficiency scores generally coincide with those obtained on a basis of the aggregate data (Baležentis, Kriščiukaitienė, 2012a). The steepest decreases in the technical efficiency were observed in 2006 and 2009.

The farm size has increased in terms of both ESU and UAA. Indeed, the economic growth was more significant: the mean size in ESU increased twofold, whereas the mean area increased by some 33%. However, the growth rates fluctuated during the research period. In spite of the increasing intensity of farming, the efficiency scores dropped in 2009 possibly due to external factors.

The rank sum test was further employed to test the links between farm expansion and efficiency at a farm level. The farm expansion was identified by changes in ESU, UAA, labour force (AWU), and assets. Accordingly, the two groups of farms were defined for each of these variables depending individual farms exhibited increase or decrease in a certain variable. Specifically, we analysed the differences of the efficiency scores for the preceding period across the two groups of farms. For instance, there were 733 observations with increasing ESU during 2004–2009. Each of these observations was attributed with respective efficiency score from the preceding period (2004–2008). Thus, the set of efficiency scores was formed for farms experienced expansion in ESU. Similarly, the set of efficiency scores was defined for farms experienced contraction in ESU. The two sets of efficiency scores were then compared by the means of the rank-sum test to test the impact of farm efficiency on their expansion. In case the expanding farms were specific with higher efficiency scores we could expect an increase in the structural efficiency. Noteworthy, the external shocks might also influence these developments.

The rank–sum test for ESU indicated that expanded and contracted farms significantly differ in their efficiency level. Specifically, the expanded farms were specific with lower efficiency (p=0.017). Therefore, increasing area, herd size etc. was not sufficiently related to increasing revenues from respective farming types. This phenomenon might be caused by inappropriate technologies or unreported income.

The similar trends were also observed regarding the farm expansion in terms of UAA. Those farms experienced increase in UAA were peculiar with lower efficiency scores in the preceding period (p=0.005).

Finally, the rank–sum test indicated that efficiency scores were equally distributed independently of farm expansion in labour input or assets. The null hypothesis of sample equality was accepted at p=0.393 and p=0.73 for labour input and assets, respectively. It might be thus concluded that efficient farms are not likely to increase their assets, albeit further studies are needed to test whether these investments cause shifts in efficiency during the following periods.

What the results do indicate is that large Lithuanian family farms are experiencing rather extensive growth and thus decreasing efficiency. Indeed, Douarin and Latruffe (2011) identified rather similar trends in efficiency change. As they argued, the farm efficiency was likely to decrease due to Single Area Payments which created certain incentives for smaller farms to stay in farming. To cap it all, one needs to develop certain benchmarking systems that would enable to streamline the strategic management of the agricultural sector and thus provide reasonable incentives for increase in efficiency here.

3. 2. Economic efficiency and its determinants

This section presents the analysis of the economic (cost) efficiency as well as its components in Lithuanian family farms. The research involved DEA and SFA as the estimators of the efficiency scores, therefore the section is structured accordingly. The results from DEA were used for the second-stage analysis based on the tobit and logit models.

3. 2. 1. Non-parametric analysis of the productive efficiency

The non-parametric method, DEA, was employed to estimate the efficiency scores. The DEA-based efficiency scores were then analysed by the means of the tobit and logit models. This sub-section presents the results of the analysis.

3. 2. 1. 1. Dynamics of the efficiency scores

The input–oriented VRS DEA model (Eq. 1.22) was employed to analyse the FADN data which were arranged into the cross–section table. The cost efficiency estimates were obtained by employing Eq. 1.24. The summary of efficiency scores is presented in Table 3.3. The latter table describes the mean values for the whole period of 2004–2009.

Considering the VRS technology, the mean technical efficiency fluctuated around 65.8%, which virtually means that average farm should reduce its inputs by some 35% and sustain the same output level to achieve the efficiency frontier (these numbers do also include the scale effect). The mean value of allocative efficiency was equal to 70.5% and indicated that the cost productivity can be increased by 29.5% due to changes in input–mix. Considering these types of efficiency, the mean economic efficiency—or, alternatively, cost efficiency—of 46% was observed for the Lithuanian family farms. Therefore, these farms should be able to produce the same amount of output given the input vector is scaled down by some 54%. Suchlike shifts, however, might not be feasible for every farm given they are specific with certain heterogeneity across farming types. Table 3.3 also suggests that the highest variation was observed for the economic efficiency estimates where coefficient of variation was 7.2% for VRS technology.

Table 3.3. Descriptive statistics of input–oriented technical (TE), scale (SE), allocative (AE), and cost (CE) efficiency scores under CRS and VRS assumptions.

	TE		SE	AE		CE	
	VRS	CRS		VRS	CRS	VRS	CRS
Arithmetic Mean	0.658	0.535	0.834	0.705	0.747	0.460	0.401
Median	0.628	0.520	0.925	0.728	0.758	0.436	0.376
Standard Deviation	0.204	0.193	0.205	0.167	0.118	0.182	0.166
Sample Variance	0.042	0.037	0.042	0.028	0.014	0.033	0.027
Coefficient of variation	0.063	0.070	0.051	0.040	0.019	0.072	0.068
Minimum	0.154	0.070	0.093	0.105	0.293	0.099	0.037
Maximum	1	1	1	1	1	1	1

The dynamics of different types of efficiency throughout 2004–2009 is presented in Table 3.4. As one can note, there were two major shocks in productive efficiency: the first one occurred in 2006, whereas the second one – in 2009. Obviously the former is related to worsened climatic conditions, for the mean grain yield dropped from 28.9 t/ha in 2005 down to 18.8 t/ha in 2006 (Statistics Lithuania, 2011). The second shock is related to some turmoil in the agricultural markets.

Table 3.4. Dynamics of the Lithuanian family farm efficiency (DEA estimates), 2004–2009.

	TE		SE	AE		CE	
	VRS	CRS		VRS	CRS	VRS	CRS
Crop farming							
2004	0.69	0.52	0.79	0.66	0.77	0.46	0.40
2005	0.61	0.47	0.80	0.64	0.73	0.39	0.34
2006	0.53	0.38	0.76	0.57	0.71	0.31	0.27
2007	0.69	0.63	0.91	0.72	0.75	0.50	0.47
2008	0.68	0.62	0.91	0.72	0.75	0.49	0.46
2009	0.57	0.46	0.84	0.65	0.75	0.37	0.34
Average	0.63	0.51	0.84	0.67	0.75	0.42	0.38
Livestock farming							
2004	0.74	0.67	0.91	0.85	0.83	0.63	0.56
2005	0.84	0.75	0.89	0.83	0.83	0.70	0.62
2006	0.77	0.67	0.87	0.79	0.78	0.60	0.52
2007	0.87	0.81	0.93	0.82	0.80	0.72	0.65
2008	0.85	0.80	0.94	0.81	0.79	0.69	0.63
2009	0.70	0.63	0.89	0.81	0.83	0.57	0.52
Average	0.80	0.72	0.90	0.82	0.81	0.65	0.58
Mixed farming							
2004	0.78	0.50	0.67	0.78	0.75	0.61	0.38
2005	0.71	0.53	0.77	0.73	0.70	0.52	0.37
2006	0.66	0.44	0.71	0.70	0.66	0.46	0.29
2007	0.72	0.59	0.82	0.78	0.75	0.56	0.44
2008	0.72	0.56	0.79	0.74	0.69	0.54	0.39
2009	0.61	0.44	0.75	0.74	0.72	0.45	0.32
Average	0.70	0.51	0.75	0.74	0.71	0.52	0.36

Note: the reported estimates are the input–oriented technical (TE), scale (SE), allocative (AE), and cost (CE) efficiency scores under CRS and VRS assumptions

Considering the variation of different types of efficiency, one can conclude that the cost efficiency (CE) was the most time–variant, whereas the allocative efficiency (AE) – the most time–invariant. Indeed, the coefficients of variation presented in Table 3.3 are 4% for AE and 7.2% for CE under VRS. Therefore, the shifts in economic efficiency can be attributed to shifts in technical and scale efficiency to a higher extent. This finding indicates that farmers tend to adjust the input–mix for their farms at a reasonable rate given the changes in prices of the production factors.

Although the discussed descriptives of the efficiency scores provide some insights, the further analysis is needed to fathom the processes affecting productive efficiency. The underlying causes and sources of inefficiency thus are further analysed by the means of tobit and logit models.

3. 2. 1. 2. Explaining inefficiency: tobit and logit models

This section explores the main determinants of inefficiency and quantifies their impact on efficiency scores or dynamics thereof. We have defined the two main foci for our post–efficiency analysis, namely (i) tobit regression for particular factors of efficiency and (ii) logit regression for factors influencing longitudinal changes in efficiency.

The following factors were chosen as regressors. The logged output (*lnOutput*) identified the scale of operation and was considered a proxy for farm size. Indeed, the question of the optimal farm size has always been a salient issue for policy makers and scientists (Alvarez, Arias, 2004; Gorton, Davidova, 2004; van Zyl et al., 1996). The soil quality index (*Soil*) was included in the models to test the relationship between the environmental conditions and efficiency. The ratio of crop output to the total output (*CropShare*) captures the possible difference in farming efficiency across crop and livestock farms. Similarly, the dummy variable for organic farms (*Organic*) was used to quantify the difference between organic and conventional farming. It is due to Offermann (2003) that Lithuanian organic farms exhibit 60–80% lower crop yields depending on crop species if compared to same values for conventional farming. The demographic variable, namely age of farmer (*Age*) was introduced to ascertain whether young farmers–oriented measures can influence the structural efficiency. Finally, the effect of production and equipment subsidies on efficiency was estimated by considering ratios of production subsidies to output (*SubsShare*) and equipment subsidies to output (*ESubsShare*), respectively.

As one can note, the autoregressive terms were included in the three tobit models (Table 3.5) to increase their robustness. The backward procedure was carried out in terms of heteroskedasticity and autocorrelation consistent (HAC) z values. Therefore, Table 3.5 presents the significant factors of efficiency.

The tobit regression (cf. Table 3.5) suggests that both cost and allocative efficiency is positively impacted by the scale of operation (i. e. the amount of output), whereas technical efficiency has no significant relation to the latter variable. Therefore it can be concluded that the larger farms are more likely to make more efficient decisions regarding input–mix. Indeed bigger quantities involved in supply and production chain management in larger farms provide more flexibility for large farms. This is especially the case in rather small market of Lithuania. Although some other studies reported efficiency to follow U-shaped curve across farm size groups (Latruffe et al. 2004), our findings might diverge from the forms, given we analyse sample particularly covering large farms. Thus only the right tail of the efficiency curve is what we focus at.

The soil index had a negative impact on the three types of efficiency, namely cost, allocative, and technical efficiency. Furthermore, these effects are negative for the whole range of the values of the latter indicator. Soil quality, hence, affects both technology and input management. This finding is likely to be an outcome of poor estimation methodology for this variable and farming practices related to areas specific with higher soil quality. Indeed, farms located in fertile areas tend to exploit extensive agriculture rather than intensive one and thus opt for less innovative technologies. Further research, however should be conducted to identify the exact factors of the negative link between soil quality index and efficiency.

Table 3.5. The tobit regression describing the impact of efficiency factors.

	CE_t			AE_t			TE_t		
	Estimate	z value		Estimate	z value		Estimate	z value	
(Intercept)	-0.06957	-1.1875		-0.18017	-3.6132	***	0.334628	5.4576	***
CE_{t-1}	0.669982	16.4166	***						
CE_{t-2}	0.097827	3.0289	**						
AE_{t-1}				0.609962	17.4355	***			
AE_{t-2}				0.1978	5.9876	***			
TE_{t-1}							0.550301	11.9596	***
TE_{t-2}							0.140399	3.1882	**
$lnOutput_t$	0.227834	14.7219	***	0.113541	10.3271	***			
$lnOutput_{t-1}$	-0.2121	-12.0894	***	-0.08851	-7.7249	***			
$Soil_t$	-0.00137	-2.4569	*	-0.00127	-2.4235	*	-0.00226	-2.3506	*
Age_t	0.001312	3.1348	**	0.001025	2.7208	**			
$Organic_t$	0.046929	1.6524	.				0.082167	2.403	*
$CropShare_t$	-0.04764	-2.6511	**						
$SubsShare_t$							-0.10502	-2.945	**
$SubsShare_{t-1}$	-0.05573	-2.8811	**						
Log(scale)	-2.32891	-41.2717	***	-2.27569	-61.3961	***	-1.72798	-49.7414	***

Notes:
(i) CE, AE, and TE stand for cost, allocative, and technical efficiency, respectively;
(ii) z values are heteroskedasticity and autocorrelation consistent (HAC) ones;
*(iii) significance codes for respective p values: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1.*

Table 3.6. Coefficients of the logit regression describing shifts in efficiency scores with respect to certain determinants of efficiency.

	CE_t			AE_t			TE_t		
	Estimate	z value	Significance	Estimate	z value	Significance	Estimate	z value	Significance
(Intercept)	-2.09318	-1.4546		-3.8793	-5.8944	***	-4.52054	-3.4166	***
$lnOutput_t$	0.353191	3.7728	***	0.379004	6.3762	***	0.46756	5.2793	***
$Soil_t$	-0.04169	-4.359	***	-0.03211	-3.1791	**	-0.03299	-3.3967	***
$CropShare_t$				0.469053	2.2075	*			
$Organic_t$	2.10544	4.1116	***				1.428548	3.4762	***
$SubsShare_t$	-3.05054	-3.0326	**				-1.54704	-2.0332	*
$ESubsShare_t$	-2.00789	-3.9171	***				-1.29849	-2.7871	**

Notes:
(i) CE, AE, and TE stand for cost, allocative, and technical efficiency, respectively;
(ii) z values are heteroskedasticity and autocorrelation consistent (HAC) ones;
*(iii) significance codes for respective p-values: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1.*

Farmer's age had a positive effect on allocative and economic efficiency, albeit this effect was negative for the youngest farmers. Thus farmer's age matters to a higher extent for younger farmers, whereas its impact decreases later on. Furthermore, farmer's age is likely to be related to economic rather than technical side of farming.

Organic farming appeared to be more efficient if compared to conventional farming. To be specific, an average organic farm exhibited cost efficiency score which was greater by a margin of 4.7%, whereas technical efficiency increased by some 8.2%. Therefore the results support Tzouvelekas et al. (2001) who argued that organic farming regulations may encourage a more reasonable application of fertilizers etc., which, in turn, determines respective technological improvements. In addition, organic farms produce more expensive production.

Due to a negative coefficient for crop output share in the total output, crop farming can be considered less efficient if compared to animal farming. Indeed, increase in crop share of 1 p. p. causes decline in efficiency of 4.8% (Table 3.4), whereas the marginal effect at the maximum crop share diminishes to 2.5%. This finding is consistent with study by Latruffe et al. (2004) who discovered similar pattern for Polish farms.

The tobit model suggests that production subsidies had a negative simultaneous effect on technical efficiency, i. e. increase of subsidies to output ratio by 1 p. p. lead to an average decrease in efficiency equal to 10%. Meanwhile, the lagged effect of production subsides on cost efficiency was also observed. Thus production subsidies affected technical efficiency rather than allocative efficiency. As for equipment subsidies, they apparently had no significant effect on level of productive efficiency.

The discussed factors determined the level of cost, allocative, and technical efficiency. The following sub–section discusses the impact of those factors on *changes* in efficiency.

The changes in efficiency scores were explored by the means of logit regression. Therefore we defined $y_k = 1$ in case a certain farm experienced increase in efficiency and $y_k = 0$ otherwise. The same factors as for tobit regression were employed. The backward procedure was carried out with respect to HAC *z*-values. Table 3.6 presents the final results.

As Table 3.6 suggests, the larger farms were more likely to experience increase in efficiency. Specifically, the increase in the total output of 1% caused increase of the odd ratio ranging between 1.4 for cost efficiency and 1.6 for technical efficiency. These numbers subsequently are translated into ratio between probabilities of events $y_k = 1$ (i. e. increase in efficiency) and $y_k = 0$, respectively.

The soil quality index exhibited a negative relation to increase in economic, allocative, and technical efficiency. These relationships can be explained by insufficient pressure for farmers who have their farms located in fertile areas to adopt innovative managerial practices.

Crop farming is more likely to achieve positive shift in allocative efficiency (effect on odd ratio accounts 1.6 times), though it is not the case for cost and technical efficiency. Indeed, crop market is rather dynamic and therefore farmers can adjust their decisions related to input–mix in a more dynamic way.

The fitted logit model imposes that farms adopted organic farming increase their odd ratio for achieving higher cost efficiency at a margin of 8.2, whereas gains in technical efficiency are also to be positively affected by the same decision.

Both production and equipment subsidies are likely to cause decrease in cost and technical efficiency, albeit they do not significantly affect allocative efficiency. These phenomena might be linked to excessive purchases of long-term assets. On the other hand, equipment subsidies tend to distort the input market and thus inflate prices of the traded inputs, viz. machinery, buildings. Furthermore, farms receiving higher production subsidies might be located in less favoured areas, where they are subject to lower productivity due to agro-climatic conditions.

As one can note, farmer's age had no significant impact on probability to experience efficiency increase. To conclude, large livestock farms adopted organic farming practices are those most likely to exhibit an increase in productive efficiency.

3. 2. 2. Parametric analysis of the agricultural efficiency

This section fits the stochastic production frontier to the micro data describing the performance of the Lithuanian family farms during 2004-2009 in order to define the current trends of efficiency and productivity in the sector. The stochastic frontier analysis (SFA) is the econometric technique employed for the latter purpose. Specifically, the technical efficiency scores, output elasticities, and the total factor productivity change were estimated.

3. 2. 2. 1. Production function and technical efficiency scores

The SFA was employed to estimate the efficiency scores for the family farms. The panel data were analysed in a cross-section way. A series of LR tests was carried out before arriving at the non-neutral model. The labour variable as well as its interactions with remaining ones turned out to be insignificant and thus were removed from the further analysis. This finding might have stemmed from methodological or economic peculiarities. As for the methodological issues, the FADN practice might need some improvements on estimation of the labour amount involved in the agricultural production. Specifically, part-time work can be the hardest observable variable. On the other hand, the Lithuanian family farms might not be eager to report the accurate figures about the paid labour force due to legal regulations.

The final specification of the stochastic translog production function is, therefore, given in Table 3.7. The time trend is not significant, but indicates a technical progress of some 4.7% per year, whereas the squared trend is negative and a significant one thus inducing that technical progress increases at a decreasing rate. The positive coefficients near interactions between the time trend and intermediate consumption and utilized land area imply that the technical progress was factor-saving in terms of the latter two types of inputs. On the other hand, the negative coefficient associated with trend and asset interaction indicates increasing asset intensity in the production processes.

As one can note, inefficiency accounted for some 67% of the total variation of the error term. The mean technical efficiency (TE) score was 0.76, which implies that output should be increased by some 30% on average.

Table 3.7. The estimated stochastic production frontier for the Lithuanian family farms (2004–2009).

	Estimate	Standard Error	z value	Pr(>|z|)	
Intercept	5.7128	2.1097	2.7078	0.006773	**
log(Int)	0.7480	0.5585	1.3393	0.180462	
log(Assets)	-1.0967	0.3207	-3.4195	0.000627	***
log(UAA)	1.5083	0.4904	3.0753	0.002103	**
(log(Int) * log(Assets))	0.0724	0.0519	1.3958	0.162764	
(log(Int) * log(UAA))	-0.1731	0.0870	-1.9906	0.046524	*
(log(UAA) * log(Assets))	-0.0001	0.0457	-0.0033	0.997404	
(0.5 * log(Int)^2)	-0.0078	0.1042	-0.0747	0.940471	
(0.5 * log(Assets)^2)	0.0339	0.0433	0.7843	0.432888	
(0.5 * log(UAA)^2)	0.1286	0.0898	1.4315	0.152288	
t	0.0466	0.1146	0.4062	0.684624	
(0.5 * t^2)	-0.0253	0.0080	-3.1427	0.001674	**
(t * log(Int))	0.0221	0.0179	1.2334	0.217425	
(t * log(Assets))	-0.0298	0.0112	-2.6738	0.0075	**
(t * log(UAA))	0.0109	0.0168	0.6451	0.518868	
sigmaSq	0.1808	0.0172	10.5371	< 2.2e-16	***
gamma	0.6665	0.0689	9.6704	< 2.2e-16	***
log likelihood value: -337.2857					
total number of observations = 1200					
mean efficiency: 0.77					

Notes: (i) *Int*, *Assets*, *UAA*, and *t* stand for intermediate consumption, asset value, utilized agricultural area, and time trend, respectively; (ii) significance codes: *** – 0.001; ** – 0.01; * – 0.05.

Fig. 3.8 depicts the mean values of TE scores across different farming types. As one can note, the mean TE had been declining since 2004 and reached its trough in 2006. This particular fall was influenced by unfavourable climatic conditions. After recovering in 2007, the TE further declined during 2008–2009. Noteworthy, the crop farms were specific with higher efficiency fluctuations if compared to livestock or mixed ones. Furthermore, the livestock farms were specific with the highest mean TE scores throughout the research period save year 2004.

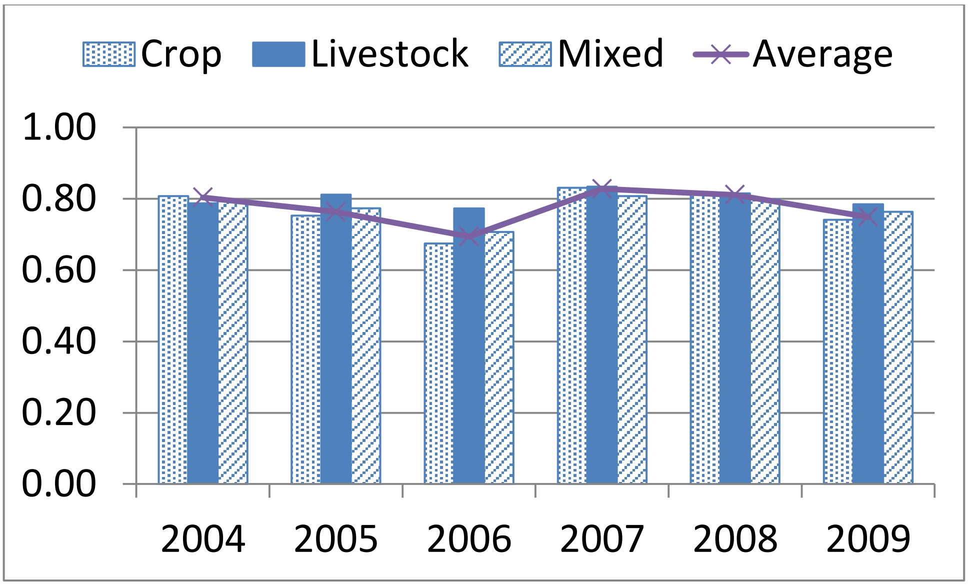


Fig. 3.8. The mean TE scores across different farming types, 2004–2009.

The previous Fig. 3.8 exhibits the mean values, whereas the underlying distribution of efficiency scores remained unknown. In order to cope with the latter issue, the kernel densities are usually employed in efficiency analyses. This type of graphic representations enables one to avoid arbitrary decisions involved in construction of the other ones (e.g. the different numbers of bins in histograms are related with different visualisations of the same efficiency score distribution). Fig. 3.9 thus exhibits the underlying distributions of the TE scores across the three farming types. The mean TE scores of each farming type are quite similar: 0.8 for livestock farms and 0.77 for both crop and mixed farms. However, the crop farm distribution is right-skewed and specific with a higher variance if compared to those of the remaining farming types. The lowest variance of the livestock farm TE score distribution implies that these farms are quite homogeneous in terms of technical efficiency, whereas crop and mixed farms tend to be more heterogeneous.

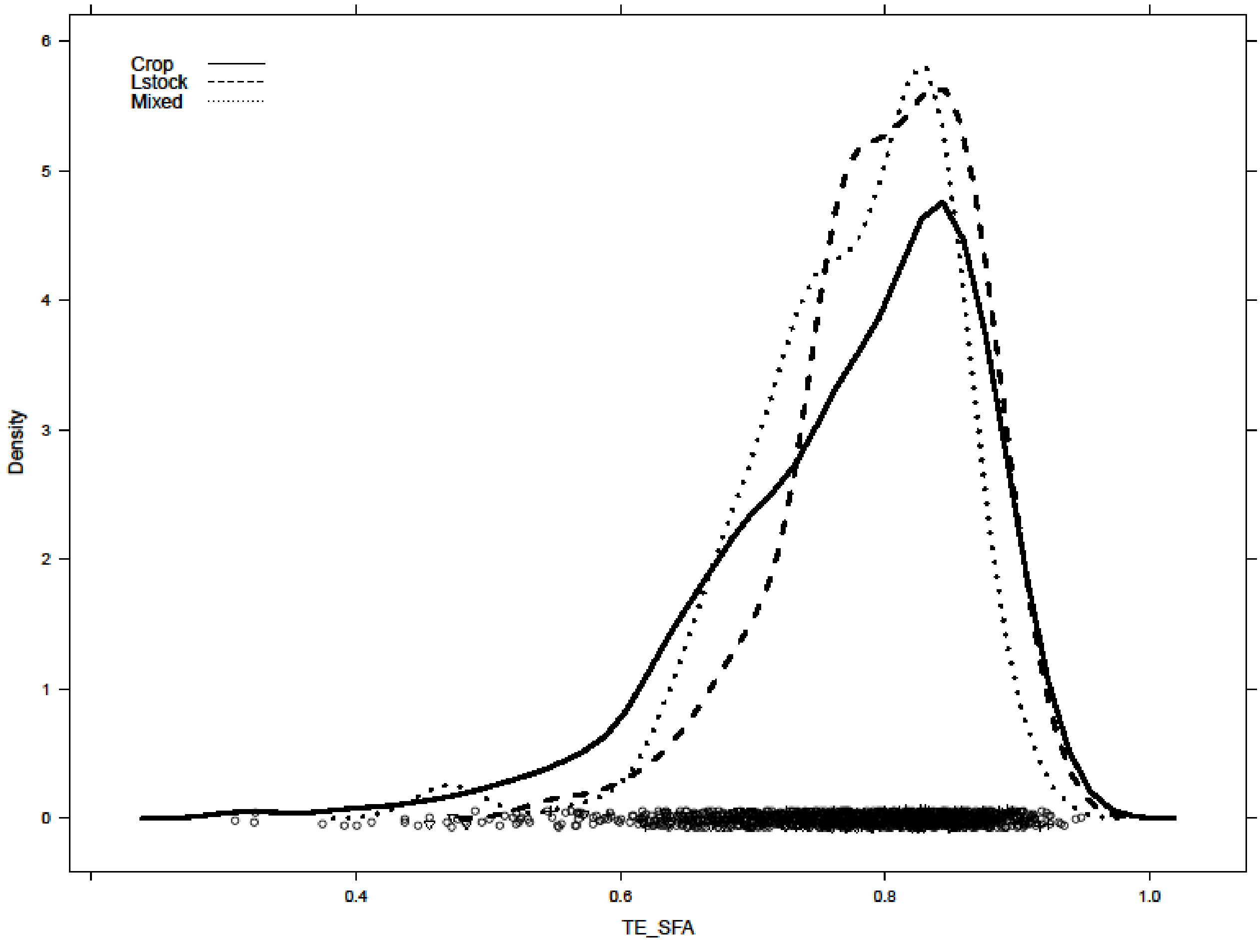


Fig. 3.9. Kernel densities of the TE scores across different farming types.

In order to test whether the differences of the mean TE are significant across farming types, the Least Significant Difference (LSD) test was employed. The results (cf. Table 3.8) imply that livestock farms had a significantly higher mean of TE scores at the confidence level of 5%. Indeed, the difference between livestock and crop farms was more significant (p=0.001) than that between livestock and mixed farms (p=0.017). Therefore, the mixed farms do benefit from animal farming in terms of efficiency gains.

Table 3.8. A Least Significant Difference *t* test for means of TE scores across different farming types.

Mean Square Error: 0.009139696

	Mean TE	SE	replication	LCL	UCL
Crop	0.7713	0.0034	890	0.765	0.778
Livestock	0.7994	0.0059	137	0.788	0.811
Mixed	0.7733	0.0059	173	0.762	0.785

alpha: 0.05 ; Df Error: 1197

Critical Value of t: 1.961948

Least Significant Difference 0.0182516

Harmonic Mean of Cell Sizes 211.2198

Means with the same letter are not significantly different.

Groups	Treatments	Means
a	Livestock	0.79935
b	Mixed	0.77329
b	Crop	0.77134

Comparison between treatments means

	Difference	pvalue	sig	LCL	UCL
Livestock - Crop	0.0280	0.0014	**	0.0108	0.0452
Mixed - Crop	0.0020	0.8060		-0.0136	0.0175
Livestock - Mixed	0.0261	0.0173	*	0.0046	0.0475

*Significance codes: *** – 0.001; ** – 0.01; * – 0.05.*

The non-parametric test (Li et al., 2009) was also employed to check whether the underlying densities of the TE are significantly different across the farming types. The non-parametric test did also confirm the difference between the underlying densities of TE scores associated with livestock and crop farming (p=0.02). The differences between densities of the mixed and livestock farms' efficiency scores were significant at p=0.03. Finally, the TE score densities for the crop and mixed farms were different at p<0.000.

To conclude, the livestock farms were specific with the highest technical efficiency. The following sub-sections analyse the main sources and factors of efficiency and total factor productivity.

3. 2. 2. 2. Output elasticities

The partial output elasticities help one to fathom the prospective ways to improve the productive efficiency with respect to the underlying productive technology. The elasticity analysis is related to factor input rationing, for scarce resources should induce higher output elasticities and shadow prices. In the sequel we will analyse the dynamics of the three inputs, viz. assets, intermediate consumption, and land as described in Coelli et al. (2005). The technical change (time elasticity) is to be analysed alongside with the total factor productivity.

The output elasticities with respect to assets are given in Table 3.9. As one can note, assets became less productive throughout the research period: An additional per cent of assets would have resulted in 0.14-0.27 increase in output in 2004, whereas it would have caused an increase of only 0.1-0.21 in 2009. This finding is alongside with the negative coefficient observed for an interaction between trend and assets. The latter developments might be related with excessive capital use (Petrick, Kloss, 2012), which, in turn, was fuelled by investment subsidies distributed in accordance with the Common Agricultural Policy after Lithuania acceded to the European Union. Noteworthy, it was the mixed farms that were specific with the lowest output elasticity to assets. Indeed, these farms have accumulated the highest amounts of fixed assets. Therefore, the investment support policy should be reconsidered for this particular farming type.

Table 3.9. Output elasticity with respect to assets, 2004–2009.

Year	Farming type		
	Crop	Livestock	Mixed
2004	0.26	0.27	0.14
2005	0.26	0.23	0.17
2006	0.25	0.22	0.15
2007	0.24	0.21	0.16
2008	0.24	0.23	0.13
2009	0.21	0.19	0.10
Average	0.25	0.23	0.14

Elasticity associated with intermediate consumption (Table 3.10) increased during the period of 2004-2009 from 0.64-0.81 up to 0.75-0.89. The increase might have been driven by improved farming practices, novel chemical products, and successful training programs. The lowest output elasticity to intermediate consumption was observed for the crop farms. Specifically, it constituted some 74-84% of the respective mean elasticity observed for either livestock or mixed farms, depending on which of them was a higher one, during 2004-2009. The crop farms are specific with inflated intermediate consumption values with fertilizer costs accounting for a significant share therein. Therefore, both introduction of new species and application of effective fertilizing schemes are still important for the crop farming. Anyway, the crop farming elasticity associated with intermediate consumption exhibited a positive trend and tended to converge with those specific for livestock and mixed farms.

Table 3.10. Output elasticity with respect to intermediate consumption, 2004–2009.

Year	Farming type		
	Crop	Livestock	Mixed
2004	0.64	0.77	0.81
2005	0.65	0.79	0.77
2006	0.66	0.81	0.79
2007	0.71	0.86	0.84
2008	0.73	0.86	0.86
2009	0.75	0.89	0.88
Average	0.69	0.83	0.83

The output elasticity with respect to utilized agricultural land was generally decreasing from 0.02-0.14 down to 0.01-0.1 during the period of 2004-2009 (Table 3.11). The range of mean elasticities across farming types, though, remained virtually invariant. The mixed farms were specific with the highest elasticity, whereas the livestock – with the lowest one and even a negative value for year 2008 (this indicates a violation of the monotonicity of a production frontier). Indeed, livestock farming does not require land as a production factor to the same extent as other farming types do. There are still some prospects to increase land productivity in the livestock farms mainly by producing fodder.

Table 3.11. Output elasticity with respect to utilized agricultural area, 2004–2009.

Year	Farming type		
	Crop	Livestock	Mixed
2004	0.09	0.02	0.14
2005	0.07	0.05	0.10
2006	0.07	0.05	0.11
2007	0.05	0.03	0.09
2008	0.03	-0.02	0.09
2009	0.04	0.01	0.10
Average	0.06	0.03	0.10

The analysis of the partial output elasticities implies that the Lithuanian family farms face rather meagre difficulties in land acquisition. For the mean partial elasticity associated with land, equal to 0.06, was the lowest one if compared to those associated with intermediate consumption or assets. The marginal asset productivity represented by respective elasticity (0.23) was much higher than that of land, albeit it was down-trended. Therefore, the excessive use of assets should be reduced by streamlining support measures under Rural Development Programme for 2014-2020. Finally, the highest output elasticity was that with respect to intermediate consumption. Indeed, this type of input is the one easy controllable and adjustable.

The total output elasticity was computed in order to test whether the underlying technology is CRS or VRS. The linear hypothesis of CRS was tested in the spirit of Eq. 3.28. The obtained statistic ($S = 0.85$) was well below the critical value. The null hypothesis about CRS was, therefore, accepted. In the remaining part of the research we therefore did not tackle the scale efficiency.

3. 2. 2. 3. Total factor productivity

The economic performance of a decision making unit should be assessed not only in terms of efficiency but also in productivity. For efficiency measures the firm-specific distance from the production frontier, whereas the total factor productivity describes the shifts of the production frontier. Therefore, a certain firm might not reduce its technological features but become less efficient due to the frontier shift, i. e. increase in the sectoral total factor productivity. On the other hand, a certain firm can maintain the same level of efficiency and become more productive in case it catches up the frontier shift and thus increases its productivity.

The total factor productivity (TFP) change was assessed across the three farming types as described by Coelli et al. (2005). Given the fact that the CRS technology was assumed on a basis of the linear hypothesis test, the TFP change was decomposed into the two terms, namely technical change (TC) and efficiency change (EC). The estimates for each farming type are given in Figs. 3.10–3.12.

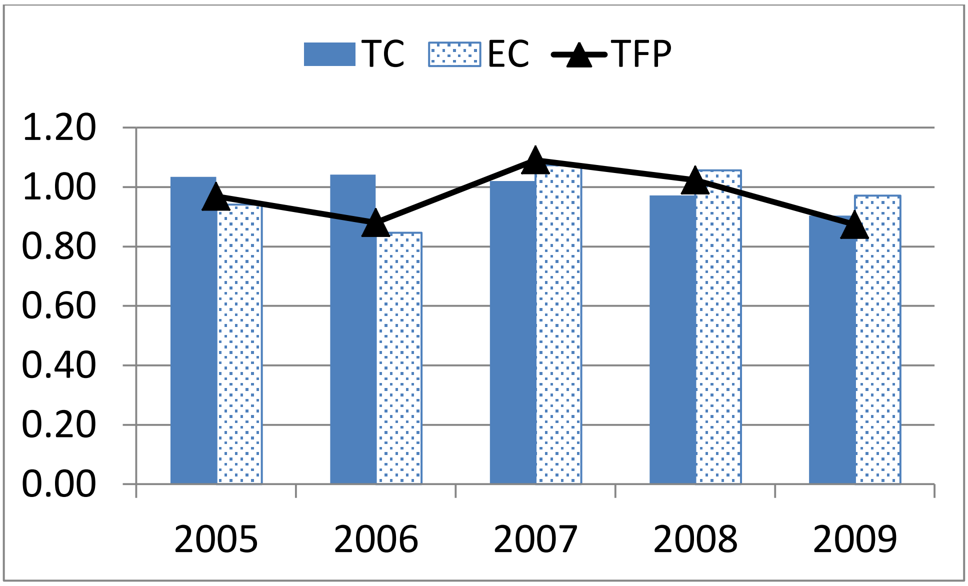


Fig. 3.10. The cumulative total factor productivity change in the crop farms, 2004-2009.

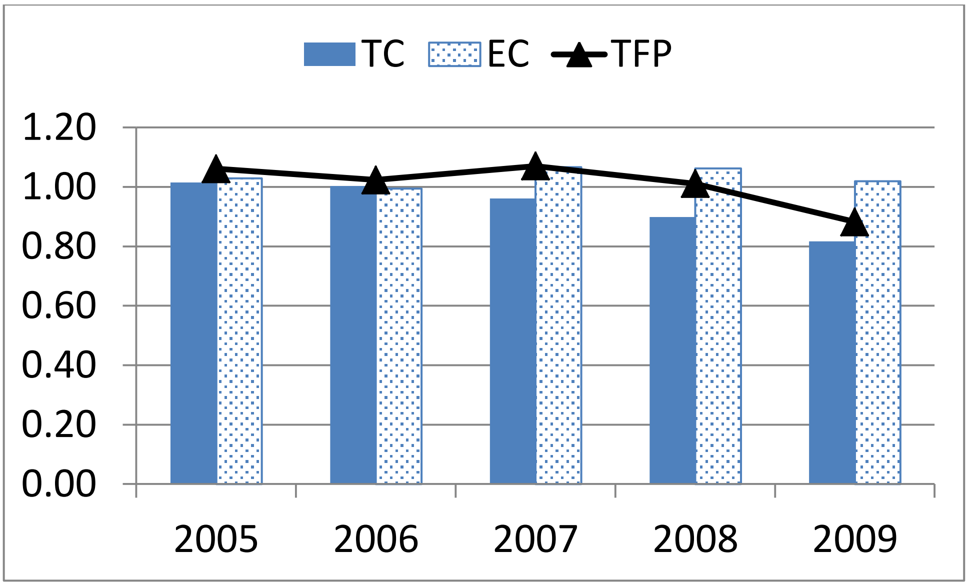


Fig. 3.11. The cumulative total factor productivity change in the livestock farms, 2004-2009.

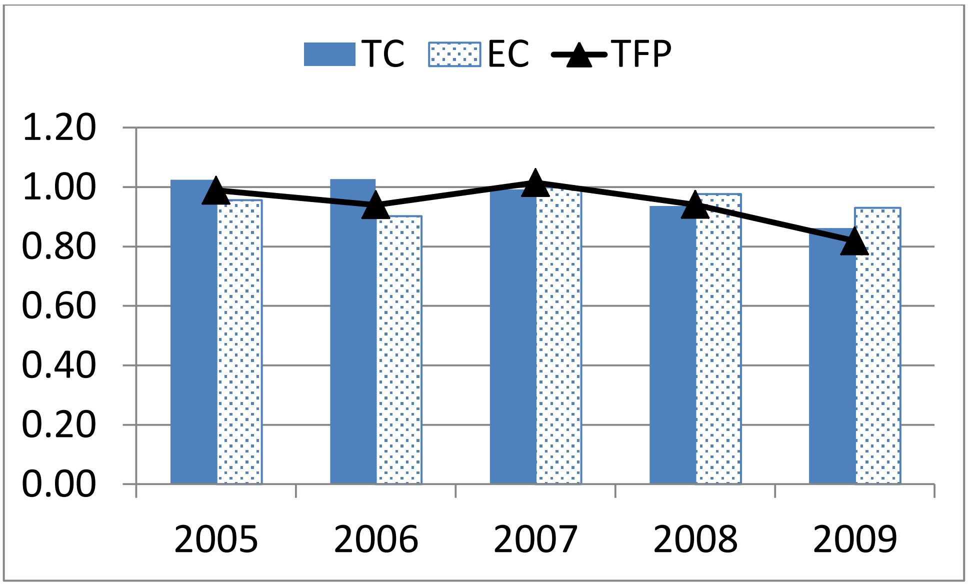


Fig. 3.12. The cumulative total factor productivity change in the mixed farms, 2004-2009.

The crop farms were peculiar with the most intensive fluctuations of the TFP (Fig. 3.10). The TFP increased during 2004–2005 and 2006–2007, whereas it decreased during 2005-2006 and 2007-2009. The decrease of 2005-2006 was mainly driven by a negative EC effect, what means that unfavourable climatic conditions decreased the TE of the crop farms. The TC, though, did not change if compared to the preceding period and the cumulative change remained greater than unity. Therefore, the production frontier did not move inwards, but the efficiency of an average crop farm tended to decrease. A certain part of the crop farms, nevertheless, remained working as productive as in the preceding period. The EC caused decrease of the TFP to margin of 3%, whereas TC – to that of 10% during the period of 2004-2009. The very TFP decreased by some 13% in the meantime.

The livestock farms were specific with the lowest fluctuations in the TFP throughout 2004-2009 (Fig. 3.11). The latter sub-sector remained virtually unaffected by the downturn of 2005-2006, albeit the subsequent periods were specific with a negative TC trend. Accordingly the TFP began to diminish after year 2007. As a result, the TC resulted in the decline of the TFP by some 18%, whereas the EC component accounted for the increase of some 2%. The resulting TFP change during 2004–2009 was a decrease of 12%. The observed changes in TFP indicate that it was the TC that reduced the TFP, whereas the livestock farms became more homogeneous in terms of the TE, because the cumulative EC remained positive (i. e. that above unity). The decreasing number of livestock is obviously related to the diminishing TFP. The frontier movement inwards could be alleviated by introducing respective support measures aimed at increasing the attractiveness of the livestock farming as an economic activity.

The mixed farming was specific with a degree of the TFP variation that lies in between those of the specialised farms (Fig. 3.12). Anyway, the mixed farms did not manage to maintain neither the TC level specific for the crop farms nor the EC experienced by the livestock farms. The mixed farming, therefore, was specific with the highest decrease in the TFP accounting for 18%. The results do indicate that the mixed farms should receive more attention when preparing the training and support programs in terms of efficient managerial and agricultural decisions.

3. 2. 3. Comparison of the results

In order to test the robustness of the obtained results one can compare the distributions of the technical efficiency scores obtained by the non-parametric DEA and the parametric SFA. Fig. 3.13 depicts the relationship between technical efficiency scores obtained by the means of the stochastic frontier analysis and output-oriented DEA model under CRS. Indeed, the VRS assumption results in virtually the same pattern of the efficiency scores.

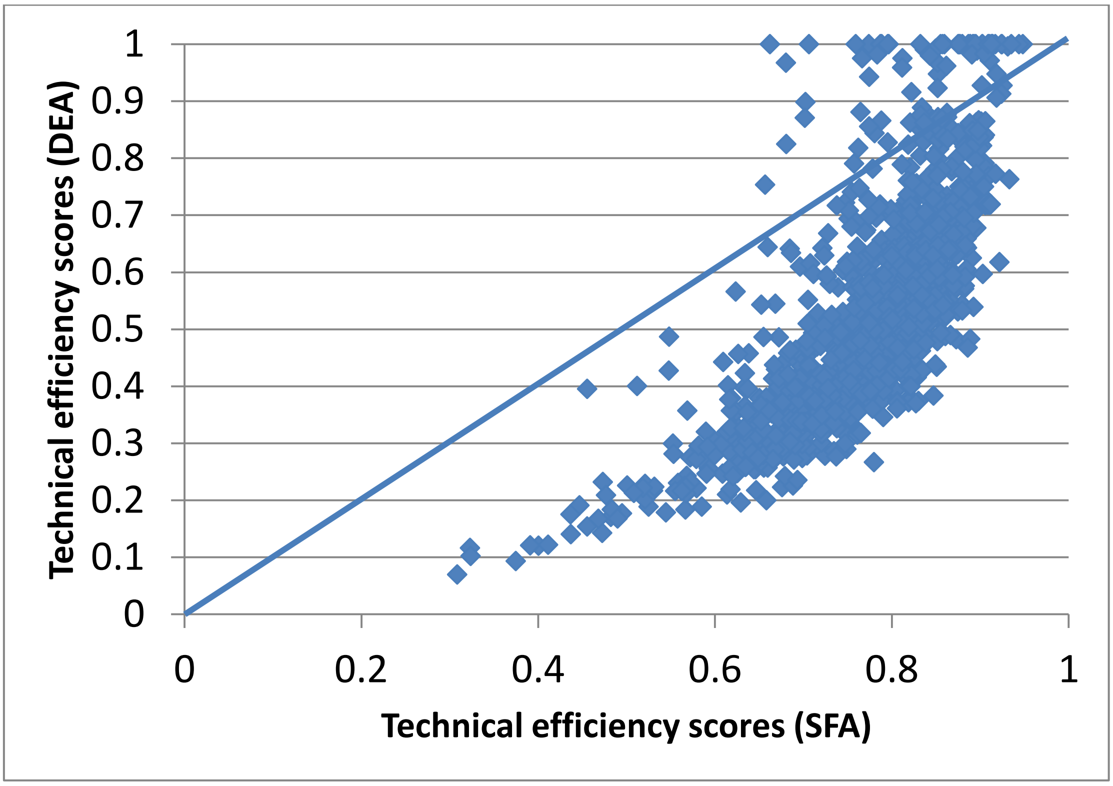


Fig. 3.13. Comparison of the TE scores obtained by DEA under CRS and SFA.

Correlation observed between these two variables was a rather high one (R=0.74). However, Fig. 3.13 suggests that the relationship is not a linear one. The DEA scores are generally lower that those obtained by SFA, for the former technique considers the whole distance between an observation and the efficiency frontier as that entailed by inefficiency. Furthermore, SFA does not allow a full efficiency, i. e. none of the observations is attributed with technical efficiency score of unity. One more factor is related purely to the methodology of this study: The employed SFA model did not contain the labour input used in DEA model due to statistical insignificance. Anyway, the convergence was achieved in the upper part of the efficiency scores' range.

Fig. 3.14 presents the mean technical efficiency scores obtained by DEA and SFA across farming types. The correlation observed between these two estimates was extremely high (*R*=0.99). However, the differences between mean efficiency observed for the livestock farms and that for the remaining farming types are much lower in SFA. It might be a result of the random error term in SFA.

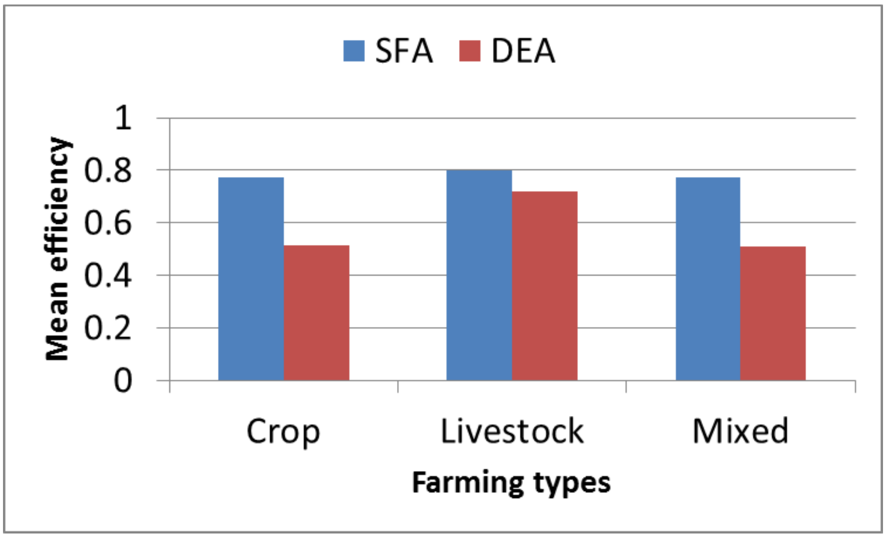


Fig. 3.14. The mean technical efficiency scores across farming types.

Given the employed dataset contained the longitudinal data, the relation between the efficiency scores obtained by DEA and SFA was analysed across the time periods, namely years 2004–2009. The following Fig. 3.15 exhibits the results. The entailed correlation was also very high (*R*=0.9). Both of the employed methods identified the two efficiency shocks in 2006 and 2009.

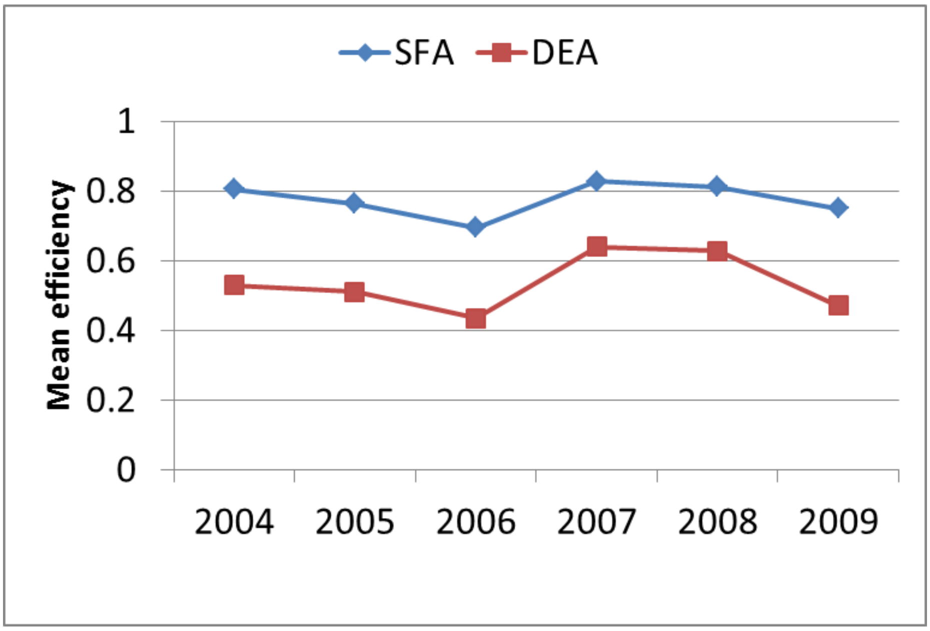


Fig. 3.15. Variation of the mean technical efficiency scores across years.

Both the non-parametric DEA and the parametric SFA identified the same patterns of efficiency in the Lithuanian family farms. The positive correlation was observed for the pooled efficiency scores as well as for the means of the different farming types or time periods. Therefore, the efficiency estimates obtained by the means of DEA and SFA can be considered as the robust ones. Generally, crop farms were specific with lower mean TE values during 2004–2009 if compared to the remaining farming types. Furthermore, the periods of 2006 and 2009 were those of the steepest decreases in TE for all farming types.

3. 3. Determinants and patterns of farm efficiency under separability

This section presents the results obtained using a fully non-parametric methodology as described by Baležentis et al. (2014). Note that it differs from the conditional efficiency measures in that the former methodology assumes separability among the environmental variables and the production frontier.

3. 3. 1. Dynamics of the productive efficiency

The efficiency scores were obtained by employing the output-oriented bootstrapped DEA model under a VRS assumption (B=2000). The *FEAR* package (Wilson, 2008) was applied to implement the model. The reported efficiency scores are Shepard measures. The difference between the original and the bootstrapped DEA scores was not decisive, i.e. a mean difference of 11 p. p. as well as difference in sample means of some 3 p. p. were observed. The highest difference was for years 2004, 2007, and 2008, which implies that the highest data variability occurred during technological expansion. This finding might indicate that some farms tended to increase their output during favorable periods in terms of climatic conditions to a greater extent than the remaining farms. Therefore, there is a need for further research into the sources and factors of convergence among Lithuanian family farms from the viewpoint of their productivity and efficiency.

Table 3.12 further explores the dynamics of the DEA efficiency scores. As can be seen, the highest discrepancy between the original TE scores and the bootstrapped ones was observed for the livestock farms (some 14 p. p.). Noteworthy, these discrepancies increased in years 2005 and 2008 to the greatest extent. One can therefore assume that the livestock farms, in particular, exhibited a delayed response to changes in crop markets.

The differences between the bootstrapped and original TE scores (cf. Table 3.12) have certain implications for bootstrapping. First, bootstrapped DEA accounted for measurement errors which emerged due to internal and external factors, as discussed in the Introduction. Second, the sampling errors were also tackled to some extent. Indeed, the differences between the mean TE scores across the farming types were much lower for bootstrapped DEA when compared to the original estimates (Table 3.12).

The bootstrapped DEA efficiency scores imply that an average farm should have increased its outputs by a factor of 2 (=1/0.5) given that the input quantities remain fixed. The same factor was 2.1, 1.7, and 2.1 for crop, livestock, and mixed farms, respectively. Table 3.121, however, presents only averages of the estimates.

Table 3.12. Average technical efficiency (TE) scores across different farming types, 2004–2009.

Year	Original TE scores				Bootstrapped TE scores			
	Crop	Livestock	Mixed	Average	Crop	Livestock	Mixed	Average
2004	0.54	0.63	0.61	0.56	0.49	0.52	0.42	0.49
2005	0.49	0.72	0.56	0.52	0.46	0.57	0.50	0.48
2006	0.37	0.69	0.56	0.42	0.37	0.59	0.45	0.42
2007	0.53	0.81	0.59	0.56	0.51	0.66	0.52	0.52
2008	0.57	0.86	0.63	0.60	0.55	0.66	0.52	0.56
2009	0.52	0.72	0.54	0.54	0.50	0.58	0.47	0.50
Average	0.50	0.73	0.58	0.53	0.48	0.60	0.48	0.50

An integrated squared difference test for equality of densities (Li et al., 2009) was employed to test for differences between the efficiency scores' densities associated with different farming types (399 bootstrap replications were carried out). The results of the test indicate that livestock farms differed from crop farms ($T_n = 14.3$, $p < .001$) as well as from mixed farms ($T_n = 14.6$, $p < .001$) in terms of efficiency densities. Coupled with the respective kernels, these findings suggest that livestock farms featured higher TE scores in general. Meanwhile, the difference between crop and mixed farms was also significant ($T_n = 2.8$, $p < .01$). The lower *p*-value implies a higher similarity between densities of TE scores for the crop and mixed farms.

3. 3. 2. Efficiency change paths

Given that we analysed the performance of Lithuanian family farms by means of panel data, it is important to define the general trends and patterns of efficiency featured by the farms. Latruffe et al. (2008) employed cluster analysis to reveal the underlying total factor productivity change paths in the Polish family farm sector. In the same spirit, we employed fuzzy clustering to identify efficiency change paths in the Lithuanian family farm sector. As already mentioned, fuzzy clustering allows partial membership of an observation to several clusters to different degrees. This means that the clusters can overlap in some ways. It was the underlying uncertainties associated with the nature of the data that made us opt for the latter technique.

The number of clusters was determined by considering principal component analysis plots and sets of observations belonging to certain clusters represented by membership scores. The excessive number of clusters resulted in extremely low membership values, or the observations belonging to overlapping clusters appeared in the same areas defined by the principal axes. After a series of iterations, we identified four clusters describing efficiency change paths of Lithuanian family farms (Fig. 3.16).

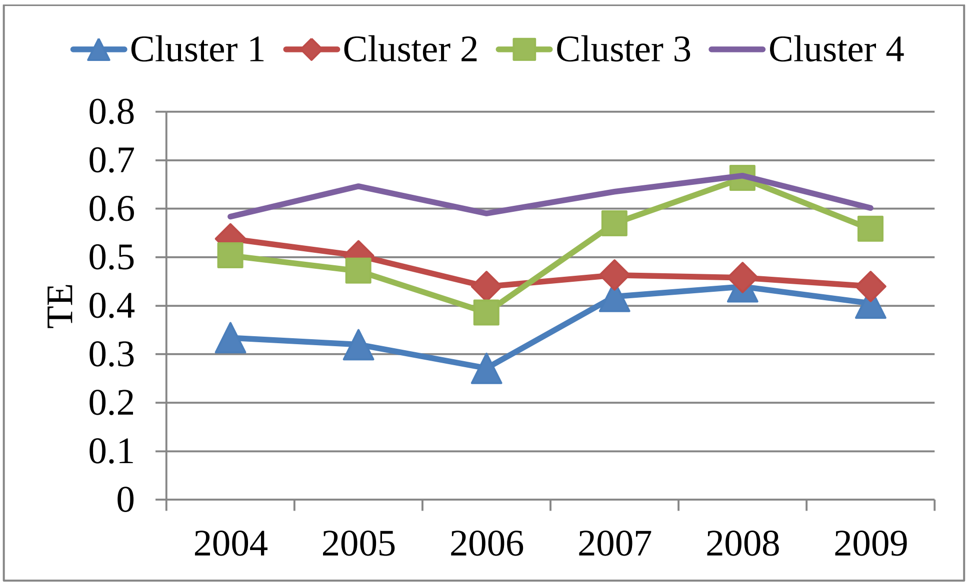


Fig. 3.16. The four efficiency change paths identified by means of fuzzy clustering.

As one can note, Clusters 1 and 3 followed virtually the same path, with a varying distance between them in terms of average efficiency. Specifically, a robust increase was observed in 2007–2008 for both of the latter clusters, whereas a decrease in 2009 was specific for Cluster 3. Similarly, Cluster 4 featured the same path during 2005–2009, but years 2004 and 2009 were ones of decline; however, these developments of TE were not so decisive when compared to those observed for Clusters 1 and 3. Cluster 3 exhibited the least stochastic dynamics of TE of all four clusters.

The highest mean TE (0.62) was observed for Cluster 4. Indeed, this cluster also had the lowest coefficient of variation for the annual means (5%). One can thus assume that Cluster 4 represents the best performing farms which managed to maintain the highest efficiency scores throughout the research period. Clusters 2 and 3 exhibited similar mean TE scores (0.47 and 0.52, respectively), although Cluster 3 had a rather high coefficient of variation (18%), whereas a value of just 8% was observed for Cluster 2. Meanwhile, Cluster 1 featured the lowest mean value of TE, viz. 0.36, and a relatively high coefficient of variation (18%). The fuzzy cluster analysis, therefore, revealed four clusters which share a similar efficiency change tendency but which diverge in terms of magnitude of the change and average values of the efficiency scores. Further analysis was carried out in order to reveal the underlying characteristics of these clusters.

A cluster can be described in terms of specialization by analysing the membership function values and the crop output share in the total output specific to each of the farms. The specialized crop farms belonged to Clusters 1–3. Meanwhile, the livestock farms were members of Clusters 2 and 4 in general, with the latter cluster being the main one in terms of the membership values. The mixed farms were assigned to Clusters 1, 2, and 4. Indeed, the highest mean membership values were observed for Cluster 4. With respect to the previous findings, one can consider Clusters 1 and 3 as those of crop farms. However, the mean values of crop output share for these two clusters were 87% and 92%, respectively, because some mixed farms were also assigned to Cluster 1. Cluster 2 contained all types of farming; however, the mean crop share for Cluster 2 was 80%, suggesting that this cluster can be considered as composed of crop farms and mixed farms engaged in crop production. Finally, Cluster 4 (crop share – 64%) was that of livestock farms and mixed farms. Indeed, Figs. 3.24 and 3.26 confirm that the livestock farms experienced the highest TE as well as the lowest fluctuations thereof. Noteworthy, Cluster 1 had both the lowest efficiency and the highest production subsidy rates, viz. 52% of output value, whereas the remaining clusters exhibited rates of 21–31%. The highest equipment subsidy rate was observed for Cluster 4 (10%), with the other clusters exhibiting rates of 7–9%. It can therefore be concluded that equipment subsidies contributed to the increase in productivity and efficiency of the livestock and mixed farms (Cluster 4), whereas production subsidies did not have such an impact.

All in all, the four clusters identified by the research imply a certain taxonomy of Lithuanian family farms. First, the family farms can be classified in terms of volatility of the efficiency scores. Specifically, Clusters 1 and 3 feature relatively high volatility, whereas Clusters 2 and 4 exhibit low volatility. Second, the family farms differ in terms of the mean TE level. Particularly, Clusters 3 and 4 represent farms with higher TE scores, whereas Clusters 1 and 2 are mainly associated with lower TE scores. Cluster 4, thus, can be considered as the best performing one. These findings can be particularly useful when tailoring rural development policy according to the specificities of the four groups of family farms. Having identified the efficiency change paths, we can now assess the impact of certain factors on the productive efficiency.

3. 3. 3. Determinants of efficiency and non-parametric regression

Given that the relationships between the environmental variables and efficiency scores might not always follow standard parametric cases, we employed non-parametric regression to analyse them. Furthermore, the non-parametric regression methodology implemented by Hayfield and Racine (2008) allows one to obtain confidence bounds for the regression and thus more robust interpretations. Specifically, a local linear regression, or weighted least squares regression, is employed for the analysis. The weights for regression are obtained by the means of a product kernel with certain bandwidth. Local linear regression then performs a linear regression on a data subsample within a small data window of the size determined by the bandwidth parameter. Note that the width of the window, i.e. bandwidth, influences the smoothness of the regression function: increasing bandwidth values lead to linear regression, whereas small bandwidths mean that regression is performed for nearly every specific observation. The kernel bandwidths were chosen via least squares cross-validation. A second-order Gaussian kernel was utilized for the continuous variables, whereas the kernel of Aitchison and Aitken (1976) was used for discrete data.

Non-parametric regression was employed to test the relationships among the bootstrapped TE scores and the three explanatory variables, namely the logarithm of farm size in hectares (*UAA*), the share of crop output in the total output (*CropShare*), and the time period (*Year*). Investigating optimal farm size is a focal point of many agricultural economics studies. We can therefore attempt to analyse the impact of farm size on TE. Farm specialization is captured by the *CropShare* variable. Finally, the variable *Year*, which we considered as an ordinal discrete variable, accounts for time-specific efficiency shocks.

Table 3.13 reports the bandwidths and *p*-values for the regressors. As one can note, the farm size variable, *UAA*, is specific with a relatively high value of bandwidth, which implies that farm size and efficiency are related in a close-to-linear way. The significance test for non-parametric regression variables suggests that all of the analysed variables are significant at a confidence level of 0.05. However, the estimates reported in Table 3.13 do not enable one to fathom the exact links among the analysed variables. For the latter purpose we further employed partial regression plots which relate each single regressor to the dependent variable while holding the remaining regressors at their medians.

Table 3.13. Results of non-parametric regression analysis.

	log(*UAA*)	*CropShare*	ordered(*Year*)
Bandwidth	9.607014	0.1108654	0.1595112
P Value	<.000 ***	0.047619 *	<.000 ***

Significance codes: *** – 0.001, ** – 0.01, and * – 0.05.

The impact of a certain variable on the efficiency scores can be analysed by means of partial regression plots (Fig. 3.27). These plots also display the bootstrapped confidence intervals. The results of the non-parametric regression suggest that increasing the farm size raises the TE slightly until the size reaches some 400 ha ($=e^6$). Note that the UAA values are presented on a log scale. Accordingly, the same increase in TE requires larger increases in UAA for the larger farms. Once the limit of 400 ha is crossed, the confidence intervals get wider, indicating that the largest farms are associated with both higher and lower efficiency scores compared to smaller farms. This finding, therefore, motivates for further research on the optimal size of family farms in Lithuania. As for farm specialization, one can note the three levels of efficiency in Fig. 3.17 across the respective farming types: livestock farms had both the highest TE scores and confidence intervals. The TE scores, though, rapidly decreased as the production structure approached that of the mixed farm. Meanwhile, the mixed farms showed a narrower range of TE scores scattered around a value of 0.5. Finally, the specialized crop farms tended to be the least efficient, as was found in the analyses described above. Inclusion of the additional explanatory variables into the non-parametric regression did not yield informative results: either they were insignificant or their distribution did not reveal any meaningful relationships.

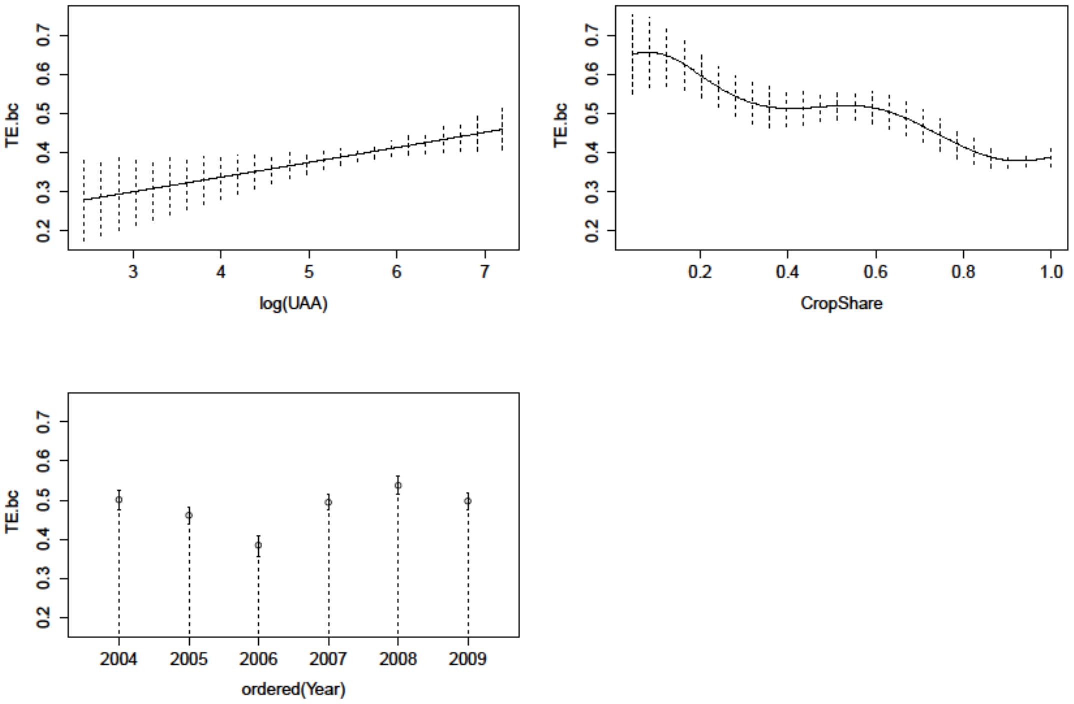


Fig. 3.17. Partial regression plots for the selected determinants of farming efficiency.

The results of the non-parametric regression analysis support the results obtained by kernel density estimation and fuzzy clustering. The key message is that crop farms are performing less efficiently when compared to mixed farms and especially compared to livestock farms. Furthermore, larger farms exhibited higher TE scores, although greater variation in efficiency scores was observed among the very largest farms (>400 ha). The non-parametric regression analysis, unlike the cluster analysis, failed to identify a significant impact of subsidies on TE.

3. 4. Estimation of the efficiency via the order-m frontiers

Initially, the ordinary FDH was employed to measure the efficiency across the three farming types. Both the input– and output–oriented FDH models (Tulkens, 1993) yielded almost the same results: The livestock farms achieved the highest level of efficiency, viz. 92%. The mixed farms came next with the efficiency scores of 82–86% depending on the model's orientation. Finally, the crop farms featured the lowest efficiency of 79–80%.

In order to examine the sensitivity of the results, the order–*m* frontier was established for both input– and output–oriented models. A set of different values of m was constructed: $m = \{25, 50, 100, 250, 400, 500, 600, 750, 1000\}$. By altering the value of *m* one can compute the share of the observations lying outside the production frontier, whether input– or output–oriented one.

The share of observations lying outside the order–*m* input frontier is plotted against the order of the frontier, *m*, in Fig. 3.18. For the small values of *m*, almost all of the observations were left out for irrespectively of the farming type. The shares of the observations outside the production frontier, though, steeply diminished with *m* increasing up to the value of 400. Note that the value of *m* indicates how many values of inputs are drawn to estimate the expected level of efficiency. For $m \geq 400$, only the share of the livestock farms outside the production frontier continued to decrease to a higher extent, whereas those associated with other farming types virtually remained stable. Specifically, some 35%, 60%, and 45% of the crop, livestock, and mixed farms respectively fell outside the production frontier at $m = 400$. These values are quite high and imply that some sort of statistical noise is present in the data. By further increasing *m* up to 1000, we observed the decrease in shares of the crop, livestock, and mixed farm observations outside the production frontier down to 28%, 47%, and 39% respectively. These figures resemble the proportions of the noise data in the whole dataset. Furthermore, the observations associated with the livestock farming can be considered as atypical ones in terms of the data set under analysis.

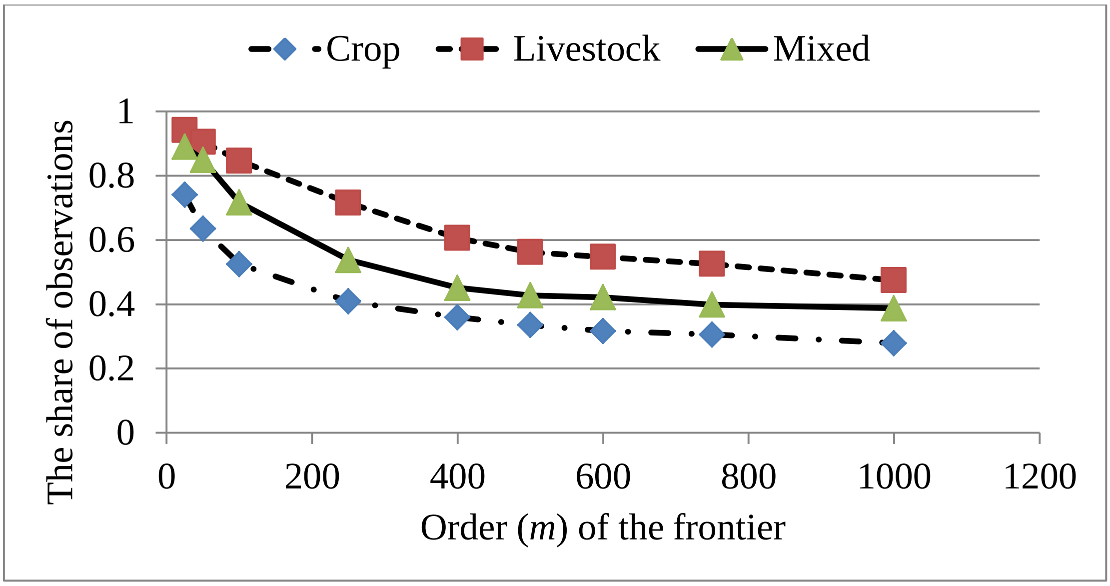


Fig. 3.18. The share of observations outside the input order-*m* frontier

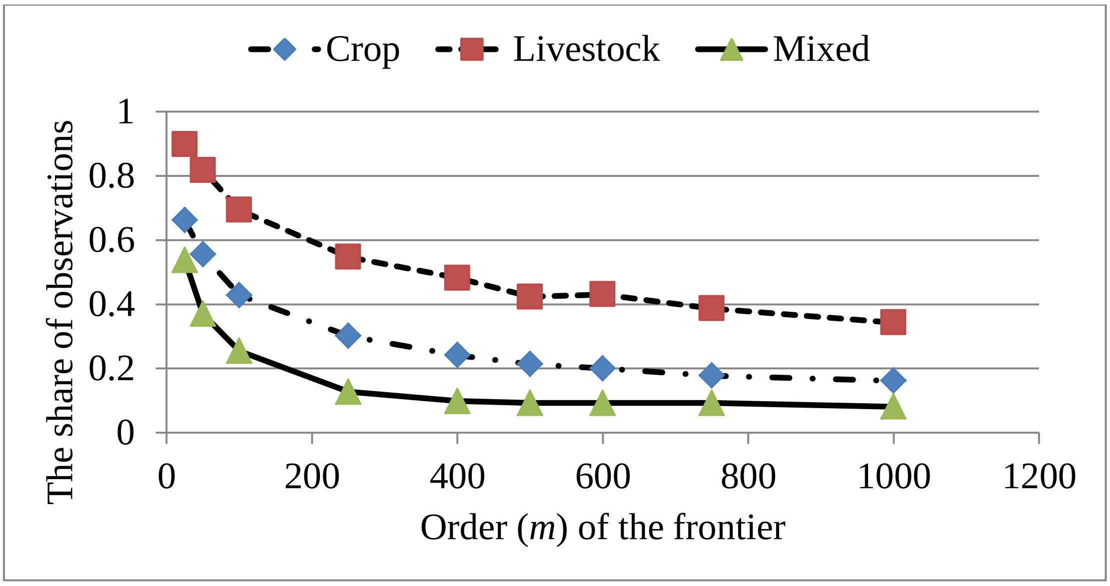


Fig. 3.19. The share of observations outside the output order-*m* frontier

As for the output order–*m* frontiers (Fig. 3.19), they rendered much lower shares of observations outside the frontier, possibly due to the univariate output values and multivariate input vectors. The shares of the observations falling outside the frontier diminished as *m* increased up to 400, whereas higher values of *m* did not induce any significant decrease. Noteworthy, the shares of observations lying outside the production frontiers were 24%, 48%, and 10% for crop, livestock, and mixed farms respectively. At $m = 1000$, these shares decreased down to 16%, 34%, and 8%. Note that in the output–oriented case the mixed farms exhibited the lowest share of observations lying outside the production frontier.

Thus, one can consider the value of 400 as the order of the partial input and output production frontiers to ensure the robustness of the analysis. Indeed, frontiers with orders $m \geq 400$ exhibit similar shares of observations outside them and the only effects remaining are those of the outlier observations.

The following Figs. 3.20 and 3.21 depict the mean efficiency scores for the input– and output–oriented models. Note that the latter results are the Farrell measures.

The input–oriented Farrell efficiency scores below unity indicate that a certain farm should reduce their inputs by the respective factor. On the contrary, the order–*m* frontiers allow for efficiency scores exceeding unity and therefore indicating that certain farms are super-efficient ones. For small *m*s, the mean values of the input–oriented efficiency scores exceeded unity thus indicating that most of the observations fell outside the production frontier. Anyway, the livestock farming remained the most efficient farming type at all levels of *m* (Fig. 3.30). The mixed farms exhibited slightly lower mean efficiency scores. Finally, the crop farms remained at the very bottom in terms of the mean efficiency scores. Note that the mean efficiency scores did not vary with *m* for the input frontier orders exceeding the value of 400.

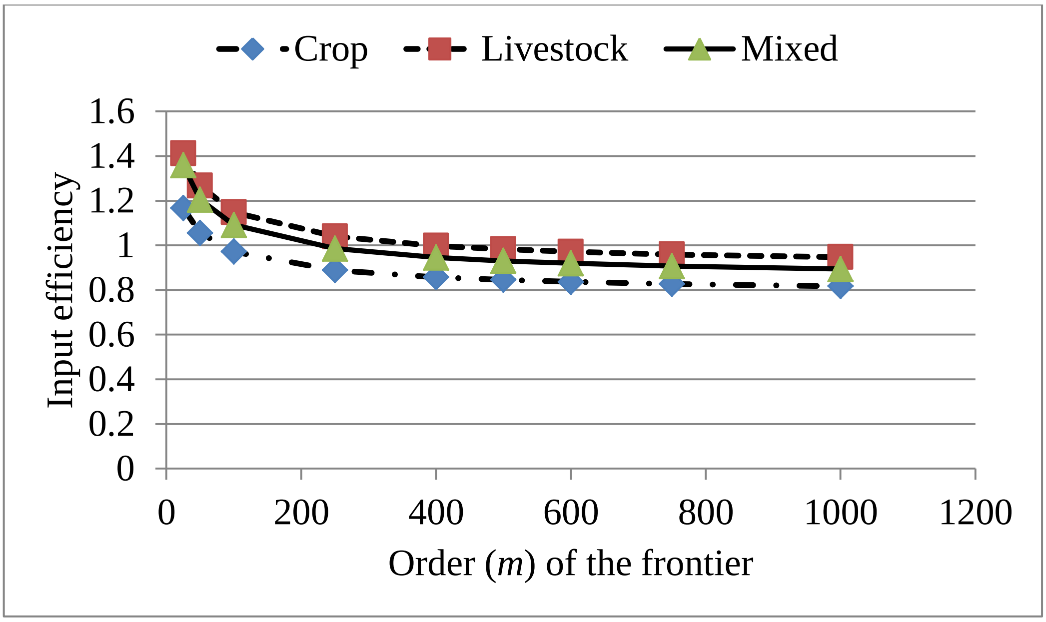


Fig. 3.20. The mean input Farrell efficiencies at different values of *m*

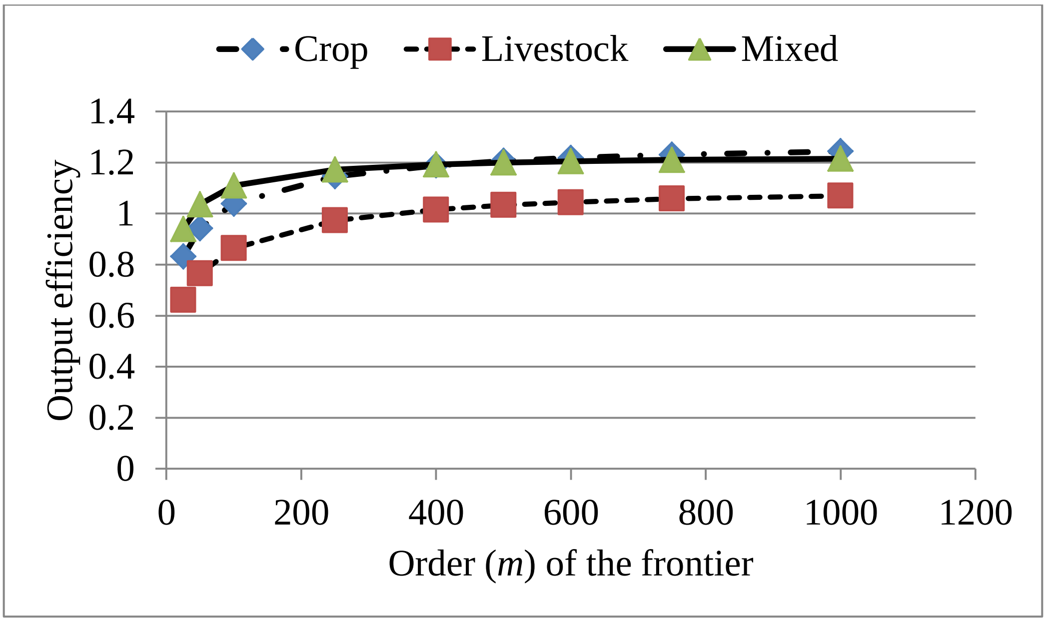


Fig. 3.21. The mean output Farrell efficiencies at different values of *m*

The patterns of efficiency had somehow altered in regards to the output–oriented frontiers. Fig. 3.21 depicts the Farrell output efficiency scores which exceed unity in case a farm is inefficient and approaches unity as a farm gets more efficient. Those farms featuring output efficiency scores below unity are considered as super–efficient ones. This time, the crop and mixed farms exhibited extremely similar values of the mean efficiency scores: For small values of m ($m \leq 100$) the mixed farms featured the lowest efficiency scores, whereas the crop farms superseded them for $m \geq 500$. Anyway, the difference between these means remained a rather insignificant one. The livestock farms remained the most efficient ones for each value of *m*.

Given the discussed findings we chose the order of the production frontiers as $m = 400$ and further analysed the distributions of the efficiency scores associated with the different farming types. Therefore, Figs. 3.22–3.23 present the kernel densities for the efficiency scores.

As for the input efficiency scores (Fig. 3.22), all the farming types featured the modal values close to unity. Obviously, the livestock farms were specific with the highest concentration of the efficiency scores equal or greater to unity. Accordingly, the mean efficiency score for the livestock farms was 1.01, i. e. an average farm was super–efficient. The corresponding values for the crop and mixed farms were 0.91 and 0.98 respectively. The first quartiles for the crop, livestock, and mixed farms were 0.77, 0.95, and 0.87 respectively. Meanwhile, the third quartiles were 1.02, 1.08, and 1.54 in that order. The latter numbers can be interpreted as the minimal factor to which top 25% efficient farms could increase their consumption of inputs given their production level and still remain efficient ones. Although the most efficient farms were the crop farms, they constituted rather insignificant share of the whole sample. Note that the maximal efficiency exceeded unity. Therefore, we can even speak of super–efficiency at this point.

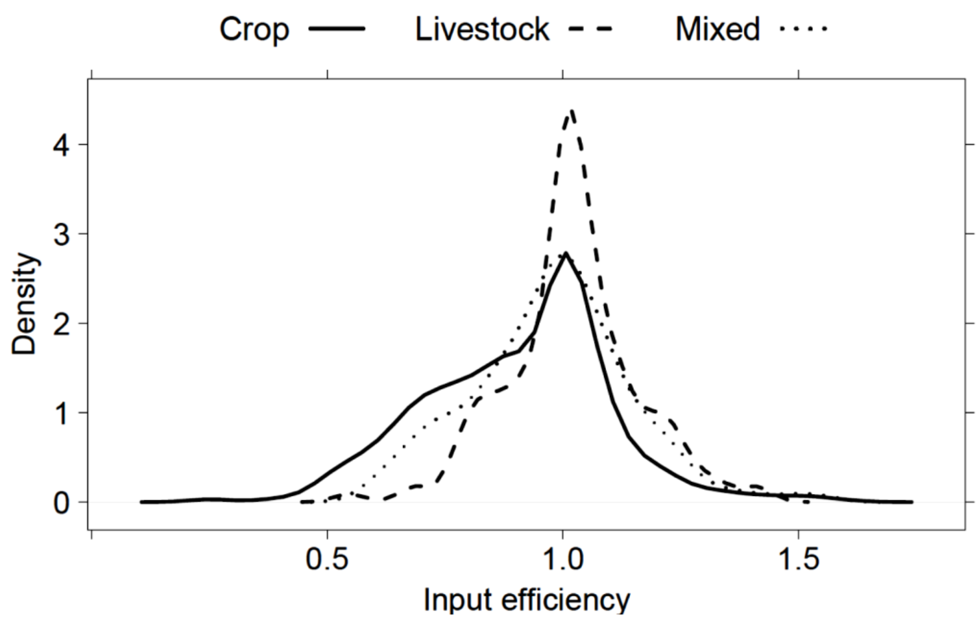


Fig. 3.22. The densities of the input-oriented Farrell efficiency scores (m=400)

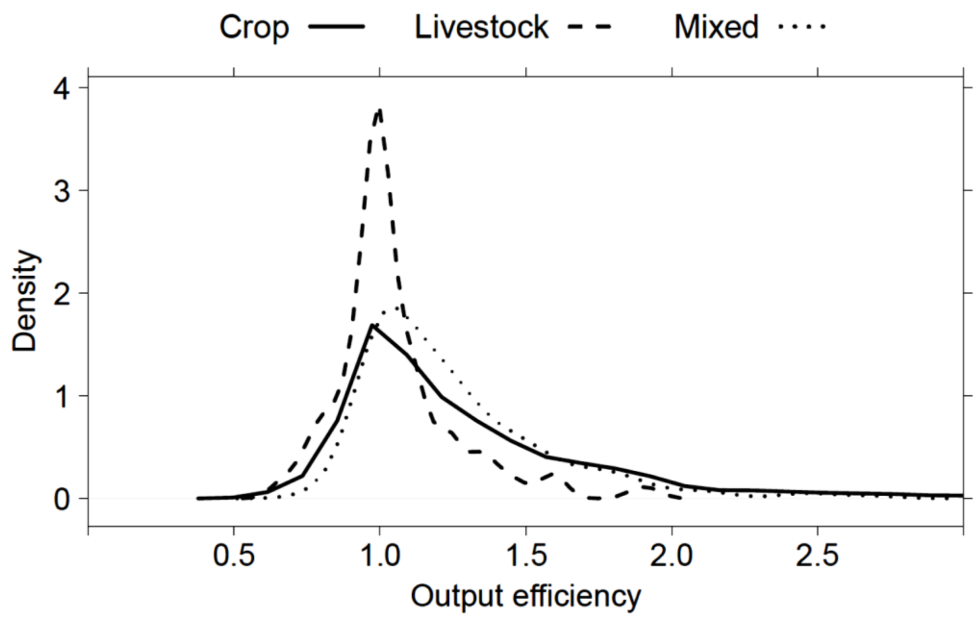


Fig. 3.23. The densities of the output-oriented Farrell efficiency scores (m=400)

The output efficiency scores were distributed in a similar way (Fig. 3.23). The livestock farms exhibited the most concentrated distribution. The mean values of the efficiency scores did not fall below unity for either farming type: 1.32 for the crop farms, 1.05 for the livestock farms, and 1.25 for the mixed farms. However, the first quartile for the livestock farms was 0.95 and thus indicated that more than 25% of the livestock farms were super–efficient ones. The corresponding values for the remaining farming types were ones. The third quartiles were 1.46, 1.11, and 1.38 for the crop, livestock, and mixed farms respectively.

3. 5. Fuzzy analysis

Say the panel data are arranged into a $(n\times T)\times(k+l)$ crisp matrix A, where $t=1,2,\ldots,T$ is a time index and $A=(I_i^j,O_r^j)_t=(x_i^{tj},y_r^{tj})$. As stated previously, the fuzzy FDH method begins with a fuzzy input-output matrix, A^*, where each element, $(\tilde{I}_i^j,\tilde{O}_r^j)$, represents a fuzzy production plan: $A^*=(\tilde{I}_i^j,\tilde{O}_r^j)=((x;a_i^j,b_i^j,c_i^j),(y;d_r^j,e_r^j,f_r^j))$.

In case of the longitudinal analysis, we employed the following aggregation to transform the panel data into a fuzzy input-output matrix:

$$(\tilde{I}_i^j,\tilde{O}_r^j)=\left((x;\min_t x_i^{tj},x_i^{t_0 j},\max_t x_i^{tj}),(y;\min_t y_r^{tj},y_r^{t_0 j},\max_t y_r^{tj})\right), \qquad (3.1)$$

where t_0 is an arbitrary base period from $t=1,2,\ldots,T$. The latter operation ensures that the resulting fuzzy production plans are based on the original observations and not on synthetic averages.

Therefore, the data are aggregated by considering the minima and maxima of the observed time series as the lower and upper bounds of the fuzzy numbers, respectively. The base period values serve as kernels for the latter numbers. In our case we had $t=2004,\ldots,2009$ and selected $t_0=2008$. The base year 2008 was chosen because it is the most recent year having featured no shocks in the agricultural production.

Using the data set described above a fuzzy input-output data matrix was established by the virtue of Eq. 3.1. The triangular fuzzy numbers were then converted into interval numbers by employing levels $\alpha=\{0,0.5,1\}$. For each α level, Eq. 3.84, a threshold value $\psi=0.3$ was used to estimate the input-oriented interval efficiencies, $E_\alpha^{in}(j)$. The average efficiency scores, $\bar{E}_\alpha^{in}$, were obtained by the virtue of the fuzzy arithmetics, see e.g., Kaufmann and Gupta (1991):

$$\bar{E}_{\alpha}^{in} = \frac{1}{n}\sum_{j=1}^{n} E_{\alpha}^{in}(j). \qquad (3.2)$$

In order to analyse the differences in efficiency across farming types, these averages were computed for the three farming types separately. Fig. 3.24 depicts the results.

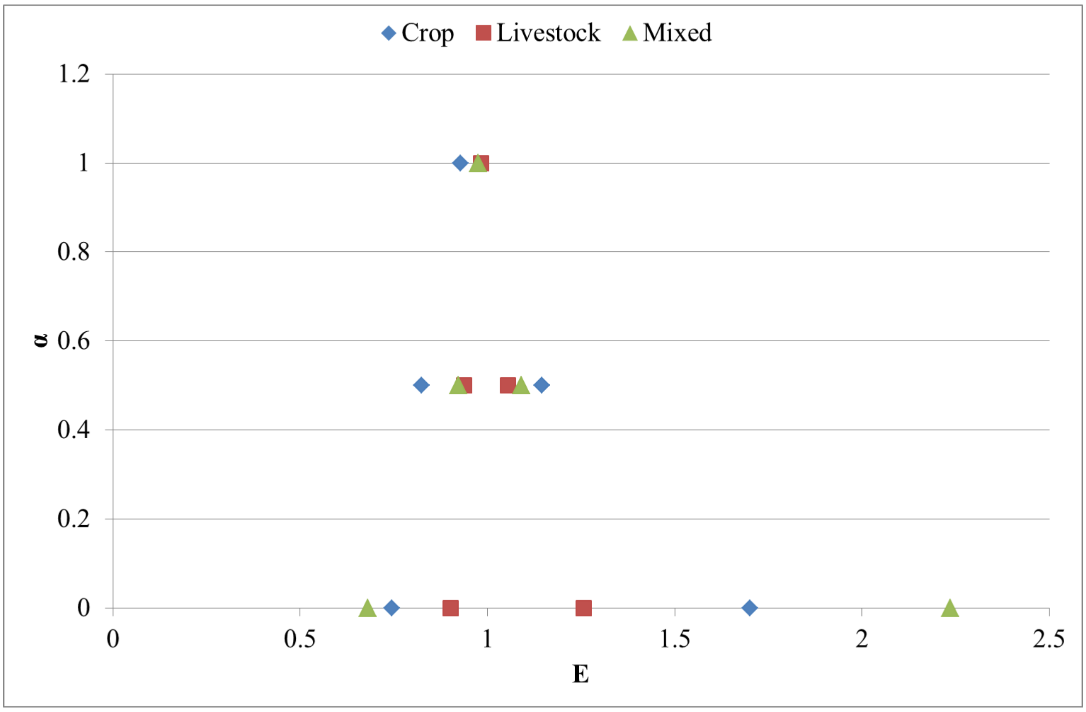


Fig. 3.24. Interval efficiencies across farming types at different α-levels.

It can be noted that the average efficiencies may exceed unity, thus becoming similar to super-efficiency measures, see e.g., Bogetoft and Otto (2011).

For $\alpha = 1$ (corresponding to crisp FDH for the year 2008) there is a rather small difference between the average efficiency scores of the three farms types: Average efficiency for crop farms is 92%, for livestock farms 98% and for mixed farms 97%. At first glance it therefore appears that average efficiencies are rather high and that livestock farms seem to be the most efficient farm type. Yet, looking at the share of fully efficient farms we find that only 18% of the livestock farms are efficient among the pooled data set whereas 39% of the crop farms and 25% of mixed farms are efficient. A traditional FDH-based efficiency analysis for the year 2008 therefore indicates that while the crop farms are predominant among the best performers of the pooled data set the average efficiency is higher among the livestock farms (with mixed farms somewhere in between). In other words, there seems to be more variation connected with the performance of crop farms.

This picture is reinforced by considering the full fuzzy FDH analysis where for α-levels lower than 1 (e.g., $\alpha \in \{0, 0.5\}$ as depicted in Fig. 3.24) we consistently have that the average efficiency score interval of livestock farms is nested within the average efficiency score interval of crop farms. This means that the uncertainty connected with estimating the average efficiency scores of livestock farms is generally lower than for crop farms and that the variation in the performance of crop farms is much higher than among livestock farms, not only between individual farms as seen for the crisp FDH, but even for the average farm over the analysed time span. Indeed, the data given in Table 1 do indicate that crop farms tend to exhibit higher variation in all of the analysed variables compared to the remaining two farming types.

A bit surprising is the fact that the support of the average fuzzy score of mixed farms is the widest and includes both that of crop and livestock farms. Note that this is not the case for $\alpha = 0.5$ as shown in Fig. 3.24.

The application of fuzzy FDH to the Lithuanian family farms enabled an assessment of the uncertainty and variation in the estimated efficiency scores of different farming types (viz. crop, livestock, and mixed farming). The results indicate that the relative efficiency associated with different farming types varied with the α-level representing the degree of uncertainty. The crisp FDH suggested the livestock farms were the most efficient ones on average, while the fuzzy efficiency scores revealed that variation in performance of the average crop farm was much higher with extremes being both better and worse than the average livestock farm. Specifically, the livestock farm average efficiency was represented by relatively narrow intervals that fell within the bounds of fuzzy efficiencies associated with the remaining types of farming. Thus, the livestock farms can be considered as more homogeneous compared to the remaining farming types for all levels of uncertainty.

3. 6. A double bootstrap inference

The double bootstrap algorithm described in the Section 2.1 was employed for the analysis. The distribution of the efficiency scores are not discussed in this paper for sake of brevity. The numbers of the bootstrap replications were set as $L_1 = 100$ and $L_2 = 2000$.

The first bootstrap loop aimed at estimating the bias-corrected output efficiency scores. The second bootstrap loop was used to estimate the confidence intervals for the parameters of the truncated regression. Analysis of the kernel distributions of the bootstrap estimates, $\hat{\hat{\beta}}^*$, enabled to make a certain inference. Noteworthy, the densities for *Time* and *UAA* covered the value of zero, which, in turn, is associated with insignificance of a coefficient. The remaining densities lie in either side of the coordinate axis.

The regression was estimated without an intercept. The confidence intervals for the parameters of the truncated regression were estimated by both the percentile method and BC_a method. The resulting intervals are given in Table 3.14. Note that the dependent variable was the output-oriented Farrell efficiency score, which gets higher values as farm becomes more inefficient. Therefore, the negative coefficients in Table 1 indicate sources of efficiency, whereas the positive ones indicate factors negatively related to efficiency.

The three variables, namely ratio of assets to labour, crop share in the total output, and production subsidy intensity, remained significant at 1% level of significance irrespectively of the method employed for estimation of the confidence intervals. Meanwhile, the farm size variable featured higher significance under the BC_a method. The time variable exhibited the same significance across both of the methods. Indeed, the time trend was significant at the confidence level of 10%.

Table 3.14. Double bootstrap estimates for determinants of the farming inefficiency.

Variables	$\hat{\beta}$	Sig.	Confidence intervals					
			$\alpha = .1$		$\alpha = .05$		$\alpha = .01$	
			BC_a method					
Time	-0.061	*	-0.113	-0.010	-0.122	0.002	-0.144	0.016
UAA	-0.154	***	-0.270	-0.051	-0.292	-0.033	-0.335	-0.002
Assets/AWU	-0.484	***	-0.634	-0.355	-0.666	-0.327	-0.722	-0.288
Crop	1.947	***	1.747	2.145	1.711	2.181	1.625	2.283
Subsidies	1.555	***	1.386	1.717	1.357	1.750	1.304	1.810
			Percentiles method					
Time	-0.061	*	-0.113	-0.009	-0.121	0.002	-0.143	0.017
UAA	-0.154	**	-0.262	-0.046	-0.283	-0.029	-0.332	0.004
Assets/AWU	-0.484	***	-0.630	-0.348	-0.659	-0.323	-0.715	-0.279
Crop	1.947	***	1.752	2.149	1.713	2.187	1.631	2.288
Subsidies	1.555	***	1.387	1.721	1.359	1.753	1.306	1.816

Significance codes: '***' - 0.01, '**' - 0.05, '*' - 0.1

The negative coefficients associated with the time trend, farm size, and ratio of assets to labour indicate that these variables contributed to increase in efficiency. Therefore, the efficiency was likely to increase during the research period given the remaining factors remained constant. The larger farms did also feature higher levels of efficiency. The latter finding might be related to both economies of scale and higher abilities for investment. The crop farms appeared to be less efficient if compared to livestock ones (the positive coefficient was observed for the corresponding variable). The production subsidies tended to decrease farming efficiency possibly due to lower incentives for adoption of innovative practices and market-oriented production.

In order to check the robustness of the obtained results, the ordinary least squares (OLS) model was also specified. The OLS estimates are presented in Table 3.15. As one can note, the coefficients associated with the model variables were specific with the same signs as in case of the truncated regression. The differences in absolute values of the coefficients might be explained by different magnitude of the variables (for instance, ratio of asset to labour might feature higher variance even after mean scaling). Indeed, both the significance and absolute value of the *Assets/AWU* increased significantly in the truncated regression model.

Table 3.15. Ordinary least squares estimates.

Variables	Estimate	SE	*t* value	*p*	Sig.
Time	-0.04138	0.01531	-2.703	0.00697	***
UAA	-0.05581	0.03191	-1.749	0.08053	*
Assets/AWU	-0.01825	0.02744	-0.665	0.50602	
Crop	1.91746	0.05759	33.293	2.00E-16	***
Subsidies	1.29016	0.06536	19.741	2.00E-16	***
R^2	0.8443	Adj R^2		0.8436	
F *p*-value	2.20E-16				

Significance codes: ‘***’ - 0.01, ‘**’ - 0.05, ‘*’ - 0.1

Obviously, the significance of the efficiency determinants varied across the truncated regression and OLS estimations. Particularly, the ratio of assets to labour was not significant in the OLS model, albeit it featured a negative coefficient. The crop and subsidy indicators featured the same significance in both cases. The time and farm size variables were significant at different levels of confidence depending on model type and method for confidence intervals. Therefore, the results yielded by the bootstrapped truncated regression can be considered as confident ones.

3. 7. Conditional efficiency measurement

Since Farrell (1957) developed the idea of relative efficiency measurement, we can distinguish two broad approaches to measure efficiency. First, parametric methods require the *a priori* specification of a production function, which is often unknown. Therefore, they can easily lead to specification errors (Yatchew, 1998). On the other hand, non-parametric methods do not require any assumptions on the functional form of the production function. Data Envelopment Analysis (DEA; Charnes, Cooper and Rhodes, 1978) can be given as a typical non-parametric frontier method. DEA is an appealing method as it does not require any assumptions regarding the functional form of the underlying production function. However, being a deterministic method in its nature, it does not account for random errors. Particularly this random variation is likely to occur in the context of farm efficiency analysis due to measurement errors, fluctuations related to operation environment, etc.

A partial frontier approach addresses these shortcomings. The partial frontiers (also referred to as the robust frontiers) are introduced by Cazals et al. (2002). The idea is to benchmark an observation not against all the observations dominating it but rather against a randomly drawn sample of these. The latter methodology has been extended by introducing the conditional measures enabling to analyse the influence of the environmental variables on the efficiency scores (Daraio and Simar, 2005, 2007a, 2007b).

The traditional Farrell's and Shepard's efficiency measures define a proportional contraction (resp. expansion) of inputs (resp. outputs). In many settings, including agriculture, the output-oriented direction is insightful as it reveals the output gap for given input levels. It can be used for benchmarking purposes as well as for policy insights in the potential improvements.

The selection of input and output variables is in line with earlier literature (e.g., Bojnec and Latruffe, 2008). For a detailed summary of the descriptive statistics, see Table C1.

Using the conditional efficiency model, we include characteristics of the operational environment. The existing literature suggests that farming efficiency might be impacted by farm size, technology, farmers' characteristics, market integration, and temporal variations. Abdulai and Tietje (2007) estimated a stochastic production frontier for German dairy farms which included a set of explanatory variables. The latter set included the ratio of assets to livestock units, farmer's age and education, off-farm employment, farm size in terms of herd size and UAA, hours worked, and expenditures for feed and livestock. Kumbhakar et al. (2014) analysed the efficiency of Norwegian grain farms by the means of SFA and used the following environmental variables: off-farm income share, subsidy income share, entrepreneurial orientation index obtained during a survey, farmer experience in years, and education dummies. Latruffe et al. (2004) considered the following variables as determinants of efficiency: total output, technical ratios (land to labour, capital to labour), the use of external factors (share of hired labour, the share of rented land), the degree of market integration (the share of marketed output), soil quality index, and farmer's age. It is due to Davidova and Latruffe (2007) that the following variables had been taken into account when analysing the patterns of farming efficiency in CEE countries: size variables (UAA), variables capturing the use of external factors (the share of hired labour, the share of rented land), and financial ratios (the ratio of debt to assets, the ratio of current debt to current assets). They argued that increasing use of external factors might render higher efficiency, for economic costs are then translated into accounting costs as well. Balcombe et al. (2008) accounted for farm size (UAA), the ratio of capital to labour, the share of hired labour, the degree of market integration, age, the share of other income, education, and time period. Bojnec and Latruffe (2013) explained the variation in the efficiency scores by considering the farm size, the share of rented land, the ratio of assets to labour input, farming type dummy, and time period dummy.

Using these insights from earlier literature, we use the following variables as potential factors of farming efficiency. First, a time trend (*Year*) to account for temporal variations in output. Second, the logged UAA (*lnUAA*) represents the scale of operation and is considered as a proxy for farm size. Thanks to using logarithms we mitigate the significant variation in the size. Third, age of the farmer (*Age*) is introduced to ascertain whether young farmers–oriented measures can influence the structural efficiency. Fourth, the ratio of crop output to the total output (*CropShare*) captures the possible difference in farming efficiency across crop and livestock farms. Fifth, the effect of production subsidies on efficiency is estimated by considering the ratio of production subsidies to output (*SubsShare*). Finally, the technological environment and capital accumulation is assessed by considering the logged ratio of assets to labour input (*lnAssetsAWU*).

In line with Daraio and Simar (2005) the size of the partial frontier is determined as value for which the percentage of super-efficient observations is constant. In our application, this corresponds to m = 400. This implies that a farm is compared to 400 randomly drawn observations consuming at most the same amount of inputs.

The mean unconditional output efficiency score is 1.29, whereas the conditional one amounts to 1.27 (Table C2). It defines for an average farm the proportionate increase in outputs that should occur in order to approach the production frontier.

To examine which variables matter in farm efficiency, we estimate the conditional efficiency framework. The ratio of the conditional over the unconditional estimates is regressed on the environmental variables by the means of the non-parametric regression. The results are presented in Table 3.16. Only two of the six variables appear to have a statistically significant influence upon the ratio: the time trend and production subsidies. Whereas the trend is significant at the level of 10%, the subsidy share is significant at 1% (Table 3.16). Although the remaining four variables are insignificant, the direction of their influence on efficiency scores might be interesting. We present the partial regression plots in Appendix B.

Table 3.16. Results of a non-parametric regression for the determinants of efficiency.

Variable	Direction of the influence	p-value	Significance
Year	Positive	0.078	*
lnUAA	U-shaped	1	
Age	Arbitrary	1	
CropShare	Negative	1	
SubsShare	Negative	<0.000	***
lnAssetsAWU	Arbitrary	1	

Level of significance: *** - 1 per cent, * - 10 per cent. Positive (negative) indicates an (un)favourable influence on efficiency, arbitrary indicates that a certain variable features no clear patterns of influence on the efficiency.

The partial regression plots for the time trend (Figs. B1-B3) indicate that there is an increasing trend in efficiency after accounting for the influence caused by remaining efficiency factors during the research period[7]. The year 2006 features a decrease in efficiency if considering the first quartile regression plot (Fig. B1). Indeed, the low efficiency gains associated with the years 2004-2007 might be due to the transformations (i.e. changes in the production and farm structure) Lithuanian farms experienced after the accession. However, the growth in efficiency during 2008-2009 is observed irrespectively of the quantiles the explanatory variables are held at. These findings suggest that Lithuanian family farms managed to improve their productive efficiency after integration in the EU, yet the growth rates are subject to changes in the operational environment and eventually turned into negative ones.

As for the land input, the partial regression plots show that it impacted the efficiency in the way of a quadratic function. However, suchlike relationship is somehow distorted at the extreme values if focusing at the first quartile of the remaining variables (Fig. B1). Generalizing the three partial

[7] Note that an increasing regression curve implies a favourable influence of a certain environmental variable on the efficiency in the output-oriented model.

regression plots for the land input, one can note that the minimal efficiency is maintained in the region of 55-150 ha (i. e. the values within $\left(e^4, e^5\right)$). Thus, the small and the large family farms seem to fall among the most efficient ones. Indeed, smaller farms might maintain higher market integration and control more parts of the supply chains thus experiencing incentives for increasing the intensity of their production processes. The main concern regarding the farming efficiency remains with those middle-sized family farms. However, the link between farm size and the efficiency score ratio is not significant in the conditional framework.

Farmers' age has no significant influence on the efficiency score ratio, albeit the partial plots indicate some decreases in efficiency for the aged farmers. Even though the variations in efficiency are rather meagre along with the age, the peak is reached at around 50 years.

The influence of the crop share in the total output differs across the quartiles of the environmental variables. In particular, the first-quartile results do indicate that both livestock and mixed farms feature higher efficiency. However, the advantage of the mixed farming vanishes when shifting to other quartiles. Therefore, the efficiency of the mixed farming is related to multiple factors and can be improved in a favourable environment. At the other end of spectrum, the crop farming appears to be less efficient irrespectively of the conditions described by different quartiles of the environmental variables. Note that the non-parametric test of statistical significance rejects the hypothesis of the variable's influence on the efficiency ratio.

The production subsidy share has a significant influence on the efficiency ratio. The partial plots (Figs. B1-B3) indicate that the subsidy rate is negatively related to efficiency. The relation is a linear one; therefore the influence of the rate of subsidies remained constant, which implies that a relative increase in subsidies with respect to the total output induces a decrease in efficiency irrespectively of the subsidy rate already achieved. The same linear relationship is observed for all quartiles of the environmental variables.

Finally, the logged ratio of assets to labour input has no significant influence on the efficiency ratio. Indeed, an increase in efficiency can be observed for the smallest values (around e^9 = 8100 LTL/AWU = 2350 EUR/AWU). A further increase in the assets per labour unit causes decrease in efficiency when considering the first quartile (Fig. B1), whereas the remaining partial plots (Figs. B2-B3) suggested that the largest values of e^{14} = 1200000 LTL/AWU = 350 000 EUR/AWU might boost the efficiency. This finding might be related to the undergoing transformations in the farms. Indeed, farms are acquiring new assets (machinery, buildings etc.) as various means of support became available under the CAP. Yet not all of these investments are able to increase the productivity in the short run. Furthermore, excessive investments might never be recovered. On the other hand, it appears that those farms peculiar with median and third-quartile values of the environmental variables are somehow successful in making the investments successful.

4. TECHNOLOGY SHIFTS IN LITHUANIAN FAMILY FARMS

This section of thesis is dedicated to analysis of the total factor productivity change in Lithuanian family farms. In order to ensure the robustness of the analysis, multiple methods are employed. Whereas the Malmquist index measures the change in TFP in between the two time periods, the Färe-Primont index allows determining the level of TFP for each period. Indeed, the Malmquist index is not a transitive one and thus does not allow to precisely measure the TFP change over multiple time periods in a chain-linked manner. As for the Färe-Primont index, it is a transitive one and thus enables to measure the change in the TFP in a more reasonable way. This section also attempts to explain the changes in TFP with respect to certain contextual variables.

4. 1. The bootstrapped Malmquist index

The bootstrapped Malmquist index was employed to estimate the changes in the total factor productivity in 200 Lithuanian family farms during 2004–2009. As it was already mentioned, the bootstrapped Malmquist indices enable to identify the significant changes in the total factor productivity. The analysed sample, therefore, was classified into the three groups each encompassed of farms that featured significant decrease, no change, or a significant increase in the Malmquist productivity indices. Given the bias-corrected estimates cannot be used unless variance of the bootstrap estimates is three times lower than the squared bias of the original estimate, the original estimates are usually reported. Consequently, the indices that did not differ from unity at $\alpha = 0.1$ were equaled to unities for the further analysis. Hereafter, these variables will be referred to as the adjusted ones.

The means of the adjusted Malmquist indices are given in Table 4.1. As one can note, the three farming types did not differ significantly in terms of the cumulative mean TFP change: these values fluctuated in between 0.82 and

0.85 across the farming types. This finding implies that the TFP had decreased by some 15–18% throughout 2004–2009. The negative TFP changes were observed for crop farms during all of the analysed periods save that of 2006–2007. Both the livestock and the mixed farms exhibited positive changes in 2004–2005 also. The steepest cumulative decrease in efficiency, represented by the EC component, was observed for the crop farms. Specifically, efficiency there decreased by some 21%. The inward movement of the production frontier, identified by the TC component, negatively affected the mixed farms: the TFP decreased by 21% due to the negative technical change. The livestock farms did also experience the same decrease in technology, which amounted for some 18%.

The two terms, EC and TC, can be further decomposed to analyse the sources of changes in efficiency and technology itself. The decomposition of the efficiency change term, EC, into the two components revealed that the scale efficiency change, SEC, did not play an important role for either of the farming types. It can thus be concluded that the underlying technology was CRS. The mixed farms, though exhibited some features of a VRS technology. The highest decrease in pure efficiency (PEC) was observed for the crop farms (23%), whereas livestock and mixed farms experienced much lower decreases of 7–8%. Decomposition of the TC component induced that the pure technical change, PTC, decreased the productivity of the crop and mixed farms by 27% and 44%, respectively, whereas the crop farms did not suffer from decrease in technology. However, the negative effect on the mixed farms was alleviated by increasing convexity of the technology: the STC component indicated a 50% increase in productivity. Therefore, the mixed farms diverged in their scale, particularly in the period of 2004–2005.

Table 4.1. The Malmquist productivity index and its decomposition across farming types, 2004–2009.

Farm type	M	EC	TC	PEC	SEC	PTC	STC
Crop	**0.82**	**0.79**	**0.95**	**0.77**	**0.96**	**0.95**	**1.00**
2004–2005	0.89	0.97	0.92	0.93	1.03	0.93	0.99
2005–2006	0.79	0.83	0.95	0.87	0.96	0.92	1.03
2006–2007	1.66	1.13	1.39	1.06	1.02	1.38	0.99
2007–2008	0.96	0.92	1.02	0.92	0.99	1.04	0.97
2008–2009	0.73	0.94	0.78	0.97	0.97	0.77	1.01
Livestock	**0.82**	**0.97**	**0.82**	**0.93**	**0.99**	**0.73**	**1.09**
2004–2005	1.19	1.02	1.12	1.02	1.00	1.02	1.11
2005–2006	0.88	0.93	0.96	0.95	0.99	0.91	1.03
2006–2007	1.13	1.06	0.99	1.01	1.01	1.03	0.98
2007–2008	0.92	0.95	1.00	0.96	0.99	0.97	1.01
2008–2009	0.76	1.02	0.77	0.99	1.00	0.79	0.97
Mixed	**0.85**	**0.94**	**0.79**	**0.92**	**0.90**	**0.56**	**1.50**
2004–2005	1.01	1.05	0.96	1.05	0.99	0.70	1.40
2005–2006	0.84	0.82	1.01	0.87	0.97	0.98	1.04
2006–2007	1.28	1.12	1.07	1.01	1.03	1.10	0.98
2007–2008	0.98	0.95	1.01	1.00	0.93	0.99	1.03
2008–2009	0.80	1.03	0.75	1.01	0.99	0.75	1.02

Notes: the geometric means of the adjusted estimates are presented; the annual data represent productivity changes, whereas farming type-specific heading rows exhibit the cumulative changes for 2004–2009.

The multivariate analysis was carried out in order to reveal the underlying patterns of the productivity change across farming types and time periods. Specifically, the multiple correspondence analysis (MCA) was applied to identify the relations between farming types, years, and TFP changes. The package *FactoMineR* (Husson et al., 2010) was utilized to implement MCA. The MCA enables to explore the relations between the categorical variables by the means of the χ^2 distance.

In our case we distinguished the three categories for estimates of the bootstrapped Malmquist productivity index and its components, namely (i) increase, (ii) no change, and (iii) decrease in TFP. Therefore, the seven variables, $M_o^k, EC_o^k, TC_o^k, PEC_o^k, SEC_o^k, PTC_o^k, STC_o^k$, were classified into the three groups by the means of the bootstrap confidence intervals. The two supplementary variables, year and farm type, were also considered in order to better describe the productivity change patterns. The resulting MCA plot is depicted in Fig. 4.1. The first two components explain some 35% of the total inertia.

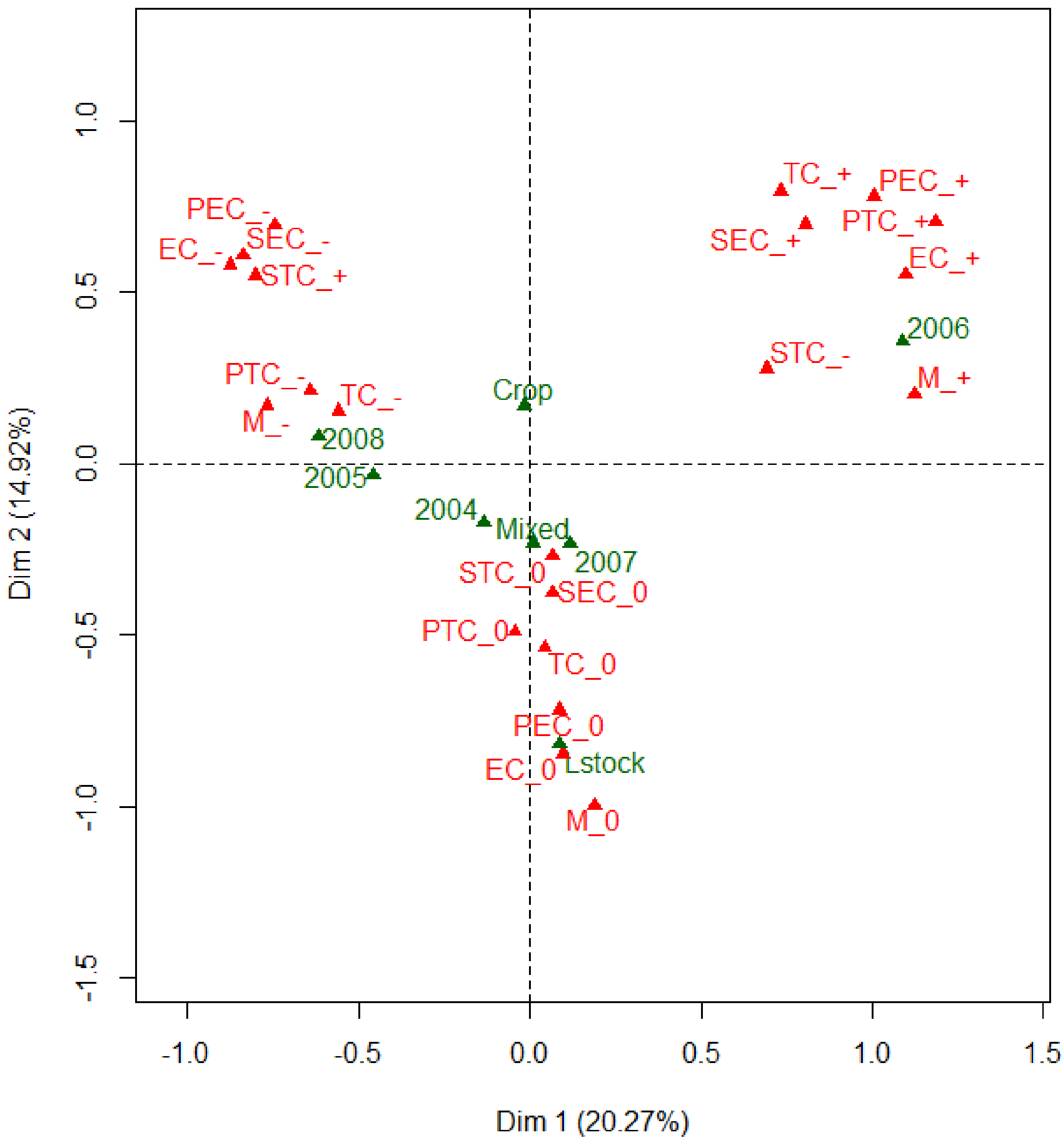


Fig. 4.1. The MCA plot describing relationships between Malmquist indices and supplementary variables.

As one can note, the three groups of productivity change indices emerged. Indeed, they were associated with a positive (NE part of the plot), negative (NW), or insignificant (S) change in productivity, respectively. Clearly, the first component axis discriminated the variables associated with a more stochastic TFP change pattern from those related to insignificant changes. The second component axis presented a gradient of productivity change, i. e. the TFP increased going along the latter axis. Note that the positive STC was associated with negative changes in TFP. The latter finding implies that technological progress was related to CRS technology, whereas technological regress featured the increasing convexity of the production frontier (i. e. VRS technology). A cluster of negative efficiency change components (EC, SC, PEC) was located further away from the origin point thus indicating that decease in efficiency resulted in steeper decrease in the TFP than decrease in other terms of the Malmquist productivity index.

All of the farming types exhibited change in the TFP close to the average, although the crop farming was located in the more stochastic area, whereas the livestock farms appeared to be the most stable in terms of the TFP change. Given all of the farming types exhibited similar level of the TFP change, the livestock farms can be considered as those better performing. The MCA plot does also confirm that the period of 2006–2007 was that of increase in the TFP, whereas the periods of 2005–2006 and 2008–2009 were associated with decrease therein.

4. 2. Productivity change with the sequential technology

The sequential Malmquist–Luenberger (SML) index was computed in the spirit of Eq. 2.15 and decomposed by employing Eq. 2.16. The results are presented in Fig. 4.2. The total factor productivity (TFP) was decreasing throughout the period of 2004–2009 with exception for 2006–2007 when the agricultural sector had been recovering after natural shocks which took place in the preceding period. Accordingly, the cumulative TFP change indicated the decrease of some 2.9% throughout 2004–2009. The technical change component, *TC*, stagnated in 2009, yet remained the most important factor of TFP growth accounting for increase of some 14% during 2004–2009. The cumulative scale efficiency term, *SEC*, fluctuated slightly above unity thus suggesting that certain shifts have occurred in the meantime. Farm expansion might be the primary cause of these developments. The decreasing pure technical efficiency, *PEC*, however, reduced the TFP by 16%. Therefore, it can be concluded that the structural support under Common Agricultural Policy together with farmers' own investments enabled to push the production frontier outwards, however the largest part of the analysed farms remained inefficient (negative catching up effect) and thus experienced decreasing TFP.

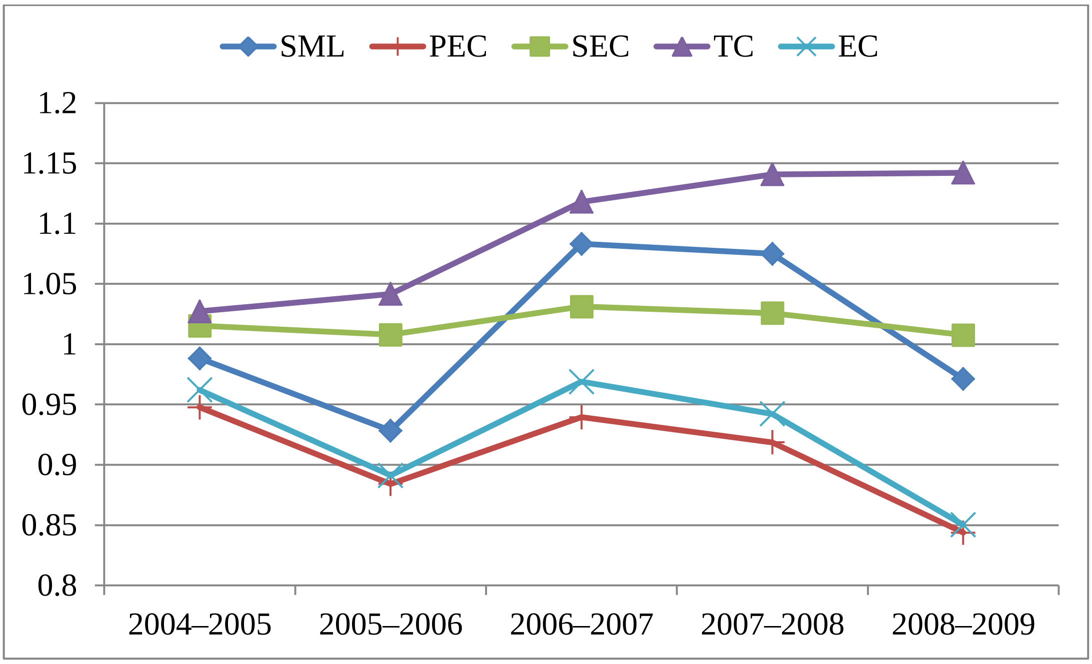


Fig. 4.2. The cumulative change in total factor productivity and decomposition of the sequential Malmquist–Luenberger index, 2004–2009.

The means of components of the sequential Malmquist–Luenberger index were computed for each farming type. Fig. 4.3 summarizes these variables. As one can note, livestock experienced increase in TFP, equal to 3.7% on average, whereas a decrease of some 2.9% was observed for the sample altogether. Although efficiency change was negative for the latter farming type, it had the highest mean increase in technical change (frontier shift). The livestock farms, therefore, were probably those pushing the production frontier outwards. Crop and mixed farms exhibited almost equal TFP change (cumulative index values of 0.97 and 0.96, respectively). Crop farms suffered from low efficiency change gains, whereas mixed farms underwent meagre technical change. In accordance with these findings, public support should be tailored to encourage mixed farm development in terms of their operation scale and innovative technologies that could shift the technological frontier. Crop farms should seek to increase their technical efficiency by the means of land reclamation and modernisation of the productive technology.

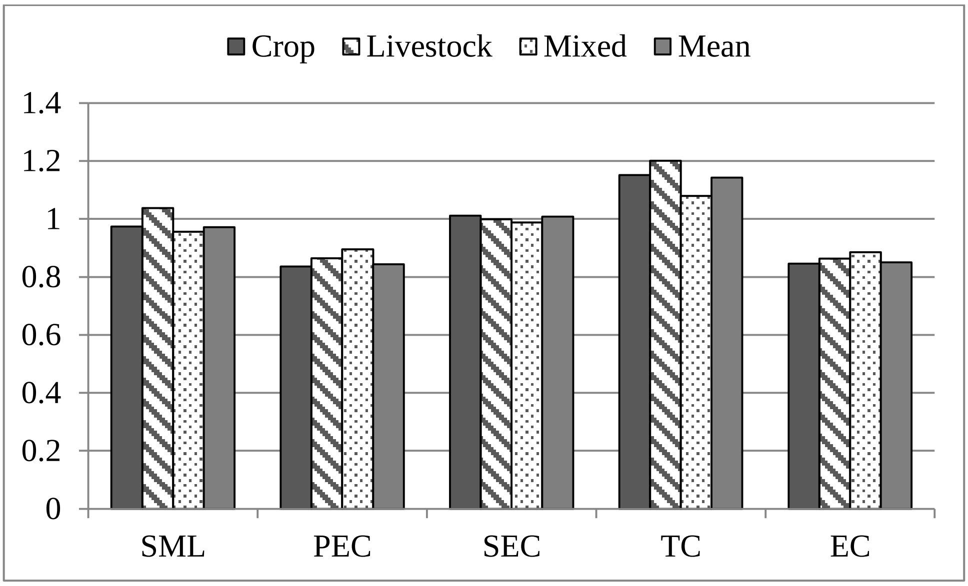


Fig. 4.3. Decomposition of the sequential Malmquist–Luenberger index across farming types (cumulative means for 2004–2009).

As Oh and Heshmati (2010) pointed out the innovative DMUs, i. e. those pushing the production frontier outwards, satisfy the three conditions:

$$TC^{t,t+1} > 1, \tag{4.1}$$

$$E_t^q(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_\mathbf{x}^{t+1},\mathbf{g}_\mathbf{y}^{t+1}) < 0, \tag{4.2}$$

$$E_{t+1}^{q}(\mathbf{x}^{t+1},\mathbf{y}^{t+1};\mathbf{g}_{\mathbf{x}}^{t+1},\mathbf{g}_{\mathbf{y}}^{t+1})=0 \quad (4.3)$$

The first condition (Eq. 4.1) discriminates those DMUs which have achieved positive technical change in between time periods *t* and *t*+1. The second condition (Eq. 4.2) restricts the set under analysis to those input–output sets of the period *t*+1 which were infeasible in the preceding period, *t*. Finally, the third condition (Eq. 4.3) stipulates that an innovative DMU should be fully efficient during the period *t*+1.

With respect to Eqs. 4.1–4.3 some 13 farms were identified as being innovators throughout 2004–2009. Indeed, ten farms were innovators during the period of 2004–2005, whereas the remaining three – during 2006–2007. Other periods, therefore, might be specific with asymmetric shifts in production frontiers. Again, ten of the farms–innovators were specialized crop farms, whereas the remaining three were specialized livestock farms. The proportion between them remained virtually the same throughout the time. Thus the share of livestock farms fluctuated in between 20% and 33%, whereas these farms constituted some 9–15.5% of the analysed sample. To cap it all, livestock farms were more likely to become innovators pushing the production frontier outwards.

4. 3. Application of the Hicks–Moorsteen index

Changes in the total factor productivity (TFP) were estimated by employing Eqs. 2.16–2.18. Tables 4.2–4.5 present the dynamics of TFP change (HM) as well as its components, namely technical efficiency change effect (TE), technology change effect (T), and activity effect (AE). The activity effect was further decomposed into scale effect, input–mix effect, and output–mix effect.

As Table 4.2 reports, the mean increase of TFP reached some 20% in the analysed sample of the Lithuanian family farms throughout 2004–2009. Note that the period of 2006–2008 was that of TFP growth, whereas the subsequent period of 2008–2009 was specific with decrease in TFP. Technology change (T) indicated that the production frontier moved inwards the origin point during 2004–2006 and 2008–2009. This finding implies that negative climatic impact as well as price fluctuations specific for the latter period resulted in an overall decrease in productivity of the agricultural sector. As a result the technology change decreased TFP growth by some 4.6%. Technical efficiency effect caused the decrease in TFP equal to 12.2%. Indeed, the latter effect was negative during the whole period of 2004–2009. The activity effect (AE) stimulated TFP growth and thus contributed to its increase by 52%. Decomposition of the activity effect revealed that it was the scale effect that caused these developments, whereas input– and output–mix effects caused decrease in TFP.

Table 4.2. Cumulative changes in TFP and its decomposition for the whole sample.

Year	HM	TE	T	AE
2005	0.959	0.944	0.952	1.068
2006	0.832	0.834	0.881	1.132
2007	1.301	0.892	1.198	1.218
2008	1.550	0.842	1.222	1.506
2009	1.199	0.828	0.954	1.519

In order to analyse the differences in TFP dynamics across different farming types, Tables 4.3–4.5 focus on crop, livestock, and mixed farms, respectively. The crop farms were specific with higher TFP decrease arising from efficiency change if compared to the mean for all farming types (21% and 17%, respectively). This difference, however, might be an outcome of measurements errors.

Table 4.3. Cumulative change in TFP and its decomposition for crop farms.

Year	HM	TE	T	AE
2005	0.918	0.920	0.938	1.063
2006	0.771	0.803	0.850	1.130
2007	1.308	0.876	1.243	1.202
2008	1.584	0.812	1.280	1.523
2009	1.200	0.793	0.995	1.521

The livestock farms exhibited higher increase in TFP, viz. 27% (Table 4.4), if compared to the mean increase of 20% for the whole sample. Indeed, it was only the livestock farms that managed to maintain TFP growth throughout the whole research period. It can therefore be assumed that livestock farms are more persistent to market shocks. Furthermore, livestock farms managed to sustain the growth of technical effect of 5.6% what does indicate that livestock farms benefited from the expanding production frontier. The latter process, though, was negatively affected by decreased livestock production prices in 2009. Noteworthy, livestock farms were specific with a lower activity effect if compared to the whole sample. Nevertheless, the decomposition of the activity effect revealed that the livestock farms faced the lowest TFP losses caused by output– and input–mix changes. Thus, livestock farms are likely to adjust the structure of both their inputs and production in a more reasonable way if compared to the other farming types. The scale effect, though, was rather meagre.

Table 4.4. Cumulative change in TFP and its decomposition for livestock farms.

Year	HM	TE	T	AE
2005	1.172	1.025	1.124	1.017
2006	1.238	0.955	1.178	1.100
2007	1.527	0.973	1.321	1.189
2008	1.557	0.950	1.309	1.253
2009	1.271	0.940	1.056	1.281

The mixed farming did also experience higher than average TFP growth rate of 27.1% with the single period of decreasing TFP in 2005–2006 (Table 4.5). The mixed farms were also specific with non-decreasing technical efficiency which is represented by a positive efficiency effect (TE) of 0.8%. On the other hand, these farms did not gain too much from the shifts in production frontier (i. e. sector–wide changes in prices, yields etc.): the technical effect resulted in TFP reduction of some 20%.

Table 4.5. Cumulative change in TFP and its decomposition for mixed farms.

Year	HM	TE	T	AE
2005	1.129	1.056	0.947	1.128
2006	0.982	0.957	0.879	1.168
2007	1.329	0.975	1.035	1.318
2008	1.604	0.997	1.016	1.583
2009	1.334	1.008	0.798	1.658

The variation of the productivity index and its terms can be assessed by analysing respective coefficients of variation (ratio of the standard deviation to the mean). The highest variation in Hicks–Moorsteen TFP index was observed for crop farms, whereas the lowest for livestock farms. The mixed farms fell in between thus confirming their ability to diversify market risks.

As for the terms of the Hicks–Moorsteen TFP index, one can note that it was technical change that was specific with the highest variation and therefore the highest effect on the TFP index. Thus, the Lithuanian family farms were mostly impacted by external factors rather than internal ones (for instance, modernization), identified by efficiency change.

What the carried out analysis of the TFP dynamics in Lithuanian family farms does suggest is that modernization of the agricultural practices is of high importance. The technical progress could be incentivized via the increased R&D expenditures as well as more reasonable distribution thereof, new education and training programmes. The activity effect is determined by scale changes as well as shifts in input– and output–mix. The ongoing expansion of large farms in Lithuania (Baležentis, 2012) might result in positive effect on TFP (indeed, this effect was already present during the research period), whereas price policy can provide a momentum for adjustments in input– and output–mix.

The aforementioned issues require further analyses, especially those based on micro data. Specifically, bootstrapping techniques could be employed to tackle the statistical noise present in the data with second–stage analysis focused on identification of factors of TFP changes. One could also define separate production frontier for respective farming types. Finally, utilization of different TFP indices would allow approaching higher level of robustness.

4. 4. The Färe-Primont index and transitive estimates

The TFP measures and indices were estimated by the virtue of the Färe-Primont TFP indices. Specifically, the levels of TFP measures and indices represent the time-specific performance of the Lithuanian family farms under a transitive multilateral framework, whereas the changes in TFP measures and indices account for dynamics thereof measured against the arbitrarily chosen reference farm.

The following Table 4.6 reports the mean values of the TFP measures for different farming types. Given the Färe-Primont index is a transitive one, all the comparisons were made with reference to year 2004 as a base period. In order to ensure the time reversal capability, the rates of TFP change were logged. As a result, the crop farms exhibited the growth of TFP of 16.5% during 2004-2009, whereas livestock and mixed farms featured TFP growth of 24.3% and 39.1% respectively. Note that years 2006 and 2009 were those of the declining TFP for all farming types. The mean TFP levels for crop, livestock, and mixed farming were 0.21, 0.28, and 0.16 respectively. The annual logged growth rates ranged in between 3.3% and 7.8% p. a.

The TFP efficiency was decomposed into the four terms, namely TFP^*, ITE, ISE, and RME. The maximal TFP (TFP^*) increased throughout the research period due to assumption of no negative technical change: the value of 0.468 was observed for year 2004, 0.5223 for 2005–2007, and 0.559 for 2008–2009. Therefore, the best performing farms managed to increase their TFP even further. Specifically, the technical change of some 17.7% had occurred during 2004–2009 (2.9% p. a.). Fig. 4.4 exhibits the kernel densities of the remaining efficiency measures for the three farming types. Indeed, these plots depict variation of the respective TFP measures for the whole period of 2004–

2009 The Gaussian kernels (Silverman, 1986) were used to approximate the underlying empirical distributions.

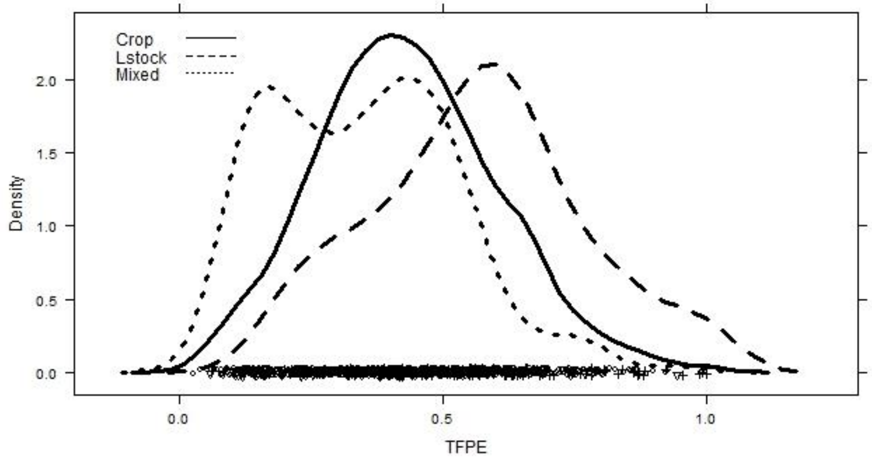
Table 4.6. Dynamics of the TFP across different farming types, 2004-2009.

Farming type	2004	2005	2006	2007	2008	2009	Mean over 2004-2009
			TFP levels				
Crop	0.196	0.194	0.151	0.226	0.251	0.231	0.208
Livestock	0.235	0.259	0.242	0.306	0.347	0.300	0.281
Mixed	0.123	0.154	0.129	0.183	0.187	0.181	0.159
TFP^*	0.468	0.522	0.522	0.522	0.559	0.559	0.525
			TFP indices (base year 2004)				
Crop	1.000	0.993	0.771	1.155	1.284	1.179	
Livestock	1.000	1.100	1.031	1.300	1.476	1.275	
Mixed	1.000	1.256	1.049	1.494	1.527	1.479	
TFP^*	1.000	1.116	1.116	1.116	1.194	1.194	
			Logged TFP changes (%)				
Crop	0.0	-0.7	-26.0	14.4	25.0	16.5	3.3
Livestock	0.0	9.5	3.0	26.2	38.9	24.3	4.9
Mixed	0.0	22.8	4.8	40.2	42.3	39.1	7.8
TFP^*	0.0	11.0	11.0	11.0	17.7	17.7	2.9

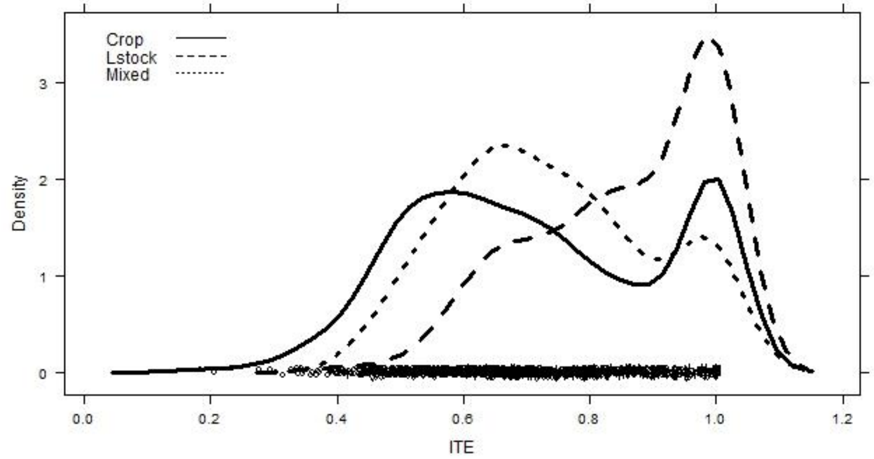
Note: TFP^* denotes the level of maximal TFP. The means of TFP levels are averages, whereas the means of TFP changes are given as $ln\left(TFP_{2009}/TFP_{2004}\right)/5$.

The upper left plot of Fig. 4.4 depicts the densities of the TFP efficiency (TFPE) scores. TFPE indicates the extent to which a certain farm is deviated from the point of maximal productivity: The lower TFPE, the lower the ratio of the observed TFP to the maximal TFP. These computations can be interpreted as a movement from point A towards point E in Fig. 2.3. Note that the point of maximal productivity, E, is located on the mix-unrestricted frontier. It was the livestock farms that exhibited the highest mean efficiency (0.53). The latter farming also exhibited the highest standard deviation (SD) of 0.19 associated with TFPE. The coefficient of variation (CV), however, was the lowest one (0.37) if compared to the remaining farming types. The crop farming featured the mean TFPE of 0.4 and SD of 0.16. Accordingly, the CV approached the value of 0.41. Finally, the mixed farming was peculiar with rather low mean TFPE of 0.30, whereas SD remained at 0.17 and CV increased up to 0.55. As the upper left plot in Fig. 4.4 suggests, the underlying density for the mixed farms was a bi-modal one. Therefore, at least two clusters of the mixed farms can be considered. The latter implies that in spite of the diversification, the mixed farms did not manage to maintain a substantial level of the TFPE as well as its variation.

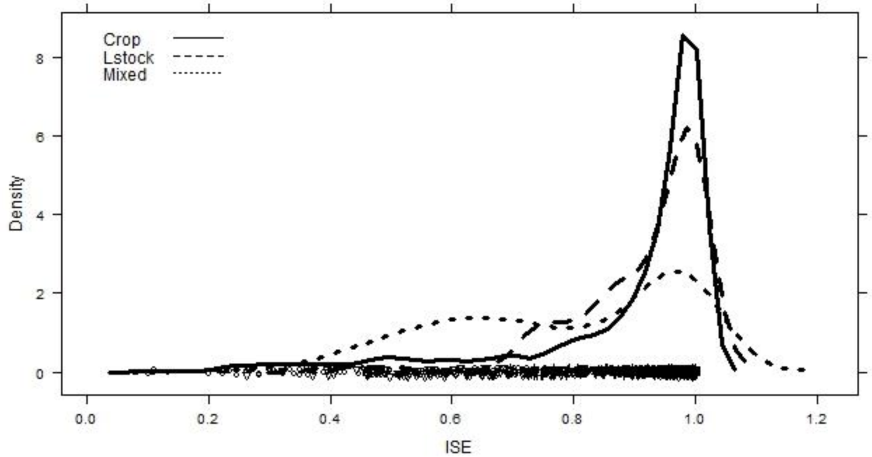
The densities for input-oriented technical efficiency (ITE) are depicted in the upper right plot of Fig. 4.4. ITE compares the observed TFP to that related to the technically efficient production plan. The latter levels of TFP are associated with, respectively, points A and B in Fig. 2.3. The ITE scores, thus can be interpreted as factors of the input contraction needed (holding the structure of the input-mix fixed) to ensure the technical efficiency. It is evident that the crop and mixed farms concentrated around the two values of the ITE with one of these values falling in between 0.4 and 0.6, and another approaching unity (i. e. technically efficient region). Indeed, the crop farming featured the lowest mean ITE, viz. 0.69. Furthermore, the SD of 0.19 resulted in the CV of 0.27, which was the highest value if compared to other farming types. The mixed farming was associated with more favourable ITE indicators: mean ITE was 0.73, SD – 0.15, and CV – 0.20. On the other hand, it was the livestock farms that were specific with the highest ITE. Particularly, the mode of the underlying density was located near the value of unity and the mean ITE was 0.85. In addition, the variation in the efficiency was also a low one (SD – 0.14 and CV – 0.16).



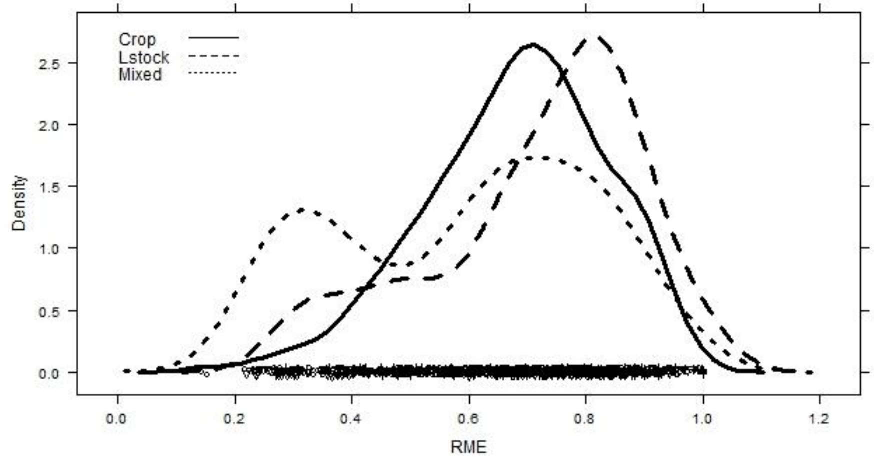
TFP efficiency



Input-oriented technical efficiency



Input-oriented scale efficiency



Residual mix efficiency

Fig. 4.4. Densities of the efficiency scores for different farming types.

Note: Bold, dashed, and dotted lines represent densities for crop, livestock, and mixed farms respectively.

The densities of the input-oriented scale efficiency (ISE) scores are given in the lower right plot of Fig. 4.4. ISE compares the TFP at technically efficient point to that prevailing at the point of mix-invariant optimal scale. Thus, holding input-mix fixed we further move from point B towards point D in terms of Fig. 2.3. As one can note, these densities are rather compact ones with means located around the point of efficiency. Therefore, it is likely that the underlying technology is a CRS one. However, this paper does not focus on the issue[8]. The livestock farming was associated with the highest mean ISE, 0.91, as well as the lowest variation thereof (SD – 0.10, CV – 0.11). The crop farms were specific with the mean ISE of 0.86 and a higher level of variation in these scores (SD – 0.17, CV – 0.20). Finally, the mixed farms diverged from the optimal scale to the highest degree: The mean ISE was 0.76, SD – 0.19, and CV – 0.26.

The lower left plot of Fig. 4.4 presents the densities of the residual mix efficiency (RME) scores across the three farming types. RME measures the TFP gains possible due to changes in the input-mix. Specifically, the TFP at mix-invariant optimal scale is compared to the TFP associated with optimal scale of the unrestricted frontier. Therefore, we look at points D and E in Fig. 2.3. The livestock farms featured the highest mean RME (0.69), albeit its variation was the second lowest one (SD – 0.17, CV – 0.25). The crop farming exhibited similar mean RSE (0.67) as well as the lowest variation thereof (SD – 0.13, CV – 0.20). The mixed farming was associated with the lowest mean RSE (0.55) and the highest variation thereof (SD – 0.20, CV – 0.37). Given the density depicted in Fig. 4.4, the mixed farms were grouped around RME levels of 0.2-0.4 and 0.6-0.8. Therefore, certain sub-types of the mixed farms did not manage to achieve the substantial level of RSE.

The results do indicate that the ITE was a decisive factor causing decrease in TFPE for crop and mixed farms. Meanwhile, the ISE constituted a serious problem for mixed farms. Indeed, these farms were the smallest ones if

[8] The bootstrapping-based tests can be employed to test the hypotheses of returns to scale (Simar, Wilson, 2002).

compared to the remaining farming types (cf. Table C1). Finally, the mix efficiency was low for all farming types indicating the need for implementation of certain farming practices allowing for optimisation of the input-mix.

The econometric models were further employed to analyse the underlying drivers of the TFP growth. The TFPE, ITE, ISE, and RME were regressed over the selected environmental variables describing farm specifics. The following factors were chosen as regressors. The utilised agricultural area (*UAA*) identified the scale size and was considered a proxy for farm size. Indeed, the question of the optimal farm size has always been a salient issue for policy makers and scientists (Alvarez, Arias 2004; Gorton, Davidova 2004; van Zyl et al. 1996). The ratio of crop output over the total output (*CropShare*) captures the possible difference in farming efficiency across crop and livestock farms. Similarly, the dummy variable for organic farms (*Organic*) was used to quantify the difference between organic and conventional farming. It is due to Offermann (2003) that Lithuanian organic farms exhibit 60–80% lower crop yields depending on crop species if compared to same values for conventional farming. The demographic variable, namely age of farmer (*Age*) was introduced to ascertain whether young–farmers–oriented policy measures can influence the structural efficiency. Finally, the effect of production subsidies on efficiency was estimated by considering ratios of production subsidies to output (*SubsShare*).

Given the analysis relied on the panel data, the *F*-test was employed to check whether the data do exhibit farm- and time-specific effects. The null hypothesis of insignificant effects was rejected at the significance level of 1%. Furthermore, the Hausman test rejected the random-effects model at the significance level of 1%. Accordingly, the two-way fixed-effects models were estimated for TFPE, ITE, ISE, and RME:

$$y_k^t = \boldsymbol{\beta}(\mathbf{z}_k^t)' + u_k + u_t + \varepsilon_k^t, \tag{4.4}$$

where y is the component of TFP ($y = \{TFPE, ITE, ISE, RME\}$), $\boldsymbol{\beta}$ is the vector of coefficients, $\mathbf{z}_k^t$ is the vector of the environmental variables, u_k is farm-specific effect, and u_t is time-specific effect. The elasticities can then be computed as follows:

$$\mathbf{e}_k^t = \boldsymbol{\beta}\mathbf{z}_k^t / y_k^t, \tag{4.5}$$

where $\mathbf{e}_k^t = \boldsymbol{\beta}\mathbf{z}_k^t / y_k^t$ is a vector of elasticities of the same dimension as $\boldsymbol{\beta}$ and $\mathbf{z}_k^t$

. The estimated models are given in Table 4.7. The ITE and RME were poorly explained by the selected variables (R^2 were 0.05 and 0.10 respectively). The results showed that the farm size had a positive effect on TFP, ISE, and RME. Therefore, the larger farms are more likely to increase their TFPE by operating at the optimal scale and adjusting their input-mixes. However, the ITE remained unaffected by the farm size. The crop share had a negative effect on TFPE, ITE, and RME. The latter finding implies that crop and mixed farms experienced lower technical and mix-efficiency as well as TFP levels. Nevertheless, these farms did not deviate from the optimal size of scale to a significant extent. The ratio of subsidies to the total output had a negative impact on TFPE, ITE, and ISE. Therefore, the increasing subsidy rate negatively affected the TFP as well as technical efficiency. Given the relation to the mix-efficiency measure (RME) was not significant, it can be concluded that the subsidies do accelerate farm growth but do not distort the input-mix. Farmer age had no significant impact on the analysed efficiency and TFP measures save that of RME: It turned out that older farmers manage to achieve higher mix-efficiency. The latter finding might be explained by the fact that more experienced farmers ensure the proper input-mix structure. Accordingly, the educational programmes for the younger farmers remain important in the light of results of the analysis. Finally, the organic farming was not associated with any significant effects on TFP and efficiency.

Given the environmental variables were expressed in different dimensions, the efficiency elasticities were computed in terms of Eq. 4.5. The results are given in Table 4.8. Farm size in hectares (*UAA*) was the least important factor in terms of its contribution to the efficiency and TFP levels. Farmer age played an important role in the context of RME. Meanwhile, the negative effect of crop share outweighed those of subsidy rate and farm size. One can further note that organic farming practice was not associated with significant changes in TFP and its components.

Table 4.7. Coefficients of the fixed-effects model.

	TFPE		ITE		ISE		RME	
UAA	0.00021	***	0.00003		0.00014	*	0.00012	*
CropShare	-0.36191	***	-0.29410	***	-0.05598		-0.17346	***
SubsShare	-0.13163	***	-0.09888	***	-0.15401	***	-0.01435	
Age	0.00105		0.00028		0.00011		0.00154	.
Organic	0.01029		-0.02610		0.03664		-0.01305	
Adj. R^2	0.13		0.05		0.10		0.02	
F-statistic	29.877	***	11.4348	***	28.6	***	5.87311	***

Note: Significance codes for respective p-values: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1.

Table 4.8. Efficiency elasticities (E) across different models.

		UAA	*CropShare*	*SubsShare*	*Age*	*Organic*
TFPE	Mean E	**0.127**	**-0.870**	**-0.201**	0.151	0.002
	E at mean	**0.120**	**-0.670**	**-0.100**	0.113	0.001
ITE	Mean E	0.018	**-0.705**	**-0.150**	0.037	-0.006
	E at mean	0.017	**-0.543**	**-0.074**	0.028	-0.003
ISE	Mean E	**0.081**	-0.135	**-0.235**	0.017	0.009
	E at mean	**0.076**	-0.104	**-0.117**	0.012	0.004
RME	Mean E	**0.073**	**-0.417**	-0.022	**0.222**	-0.003
	E at mean	**0.069**	**-0.321**	-0.011	**0.167**	-0.001

Note: Bold figures are those associated with significant regression coefficients.

All in all, the TFP efficiency of the Lithuania family farms was mainly determined by the technical and mix-efficiency during 2004–2009. These measures, in turn, were better for livestock farming if compared to mixed and crop farming. Specifically, the increase of crop share in the total output of 1% caused decrease in the TFPE of 0.87% on average. An increase in subsidy rate of the same margin resulted in decrease in TFPE of 0.2% on average.

5. FEATURES OF THE UNDERLYING PRODUCTIVE TECHNOLOGY

This part of the thesis aims to analyse the underlying productive technology of Lithuanian family farms. Therefore, the technical change is analysed with respect to change in the input productivity. Another important issue to be addressed is that of the optimal farm size (i. e. returns to scale). Finally, the farming types are compared with respect to the associated production frontiers.

5. 1. Technical bias

The input-biased technology change can be analysed in terms of certain combinations of the input-mix ratios and the *IBTC* component of the Malmquist productivity index (cf. Table 2.1). The analysis proceeds by considering each possible combination of two inputs. In case the technology change is non-neutral, two combinations are related to an input saving change, whereas the remaining two are related to input-consuming change for each of the two inputs analysed. In the sequel, therefore, we report only the outcomes, i. e. the nature of technology change, of the discussed combinations. The following Table 5.1 describes the nature of TCs observed during different periods across farming types.

The crop farms exhibited labour-using TC during 2004-2009. Specifically, 51 percent of crop farms featured labour-using and intermediate consumption increasing TC. In addition, 54 percent of crop farms exhibited labour-using and asset-saving TC. However, 53 percent of crop farms underwent labour-saving and land-using TC. The latter farming type encountered land-using TC with respect to all remaining factors. Specifically, 53-56 percent of crop farms exhibited land-using TC depending on the reference factor. The majority of crop farms (i. e. 51-56 percent) faced intermediate consumption saving TCs against land and labour. Though, only

46 percent of crop farms experienced intermediate consumption saving and asset-using TCs. Finally, 54-56 percent of crop farms exhibited an asset-saving TC depending on the reference factor. All in all, crop farming was peculiar with land-using and asset-saving TC, whereas labour-using and intermediate consumption saving TCs were observed only for certain combinations of inputs. However, the differences between the shares of crop farms exhibiting different patterns of the TCs were not large, i. e. these shares were close to 50 percent.

Livestock farms encountered labour-saving TC with respect to land and asset factors (55 percent), whereas only 47 percent of these farms faced a labour-saving and intermediate consumption increasing TC. One can further conclude that a land-using TC prevailed in the crop farming: 45 percent of crop farms featured land-saving and labour-using TC, 44 percent of them – land-saving and intermediate consumption increasing TC, whereas 52 percent – land-saving and asset-consuming TC. The largest share of livestock farms (53-57 percent depending on the reference factor) exhibited an intermediate consumption saving TC. Depending on the reference factor, some 52-57 percent of livestock farms encountered an asset-consuming TC. Thus, livestock farms generally experienced intermediate consumption and asset saving TCs against all the remaining inputs, whereas labour-saving and land-using TC varied with the reference inputs.

Table 5.1. Farm structure in terms of the input-biased TC, 2004-2009 (percent).

	x_2 -saving / x_1 -using	x_2 -using / x_1 -saving	x_3 -saving / x_1 -using	x_3 -using / x_1 -saving	x_4 -saving / x_1 -using	x_4 -using / x_1 -saving	x_3 -saving / x_2 -using	x_3 -using / x_2 -saving	x_4 -saving / x_2 -using	x_4 -using / x_2 -saving	x_4 -saving / x_3 -using	x_4 -using / x_3 -saving
Crop farming												
2004-2005	49	51	51	49	39	61	52	48	44	56	41	59
2005-2006	55	45	37	63	60	40	29	71	56	44	64	36
2006-2007	26	74	32	68	40	60	54	46	52	48	48	52
2007-2008	52	48	69	31	59	41	78	22	58	42	41	59
2008-2009	53	47	64	36	74	26	65	35	73	27	76	24
Average	47	53	51	49	54	46	56	44	56	44	54	46
Livestock farming												
2004-2005	67	33	72	28	56	44	67	33	50	50	50	50
2005-2006	60	40	56	44	48	52	36	64	36	64	44	56
2006-2007	32	68	26	74	29	71	35	65	35	65	52	48
2007-2008	30	70	75	25	50	50	90	10	65	35	30	70
2008-2009	41	59	55	45	50	50	68	32	64	36	68	32
Average	45	55	53	47	45	55	56	44	48	52	49	51
Mixed farming												
2004-2005	54	46	58	42	75	25	54	46	79	21	58	42
2005-2006	52	48	59	41	41	59	45	55	45	55	41	59
2006-2007	22	78	56	44	70	30	67	33	74	26	74	26
2007-2008	59	41	81	19	56	44	78	22	52	48	33	67
2008-2009	35	65	94	6	100	0	87	13	94	6	90	10
Average	44	56	70	30	69	31	67	33	69	31	60	40

Note: *x*s denote respective factors: x_1 denotes labour in AWU, x_2 - UAA in ha, x_3 - intermediate consumption in Lt, and x_4 - assets in Lt.

The structure of mixed farms was a more uneven one if compared to those of the discussed farming types. Clearly, some 70 percent of mixed farms exhibited labour-using and asset- or intermediate consumption saving TCs. Some 56 percent of mixed farms, though, showed labour-saving and land-using TC. Most of the mixed farms (i. e. 56-69 percent depending on the reference input) featured land-using TCs. Intermediate consumption saving TCs prevailed in mixed farming against labour and land (70 percent and 67 percent, respectively), however, only 40 percent of mixed farms encountered an intermediate consumption saving and asset-using TC. Finally, 60-69 percent of mixed farms faced asset-saving TYCs with respect to labour, land, and intermediate consumption. Accordingly, mixed farms can be considered as those peculiar with increasing land use and decreasing capital consumption. Labour-using and intermediate consumption saving TCs did also hold for most of the analysed factors.

The analysed TFP indices suggested that all the farming types experienced some sort of land use intensification, for the observed TC was land-using and labour-saving. These trends might be explained by increasing size of the farms engaged in the industrial farming on the one hand, and decreasing rural population on the other hand. However, the relative amount of labour decreased if compared to respective changes in the intermediate consumption and assets. These findings might be associated with the farm modernisation and subsequent increase in productivity of assets and intermediate consumption. Here one can also note that some 51 percent of the crop farms as well as 70 percent of the mixed farms exhibited growth in the productivity of the intermediate production during 2004-2009, whereas the respective proportions associated with asset to labour ratio were 54 percent and 69 percent. As for the livestock farms, the relative amount of assets used in the production process generally increased with respect land or labour. The latter finding implies that the livestock farms might have accumulated excessive amounts of capital. Anyway, appropriate measures of marketing might increase the revenue in a longer run and thus increase the productivity of capital.

5. 2. Returns to scale across farming types

The prevailing returns to scale were analysed with each farming type. The qualitative method described in the preceding section was employed to classify the observations with respect to the RTS.

The crop farms were mainly operating under a sub-optimal scale. Indeed, some 71% of the observations associated with the latter farming type exhibited IRS, whereas 22% operated under DRS and the remaining 7% featured CRS (i. e. they operated in the range of the MPSS). Indeed, crop farms exhibited a decreasing share of farms operating at the sub-optimal scale (Fig. 5.1): The share of suchlike farms dropped from 76% in 2004 to 68% in 2009. The share of farms operating at CRS increased from 7% up to 9% throughout the same period. The share of farms operating at the DRS (i. e., the supra-optimal scale) increased from 18% up to 23%. The aforementioned developments can be explained by crop farm expansion occurred during the research period.

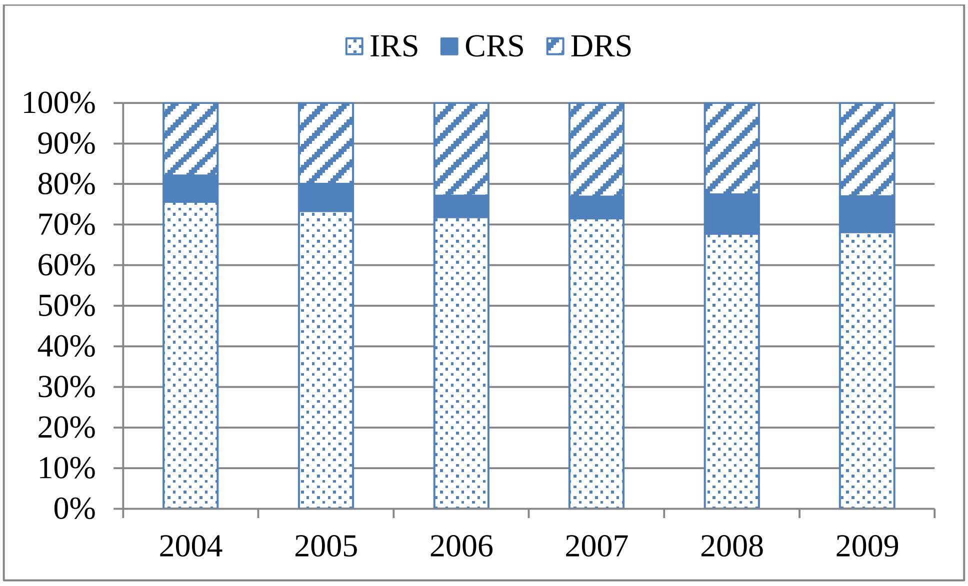


Fig. 5.1. The structure of crop farms in terms of RTS, 2004-2009.

The mixed farms did also mainly operate in the range of the IRS (69% of the relevant observations). Some 16% of the observations exhibited

CRS, yet another 15% featured DRS. Indeed, the structure of crop farms was a relatively stable one in terms of RTS. Fig. 5.2 presents the mixed farm structure in terms of the prevailing RTS.

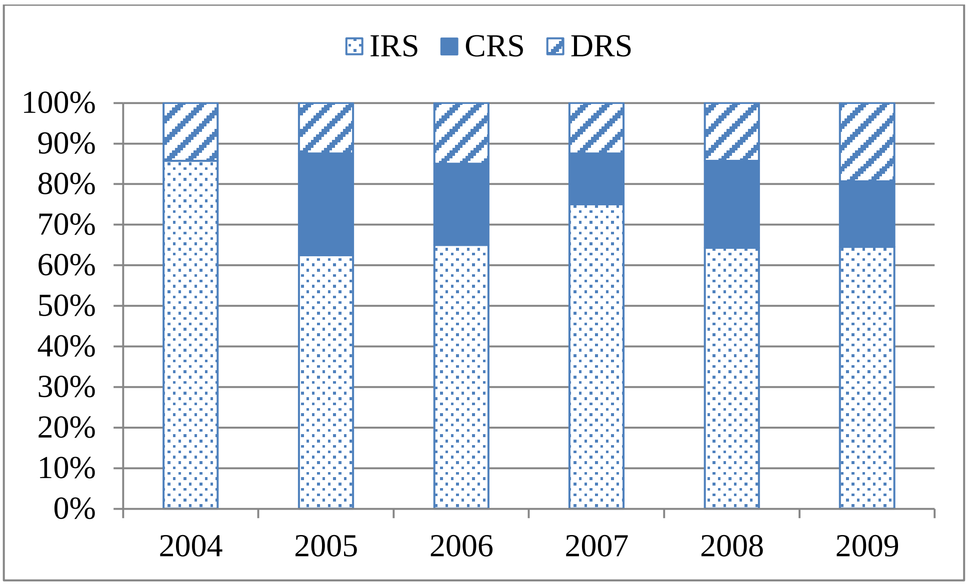


Fig. 5.2. The structure of mixed farms in terms of RTS, 2004-2009.

The livestock farming exhibited high variation in RTS. The share of observations associated with IRS decreased from 63% down to 59% (52% on average). However, the years 2004 and 2009 were specific with increases in shares of farms operating under the sub-optimal scale: Even 59-71% of the livestock farms operated under IRS during those periods. Some 26% of the livestock farms operated at the MPSS on average. The share of the livestock farms operating at the supra-optimal scale varied significantly across the years with the average value of 22%. Fig. 5.3 presents these developments.

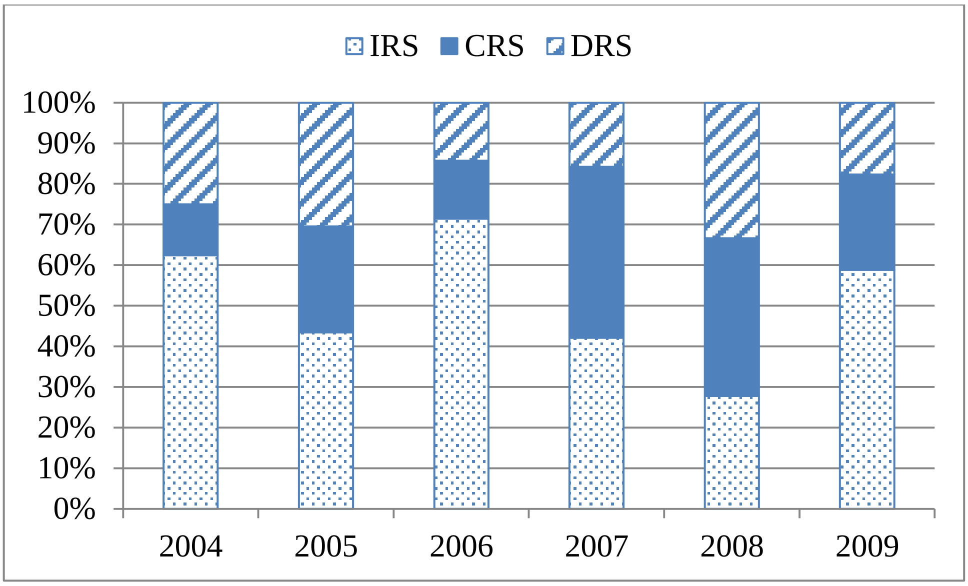


Fig. 5.3. The structure of livestock farms in terms of RTS, 2004-2009.

Results of the qualitative assessment of RTS across farming types did indicate that most of the analysed farms operated at a sub-optimal scale. The highest share of farms operating under IRS was observed for the crop and mixed farming (71% and 69% respectively). On the other hand, it was the livestock and mixed farms that exhibited the most frequent occurrences of DRS (22% and 15% respectively). The results revealed that the livestock farms can be considered as those operating at the optimal scale size to the highest extent (26% of observations) if compared to mixed (16%) or crop (7%) farms. However, the livestock farms did also exhibit the highest variation in the operation scale. Therefore, the agricultural policy should support consolidation of the crop farms to some extent. The livestock farms, though, might require some additional income smoothing measures.

5. 3. Elasticity of scale across farming types

The patterns of the prevailing returns to scale and scale elasticity were analysed across the three different farming types, viz. crop, mixed, and livestock farming. The analysis aimed at estimating the MPSS. Specifically, the three main variables describing the observed scale size were chosen for the research: UAA in hectares, land input in AWU, and the total output in Litas.

The relationships between each of the latter variables and scale elasticity were quantified by employing the log-log regression, which appeared to feature the best fit. The values of the scale elasticity were truncated at 3 to improve the visualisation. Both input- and output-oriented models were considered for inefficient observations. The efficient ones were treated as reported by Banker and Thrall (1992). Furthermore, certain ratios were then derived in order to analyse the labour intensity and land productivity at the MPSS. Note that the projections of the inefficient observations were analysed instead of the original data. Otherwise, the input (output) values would be inflated (contracted) due to technical inefficiency. Thus, one can focus solely on the scale efficiency by analysing the projections.

In the sequel, we will analyse the results across the three farming types, viz. crop, livestock, and mixed farming. The corresponding equations describing the relationships between input (output) indicators and the scale elasticity measure were estimated. The optimal values of inputs and outputs were obtained by setting scale elasticity equal to one, logging both sides of the equation and then solving it for the variable of interest.

For sake of brevity, the input-elasticity plots are omitted. Table 5.2 summarises the results for the crop farms. Generally, crop farms of some 250 ha in size appeared to be those operating in the region of CRS. However, the lower and upper values obtained for the efficient farms diverged from the latter figures to a certain extent. Noteworthy, Vasiliev et al. (2008) employed DEA and estimated that the optimal Estonian grain farm size should fall in the range of 239-341 ha. Meanwhile, Luik et al. (2009) concluded that the same figure should be in between 200 and 600 ha. As for the labour force, the optimal amount was some 3 AWU. Finally, the total output in the region of CRS was 600-700 thousand Lt (ca. 175-200 thousand EUR).

Table 5.2. The most productive scale size for the crop farms (2004–2009).

Indicators	Inefficient farms		Efficient farms	
	ε_t^{in}	ε_t^{out}	$\varepsilon_t^{\min}$	$\varepsilon_t^{\max}$
UAA, ha	257	255	83	409
Labour, AWU	3	3.4	1.4	5.3
Total output, Lt	709,137	609,460	147,413	1,011,939
UAA per labour unit, ha/AWU	84	75	58	78
Land productivity, Lt/ha	2,759	2,391	1,766	2,476
Labour productivity, Lt/AWU	216,067	179,305	103,089	192,277

The farm size can also be analysed in terms of the relative indicators (i. e. ratios). The results did indicate that the amount of land per one unit of labour (AWU) fell in the interval of 58-84 ha. The total output generated per one hectare of UAA ranged in between 1.8 and 2.8 thousand Lt. Meanwhile, the amount the total output per unit of labour (AWU) associated with CRS was 100-216 thousand Lt.

Considering the inefficient farms, the MPSS for the livestock farms was achieved at some 140 ha of the UAA (Table 5.3). The labour force employed at the livestock farms operating at the optimal scale reached some 4.5 AWU and, thanks to the different technology, exceeded the respective figure for the crop farming. Meanwhile, the total output in the region of CRS was 438-478 thousand Lt.

Table 5.3. The most productive scale size for the livestock farms (2004–2009).

Indicators	Inefficient farms		Efficient farms	
	ε_t^{in}	ε_t^{out}	$\varepsilon_t^{\min}$	$\varepsilon_t^{\max}$
UAA, ha	139	147	44	221
Labour, AWU	4.5	4.3	2.1	6.6
Total output, Lt	478,938	438,801	141,411	821,745
UAA per labour unit, ha/AWU	32	34	20	33
Land productivity, Lt/ha	3,438	2,988	3,240	3,719
Labour productivity, Lt/AWU	105,460	102,868	66,337	123,720

The relative livestock farm size in the region can be described as follows: The amount of UAA per one unit of labour was 20-34 ha. Land productivity fluctuated around some three thousand Lt, whereas labour productivity ranged in between 66 and 124 thousand Lt. Note that these figures are lower than the respective ones associated with the crop farming. Accordingly, livestock farming might be less appealing at least in the range of CRS.

Table 5.4 presents the main results regarding the optimal scale of the mixed farms. As one can note, these farms fell in between the specialised crop and livestock farms in terms of UAA and labour input. However, the mixed farms are more similar to the livestock ones: The UAA was 82-195 ha, whereas the labour input amounted to 2.9-4 AWU (based on inefficient observations).

Table 5.4. The most productive scale size for the mixed farms (2004–2009).

Indicators	Inefficient farms		Efficient farms	
	ε_t^{in}	ε_t^{out}	$\varepsilon_t^{\min}$	$\varepsilon_t^{\max}$
UAA, ha	195	82	59	249
Labour, AWU	4.0	2.9	2.3	5.2
Total output, Lt	373,434	174,804	109,866	508,227
UAA per labour unit, ha/AWU	50	28	26	48
Land productivity, Lt/ha	1,914	2,137	1,866	2,039
Labour productivity, Lt/AWU	93,883	59,797	48,325	97,503

The ratios describing farm size at the optimal scale were more consistent across the approaches of measurement. The results did indicate that scale efficiency had been ensured at farms which maintained the ratio of UAA and labour force at 26-50 ha/AWU. The land productivity fell into the interval of 1.9-2.1 thousand Lt/ha. the mixed farms operating at CRS exhibited the labour productivity of 48-98 thousand Lt/AWU.

The quantitative analysis of the returns to scale in the Lithuanian family farms suggested that the crop farms should be some 250 ha in size with labour force amounting to 3-3.4 AWU. The total output associated with the optimal scale was 600-700 thousand Lt.

The livestock farms should be smaller in terms of land (some 140 ha), albeit larger in terms of labour (4.3-4.5 AWU). Indeed, the total output associated with the optimal scale of production, 438-478 thousand Lt, suggests that the labour productivity in livestock farming (some 100 thousand Lt/AWU in the region of CRS) would be lower if compared that in the crop farming (180-216 thousand Lt/AWU in the region of CRS). Therefore, the livestock farming needs certain measures aimed at increasing the total output in order to increase its attractiveness and viability.

The mixed farming featured the size 82-195 ha and 2.9-4 AWU. The land productivity fluctuated around two thousand Lt/ha in the region of CRS, whereas the labour productivity ranged in between 60 and 93 thousand Lt/AWU. This farming type, therefore, featured the lowest land and labour productivity thus implying some sort of diseconomies of scope.

The carried out analysis revealed that the absolute measures of the farm size varied rather highly with the measurement approach. The relative measures, though, were less variant ones. Accordingly, it might be more reasonable to speak of farm size in terms of the relative measures, e g. the amount of land per worker, land productivity, labour productivity.

5. 4. Program and managerial efficiency

The sub-sample MEA enables to compare farming efficiency in terms of farming type-specific technology. Such type of efficiency is referred to as the **managerial efficiency**. It implies that slack in a certain input consumption may be caused by shortcomings in the managerial practice, whereas slacks caused by farming type specifics remain ignored. Note that this type of analysis is Stage 1 of the program efficiency MEA framework (see Section 2.3).

The input-specific benchmarks across the three subsamples are given in Tables 5.5 and 5.6. As one can note, the efficiency scores for the crop farms in the latter two tables are quite close to those obtained in the full sample (cf. Tables 4.26 and 4.27). This means that the crop farms were mainly determining the pooled efficiency frontier and crop farming thus is specific with little program inefficiency. Assets thus remained as one of the most important factors of inefficiency (29–41% contraction thereof is needed for an average crop farm depending on the RTS assumption). The low values of land use efficiency under CRS stress the need for land productivity increase in crop and mixed farms.

Table 5.5. Sub-sample MEA efficiency scores for inefficient farms (VRS).

Farming type	Labour	Land	Intermediate consumption	Assets	DEA
Average					
Crop farms	0.57	0.54	0.56	0.49	0.57
Livestock farms	0.71	0.71	0.76	0.71	0.76
Mixed farms	0.72	0.71	0.78	0.71	0.77
Minimum					
Crop farms	0.17	0.13	0.14	0.09	0.15
Livestock farms	0.34	0.34	0.46	0.39	0.41
Mixed farms	0.35	0.35	0.48	0.28	0.46

Table 5.6. Sub-sample MEA efficiency scores for inefficient farms (CRS).

Farming type	Labour	Land	Intermediate consumption	Assets	DEA
Average					
Crop farms	0.44	0.49	0.52	0.45	0.49
Livestock farms	0.55	0.59	0.71	0.67	0.68
Mixed farms	0.46	0.57	0.67	0.59	0.64
Minimum					
Crop farms	0.03	0.04	0.10	0.04	0.07
Livestock farms	0.21	0.21	0.31	0.36	0.36
Mixed farms	0.16	0.23	0.31	0.23	0.32

Livestock farms were specific with the highest benchmarks in their sub-sample if compared to other sub-samples. This means that livestock farms were more homogeneous in terms of their performance and technologies. The CRS efficiency scores indicate that livestock farms should reduce their labour and land inputs by 45% and 41%, respectively.

The mixed farms had similar benchmarks as the livestock farms under VRS, although they were somehow lower for mixed farms under CRS. Hence, the crop farming was specific with higher variation in farm size, which was not followed by respective changes in output level.

The differences observed between DEA and MEA efficiency scores across the full sample and farming type sub-samples indicates that the efficiency arose due to both managerial and program, viz. farming type, factors. The Stage 2 of the program efficiency MEA was employed to explore these issues.

The program efficiency can be assessed by adjusting the observed production plans so that they become efficient ones within a certain program. In our case we have a sample of the Lithuanian family farms which focus either on livestock or crop or mixed agricultural production. Accordingly, the three programs correspond to the aforementioned farming types. First we proceed with visualization of the program efficiency in the Lithuanian family farm sample. Second, the Stage 2 of the program efficiency MEA is implemented to obtain exact estimations.

In order to visualise the pooled frontier (envelope) one needs to define the program frontiers. Two inputs, at most, can be used for the latter purpose. Given we have four inputs plus one output, the inputs were aggregated into costs by considering respective input prices. The land price was obtained from the Eurostat and assumed to be uniform for all farms during the same period. The labour price is average salary in agricultural sector from Statistics Lithuania. The price of capital is depreciation plus interests per one Litas of assets. Meanwhile, the intermediate consumption is directly considered as a part of total costs. Thereafter, labour and intermediate consumption as well as land and assets were merged into the two cost indicators. Subsequently, these indicators were scaled by output indicator. As a result, we had the two input indicators, viz. labour and intermediate consumption intensity, and land and asset intensity. The sub-sample MEA was then implemented on each of the three subsamples in terms of the two aforementioned aggregate input indicators. These MEA models yielded optimal values of the two indicators, which virtually determined the program frontiers (Fig. 5.4). The CRS were implicitly assumed by employing the MEA model without outputs.

The convex pooled frontier was then defined (note the solid line in Fig. 5.4). It covers some parts of the sub-sample frontiers as well as an inter-envelope. It is evident that the pooled frontier mainly consists of the crop farm observations. These farms, therefore, can be considered as those possessing the highest productive potential. Anyway, the previous results did indicate that the crop farms were specific with a wide range of efficiency scores, which indicates the lack of managerial efficiency. It is obvious that crop farms are also specific with a higher variation in the efficiency scores due to the nature of the cropping.

The livestock farms' frontier did also determine the shape of the pooled frontier. The largest part of the livestock frontier, though, remained enveloped by the crop frontier. This finding indicates that livestock farming can successfully compete with crop farming in terms of production factor productivity. The mixed farm frontier, nevertheless, remained totally dominated by crop and livestock frontiers and thus did not affect the pooled frontier. One can thus consider the specialized farms as those better off if compared to the mixed ones.

After visualising the general trends of efficiency, we implemented Stage 2 of the program efficiency MEA. Specifically, the MEA was employed for the four inputs – one output model to assess the program efficiency in terms of the four inputs, namely land, labour, intermediate consumption, and assets. Tables 5.7 and 5.8, thus, report the estimates under VRS and CRS assumptions, respectively.

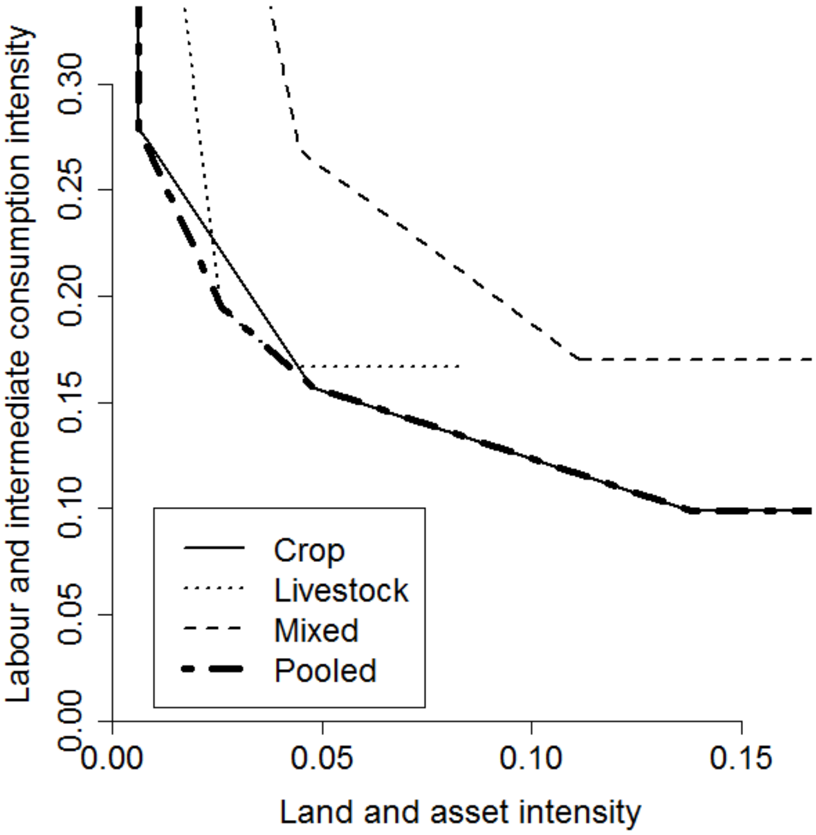


Fig. 5.4. Program frontiers and the pooled frontier based on aggregate input indicators.

The data in Tables 5.7 and 5.8 enable to define the patterns of the program efficiency in a more detailed manner. The crop farms were specific with the lowest level of program inefficiency with efficiency scores ranging between 0.95 and 0.97. The CRS assumption resulted in the increased land use inefficiency (9%), which is, nevertheless, a low one. Meanwhile, the asset inefficiency of 9% under VRS and 14% under CRS was the peculiar for the livestock farms. The highest slack under CRS was that of labour (20%) for the livestock farms, which implies that larger livestock farms might be specific with excessive labour use. In accordance with Fig. 5.4, the mixed farms had the highest rates of program inefficiency across all of the inputs. Specifically, the labour and asset inefficiency were the two major problems in this farming type.

Table 5.7. Stage 2 of the program efficiency MEA for inefficient farms (VRS).

Farming type	Labour	Land	Intermediate consumption	Assets
Average				
Crop farms	0.95	0.97	0.95	0.95
Livestock farms	0.85	0.88	0.90	0.81
Mixed farms	0.81	0.80	0.81	0.76
Minimum				
Crop farms	0.72	0.56	0.42	0.42
Livestock farms	0.62	0.41	0.46	0.42
Mixed farms	0.57	0.53	0.54	0.55

Table 5.8. Stage 2 of the program efficiency MEA for inefficient farms (CRS).

Farming type	Labour	Land	Intermediate consumption	Assets
Average				
Crop farms	0.91	0.97	0.95	0.95
Livestock farms	0.80	0.90	0.93	0.86
Mixed farms	0.61	0.71	0.76	0.67
Minimum				
Crop farms	0.32	0.51	0.45	0.57
Livestock farms	0.44	0.55	0.54	0.40
Mixed farms	0.29	0.36	0.51	0.31

The results of the Stage 2 do indicate that program inefficiency is quite acute amongst the mixed farms. Asset and labour inefficiencies there need to be alleviated in order to reduce the program inefficiency. Indeed, sector-wide measures are needed for that.

The two–stage MEA, therefore, enabled us to identify managerial and program efficiencies across different farming types and inputs. Stage 1 was carried out in the three sub-samples (cf. Tables 5.5 and 5.6). The managerial inefficiency was extremely high amidst the crop farms. Indeed, it ranged from 51% in assets to 43% in labour under VRS. Livestock farms were specific with the lowest managerial inefficiency. After imposing the CRS assumption, asset and labour slacks were the highest ones if compared to those of other inputs. On the other hand, intermediate consumption remained the most efficiently utilized input. Certainly, this particular input is one of the easiest observed and controlled. Extremely low values of intermediate consumption efficiency in the crop farms underlines the need for further improvements in crop mix and cropping practice in general. The low managerial efficiency in crop farming might also be related to relatively higher public support allocated to the latter sector.

The analysis of program inefficiency (Stage 2 of the program MEA) indicated that crop farms are those defining the pooled frontier (Fig. 5.4 and Tables 5.7–5.8). Therefore, they have the lowest values of input–specific program inefficiency. Livestock farms are also partially determining the shape of frontier, whereas the mixed farms are determining the VRS frontier, but not the CRS one. The lowest program efficiency, hence, was observed for the mixed farms. Labour and assets are the two most problematic inputs in terms of program inefficiency for all farming types. Generally, the specialized farming appeared to be more efficient in terms of the program efficiency. Indeed, it is related to long-term and deeper acquisition of farming practice, which positively affects the quality of human capital.

The results indicate that benchmarking and modernization currently are the most important issues for the crop and, partially, mixed farms. These measures should reduce the managerial inefficiency specific for these two types of farming. That the crop farms determined the shape of the pooled frontier in Stage 2 MEA, and the lowest efficiency scores were observed for this farming type as well (cf. minima in Tables 5.5–5.6), seems to indicate that stochastic events like changing weather conditions could be partly to blame for the high variation in performance as compared to the more stable pattern of the livestock farms. Accordingly, income smoothing measures seems of importance for crop farms. The Rural Development Programme for Lithuania 2014–2020 should opt for income smoothing measures and establish specific requirements which could substantially smoothen the crop farm income.

The livestock farms seem to better off in comparison to the remaining farming types, although they generate lower volume of output due to program inefficiency. Accordingly, livestock farmers need to be motivated to improve their program efficiency. This could for example be done in connection with production subsidies. These subsidies should be provided given that the farms demonstrate certain degrees of innovation in their production processes. In particular, the labour component seems badly utilized and should be improved.

5. 5. Context-dependent efficiency

The output-oriented context DEA model was employed to stratify the observations. Indeed, the input-oriented model yielded the same results. The farm sample was therefore divided into the nine levels of efficiency (i. e. strata) until no observations remained under the production frontier. The emerged strata contained observations associated with different farming types. Therefore, it is possible to quantitatively and qualitatively analyse the distribution of the farms in terms of their relative efficiency. Table 5.9 below summarizes the distribution of observations across the levels of efficiency.

Table 5.9. The distribution of observations across levels of efficiency (per cent).

Farming types	Strata								
	1	2	3	4	5	6	7	8	9
Crop	7	10	12	15	37	10	6	3	1
Livestock	18	22	26	18	16				
Mixed	9	10	14	22	43	2			

The distribution of the efficiency scores can be described in terms of the strata, l, at which a certain observation became fully efficient, i. e. $\theta^{*}(k,l)=1$. Evidently, most of the observations fell into the 4^{th}-5^{th} strata (i. e. efficiency levels). However, some differences emerged among the farming types.

Specifically, some 37% of the crop farm observations were efficient at stratum 5, whereas another 15% were efficient at stratum 4. Some observations did also fall in the most extreme strata. As for the livestock farms, these were mainly concentrated within strata 2-3. However, these observations covered strata 1-5 in a rather even manner. Note that the extreme strata were not covered by observations associated with the latter farming type. Finally, the mixed farms were mainly concentrated in strata 4-5. Noteworthy, the mixed farms were rather compact in terms of their distribution across the efficiency levels (strata). The results thus showed that the livestock farms were dominating other farming types, i. e. most of these farms appeared on the lower-order strata associated with higher efficiency scores.

Identification of the underlying levels of efficiency (strata) enables one to quantify the differences in efficiency. Firstly, it is possible to analyse the efficiency scores obtained with respect to the first efficiency level, which, indeed, is the global production frontier. Fig. 5.5 presents the intervals of the (global) efficiency scores for each stratum. As one can note, livestock and mixed farms featured narrow ranges, whereas crop farms exhibited wider ones. Indeed, the minimal values of efficiency ranges were much lower for crop farms if compared to other farming types.

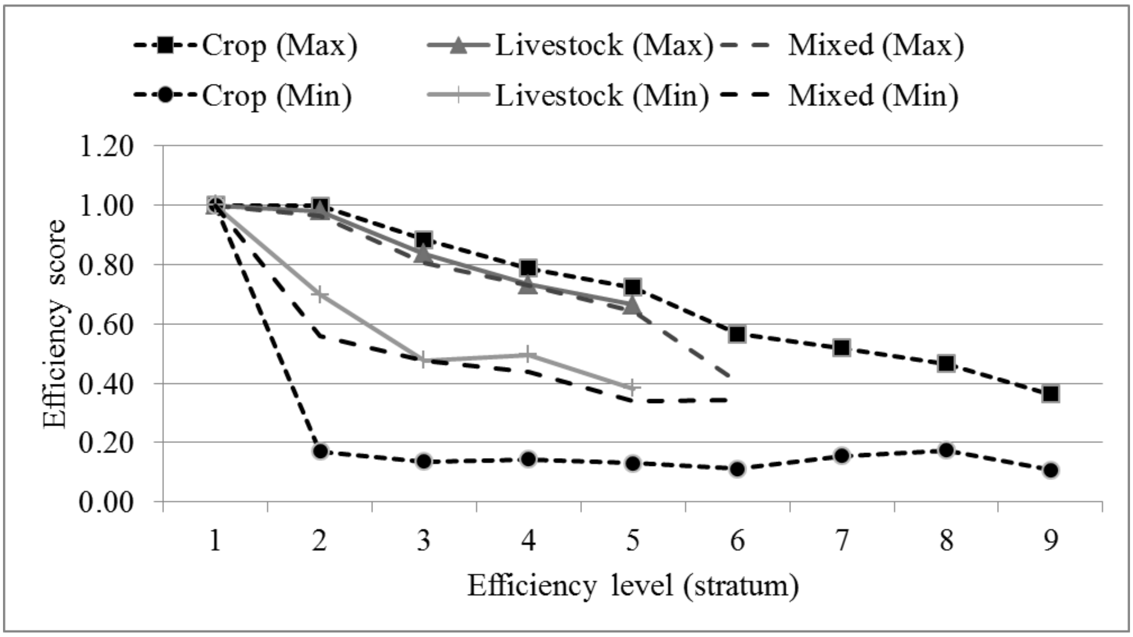


Fig. 5.5. The ranges of the inverse Farrell output efficiency scores across efficiency levels.

The carried out context-dependent data envelopment analysis grouped Lithuanian family farms into certain strata associated with different productivity levels. As a result, the crop farms were grouped into the nine strata associated with different levels of efficiency, the livestock farms were grouped into the five strata, and the mixed farms were grouped into the six strata. Therefore, the crop farms appeared to be the most heterogeneous in terms of efficiency and productivity.

6. CONSISTENCY CHECK

Up to now, the research employed the FADN data set for years 2004-2009. Indeed, the end of the said period coincides with economic turmoil. We therefore attempted to check the consistency of the obtained results by fitting models used in Sections 3.3 and 3.6 to the extended data set.

The extended data set contains the same variables as discussed in Section 2.4, yet the time span is increased to cover years 2004-2011. The extended data set is a balanced panel comprising 1304 observations in total.

Results of non-parametric regression are presented in Fig. 6.1. As one can note, these virtually re-iterate those depicted in Fig. 3.17. The only difference is an increase in crop farm efficiency. Anyway, livestock farming appear to be the most efficient on average. These differences might have been caused by both changes in relative performance and sample structure.

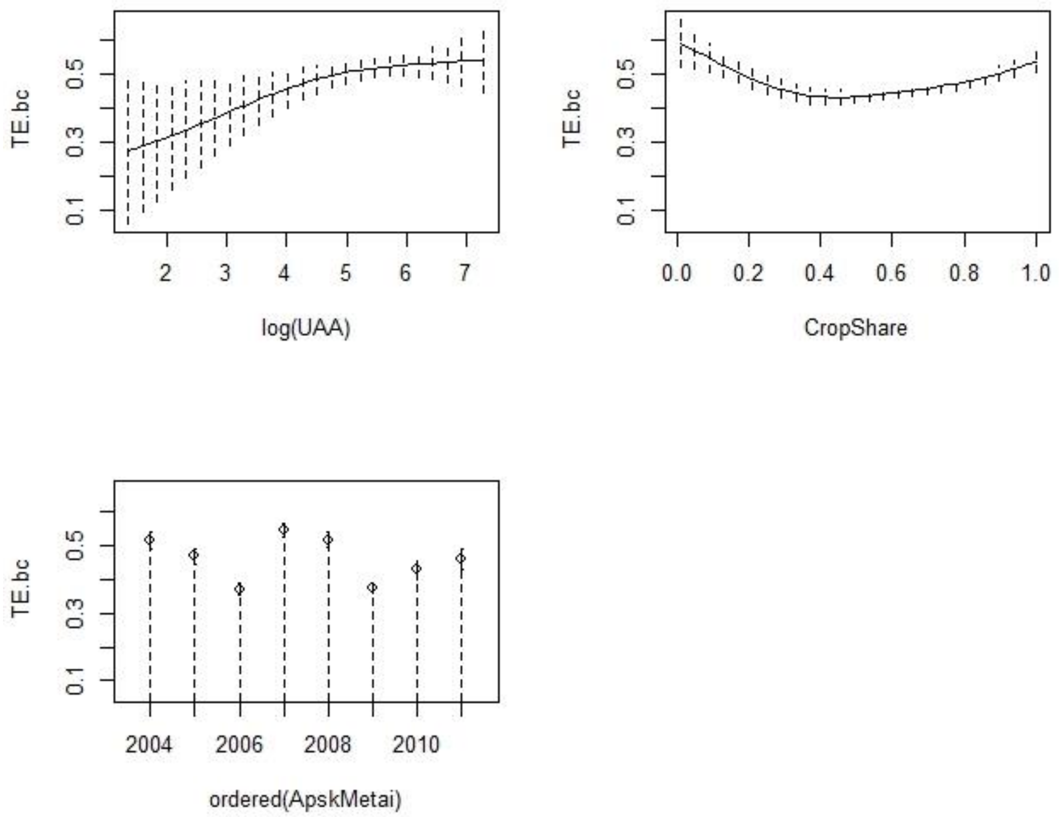


Fig. 6.1. Partial regression plots (2004-2011).

The following Table 3.13 presents the bandwidths and *p*-values. Obviously, all the variables were statistically significant at 1%.

Table 6.1. Results of non-parametric regression analysis (2004-2011).

	log(*UAA*)	*CropShare*	ordered(*Year*)
Bandwidth	1.447169	0.1780017	0.04444178
P Value	<.000 ***	<.000 ***	<.000 ***

Significance codes: *** – 0.001, ** – 0.01, and * – 0.05.

The double bootstrap analysis was also re-iterated with the extended data set. The resulting truncated regression's coefficients are given in Table 6.2. The new results can be compared against those in Table 3.14.

Table 6.2. Double bootstrap estimates for determinants of the farming inefficiency (2004-2011).

Variables	$\hat{\hat{\beta}}$	Sig.	Confidence intervals					
			$\alpha = .1$		$\alpha = .05$		$\alpha = .01$	
			BC_a method					
Time	0.175	***	0.114	0.240	0.103	0.256	0.082	0.280
UAA	-0.073		-0.240	0.095	-0.278	0.122	-0.331	0.177
Assets/AWU	-0.167	*	-0.361	-0.007	-0.397	0.024	-0.506	0.078
Crop	0.714	***	0.321	1.051	0.249	1.113	0.068	1.225
Subsidies	1.520	***	1.394	1.649	1.372	1.678	1.331	1.730
			Percentiles method					
Time	0.175	***	0.111	0.237	0.100	0.251	0.076	0.276
UAA	-0.073		-0.242	0.094	-0.278	0.119	-0.331	0.176
Assets/AWU	-0.167		-0.347	0.006	-0.381	0.032	-0.483	0.091
Crop	0.714	***	0.339	1.066	0.274	1.134	0.086	1.236
Subsidies	1.520	***	1.392	1.646	1.370	1.676	1.322	1.721

Significance codes: '***' - 0.01, '**' - 0.05, '*' - 0.1

Results obtained for the extended data set do not contradict to those based on the original data set. The only significant difference is a change in the direction of the time trend: The extended data set suggests a negative time trend. However, this can be a direct outcome of expansion of timespan. Farm size features a positive effect upon efficiency, yet the associated coefficient is no longer significant. The asset-labour ratio is also specific with the same direction of the relationship. However, it is insignificant according to the percentiles method. The remaining two variables, viz. crop share in the total output and production subsidy intensity, featured the same kind of relationships with the efficiency.

The carried out analysis suggests that the extension of the time series did not render decisive changes in the patterns of efficiency. We utilised models with exactly the same variables as it was the case with the original data set in order to ensure the comparability. Therefore, further analyses should attempt to apply the methodologies proposed in this thesis with the extended data set in order to reveal a possible impact of inclusion of additional variables into analysis.

7. RESEARCH LIMITATIONS

The time period of the research (2004-2009) should be extended in future researches. However, for this research we opted for the latter time-span due to the following reasons: 1) the FADN practice in Lithuania started on 2004; 2) the agricultural censuses were carried out in 2003 and 2010, thus the results of the research can be compared to those obtained during the censuses to a certain extent; 3) given the FADN sample changes every year, an increase in the time-span would result in a decreasing number of farms in a balanced panel (in this particular research we had 200 family farms, whereas increase in the time-span of two more years would decrease that number to some 160 farms). Yet the results have been validated by employing the extended data set covering years 2004-2011.

The carried out research assumes the same underlying technology for all farming types in order to ensure the comparability of the results. Even though this is not unusual in exploratory researches, the future studies could aim at estimating the specific frontiers for each farming type. In the latter setting the application of econometric methods (viz. SFA) is particularly appealing as the stochastic frontiers can account for various efficiency effects and thus ensure even deeper insights into the underlying technology.

Yet another shortcoming of the research lies in that it focuses on the family farms. Indeed, the corporate farms exhibit increasing importance in both the livestock and crop farming. Therefore, the avenue for further researches is definitely the analysis of the corporate farm performance. However, the FADN sample for corporate farms is rather small (some 40 observations per annum).

The present study analyses Lithuanian family farm performance. Indeed, the common market prevailing in the EU implies that agricultural sectors of the EU Member States are to compete in certain areas of production. Therefore, it is important to conduct the relevant analyses aimed at international comparisons.

CONCLUSIONS

1. Multi-criteria assessment of the agricultural sector performance based on the National Accounts data shows that the total factor productivity in the latter sector decreased after accession to the European Union. Indeed, the overall rank based on the multi-criteria assessment indicates that the agricultural sector falls within the last quartile of the analysed economic sectors. Therefore, there is a gap in the productivity of Lithuanian agricultural sector which needs to be filled in order to ensure a proper success in competition among the economic sectors for resources.
2. The carried out research showed that the technical inefficiency is the most important obstacle for productivity increase in Lithuanian family farms, whereas the scale inefficiency alongside the allocative inefficiency remained less important causes of overall inefficiency. However, the mixed farms featured the lowest scale efficiency thus indicating that farm size is particularly misbalanced for that farming type. Therefore, the public support should be streamlined to provide the mixed farms with means for further expansion or increase in specialisation.
3. Analysis of the efficiency factors implies that larger farms are more efficient, therefore the agricultural policy should pay more attention towards the rational farm structure in Lithuania. The crop farms appear to be less efficient if compared to the mixed or livestock farms. Therefore, the payment schemes need to be adjusted so that crop farms were not over-subsidised. Indeed, the increasing subsidy rate is associated with a decrease in efficiency. The latter finding once again stresses the need for further improvements in the support policy.
4. The proposed fuzzy Free Disposal Hull methodology shows that crop farms feature the largest spread of the fuzzy efficiency scores. Anyway, this lead to an unfavourable mean efficiency level in case of the highest degree of uncertainty. This finding implies that livestock farms perform better during the long run yet they achieve inferior results during the most favourable

periods for crop farming. Accordingly, the income support measures are particularly relevant for Lithuanian livestock sector.

5. The production frontier of the family farms moved outwards as a result of the technological progress during the research period (in case a sequential technology is assumed). Though the technical change contributed to increase in the total factor productivity, the efficiency change did not follow the same pattern. Indeed, the crop farms featured the lowest efficiency gains. These findings are supported by those obtained by the means of the fuzzy Free Disposal Hull. Innovative decision making units – family farms – were identified in terms of distance function and productivity index values. The results do indicate that livestock farms are more likely to become innovators pushing the production frontier outwards.
6. The analysis of program inefficiency indicates that crop farms are those defining the pooled production frontier. Therefore, they have the lowest values of input–specific program (farming type) inefficiency. Livestock farms are also partially determining the shape of frontier, whereas the mixed farms are determining the variable returns to scale frontier, but not the constant returns to scale one. The lowest program efficiency, hence, was observed for the mixed farms. Labour and assets are the two most problematic inputs in terms of program inefficiency for all farming types. Generally, the specialized farming appeared to be more efficient in terms of the program efficiency. Indeed, it is related to long-term and deeper acquisition of farming practice, which positively affects the quality of human capital. The results indicate that benchmarking and modernization currently are the most important issues for the crop and, partially, mixed farms. These measures should reduce the managerial inefficiency specific for these two types of farming.
7. The bias-corrected Malmquist index analysis indicates that crop farming is peculiar with land-using and asset-saving technical change (i. e. change in the marginal rate of technical substitution), whereas labour-using and intermediate consumption saving technical changes were observed only for

certain combinations of inputs. As for livestock farms these generally experienced intermediate consumption and asset saving technical changes against all the remaining inputs, whereas labour-saving and land-using technical change varied with the reference inputs. Finally, mixed farms can be considered as those peculiar with increasing land use and decreasing capital consumption. Therefore, asset use efficiency is likely to increase throughout the time ceteris paribus, whereas labour remains among the most inefficient factors of production.

8. The quantitative analysis of the returns to scale in the Lithuanian family farms suggests that the crop farms should be some 250 ha in size with labour force amounting to 3-3.4 AWU. The livestock farms should be smaller in terms of land (some 140 ha), albeit larger in terms of labour (4.3-4.5 AWU). The mixed farming features the optimal size 82-195 ha and 2.9-4 AWU. These findings do imply that the farm size limitations of 500 ha are not too restrictive with respect to Lithuanian family farms. These measures are based on neoclassical economic theory and therefore do not consider other dimensions of sustainability in an explicit manner.
9. The variance of efficiency among crop farms could be reduced by introducing and encouraging novel crop rotation schemes in less favoured areas. An additional measure for both crop and mixed farming could be optimization of the tractor power, which could affect the levels of intermediate consumption and assets. Cooperation and further mechanization can be given as the key recommendations for the livestock farms. A web-based benchmarking system of Lithuanian family farms would enable farmers to fathom relative level of their performance.
10. Further researches could focus on international comparisons based on growth accounting databases like EU KLEMS and the World Input-Output Database. Indeed, suchlike analyses would enable to identify the possible development paths for Lithuanian agriculture.

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Annex A. Abbreviations and initial data for multi-criteria assessment.

Table A1. Aggregates of Statistical Classification of Economic Activities (NACE Rev. 2) used in the research.

NACE code	Economic activity
A	Agriculture, forestry and fishing
B	Mining and quarrying
C10_TO_C12	Manufacture of food products, beverages and tobacco
C13_TO_C15	Manufacture of textiles, wearing apparel, leather and related products
C16_TO_C18	Manufacture of wood, paper, printing and reproduction
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22_C23	Manufacture of rubber and plastics products
C24_C25	Manufacture of basic metals and fabricated metal products, except machinery
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29_C30	Manufacture of transport equipment
C31_TO_C33	Manufacture of furniture; jewellery, musical instruments, toys
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycle
H	Transportation and storage
I	Accommodation and food service activities
J58_TO_J60	Publishing, motion picture, broadcasting activities
J61	Telecommunications
J62_J63	IT services
K	Financial and insurance activities
L	Real estate activities
M69_TO_M71	Legal and accounting activities; activities of head offices
M72	Scientific research and development
M73_TO_M75	Advertising and market research; other professional activity
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q86	Human health activities
Q87_Q88	Residential care activities; social work activities without accommodation
R	Arts, entertainment and recreation
S	Other service activities

Table A2. Decision matrix for multi–criteria decision making.

	1. Mean TE	2. CV (TE)	3. Mean TFP change	4. CV (TFP)
	MAX	MIN	MAX	MIN
A	0.739	0.180	0.953	0.169
B	0.775	0.160	0.957	0.094
C10_TO_C12	0.665	0.124	1.013	0.081
C13_TO_C15	0.676	0.171	0.985	0.087
C16_TO_C18	0.666	0.095	0.999	0.101
C20	0.731	0.302	1.076	0.180
C21	1.000	0.000	1.126	0.209
C22_C23	0.665	0.176	1.014	0.122
C24_C25	0.502	0.151	1.038	0.088
C26	0.407	0.249	1.054	0.144
C27	0.500	0.205	0.985	0.103
C28	0.580	0.144	1.022	0.123
C29_C30	0.614	0.190	1.031	0.101
C31_TO_C33	0.639	0.139	1.022	0.067
D	0.634	0.169	1.030	0.113
E	0.419	0.062	1.017	0.073
F	0.756	0.161	0.997	0.070
G	1.000	0.000	0.986	0.038
H	0.932	0.102	1.005	0.060
I	0.844	0.066	0.992	0.036
J58_TO_J60	0.585	0.115	0.967	0.098
J61	0.951	0.079	1.000	0.076
J62_J63	0.741	0.165	1.005	0.177
K	0.684	0.273	1.035	0.196
L	1.000	0.000	0.994	0.050
M69_TO_M71	0.956	0.067	1.022	0.118
M72	0.945	0.149	1.003	0.339
M73_TO_M75	0.833	0.094	1.035	0.059
N	0.626	0.121	1.030	0.106
O	0.805	0.051	0.997	0.103
P	1.000	0.000	0.998	0.095
Q86	0.796	0.036	0.997	0.077
Q87_Q88	0.633	0.230	1.018	0.135
R	0.513	0.140	0.999	0.125
S	0.857	0.167	0.951	0.169

Annex B. Partial regression plots for the output order-*m* efficiency measures.

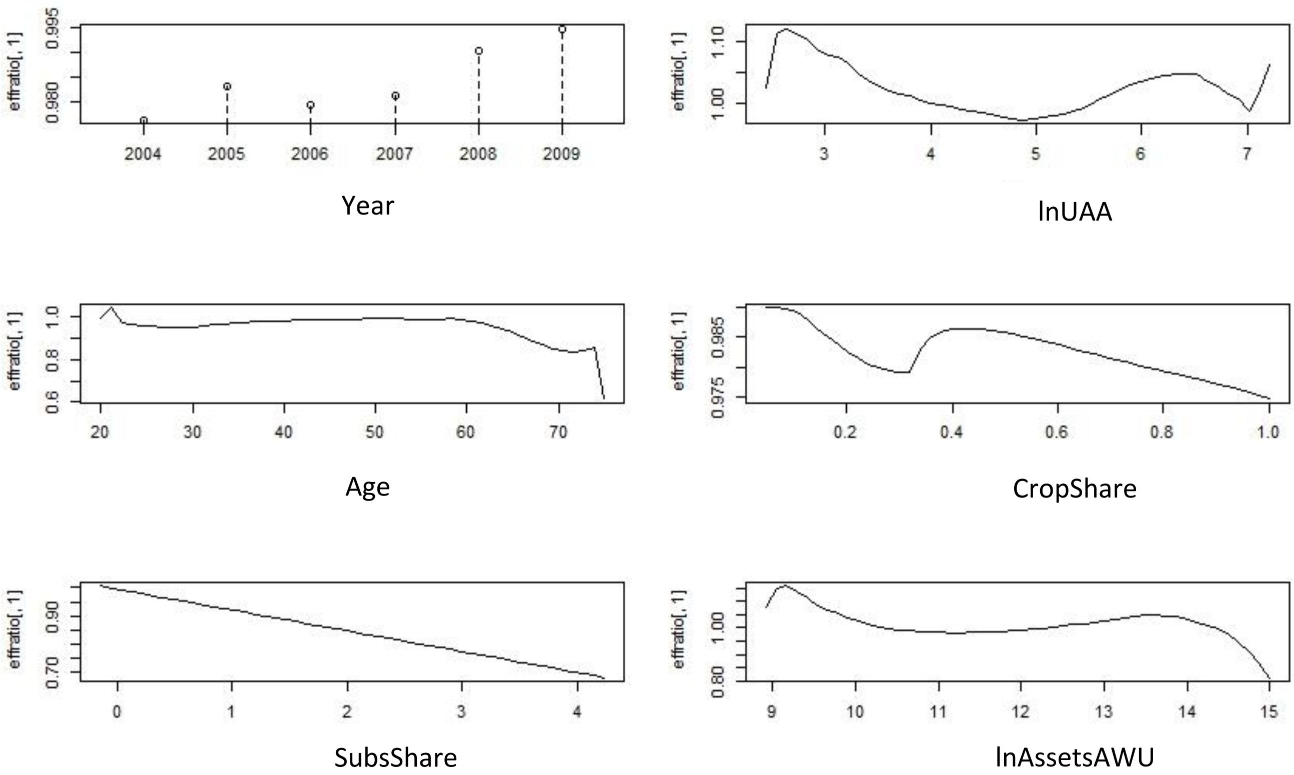

Fig. B1. Results of the non-parametric regression (variables held at the first quartile).

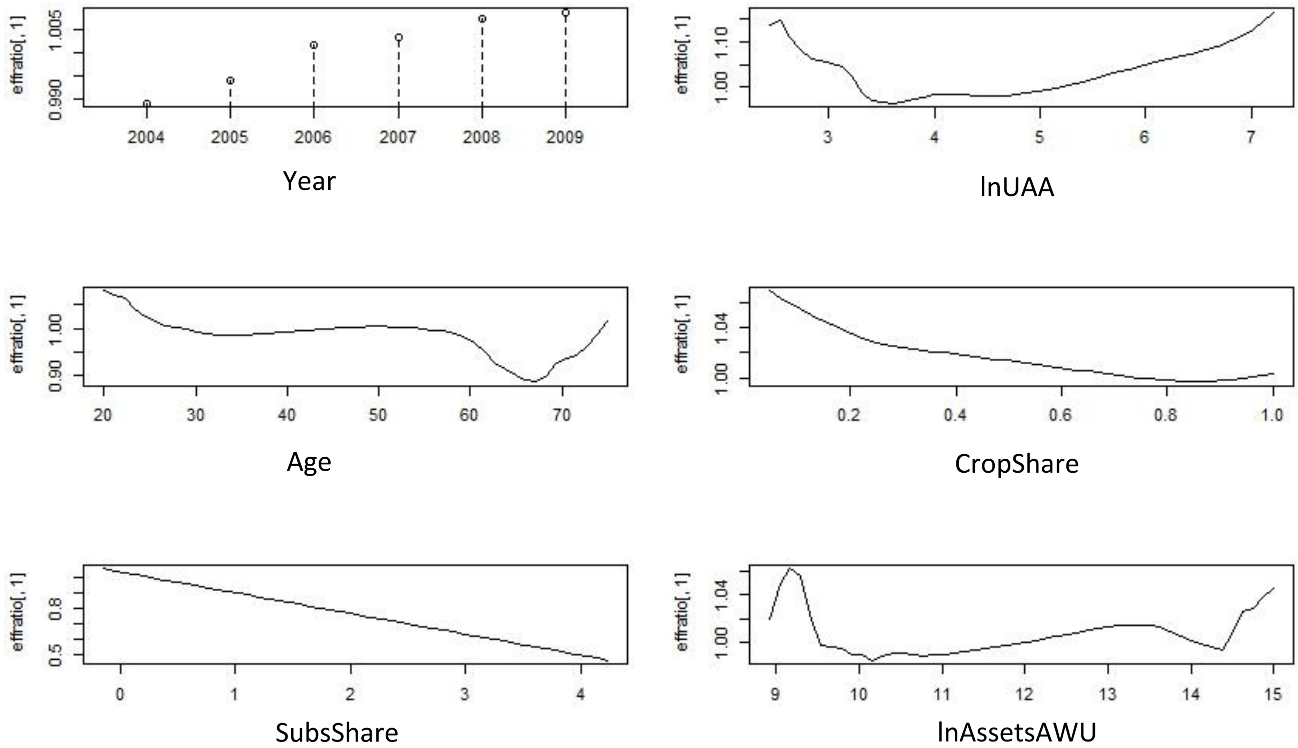

Fig. B2. Results of the non-parametric regression (variables held at their medians).

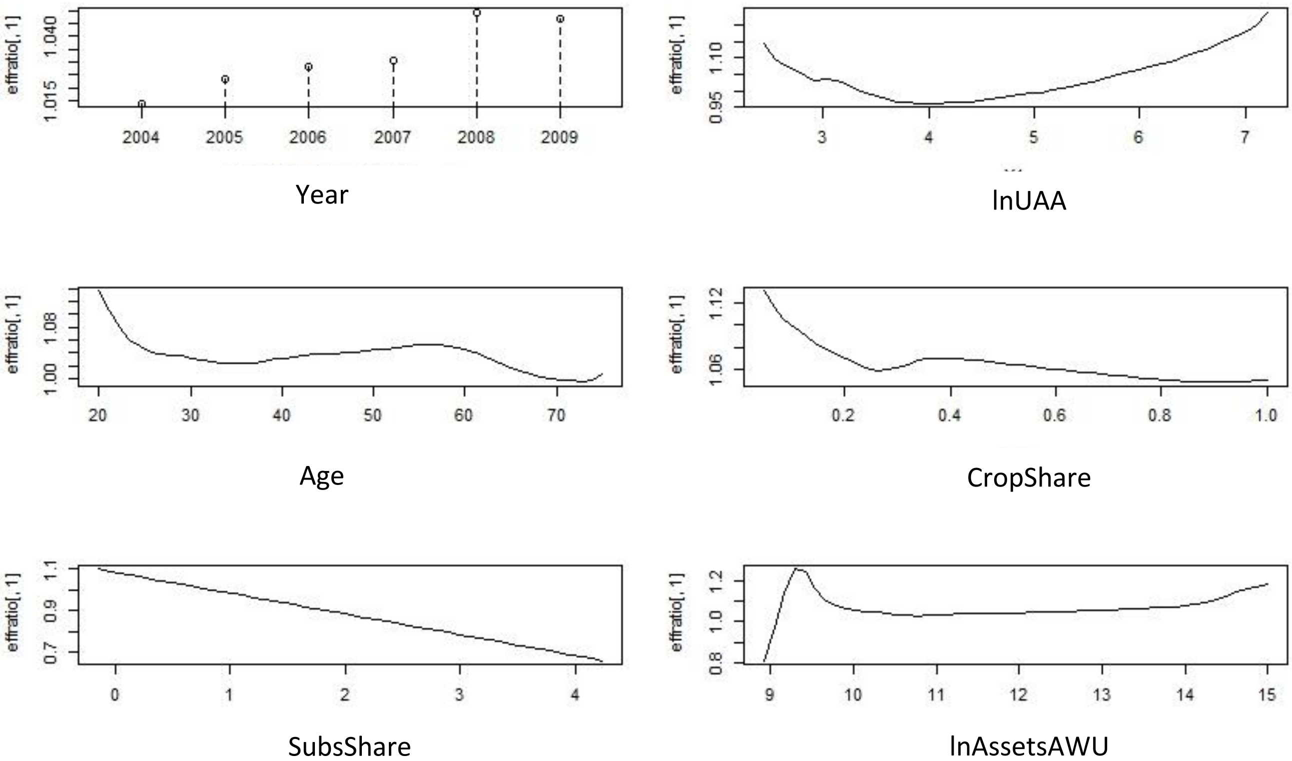

Fig. B3. Results of the non-parametric regression (variables held at the third quartile).

Annex C. Descriptive statistics.

Table C1. Descriptive statistics for input/output and context variables.

	UAA, ha	Labour input, AWU	Intermediate consumption, LTL	Assets, LTL	Total output, LTL	Age	Crop share	Subsidy share	Assets per AWU
					Average				
Crop	286	4	325853	949286	512539	47	0.96	0.33	269053
Livestock	130	4	224338	1031422	457454	46	0.23	0.24	241612
Mixed	122	3	142240	521821	237848	50	0.48	0.41	136315
Average	244	4	287793	897037	466648	47	0.81	0.33	246784
					Standard deviation				
Crop	234	3	325126	1129777	559449	9	0.08	0.38	271595
Livestock	89	2	195030	934411	398492	10	0.07	0.19	191573
Mixed	122	2	173447	753183	292032	11	0.09	0.42	124295
Average	220	3	302653	1072942	520993	9	0.28	0.37	251403
					Minimum				
Crop	13	1	11347	14900	5857.383	20	0.66	0.00	7450
Livestock	23	1	17440.15	75030.4	31164.4	32	0.05	0.08	26225
Mixed	12	1	12262.45	26985.46	10305.58	22	0.35	0.00	13493
Average	12	1	11347	14900	5857.383	20	0.05	0.00	7450
					Maximum				
Crop	1343	24	2366977	9573987	4305269	75	1.00	3.94	3244696
Livestock	381	13	1013102	4917426	1653348	71	0.34	1.44	1238746
Mixed	544	13	855155.7	5040197	1421075	74	0.66	4.23	884245
Average	1343	24	2366977	9573987	4305269	75	1.00	4.23	3244696

Table C2. Descriptive statistics of the efficiency measures.

	Unconditional	Conditional
Average	1.29	1.27
Min	0.69	1.00
Max	6.02	4.93
Standard deviation	0.51	0.42
Coefficient of variation	0.39	0.33