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Methods in Economic Farm Modelling

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Kurzfassung

Methoden zur ökonomischen Modellierung landwirtschaftlicher Betriebe

Die Arbeit untersucht und entwickelt Methoden zur Bewertung von landwirtschaftlichen Betrieben im Rahmen der Effizienzanalyse und zur Abschätzung von Anpassungsreaktionen induziert durch die Veränderung von politischen und wirtschaftlichen Rahmenbedingungen. Die Dissertation ist in vier Hauptkapitel gegliedert.

Im *Kapitel 2* wird die Methodik der Effizienzanalyse, bekannt unter dem Namen Data Envelopment Analysis (DEA) um den Ansatz zur Ableitung von Konfidenzintervallen erweitert, um die Aussagekraft der Effizienzmaße zu überprüfen. Die Bewertung und der Vergleich von landwirtschaftlichen Betrieben mit DEA sind in der Literatur häufig zu finden. Dabei werden die Ursachen von Ineffizienz oft mittels einer anschließenden Regressionsanalyse ermittelt. Die abgeleiteten Konfidenzintervalle zeigen jedoch deutlich, dass ohne Berücksichtigung der stochastischen Natur der Effizienzmaße kaum aussagekräftige Schlussfolgerungen über die wahre Natur von Ineffizienzen gegeben werden können.

Im *Kapitel 3* wird das Simulationsverhalten von mathematischen Programmierungsmodellen (MP) induziert durch die Veränderung von politischen und wirtschaftlichen Rahmenbedingungen untersucht. Im Gegensatz zur Anwendung auf einzelbetrieblicher Ebene, wo eine Spezifizierung des Modells durch vergleichweise viele Informationen erfolgen kann, sind Analysen zur Politikfolgenabschätzung häufig nur sinnvoll, wenn diese auf repräsentativen Betriebsgruppen basieren und damit aggregierte Effekte quantifiziert werden können. Zur Spezifizierung der entsprechenden Modelle stehen jedoch oftmals nur wenige Informationen zur Verfügung. Weiterhin besteht das Problem, dass wichtige Entscheidungsvariablen den beobachteten Werten entsprechen sollten, was als Kalibrierung des MP-Modells bezeichnet wird. Um dennoch MP-Modelle für repräsentative Politikfolgenabschätzung auf Betriebsebene nutzen zu können, sind positiv-mathematische Programmierungsmodelle (PMP), die mittels einer nicht-linearen Komponente der Zielfunktion das Model kalibrieren und das Simulationsverhalten mitbestimmen, entwickelt worden. Der Einfluss verschiedener vorgeschlagener PMP Methoden auf das Simulationsergebnis werden mit dem Betriebsgruppenmodel FARMIS quantifiziert und *ex post* mit beobachteten Werten verglichen. Dafür werden 45 Betriebsgruppen benutzt. Auf diese Betriebsgruppenmodelle werden die PMP-Kalibrierungsmethoden für das Jahr 1996/97 angewendet und beobachtete Deckungsbeiträge aus dem Jahr 2002/03 als Schock implementiert. Aus dem Vergleich wird ersichtlich, dass das Simulationsverhalten stark durch die Wahl des PMP Verfahrens bestimmt wird. Im *Kapitel 4* wird eine Schätzmethodik von

fruchtartenspezifischen Input Koeffizienten in MP-Modellen entwickelt. Fehlende Daten über die Inputallokation auf Fruchtartenebene, wie zum Beispiel der Düngemitteleinsatz im Weizen oder die Höhe der Pflanzenschutzaufwendungen in der Zuckerrübenproduktion, sind ein Problem bei der Spezifizierung von aggregierten Betriebsgruppenmodellen. In Buchführungsergebnissen werden nur die Gesamtaufwendungen im Betrieb dokumentiert. In aggregierten MP-Modellen spielt die explizite Darstellung der Input Allokation jedoch eine immer wichtigere Rolle, um Umwelteffekte, wie zum Beispiel den Stickstoffeintrag aus der Landwirtschaft, abbilden und daraufhin Alternativen modellieren zu können. In der Vergangenheit wurden Input-Mengen entweder *ad hoc* von Informationen aus Bewirtschaftungs-handbüchern auf alle Betriebsgruppen übertragen oder von den Gesamtinputmengen aus Betriebsabschlüssen eine Input-Output Regression geschätzt. Der in dieser Arbeit vorgestellte Ansatz kombiniert die Regression mit der Schätzung des MP-Models basierend auf einzelbetrieblichen Daten. Der entwickelte Schätzansatz wird auf belgische Buchführungsergebnisse angewandt, die Informationen über die Input Allokation auf Fruchtartenebene zur Evaluierung der Ergebnisse enthält. Im Vergleich zur Regression lassen die Ergebnisse erkennen, dass der Schätzansatz die Beobachtungswerte besser widerspiegelt. *Kapitel 5* präsentiert ein Betriebs-gruppenmodell für die EU-27 und ein dafür entwickelten Schätzansatz zur Konsistenzrechung der CAPRI Datenbank (Common Agricultural Policy Regional Impact) und der Daten der Europäischen Betriebsstrukturerhebung (FSS). Der Schätzansatz basiert auf Daten der FSS, die aus mehreren Gründen inkonsistent mit den Daten von CAPRI sind. Ein möglicher Weg die Konsistenz zu erreichen, könnte eine lineare Skalierung der Betriebsdaten sein. Als Folge könnte jedoch die Betriebsgruppenstruktur aus FSS (Betriebsgruppentyp und -größe) verloren gehen. Um dieses Problem zu umgehen wurde für das Betriebsgruppenmodell eine Methode zur betriebstypen- und betriebsgrößenkonsistenten Schätzung entwickelt. Ein Vergleich mit der linearen Skalierungsmethode zeigt, dass die entwickelte Methode einer einfachen Skalierung vorzuziehen ist, weil damit sichergestellt werden kann, dass die Betriebsstrukturinformationen von FSS in den geschätzten Betriebsmodellen erhalten bleiben.

Abstract

Methods in Economic Farm Modelling

The objective of this thesis is to develop methods for the evaluation of agricultural firms using efficiency analysis and to develop and assess farm responses in mathematical programming (MP) models to changing political and economic conditions. The dissertation is structured in four main parts.

Chapter 2 extends Data Envelopment Analysis (DEA) by incorporating confidence intervals in the evaluation of the resulting point estimates. In the literature, agricultural farms are often evaluated and compared based on DEA, where causes of inefficiencies within a farm group are often analysed by regressing efficiency measures on other variables. However, when confidence intervals are taken into account, the results of this analysis show that neglecting the stochastic nature of efficiency measures cannot produce any valid conclusions about the real nature of inefficiencies. Hence, DEA efficiency measures need to be carefully interpreted, and further research is necessary before this methodology can be used as a standard approach for evaluating the efficiency of farms and other firms.

Chapter 3 analyses the responses of MP farm group models induced by a change in political and economic conditions. MP models are widely used as decision models in agricultural economics. In contrast to an application on the farm level with considerable modelling detail, an analysis of macroeconomic effects is often only reasonable if it is based on representative farms. However, only sparse information is available for the specification of aggregated representative farm groups. Furthermore, decision variables should reflect observed behaviour through a process known as calibration of MP models. Positive Mathematical Programming (PMP) has been developed for this purpose, a method that calibrates the objective function with the help of a non-linear costs component and determines simulation behaviour. The influence of the different proposed PMP variants on simulation results is compared *ex post* with observed values using the representative farm model FARMIS. This is done through 45 farm groups; these data were obtained from the German Farm Accountancy Data Network (FADN). Based on these farm groups, PMP calibration methods are applied for the year 1996/97, and a shock is introduced for observed gross margins of 2002/03. Comparison of the calibration methods reveals that the simulation strongly depends on the PMP method applied.

Chapter 4 develops an estimation method for the specification of crop-specific input coefficients in MP models. The lack of information about input allocations for different crop levels, *e.g.*, fertiliser inputs for wheat or the level of pesticides used for sugar beets, provides a challenge for the specification of aggregated farm type models. In farm accounting records available for farm group models, often only total inputs per farm are reported. In aggregated MP farm type models, the explicit

representation of input allocation plays an increasingly important role, for example in the representation of environmental effects such as nitrogen intake, and subsequently in the modelling of policy alternatives. In the past, crop-specific inputs were either implemented *ad hoc* in MP models based on management handbooks, or were based on total input levels that were estimated with input-output regressions. This chapter presents an approach that combines the regression approach with the estimation of a farm supply model using single farm data. The relationship between the MP and the linear regression model is defined, and an estimation approach based on the optimal condition of the farm is presented. The developed estimation approach is applied to Belgian FADN data, where input allocations for various crop levels are collected in the database. A comparison of observed and estimated data is possible to validate the suggested method. The results show that the developed estimation approach successfully models the observed values of input allocation, in contrast to the regression estimation. Furthermore, this approach leads to a crop-specific breakdown of variable inputs and a representation of the resulting farm type with a fully specified non-linear component.

Chapter 5 presents the farm type module developed in the modelling system CAPRI (Common Agricultural Policy Regional Impact). The integration of farm types into the modelling system CAPRI provides the chance to directly quantify the effects of market policies and developments on the farm level and to reduce the aggregation bias, resulting in an improved localisation of farm type related environmental effects. The farm types in CAPRI are based on data from the European Farm Structure Survey (FSS). For several reasons, these data are not consistent with the CAPRI database. One possible way to overcome these inconsistencies would be a simple linear up- and down-scaling of FSS to the quantity structure of the CAPRI database. However, this method could lead to a loss of information about the type and size of the farm group from FSS. To avoid this effect, an estimation approach is developed covering EU-27 that does not violate the type of farming or the economic size of the farm types.

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Chapter 1. Introduction

1.1 Background

The Common Agricultural Policy (CAP) of the European Union led to increased agricultural production in Europe during the 1960s and 1970s, resulting in structural overproduction, expensive storage costs, and negative environmental effects. In the 1980s, the EU began systematic reforms to remove overproduction, consider negative impacts on the environment, and avoid dumping excess production into world markets. At the beginning of the 20th century, the CAP increased its focus on externalities of agricultural production and the contribution of the farming sector to rural development. To satisfy legally required impact assessments (IA) of the European Commission (COM, 2002) and also to support national governments, the research community developed and applied tools to support and accompany the policy-making process. Multi-commodity country-specific models such as those reported in Banse et al. (2004), OECD (2007), and Bartova et al. (2007) were complemented with regionalised assessment tools (see, *e.g.*, Britz & Witzke, 2008; Gömann et al., 2007) as responses to the CAP movement from price to direct income support. However, regionalised supply models consider all farms in a region as a territorial aggregation, which can lead to bias given the evolution and growing importance of policy instruments and legislation and their differential impact depending on individual farm characteristics such as farm revenues, herd sizes, stocking densities, or fertiliser applications. To account for the heterogeneity in the agricultural sector and to be able to conduct IA to evaluate the consequences of policy implementations on the farm level within the various farming systems across Europe, *methods in economic farm modelling* were developed. Economic farm modelling is based on micro-level data on agricultural firms, and differentiates decision-makers through properties such as crop patterns, type of farming, animal density, economic size, and legal form. The development and evaluation of farm tools for IA requires a great deal of data to represent the heterogeneous structure of the farming level and to infer information on input-output relationships and income. Official statistics for agricultural farm level analysis mainly come in two forms. The first is the Farm Structure Survey (FSS), which aims to survey the structure of agricultural holdings. This survey contains country and regional level information on land use, animal head sizes, and the work force. This survey is available from Eurostat and is collected every three years as a sample survey and every ten years as a complete survey. The second data source is the European Commissions Farm Accountancy Data Network (FADN), which collects accounting information at the farm level and is the most important source when conducting country-wide farm related IA. The European FADN is collected annually and is sourced by national accounting data. The two databases are accessible for developing policy IA tools under specific rules that regulate the transmission of data, subject to statistical confidentiality.

1.2 Objectives and methodological approaches

Against this background, the aim of this dissertation is to contribute to the research field of economic farm modelling by developing methods that improve tools for IA of the CAP in Europe. The thesis gives special attention to four different methods in farm economics. The first method deals with the problem of measuring and comparing the performance of farmers, given that a farm produces more than one output and uses more than one input. The heterogeneity of the farming system with respect to the composition and economic size of an individual farm makes it difficult to differentiate economic performance. Data Envelopment Analysis (DEA) as a frontier method defines an efficiency score for a farm relative to the best farms in the sample. The objective of the study is to answer whether DEA as a non-parametric approach yields robust efficiency rankings with respect to statistical significance (Chapter 2). A further topic of this thesis is the assessment of the impact of different calibration methods on the explanatory power of mathematical farm group models, which are often superior to econometric estimated models because they are better able to include policy instruments such as quotas and environmental restrictions (Chapter 3). However, these models need to be calibrated, using Positive Mathematical Programming (PMP) methods. Also, problems of missing information and inconsistent databases arise. One research question results from the lack of information on the input allocation per enterprise. Since input allocation is not available, this study aimed to develop a possible extension of the standard linear regression approach to estimate the input allocation (Chapter 4). Methodological development is also required when confronting the inconsistencies in data sources that are often caused by the statistical confidentiality regulations or by differences in time dimensions and definitions (Chapter 5). The objectives and the methods used to accomplish them are briefly introduced in the remainder of this section.

1.2.1 Efficiency analysis with DEA

In efficiency analysis, each farm receives an efficiency score relative to the best practice, represented by a frontier (Farrell, 1957). There are two main techniques used to estimate the frontier and to calculate the efficiency score - namely, the stochastic frontier approach and DEA. The former uses statistical methods to estimate the frontier and the latter uses mathematical programming to calculate efficiency scores compared to the best observed praxis. The efficiency score is a performance indicator. Often, a second stage regression of those scores on explanatory variables such as off-farm earnings and tenure status is used to identify the reasons for the efficiency or inefficiency. The DEA methodology is a technique widely used in agricultural applications. The importance of performing statistical inference on efficiency scores is concerned applying Simar & Wilson's (2004) smoothed homogeneous bootstrap procedure to investigate bias, variance and confidence intervals for the attained DEA efficiency scores. Based on confidence intervals for efficiency scores, the effect of input aggregation and returns to scale on the efficiency ranking is demonstrated using a statistic that facilitates a comparison of the quality of the efficiency rankings.

1.2.2 Response behaviour of PMP methods

Heckelei & Wolff (2003) have analytically shown the arbitrariness of the response of PMP calibration methods for MP models. Against this backdrop, the effect of the PMP calibration method on the supply response is investigated using the German wide farm model FARMIS[1] in an *ex post* framework. The resulting response of the different calibration methods is compared to the observed behaviour. The approach uses 845 identical farms over eight years from the German FADN; these farms were aggregated into 45 farm groups. The groups are calibrated for the accounting year 1996/97, and the observed gross margins from the year 2002/03 were applied as impacts. All investigated calibration approaches rely on the assumption that an observed production activity of a farm group is the result of profit maximising behaviour. The production economic criterion - marginal revenue equals marginal cost - is used to derive the calibration parameters for the PMP approach. When the PMP methodology was published by Howitt (1995), only the diagonal elements of the additional cost matrix were identified. The first three PMP calibration methods considered in this investigation belong to that group of calibration approaches, and were introduced by Howitt & Mean (1983), Paris (1988), and Helming et al. (2001). The other calibration approaches try to recover cross-activity relationships. The literature has already provided some examples (Paris & Howitt, 1998; Heckelei & Britz, 2000). For this *ex post* assessment, the maximum entropy techniques proposed by Paris & Howitt (1998) are considered. Furthermore, a method proposed by Heckelei & Wolff (2003) to estimate rather than calibrate the model based on the first order condition, is presented for a selected farm group. Although Jansson (2007) applied a similar method using Bayesian estimation with sector data, this approach represents the first use of time series data from FADN while employing General Maximum Entropy (GME) as an estimator.

[1] see Offermann et al., 2006; Hüttel et al., 2006; Isermeyer et al., 2005; Kleinhanß et al., 2006

1.2.3 *Input allocation problem*

The ability to explicitly define input demand per activity is one advantage of MP models compared to econometrically estimated farm models with implicit representations of input demand. Additionally, the link between economic models and explicit bio-physical models makes the reliability of input coefficients such as fertiliser and pesticide application rates per crop very important. While official statistics provided in FADN unfortunately do not contain information about the input allocations for production activities, FADN does offer data on the total farm or sector purchases of various input categories. The total amount of inputs per farm and the output per crop were often used to estimate the input allocation for activities by using linear regression (Errington, 1989; Ray, 1985; Midmore, 1990; Léon et al. 1999). Thus, crop-specific inputs in supply models are rarely based on real observations, but instead are estimated before the actual supply model is set up. This regression approach is extended by proposing and applying an innovative estimation approach for farm group programming models using GME. The proposed set-up simultaneously determines the cost function parameters and the input allocations for production activities. This methodology is applied to Belgium FADN data on arable farms, for which the available input allocations allow for a validation of the estimation approach.

1.2.4 *Consistent disaggregation of a sector model into farm types*

Disaggregation of the supply models of the Common Agricultural Policy Regional Impact model (CAPRI) into farm group models was previously performed by Adenäuer et al. (2006a, 2006b). The major disadvantage of this approach is that during the disaggregation, the farm group data, previously derived from FADN and used as disaggregation information, could lose the characteristics of the type of farming and economic size because regional sectors had to be disaggregated as consistent break-down. This is necessary for maintaining a harmonised database across scales, which allows for an iterative link between supply and market modules. A comparison of the differences between FADN and FSS in comparison to the sector model data has shown that FSS fits the sector model data better. Therefore, an estimation approach is developed to smoothly integrate the information from FSS with the top-down disaggregation approach. FSS is a well-established statistical database that is harmonised across Europe and has suitable coverage by farm type. However, even when using FSS, which itself underlies as source of many of the regional statistics for CAPRI, there are still inconsistencies when compared with regional CAPRI data. First, regional models consider a three-year average, whereas FSS is available for different Member States and different years, so that no three-year average is available. Additionally, regional supply models deviate from official statistics because they are already consistent (*e.g.*, closed market balances), complete (*i.e.*, data gaps have been filled using econometric routines), and harmonised over time with regards to product/activity classifications (*e.g.*, aggregation of the cheese or wheat market commodities). Furthermore, regulations on statistical confidentiality define the transmission of FSS data. Specifically, all FSS data on farm groups used as disaggregation information are rounded to the tenth digit, and individual farm data, which accounts for more than 80 percent of a variable, is deleted from the farm group. Production statistics in CAPRI thus differ slightly compared to the original statistics. Therefore, deviations exist between sector models and matching annual FSS data. These inconsistencies in the data could be easily removed by multiplying each production level in FSS with a variable-wise correction factor that is calculated from the given regional level and the sum of the farm types from FSS. However, this approach could first lead to a violation of political requirements for set-aside in the farm groups. Second, and more importantly, correction of activity levels could change the farming patterns such that a different type of farming or a different economic size results. The resulting farm types would no longer represent the actual farming structure observed in FSS. Last but not least, these changes could generate unrealistic farm programs. To avoid this, it is necessary to replace the simple scaling approach with a statistical estimator that ensures regional consistency and compliance with set-aside obligations but prevents changes in the type of farming and economic size of the farm groups. We propose the application of a Bayesian motivated estimation framework that treats the available FSS disaggregated information as a random variable. The disaggregated data provides prior information composed of consistency and definition based conditions. The combination of these parameters provides posterior estimates that fulfil the top-down disaggregation requirement while exhausting the information content of the FSS data. As result the farm type models in CAPRI have two unique attributes. First, the reduction of the aggregation bias leads to more profound impact assessments for farm and agri-environmental related policy changes and reduces the difficulty in bridging results from very highly aggregated models and bio-physical models. Second, the integration of farm types in CAPRI, compared to a standalone farm type approach, gains from endogenous price feedback through the global market model in CAPRI, and enables a direct assessment of the effect of EU-wide market policies on farming systems.

1.3 Structure of the thesis

This thesis contains six chapters. Chapter 1 outlines the background, the objective, and the methodological approaches.

Chapter 2 begins with a review of the concept of efficiency, explains the bootstrapping approach, outlines the smoothed bootstrap approach for deriving confidence intervals in Section 2.2, and introduces model specification and summary statistics in Section 2.3 that are used to measure the degree of overlapping confidence intervals. Section 2.4 then discusses the estimation results. The final section concludes and points to promising future research opportunities. The author's interest in the research topic of this chapter began during his study at the Imperial College at Wye, where his master's degree focused already on DEA methods. The work presented in this chapter and the resulting publication is mainly the outcome of the work the author did during his time at the von Thünen Institute (former FAL) Institute for Farm Economics in Braunschweig. The paper of this chapter has been published as Gocht & Balcombe (2006) in Agricultural Economics.

Chapter 3 investigates the response behaviour of selected PMP approaches using an *ex post* framework on German FADN time series data from 1996/97 to 2002/03. After the introduction, Section 3.2 explains the concept of PMP and points out the methodology used to calibrate MP farm models to observed production. The following Section 3.3. describes the *ex post* approach by first describing the methods used to calibrate the parameters of the cost function, and then introduces the data and discusses implementation of the calibration methods. Afterwards, Section 3.4 discusses the findings and conclusions are drawn in Section 3.5. This chapter is a modified version of Gocht (2005) published as part of the proceedings of the 89th European Seminar of the European Association of Agricultural Economists. Although relevant literature that emerged after this article's publication was included in the current chapter, the *ex post* evaluation was not further developed since publication.

Chapter 4 proposes and applies an innovative estimation approach for farm group programming models using GME. After the introduction Section 4.2 reviews the literature. Section 4.3 presents the derivation of the conceptual farm group model. Section 4.4 develops the empirical model based on the aforementioned discussion, introduces the data, and describes the estimation approach. A discussion about Non-sample information is also included. Section 4.5 evaluates how the simultaneous estimation of input allocations and behavioural models compares with a separate linear regression, as employed in the literature. The results are discussed with respect to the resulting input allocation and the fit of the behavioural model. Furthermore, a sensitivity analysis of the results is performed in order to validate the support point design. Section 4.6 concludes the chapter and discusses further promising research directions. A prior version of this work was presented at the 107th EAAE Seminar by Gocht (2008). The current version of the chapter was developed with T. Heckelei and submitted to the Journal of Agricultural Economics.

Chapter 5 motivates and explains the EU-wide farm type model in CAPRI through its characterisations and develops an estimation approach to consistently disaggregate the sector models in CAPRI into farm type models using FSS. The chapter starts with an introduction and continues with the motivation for the development of the model with respect to agricultural policy. Section 5.3 discusses the characteristics of the farm types in CAPRI. The disaggregation problem is outlined in Section 5.3.1, which follows a detailed discussion on the layout of the disaggregation estimator by starting with data constraints before defining the estimator. Section 5.5 presents the FSS data and presents a comparison to FADN data. Section 5.6 analyses the extent to which the proposed estimator leads to an improved presentation of the farming structure by comparing the finding to a fixed variable-wise number scaling approach. Section 5.7 discusses the results and draws conclusions. A report about the farm types in CAPRI will be available in Gocht (forthcoming). Furthermore, Adenäuer et al. (2006a) and Adenäuer at al. (2006b) are prior studies closely related to the work presented in this chapter. The paper of the chapter was written with W. Britz (University of Bonn) and has been submitted for a special issue organised by JRC-IPTS Seville for the Journal of Policy Modelling.

At the end Chapter 6 concludes and identifies areas worth further investigation.

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Chapter 2. Ranking efficiency units in DEA using bootstrapping an applied analysis for Slovenian farm data*

Abstract

This article explores how data envelopment analysis (DEA), along with a smoothed bootstrap method, can be used in applied analysis to obtain more reliable efficiency rankings for farms. The main focus is the smoothed homogeneous bootstrap procedure introduced by Simar and Wilson (1998) to implement statistical inference for the original efficiency point estimates. Two main model specifications, constant and variable returns to scale, are investigated along with various choices regarding data aggregation. The coefficient of separation (CoS), a statistic that indicates thedegree of statistical differentiation within the sample, is used to demonstrate the findings. The CoS suggests a substantive dependency of the results on the methodology and assumptions employed. Accordingly, some observations are made on how to conduct DEA in order to get more reliable efficiency rankings, depending on the purpose for which they are to be used. In addition, attention is drawn to the ability of the SLICE MODEL, implemented in GAMS, to enable researchers to overcome the computational burdens of conducting DEA (with bootstrapping).

JEL classifications: C15, D31, Q10

Keywords: Data envelopment analysis; Bootstrapping; Agriculture; Technical efficiency; Confidence intervals; Slice DEA model; GAMS

2.1 Introduction

Data Envelopment Analysis (DEA) is a potentially useful technique for measuring efficiency. But some concerns need to be addressed before DEA can be accepted as a routine tool in applied analysis. Since DEA is an estimation procedure which relies on extremal points, it could be extremely sensitive to data selection, aggregation, model specification and data errors. These points must be borne in mind when investigating the efficiency of farms. Since DEA is a technique which is widely used in agricultural applications, this paper aims to show the importance of performing

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statistical inference on efficiency scores in that context, because the performance of farms can be heavily influenced by measurement errors and effects like weather, shocks and diseases. Furthermore most agricultural scientists have ignored the sampling noise in DEA estimates, despite the growing literature on the statistical properties of DEA estimators.

Therefore, this paper addresses how the Simar and Wilson (SW) smoothed homogeneous bootstrap procedure[1] can be used to investigate bias, variance and confidence intervals for the attained efficiency scores in order to get more reliable efficiency rankings. Based on the confidence intervals for the efficiency scores, it is demonstrated how the choice of input aggregation and returns to scale affect the ranking of the Decision Making Units (DMU). A Slovenian data set will serve as the background against which these issues are discussed. To analyse the findings, a statistic called coefficient of separation (CoS) is introduced, which facilitates a comparison of the quality of the efficiency rankings for the sample farms used in the investigation. In addition, attention is drawn to the ability of the SLICE model, implemented in GAMS, to enable researchers to overcome the computational burdens of conducting DEA (with bootstrapping).

The article is structured as follows: in Section 2.2, the "concept of efficiency" is introduced briefly along with some history regarding DEA analysis. Further, the statistical model and the smoothed homogeneous bootstrap procedure are reviewed briefly. In Section 2.3, the data, the model specifications and the methods used to compare the findings are introduced. Finally, the findings are discussed in Section 2.4, along with implications for the practical implementation of DEA. At the end, conclusions are drawn and areas worth further investigation are identified.

2.2 Methods

2.2.1 The concept of efficiency

The concept of economic efficiency is generally assumed to consist of two components: technical efficiency and allocative efficiency. Broadly, the former is defined as the capacity and willingness of an economic unit to produce the maximum possible output from a given bundle of inputs and technology. The latter is defined as the ability and willingness of an economic unit to equate its specific marginal value

[1] Bootstrap procedures suggested by Ferrier and Hirschberg (1999) or Löthgren (1998) are not taken into account, because SW (1999a, 1999b, 2000) have shown that these procedures give inconsistent estimators.

product with its marginal cost. Farrell (1957) developed an isoquant method to measure efficiency in frontier models. He suggested either the use of a nonparametric piecewise linear convex isoquant or the use of a parametric function fitted to the data in a way that no point should lie to the left of or below the frontier.

Farrell (1957) introduced technical efficiency as a relative notion, relative to best-observed practices in the group. To get the "relative" technical efficiency of the *k*th firm, we have to calculate the actual output divided by the maximum feasible observable output. Because the actual output is observable, the maximum output must be estimated. To get the maximal output, there are different methods.

The majority of early economists followed a parametric approach. However, economists at Berkeley advanced a programming approach for piecewise linear frontier production functions that went largely unnoticed by the research community (Forsund and Sarafoglou, 2002).

Charnes et al. (1978) (CCR) showed that the Farrell unit isoquant model was a special case of the ordinary linear programming problem. At first, in operational research and management science, but later also within economics, CCR started a new active research field, popularly called DEA. For the applied economists, the great advantage compared to the aforementioned frontier approaches was the possibility for using multiple outputs in a primal approach. DEA encompasses a variety of related models for evaluating performance of the DMU. Another advantage of the DEA approach is that it places no restrictions on the functional form of the frontier and it does not impose any (explicit) distributional assumption on the firm specific efficiency. DEA can accommodate multiple outputs and inputs but is extremely sensitive to variable selection and errors.

DEA focuses on deriving results for each DMU. On the other hand, the stochastic frontier analysis (SFA) approach, as originally proposed by Aigner et al. (1977) and subsequent refinements (e.g., the Bayesian Frontier Approaches in Fernández et al., 1997, 2000, and classical approaches in Coelli et al., 1998), of this model can test hypotheses about the underlying technology and determinants of efficiency. Banker (1996) and Grosskopf (1996) collectively provide a survey of statistical inference on nonparametric, deterministic, linear programming-based frontier models. Several researchers have tried to compare results of applications of different estimation methods based on the same set of data. De Borger and Kerstens (1996) and Bauer et al. (1998) attempt to give guidelines about what sort of methodology should be employed. Banker et al. (1985), Sharam et al. (1999), and Plessmann (2000) compared DEA with other estimation methods, whereby the structure of production was unknown. Gong and Sickles (1992) utilized Monte Carlo techniques to control the underlying technology and compared SFA with DEA. The overarching conclusion is that if the functional form is close to the underlying technology, SFA outperforms DEA. However, DEA seems to be more appropriate when the knowledge about the underlying technology is weak (Kalirajan and Shand, 1999). The practical advantage of dealing with multiple outputs is also very real. While stochastic frontier multiple-output "distance functions" have been estimated in the literature (Morrison Paul et al., 2000), the choice and use of appropriate instruments to deal with problems of endogeneity has not been sufficiently addressed.

From these surveys, it becomes evident that for DEA to be viewed as a true competitor to SFA, point estimates of efficiencies are not enough. Fortunately, there is now a considerable body of research that has characterised the statistical property of DEA estimators. SW (1998) proposed a general methodology for bootstrapping in frontier models to conduced confidence intervals, and in subsequent articles (e.g., SW, 2000a, 2000b) the method has been further elucidated and developed. More recent work has also examined the properties of two-step estimators explaining efficiency and adaptations of the standard bootstrap (SW, 2003). However, the question of which method, SFA or DEA, is the best very much dependent on the nature of and knowledge about the data-generating process (DGP). Without a priori knowledge of the DGP, a nonparametric approach such as DEA would seem to have distinct advantages, since the constraints that it imposes on the technology are arguably less severe than parametric methods. Nevertheless, the choice of DEA does not completely decide on the nature of model choice. The premise of this article is that there is still room for guidance on the nature of model choice, particularly with regard to the choice of constant return to scale (CRS) or variable returns to scale (VRS), and its subsequent impact on the confidence intervals derived from bootstrapping.

Finally, from a practical point of view, the application of bootstrapping methods needs to be efficient in terms of computational time. Within the economics literature, the applications of bootstrapping methods have been constrained for this reason. With standard approaches, DEA becomes excessively time consuming to bootstrap as the sample size grows (growing at a rate approximately related to the sample size squared). Here, unlike most existing studies, we employ the SLICE module within GAMS. When using this method, computational expense can no longer be considered a reason for not conducting statistical inference on DEA results with bootstrapping.

2.2.2 Bootstrapping in DEA

Bootstrapping is a method of testing the reliability of a data set by creating a pseudo-replicate data set. Bootstrapping allows you to assess whether the distribution has been influenced by stochastic effects and can be used to build confidence intervals for point estimates, which normally cannot be derived analytically. Random samples are obtained by sampling with replacement from the original data set, which provides an estimator of the parameter of interest. SW (1998)[2] introduced a DEA bootstrap where the DGP is repeatedly simulated by re-sampling the sample data and applying the original estimator to each simulated sample. The bootstrap method is based on the idea that the bootstrap distribution will mimic the original unknown sampling distribution of the estimators of interest (using a nonparametric estimate of their densities). Hence, a bootstrap procedure can simulate the DGP by using Monte Carlo approximation and may provide a reasonable estimator of the true unknown DGP.

The efficiency for a given point (x_k, y_k) is

$$\theta_k = \min\{\theta \mid \theta x_k \in X(y_k)\}$$

where $X(y_k)$ is a input requirement set. If $\theta_k = 1$, the unit k is input efficient. $\theta_k \leq 1$ represents the feasible proportionate reduction of inputs the DMU could realize, if y_k were produced efficiently. SW (1998) denote the efficient level of input corresponding to the output level y_k as $x^{\theta}(x_k \mid y_k) = \theta_k x_k$. Note that θ_k is a radial measure of the distance between (x_k, y_k) and the corresponding frontier. Unfortunately, θ_k is unknown because $X(y)$ and $\theta_k x_k$ are unknown.

2.2.3 The data generating process

Suppose the DGP, P generates a random sample $\chi = \{(x_k, y_k \mid k = 1,...,n)\}$. Using the data χ with a nonparametric method

$$\hat{\theta}_k = \min\left\{\theta \mid y_k \leq \sum_{i=1}^{n} \gamma_i y_i \mid \theta x_k \geq \sum_{i=1}^{n} \gamma_i x_i \mid \sum_{i=1}^{n} \gamma_i = 1, \gamma_i \geq 0 \mid \theta \geq 0 \mid i = 1,...,n\right\}. \qquad (2.1)$$

To obtain $\hat{X}(y)$, $\partial \hat{X}(y)$, it is possible to estimate its efficiency

$$\hat{\theta}_k = \min\{\ \theta \mid \theta x_k \in \hat{X}(y_k)\ \}.$$

Because the DGP P is unknown, the bootstrap procedure is used to determine the DGP $\hat{P}$ as a reasonable estimator of the true unknown DGP generated through the data χ. The efficiency estimates can be considered as a new population, from which it is possible to draw a new data set

$$\chi^* = \{\ (x^*_i, y^*_i) \mid i = 1,...,n\ \}.$$

This pseudo-sample defines the corresponding quantities $\hat{X}^*(y)$ and $\partial \hat{X}^*(y)$. Note that conditionally on χ, the sampling distribution of the estimators $\hat{X}^*(y)$ and

[2] As a recent published article which further investigates the bootstrap method we refer to SW, 2004.

$\partial \hat{X}^*(y)$ are known, since $\hat{P}$ is known. Analytically, $\hat{P}$ could be difficult to compute, therefore Monte Carlo Approximation is employed to obtain the sampling distributions using $\hat{P}$ to generate B pseudo-samples $\mathcal{X}_b^*$, where b =1, …, B and pseudo-estimates of the efficiency scores. The empirical distribution of these pseudo-estimates gives an approximation of the unknown sampling distribution of the efficiency scores.

2.2.4 Smoothed bootstrap procedure

Unfortunately, this "naïve" bootstrap yields inconsistent estimates. Therefore, SW introduced a homogeneous smoothed bootstrap procedure. An easily implemented algorithm for consistently generating the bootstrap values $\hat{\theta}_b^*$ from a kernel density estimate is given in SW (1998) and is summarized in the following steps:

(a) First, for each DMU k given the input-output data (x_k, y_k) $k = 1,...,n$, compute $\hat{\theta}_k$ by the linear program to get the efficiency estimators. Here the linear model specifications are different estimators of the same unknown θ_k. Hence, $\hat{\theta}_k$ estimators are random variables and merely specific realizations of different random variables.

(b) Generate the smoothed bootstrap sample $\theta_1^*,...,\theta_n^*$ for $i = 1,...,n$ by letting $\beta_1^*,...,\beta_n^*$, a simple bootstrap sample from $\hat{\theta}_1^*,...,\hat{\theta}_n^*$ obtained by drawing uniformly with replacement.

Define sequences

$$\tilde{\theta}_i^* = \begin{Bmatrix} \beta_i^* + h\varepsilon_i^* & \text{if } \beta_i^* + \varepsilon_i^* \leq 1, \\ 2 - \beta_i^* - h\varepsilon_i^* & \text{otherwise} \end{Bmatrix}, \tag{2.2}$$

and obtain the corrected bootstrap sample by

$$\theta_i^* = \overline{\beta}^* + 1/(\sqrt{1+h^2 / \hat{\sigma}_{\hat{\theta}}^{\,2}})(\tilde{\theta}^*{}_i - \overline{\beta}^*), \tag{2.3}$$

with $\overline{\beta}^* = 1/n\sum_{i=1}^{n}\beta_i^*$ and $\hat{\sigma}_{\hat{\theta}}^{\,2}$ is the sample variance of $\hat{\theta}_1^*,...,\hat{\theta}_n^*$.

Making these corrections ensures that the sample values have the same mean and variance as the original values. Here h is called the bandwidth factor and ε_i^* is a random deviate drawn from the standard normal. SW discussed in detail how to calculate the bandwidth factor. If the data ($\hat{\theta}$) is normal distributed, then one may use the normal reference rule and set the bandwidth by

$$\hat{h} = 1.06\hat{\sigma}_{\hat{\theta}} n^{-1/5}$$

In cases where the data is not normal distributed, as in the case of DEA estimates, SW (2004) suggested the to employ least square cross-validation, which involves choosing the bandwidth that minimizes an approximation to mean integrated square error; see Silverman (1986) for details. In order to obtain *h* in our study, the least square cross-validation approach[3] was applied.

(c) Next, use the smoothed bootstrap sample sequence to compute new data

$$\chi_b^{*} = \left\{\left(x^{*}_{ib}, y_i\right) \mid i = 1,...,n\right\},$$

where

$$x^{*}_{ib} = (\hat{\theta}_i / \hat{\theta}^{*}_{ib})x_i, \ \{i = 1,...,n\} \text{ and}$$

(d) compute the bootstrap efficiency estimates

$$\left\{\hat{\theta}^{*}_i \mid i = 1,\dots,n\right\}$$

by solving the DEA model for each DMU but using the new data χ_b^{*}. For example, for DMU *k* the bootstrap estimates $\hat{\theta}^{*}_{k,b}$ can be obtained by solving

$$\hat{\theta}^{*}_{k,b} = \min\left\{\theta > 0 \mid y_k \leq \sum_{i=1}^{n}\gamma_i y_i \mid \theta x_k \geq \sum_{i=1}^{n}\gamma_i x_{i,b}{}^{*} \mid \sum_{i=1}^{n}\gamma_i = 1, \gamma_i \geq 0,\ i,...,n\right\}. \quad (2.4)$$

Finally, repeat step (b)-(d) *B* times to provide for *k* =1,…, *n* a set of estimates

$$\left\{\ \hat{\theta}^{*}_{k,b} b = 1,...,B\ \right\}.$$

In our case, we set *B* = 2,000 to ensure adequate coverage of the confidence intervals. The bootstrap efficiency scores $\hat{\theta}^{*}_k$ represent approximations to the $\hat{\theta}_k$, just as the DEA efficiency scores $\hat{\theta}_k$ represent approximations to θ_k.

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[3] The software package "XPlore" was used to calculate *h*.

2.2.5 Bootstrap bias corrections

The empirical bootstrap distribution can be used to estimate the bias. An estimate of the bias is defined as the difference between the empirical mean of the bootstrap distribution and the original efficiency point estimates. As shown above, the bootstrap estimates $\{\hat{\theta}^{*}_{k,b} = 1,...,B\}$ are biased by construction (SW, 2000a).
By definition,

$$BIAS\left(\hat{\theta}_k\right) = E\left(\hat{\theta}_k\right) - \theta$$

the empirical bootstrap bias for the original estimator $\hat{\theta}_k$ is therefore

$$BIAS_B(\hat{\theta}_k) = B^{-1}\left(\sum_{b=1}^{B}\hat{\theta}^{*}_{k,b}\right) - \hat{\theta}_k .$$

The bias-corrected estimator is obtained by subtracting the bias from the original efficiency estimates. However, the bias correction introduces additional noise and could have a higher mean square error than the original point estimates, which can be avoided for the interval estimation using the automatic correction below.

2.2.6 Confidence intervals

To find confidence intervals, SW proposed the modified percentile method. They introduce an improved procedure to derive confidence intervals, which automatically corrects for bias without explicit use of a noisy biased estimator. Using the bootstrap score, we can build confidence intervals for each *k*. If we know the distribution of $\left(\hat{\theta}^{*}(x,y) - \theta(x,y)\right)$, it would be possible to find a_α, b_α such that

$$\Pr(-b_\alpha \le \hat{\theta}_k\,(x_0, y_0) - \theta\ (x_0, y_0) \le -a_\alpha) = 1 - \alpha \qquad (2.5)$$

Because a_α, b_α are unknown, we use

$$\left\{\hat{\theta}^{*}_{k,b} b = 1,...,B\right\}$$

to find values $\hat{b}_\alpha, \hat{a}_\alpha$ such that

$$\Pr(-\hat{b}_\alpha \le \hat{\theta}^{*}_{k,b}(x_0, y_0) - \hat{\theta}_k(x_0, y_0) \le -\hat{\alpha}_\alpha \mid \hat{P}(\chi_n)) = 1 - a\,. \qquad (2.6)$$

Finding $\hat{b}_\alpha, \hat{a}_\alpha$ entails sorting the values $\hat{\theta}^{*}_{k,b}(x_0, y_0) - \hat{\theta}_k(x_0, y_0)$, b =1,…, B in increasing order and then deleting $[(\alpha/2)\times 100]\%$ of the rows at either end of the list and setting $-\hat{b}_\alpha, -\hat{a}_\alpha$ to the endpoints of the array with $\hat{a}_\alpha \le \hat{b}_\alpha$. The $1-\alpha$ percent confidence interval is then;

$$\hat{\theta}_k(x_0, y_0) + \hat{a}_\alpha \leq \theta(x_0, y_0) \leq \hat{\theta}_k(x_0, y_0) + \hat{b}_\alpha \, . \tag{2.7}$$

This procedure is repeated n times to obtain n confidence intervals, one for each farm. As a side note, the $\hat{a}_\alpha \leq 0, b_\alpha \leq 0$ and the $\hat{\theta}_k$ will lie above the confidence interval. For proof, see Voelker (2002).

2.3 Data and model specification

2.3.1 Data

This article uses Slovenian farm cross-sectional data to investigate how efficiency ranking depends on the model specifications and how confidence intervals can be used to give further insights into the validity of the efficiency scores. The data used in this study is based on the Research Institute for Agricultural and Food Economics farm cost database in Slovenia in 1996. Sixty-nine Slovenian arable farms were selected for the investigation. After the data set was corrected for outliers, the mean normalized procedure (Sarkis, 2002) was applied. The four inputs are (1) purchased seed, home grown seed; (2) purchased fertilizer, manure; (3) chemicals, other direct costs, wages; and (4) services and other cost (all inputs are in monetary terms). Output was defined as production of wheat in metric tons.

2.3.2 Coefficient of separation

In order to provide a summary statistic of the degree of overlap between confidence intervals, a useful measure is introduced in this study, which is called "the CoS" (Latruffe et al., 2005). This statistic is calculated by taking each farm in turn and then identifying the farms in the sample that are significantly more efficient than it, that is to say the farms with a lower bound strictly greater than the upper bound for the farm in question.

More precisely, let $N_n =$ no. of farms "significantly" greater than n other farms where $n = 1, 2, ...N-1$ and $N =$ total number of farms. Thus, $N_1 =$ is the number of farms significantly greater than one farm, N_2 is the number of farms significantly greater than two farms. Under perfect separation, we would observe

$$N_n = (N-n)\,, \tag{2.8}$$

for $n = 1, 2..........N-1$. Noting the identity

$$\frac{2}{N^2}\sum_{n=1}^{N-1} (N-n) + \frac{1}{N} = 1\,, \tag{2.9}$$

a "CoS" can be constructed as

$$CoS = \frac{2}{N^2}\sum_{n=1}^{N-1} N_n + \frac{1}{N} . \tag{2.10}$$

Under perfect separation this will be one from the identity above

$$CoS = \frac{2}{N^2}\sum_{n=1}^{N-1}\left(N-n\right) + \frac{1}{N} = 1 . \tag{2.11}$$

Obviously, if $N_n = 0$ for all N , then $CoS = 1/N$ (nearly zero for a large number of farms). Hence, the CoS is a summary statistic which is calculated by taking each firm and identifying the farms in the sample that are significantly more efficient (at a given significance level). The statistic tells us (approximately) what percentage of the sample is significantly less efficient than a given percentage of the sample, after the sample has been ranked. The CoS serves to demonstrate the fact that wider intervals mean higher probability of overlapping intervals. In essence, the smaller the CoS (at a given level of significance), the less we can differentiate between farm efficiencies, given the confidence intervals obtained by the bootstrap.

2.4 Estimation and results

DEA was performed using both CRS and VRS for a 2-input/1-output and 4-input/1-output case. For the 2-input cases, the inputs 1/2 and 3/4 were aggregated. The confidence intervals and the bias-corrected efficiencies were estimated using the homogeneous smoothed bootstrap procedure introduced in previous sections with 2,000 bootstrap draws.

The results for the estimated confidence interval for the 2-input case, VRS/CRS, are shown in Fig. 2-1.

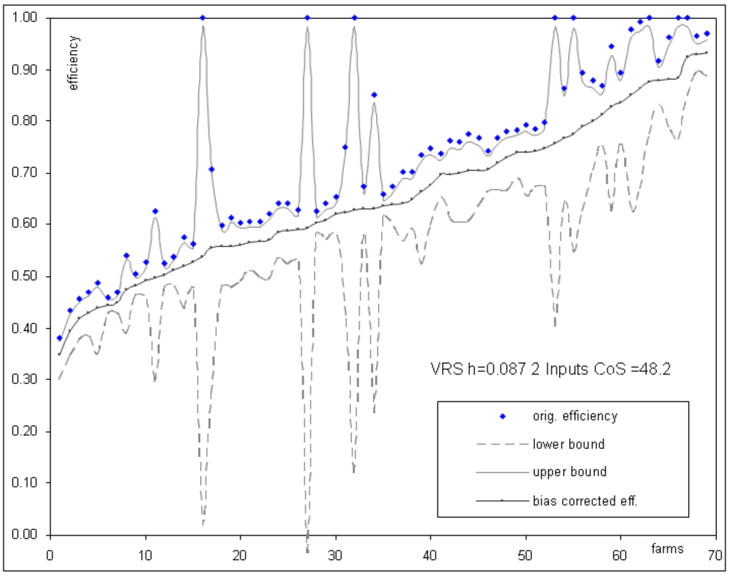

Fig. 2-1 a: Confidence intervals and point estimates for VRS with two inputs

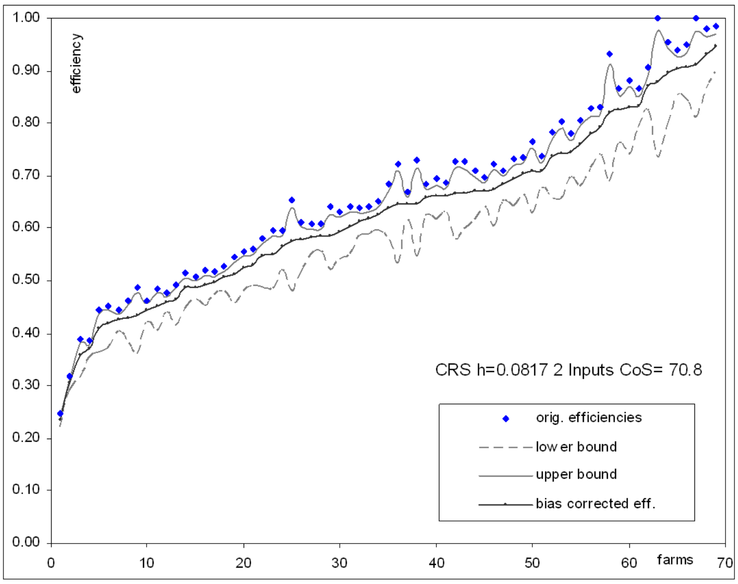

Fig. 2-1 b: Confidence intervals and point estimates for CRS with two inputs.

Fig. 2-1 depicts the sample observations ordered by the bias-corrected efficiency score. The 95% confidence intervals for each farm are represented by the lower dashed line and the upper solid line, and original efficiencies are indicated by the respective symbols. It is evident that the original efficiencies are not included in the confidence interval. This result is not dependent on any particular DGP and is an intrinsic outcome of the theory behind the construction of these intervals, as outlined in equations (2.5)-(2.7). Importantly, the efficiency ranking of the original farm efficiencies changed compared to the bias-corrected efficiencies ranking. Farms that seemed to be perfectly efficient are ranked at a lower level, particularly in the VRS case when the bias-corrected efficiencies are considered. While we cannot provide an intuitive explanation for this, it is evident that while some farms were measured as perfectly efficient in the first instance, the bootstrap suggested that they were measured with large degree of noise and this has also been reflected in a large bias correction downward. In contrast, some farms that are not on the frontier will be ranked on a higher level relative to the other farms. The estimated confidence intervals for the CRS case are narrower than the confidence intervals of the VRS, which can be explained by the greater curvature of the frontier in the VRS case, where many sample observations will typically have efficiency estimates equal to unity (SW, 2004).

Fig. 2-1 reveals that the estimated bias is negative and in many cases quite large. Among the observations which were originally efficient, the lower boundary for the estimated 95% confidence intervals ranges from 0.73 to 0.81 in the CRS case, and from 0.02 to 0.85 in the VRS case for the 2-input models.

For one particular DMU, an original efficiency score of 1.00 was estimated. The bias-corrected efficiency was 0.57 and the lower and upper boundaries of the confidence interval are 0.02 and 0.98, respectively. Wide confidence intervals for particular DMUs have also been found by SW (2000b). Nevertheless, there are observations where the confidence interval is quite small, in particular for the 2-input CRS case. The widths of the confidence intervals vary considerably over the sample size, especially for the VRS case and for more than two inputs. Brümmer (2001) states that it is easier to identify the observations with low-efficiency scores than to identify high performers in his sample. The same observation can be made for the Slovenian farm sample, in particular for the VRS model.

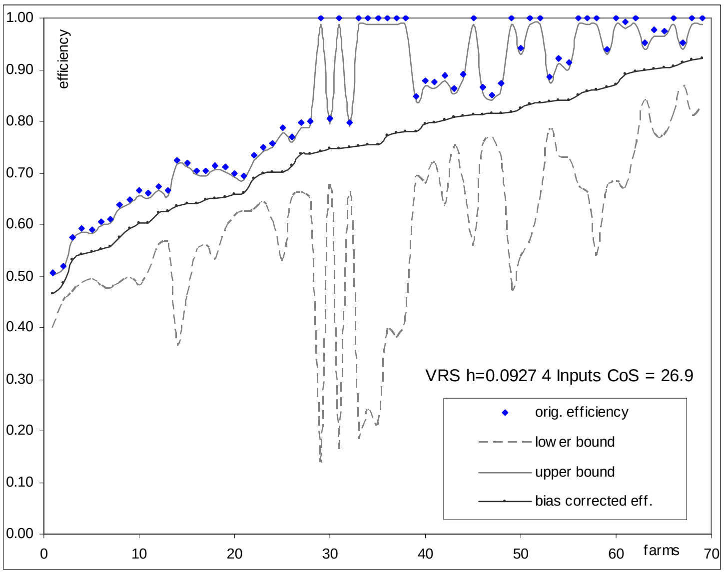

Fig. 2-2 a: Confidence intervals and point estimates for and VRS with four inputs

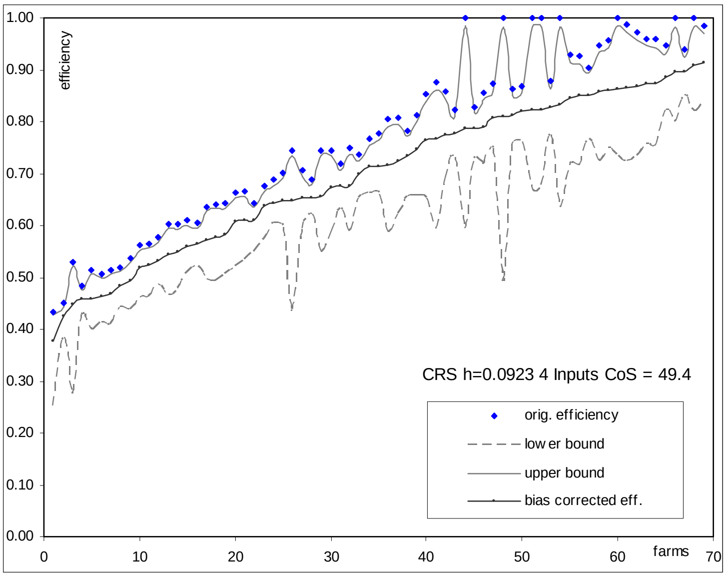

Fig. 2-2 b: Confidence intervals and point estimates for CRS with four inputs

Fig. 2-2 depicts the 4-input case. The width of the confidence intervals for the VRS as well as for the CRS increases, and hence the CoS declines (Table 2-1).

Number of input	Return to scale	Coefficient of separation (%)
2	CRS	70.8
2	VRS	48.2
4	CRS	49.4
4	VRS	26.9

Table 2-1: Coefficient of Separation for the different model specifications

The highest CoS is reached in the case of the 2-input-CRS specification and the lowest by the 4-inputs-VRS. If the discriminatory power was improved by increasing the number of inputs, the CoS declined by around 20%, independent of the choice of returns to scale.

Many studies use these estimates in subsequent analysis, taking DEA scores and regressing them against potential explanatory variables such as education and so on. The implication of the analysis above-mentioned analysis is that the dependent variable is measured with considerable noise.

The results do highlight that there are important decisions to be made with regard to using CRS or VRS. The former may be more biased, but if the consequences of using VRS is that the confidence intervals are very wide, then CRS might actually outperform it according to a mean square error criteria. Thus, there is a bias versus efficiency tradeoff here that is much the same as the tradeoff between using a flexible or parsimonious functional form in SFA. The recent work of SW (2003) still requires a choice of CRS or VRS. Therefore, we suspect that our conclusion remain relevant even when the revised bootstrap procedures are used.

To compute the confidence intervals, it is necessary to solve $n \times b$ linear programs. The GAMS/DEA tool was added to the GAMS system, which very efficiently solves linear and mixed integer DEA programs (Ferris and Voelker, 2000; Voelker, 2002). By using the SLICE module in GAMS and CPLEX, it was possible to significantly reduce the calculation time[4] (Table 2-2). Several performance runs were made to test the power of the GAMS/DEA SLICE module and the finding was that there is no computational burden for models with up to 2,500 DMU, eight inputs and 1 output. Therefore, a sensitivity analysis on DEA estimates using bootstrapping

[4] Using Hardware Intel® Pentium® 3 processor 800 MHz. We note that this is a considerable improvement on the equivalent procedure conducted in GAUSS using Simplex or QPROG to solve the linear programs. Using a superior 2.4Ghz Pentium 4, it still required 48 hours for 2,000 bootstraps with 500 DMUs, and extrapolating this would suggest 10 or 12 days for 2,500 DMUs.

may be implemented as a standard routine, at least from the computational point of view.

Number of bootstraps	Number of DMUs	Number of outputs	Number of inputs	Solving time
2,000	80	4	1	47 min
2,000	1,000	4	1	7 hours, 24 min

Table 2-2: Solution time for (CPLEX) Slice Interface DEA (BBC)

2.5 Conclusion

As shown in the different model specifications, we would suggest that any DEA study should employ bootstrapping as standard practice to detect the reliability of efficiency ranking. When bias-corrected efficiencies were used to rank the farm sample, the ranking order changed compared to the ranking order of the original efficiencies. Farms that seemed to be perfectly efficient as indicated by the original efficiency (point estimate) became less efficient as depicted in Figs. 2-1 and 2-2.

Bootstrap interval estimation of technical efficiency can be used to assess DEA results. But again, the confidence intervals depend on the model and on the aggregation assumptions. The CoS proved a useful summary statistic in assessing the degree to which farms could be differentiated on efficiency grounds. We found that a large proportion of the farms in the sample could not be usefully separated from many other farms with any degree of confidence, particularly when using VRS. Consequently, we would recommend that researchers should be guarded about making definitive judgments about individual units on the basis of efficiency scores alone.

On the basis of our results, we suggest always doing both CRS and VRS subject to different input and output aggregations, whereby if the bootstrap standard errors for VRS are too large, the CRS can be used for subsequent analysis. We also suggest to try to increase the input aggregation subject to the purpose for which the results are to be used. The CoS gives a useful statistic in order to assess and compare the different resulting model specifications. Researchers should also be aware that the ranking of the original efficiencies may change if the bias-corrected efficiencies are used to interpret the relative performance of the sample.

Apart from the different model specifications, it is important to set up a computational framework that ensures a convenient calculation of confidence intervals for DEA. By using the SLICE model in GAMS, the statistical properties of the estimator can easily be investigated for any applied study. Further research might exploit the high performance of the programmed GAMS/SLICE bootstrap procedure. This might extend the work conducted by SW by conducting Monte Carlo experiments on more than two dimensions of inputs and outputs while also increasing the number of DMUs. Moreover, we would suggest that other related procedures such as the bootstrapping of Malmquist indicies (e.g., SW, 1999c) might be facilitated using the SLICE approach.

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Chapter 3. Assessment of the response behaviour of different calibration approaches for farm programming model*

Abstract

This article investigates the response behaviour of mathematical programming models using farm groups derived from the German Farm Accountancy Data Network (FADN) and calibrating them using different Positive Mathematical Programming (PMP) methods for the year 1996/97. Afterwards, gross margins for the year 2002/03 are applied. By comparing the simulated and observed production in 2002/03 it can be shown that the simulated production only poorly recovers the observed production and that the response behaviour is strongly influenced by the applied PMP calibration method. Calibration with exogenous elasticities overcomes problems arising from the original PMP calibration method. In contrast to all other considered PMP methods the calibration with Maximum Entropy (ME) can also estimate cross-diagonal elements of the cost function. However, the specification (support point settings) seems unfavourable because the model does not result in different response behaviour. We also demonstrate using one particular farm group that the explicit optimisation model, which offers the possibility to incorporate prior information and avoids the general misspecification of PMP, can be used with FADN time series to estimate the cost function parameters. However, further research is necessary to overcome computational problems to apply this method for sector-wide farm group models.

Keywords: PMP, *ex post* evaluation, FADN

3.1 Introduction

The lack of detailed data for sector-wide farm modelling unavoidably leads optimisation of linear mathematical programming models to a solution far from the

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observed production. In order to prevent this problem, models are calibrated to the observed production using the Positive Mathematical Programming (PMP) method, originally introduced to a wider range of economists by Howitt (1995). The production economic criterion, *i.e.*, marginal revenue equals marginal cost, is used to derive the calibration parameters. Observed average costs are used in a three-step procedure to derive additional unobservable costs per crop, which are brought into the parameters of the non-linear PMP term of the optimization model. These modifications of the objective equation, however, have an impact on the resulting simulation behaviour, through the choice of the functional form of the PMP term and by the parameterization of the non-linear term.

PMP was criticised for its arbitrary simulation behaviour in several papers, *e.g.*, Heckelei (2002), Heckelei & Britz (2000), and Heckelei & Wolff (2003). These studies attempt to overcome the drawbacks of PMP, by focusing on formal econometric estimation procedures to obtain better-justified non-linear parameters from time series or cross-sectional data. Of major importance was the introduction of ME and related techniques (Golan et al., 1996) used to estimate the non-linear part of the objective function, even when the model is underdetermined, *e.g.*, Paris & Howitt (1998) and Paris (2001). Heckelei & Wolff (2003) proposed a general alternative to PMP in calibrating and estimating agricultural programming models based on the first order conditions of the optimisation model. Jansson (2007) extended the approach to Bayesian estimation using the sector model CAPRI (Britz & Witzke, 2008). For sector-wide farm modelling approaches (e.g., Offermann et al., 2005; Jones et al., 1995; Arfini & Paris, 1995), however, the PMP method is still commonly used to determine the cost function parameters and therefore influences the simulation behaviour of the farm group model during policy analysis.

The objective of this paper is to evaluate the impact of the cost function parameter determination of several prominent PMP calibration approaches on the resulting response behaviour of the model. The analysis is embedded into an *ex post* framework for arable farms in Germany, for which the available time series is sufficient to validate the different PMP calibration approaches with respect to observed production. The general approach is to use the farm group model FARMIS[1] and to build up farm supply models for the year 1996/97, using different PMP methods to calibrate the models to observed production. Afterwards, the supply model is shocked using gross margins observations from the year 2002/03, and the simulated production is compared with that observed in 2002/03.

This paper is structured as follows: Section 3.2 briefly reviews the general PMP approach to calibrating mathematical programming models. Section 3.3 discusses the

[1] FARMIS is a farm group supply model for Germany developed at the vTI-Braunschweig (Offermann et al., 2006; Hüttel et al., 2006, Isermeyer et al., 2005; Kleinhanß et al., 2006).

PMP calibration methods that were considered, presents the data and explains the implementation of the cost function estimation. In Section 3.4, the results are discussed. The last section concludes and critically focuses on the remaining problems with the discussed PMP methods, and points out further research directions.

3.2 The concept of PMP

PMP uses the information contained in dual variables of a linear programming model (LP), which are bound to the observed activity levels applied through calibration constraints. A non-linear objective function is derived in such a way that the optimal solution will exactly reproduce the observed activity levels without employing any additional constraints. The use of a non-linear objective function helps to prevent the model from generating overspecialised solutions. In the literature, this approach is called the three stage PMP approach (Howitt, 1995). In the *first step*, the following linear programming problem is considered:

$$\max_{x} Z = \mathbf{p}'\mathbf{x} - \mathbf{c}'\mathbf{x}$$

subject to

$$\mathbf{Ax} \leq \mathbf{b}[\boldsymbol{\lambda}], \quad \mathbf{x} \geq 0 \tag{3.1}$$

where Z denotes the objective function value, $\mathbf{p}$ is the $(\mathrm{N}\times 1)$ vector of product prices, $\mathbf{x}$ is the $(\mathrm{N}\times 1)$ vector of production activity levels, $\mathbf{c}$ is the $(\mathrm{N}\times 1)$ vector of costs per unit of activity, $\mathbf{A}$ denotes the $(\mathrm{M}\times \mathrm{N})$ matrix of coefficients for resource constraints, $\mathbf{b}$ is the $(\mathrm{M}\times 1)$ vector of available resource quantities and $\boldsymbol{\lambda}$ is the $(\mathrm{M}\times 1)$ vector of dual variables associated with the resource constraints. Applying the calibration constraints, the solution will be forced to the observed activity level.

$$\max_{\mathrm{x}} \mathrm{Z} = \mathbf{p}'\mathbf{x}\text{-}\mathbf{c}'\mathbf{x}$$

subject to

$$\mathbf{Ax} \leq \mathbf{b}[\boldsymbol{\lambda}], \quad \mathbf{x} \leq \left(\mathbf{x}^{\mathrm{o}} + \boldsymbol{\varepsilon}\right) \quad [\boldsymbol{\rho}], \ \mathbf{x} \geq \mathbf{0} \tag{3.2}$$

The $(\mathrm{N}\times 1)$ vector $\mathbf{x}^{\mathrm{o}}$ denotes the observed activity levels; the $(N\times 1)$ $\boldsymbol{\varepsilon}$ is a vector of small positive numbers, which guarantees that all resource constrains remain binding; and $\boldsymbol{\rho}$ are the dual variables associated with the calibration constraints. Let us now consider an example of wheat and corn, with gross margins of 300 €/ha and 100 €/ha, respectively, and land resources of 30 hectares. Without any additional calibration constraints, wheat would be the preferred activity and the dual of land would be 300 €/ha. If calibration constraints of 20 hectares for wheat and 10 hectares for corn are included, the preferred activity would still be wheat and corn would be the marginal activity. The vector $\mathbf{x}$ can, hence, be divided into two subsets: a vector of preferred activities $\mathbf{x}^p$, which is constrained by the calibration constraint, and a vector $\mathbf{x}^m$ of marginal activities, which is bounded by the resource constraint. In the *second step*, the non-linear objective function will be calculated such that under the production economic criterion – marginal revenue equals marginal cost – the model will obtain the observed production as a solution. The dual values will certainly be smaller than those obtained in equation (3.1) because the marginal, rather than the preferred, activities determine the dual values of the resource constraint (Heckelei, 2002).

The concept of PMP can therefore be understood as detecting the hidden costs for each crop, in order to obtain a solution to the programming problem that is calibrated to include the “true” costs of farming. Hence, the farm’s production is assumed to be already at an economic optimum. The nature of the hidden costs is unknown, and hidden costs are viewed as a consequence of any factors that could contribute to increasing marginal costs. Decreasing marginal returns can be caused by increasing marginal costs while marginal revenues remain constant. Alternatively, the PMP approach can also be specified for decreasing marginal returns based on decreasing marginal crop yields and constant marginal costs.

Both approaches can be implemented by taking either costs or production functions for the parameter estimation. In the remainder of the paper, the most frequent PMP approach in the form of increasing marginal costs is discussed. Due to the lack of strong arguments, the often-applied quadratic function is used in this application, whereas Paris & Howitt (1998) also discussed other functional forms. In principle, any type of non-linear function convex in activities can be applied. The following ‘variable cost function’ can be taken as the non-linear part of the object function.

$$\mathbf{c}^{\mathrm{v}} = \mathbf{d}'\mathbf{x} + \frac{1}{2}\mathbf{x}'\mathbf{Q}\mathbf{x}, \qquad (3.3)$$

$\mathbf{c}^{\mathrm{v}}$ is an $(N \times 1)$ vector of variable costs and $\mathbf{d}$ denotes the $(\mathrm{N} \times 1)$ vector of parameters associated with the linear term. The $(\mathrm{N} \times \mathrm{N})$ symmetric, positive (semi-) definite matrix $\mathbf{Q}$ is associated with the quadratic term. To reconstruct the parameters of the $\mathbf{Q}$ Matrix and the $\mathbf{d}$ vector, the ‘marginal variable cost’ has to fulfil:

$$\mathbf{MC}^{\mathrm{v}} = \frac{\partial \mathbf{C}^{\mathrm{v}}\left(\mathbf{x}^{o}\right)}{\partial \mathbf{x}} = \mathbf{d} + \mathbf{Q}\mathbf{x}^{o} = \mathbf{c} + \boldsymbol{\rho}. \qquad (3.4)$$

Providing the PMP coefficients are recovered, the final non-linear programming problem can be specified as:

$$\max_{x} Z = \mathbf{p}'\mathbf{x} - \mathbf{d}'\mathbf{x} - \frac{1}{2}\mathbf{x}'\mathbf{Q}\mathbf{x} \tag{3.5}$$

subject to

$$\mathbf{A}\mathbf{x} \leq \mathbf{b}\left[\boldsymbol{\lambda}\right], \mathbf{x} \geq 0. \tag{3.6}$$

For the *ex post* scenarios, different approaches exist for recovering the parameters of the cost function, which are discussed in the next section.

3.3 Ex post approach

This section describes the methods considered in the *ex post* approach to obtain the parameters of the cost function, introduces the data, and describes the implementation of the method.

3.3.1 Methods to recover the parameters of the cost function

We consider the following PMP calibration methods for the *ex post* analysis:

i) *Original PMP*

ii) *Paris (1988)*

iii) *Exogenous elasticities*

iv) *Maximum Entropy*

We will also discuss *v) FOC* the method proposed by Heckelei & Wolff (2003) which estimates the parameters of the cost function combined with the first order condition and more than one observation. This method is not applied to all farm groups of the *ex post* framework, but only for one particular farm[2].

All methods have to solve equation (3.4) in order to calibrate the programming model to observed production. The PMP approaches from i) to iii) belong to the group where the diagonal elements are calculated and off-diagonal elements are set

[2] During the study it became clear that numerical problems did not allow for using the method for all farm groups. The increased number of observations, combined with the differentiated set of crop activities, generates considerable computational demand. In addition, initial numerical difficulties must be overcome.

to zero. The remaining approaches try to recover the full $\mathbf{Q}$ matrix, and, therefore, account for cross-effects between crops.

i) Original PMP

Here, the estimation of the non-linear cost function was solved by letting $\mathbf{d} = \mathbf{c}$ and setting all off-diagonal elements of **Q** to zero (Howitt & Mean, 1983; Arfini & Paris, 1995; Bauer & Kasnakoglu, 1990). The *N* diagonal elements of $\mathbf{Q}$, indicated as q_{ii}, are calculated as:

$$q_{ii} = \frac{\rho_i}{x_i^o} \quad \forall i = 1,...,N \ . \tag{3.7}$$

This specification gives a linear cost function for the 'marginal' activities, caused by the zero dual value of the marginal activities $\mathbf{x}^m$. The resulting simulation behavior is determined through the linear cost function of the marginal activity.

ii) Paris (1988)

Paris (1988) tried to respond to the additional need for prior information that arose when the original PMP approach was improved and developed a modified version, setting $\mathbf{d}$ equal to zero along with the off-diagonal elements of $\mathbf{Q}$, and then calculating the diagonal elements of $\mathbf{Q}$ by

$$q_{ii} = \frac{c_i + \rho_i}{x_i^o} \quad \forall i = 1,...,N \ , \tag{3.8}$$

which achieves positive diagonal elements of **Q** also for the marginal activities. The vector $\boldsymbol{\rho}$ denotes the dual values of the constrained linear programming model, $\mathbf{x^o}$ is the observed crop allocation and $\mathbf{c}$ is a vector of observed costs from the linear formulation.

iii) Exogenous elasticities

The method uses exogenous elasticities to recover the parameters of the marginal cost function (Helming et al., 2001; Osterburg et al., 2001). The off-diagonal elements of $\mathbf{Q}$ are set to zero. In the *ex post* analysis, land allocation elasticities with respect to own gross margins $\boldsymbol{\varepsilon}$ elasticities are considered for the calculation of the diagonal elements of $\mathbf{Q}$. The exogenous land allocation elasticity can be used to calculate $\mathbf{Q}$ because the partial derivative $\partial x_i / \partial p_i$ is equal to q_{ii}^{-1}.

$$q_{ii} = \frac{1}{\varepsilon_{ii}} \frac{p^o{}_i}{x^o{}_i} \quad \forall i = 1,...,N \ . \tag{3.9}$$

In order to satisfy the calibration condition in equation(3.4), the linear parameter of the variable cost function (equation(3.3)) is set to:

$$d_i = c_i + \rho_i - q_{ii} x^o{}_i \quad \forall i = 1,...,N \,. \tag{3.10}$$

iv) Maximum Entropy

Paris & Howitt (1998) addressed the potentially arbitrary parameter specification problem by suggesting a Maximum Entropy (ME) procedure to generalise and objectify the calibration phase. The information is given by the marginal costs from the first step (3.2), setting $\mathbf{d} = 0$ and the observed output levels. If each farm realises N products with $i = 1, \ldots, N$, $N(N+1)/2$ parameters must be estimated, which results in an ill-posed estimation problem. Using this information, the marginal cost function as in (3.4) results in:

$$\mathbf{mc}^{\mathbf{v}} = \boldsymbol{\rho} + \mathbf{c} = \mathbf{Qx^o} \tag{3.11}$$

The corresponding formulation in matrix notation of the maximum entropy problem for estimation of the full $\mathbf{Q}$ matrix as shown in Paris & Howitt (1998) is repeated for sake of traceability.

$$\max_{\mathbf{p_d}, \mathbf{p_l}} \mathrm{H}(\mathbf{p_d}, \mathbf{p_l}) = -\mathbf{p_d}' \ln \mathbf{p_d} - \mathbf{p_l}' \ln \mathbf{p_l} \tag{3.12}$$

subject to

$$\mathbf{MC} = \mathbf{Qx^o} = \mathbf{LDL}'\mathbf{x^o} = (\mathbf{Z_l p_l})(\mathbf{Z_d p_d})(\mathbf{Z_l p_l})' \mathbf{x^o} \tag{3.13}$$

$$1 = \mathbf{l}'\mathbf{p_l} \quad \forall\, k = 1,...,L \tag{3.14}$$

$$1 = \mathbf{l}'\mathbf{p_d} \quad \forall\, k = 1,...,D \tag{3.15}$$

$\mathbf{p_l} > 0$ and $\mathbf{p_d} > 0$,

where H denotes the entropy measure, $\mathbf{mc}$ denotes the marginal cost vector of dimension N, $\mathbf{x}$ is the allocation vector of size N, $\mathbf{Z_l}$ and $\mathbf{Z_d}$ are the support matrices, and $\mathbf{p_l}$ and $\mathbf{p_d}$ are the individual probabilities. The formulation of the $\mathbf{Q}$ matrix in (3.13) satisfies the theoretical requirement of a symmetric positive semi-definite matrix, which ensures the Cholesky factorisation. (3.14) and (3.15) ensure that the probabilities sum up to one, with $\mathbf{l}$ as a summation vector.

v) First order condition with multiple data points

Paris & Howitt (1998) suggested in their conclusions that their approach with ME offers the ability to make use of more than one observation in time. In this context, PMP with multiple cross sectional data points was applied by Heckelei and Britz (2000). They extended the ME formulation to multiple observations but still used the PMP procedure. A limited theoretical basis for the PMP approach leads one to argue for alternative approaches to the estimation of explicit optimisation models without any PMP elements. Such an approach was introduced by Heckelei & Wolff (2003), who stated that, assuming that the optimal land allocation satisfies the land constraints[3], the first order condition of the problem for the observations T with $t = 1, \ldots, T$ can be obtained by using the Lagrangian formulation:

$$\mathbf{gm_t}^{\mathbf{o}} - \boldsymbol{\lambda}_{\mathbf{t}}\mathbf{A} - \mathbf{d} - \mathbf{Q}(\mathbf{x_t}^{\mathbf{o}} - \mathbf{e_t}) = \mathbf{0} \quad \forall \mathbf{t} \tag{3.16}$$

$$\mathbf{A}'(\mathbf{x}_{\mathbf{t}}^{\mathbf{o}} - \mathbf{e}_{\mathbf{t}}) = \mathbf{b}_{\mathbf{t}}^{\mathbf{o}}, \tag{3.17}$$

where $\mathbf{e}$ is added as an $(N \times 1)$ vector of stochastic error terms over T periods to the observed land allocation $\mathbf{x}^{\mathbf{o}}$ to obtain the optimal land allocation. $\boldsymbol{\lambda}_{\mathbf{t}}$ denotes the shadow price vector ($M \times T$) for land, estimated endogenously. Bringing the Entropy criteria into the error term is done by the multiplication of matrix $\mathbf{V}$ with the vector of probabilities $\mathbf{w}$.

$$\mathbf{e_t} = \mathbf{V}\mathbf{w_t} \tag{3.18}$$

Heckelei & Wolff (2003) showed that in the case of a small sample, the use of external elasticities provides a way to include additional information when a sufficient series of observations is missing. For our farm group, the number of observations is small (1996 to 2000), therefore, we introduce prior information on supply elasticities to specify our model, following Heckelei & Wolff (2003):

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3 The price vector in (3.5) is replaced by a vector of gross margins ($\mathbf{gm}$)

$$\mathbf{V}^{\varepsilon}\mathbf{w}^{\varepsilon} = \text{diag}\left(\left(\mathbf{Q}^{-1} - \mathbf{Q}^{-1}\mathbf{A}'\left(\mathbf{A}'\mathbf{Q}^{-1}\mathbf{A}\right)^{-1}\mathbf{A}\mathbf{Q}^{-1}\right) \odot \left[\frac{\mathbf{gm}}{\bar{\mathbf{I}}^{\circ}}\right]'\right). \tag{3.19}$$

[4]

The Generalised Maximum Entropy (GME) approach is employed for the estimation problem (Golan et al., 1996) as follows:

$$\max_{\mathbf{w_t},\mathbf{w}^{\varepsilon},\mathbf{Q},\mathbf{L},\boldsymbol{\lambda}_t} \mathrm{H}\left(\mathbf{w},\mathbf{w}^{\varepsilon}\right) = -\sum_{\mathbf{t=1}}^{\mathbf{T}} \mathbf{w_t}'\ln \mathbf{w_t} - \mathbf{w}^{\varepsilon}{}'\ln \mathbf{w}^{\varepsilon} \tag{3.20}$$

subject to (3.16), (3.17), (3.18), (3.19) and

$$\mathbf{Q} = \mathbf{LL}' \text{ with } \mathrm{L}_{ij} = 0 \quad \forall \quad j > i \tag{3.21}$$

$$\mathbf{l}'\mathbf{w_t} = 1 \quad \forall i,t \tag{3.22}$$

$$\mathbf{l}'\mathbf{w}^{\varepsilon} = 1 \quad \forall i,t \tag{3.23}$$

H denotes the entropy measure and equation (3.21) guarantees the positive (semi-) definiteness of **Q**, based on the Cholesky factorisation. Equations (3.22) and (3.23) ensure that the probabilities add up to one, where $\mathbf{l}$ is a summation vector.

3.3.2 Data

The assessment of the calibration methods is performed using farm data from the FADN. In order to aggregate the farm group, identical arable farms between 1996/97 and 2002/03 are selected. From about 6000 existing farms records in Germany, 845 arable farms were used for the *ex post* evaluation. The aggregation and stratification of the single farm accounts in farm groups was done with the program WFARMIS (Gocht, 2004) and resulted in 45 farm groups. The following figures present the farm groups selected for the application, aggregated into four regions. Figure 3-1 depicts the total amount of arable land for the 45 aggregated farm groups from 1996 to 2003. The use of arable land increased in the north by around 7 percent, in the centre of Germany by 11 percent and in the south by 9 percent. In the eastern part the arable area increased only by three percent, due to the restructuring process after the reunification of Germany.

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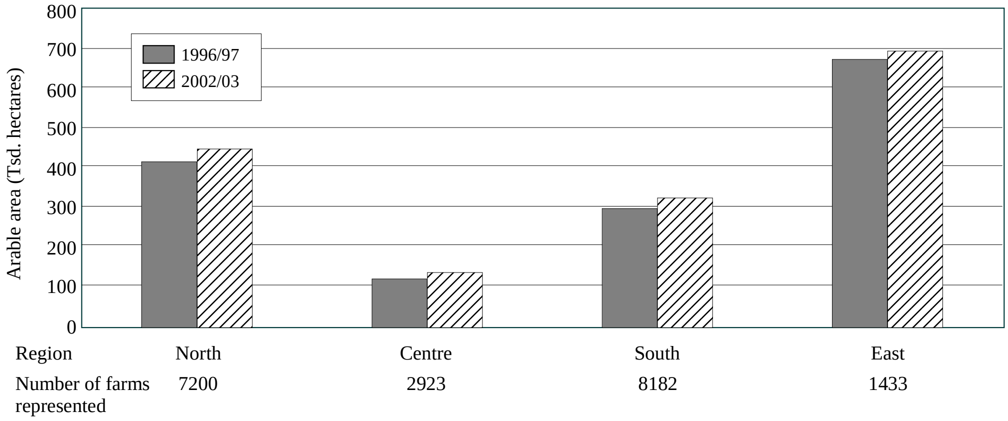
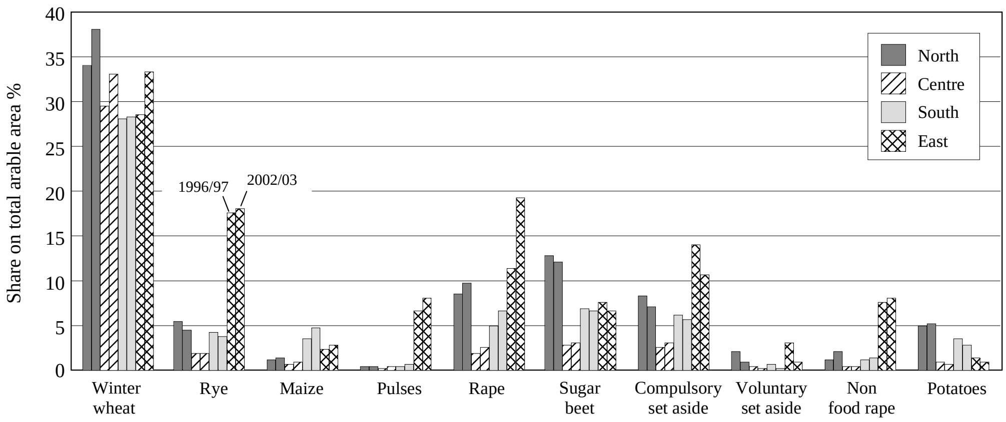
[4] The symbol $\odot$ represents the element wise product of two matrixes.



Source: FARMIS 2004, FADN Germany.

Figure 3-1: Total arable land in 1996/97 and 2002/03, grouped by region

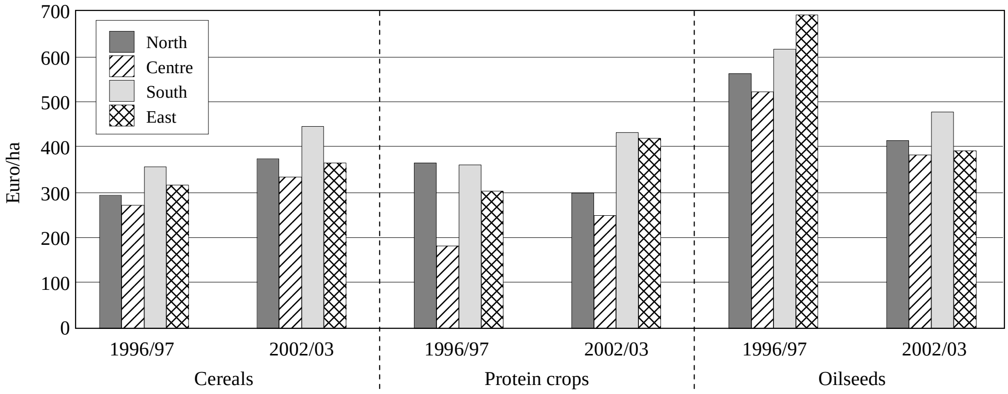
Figure 3-2 shows the crop allocation on the arable land in 1996/97 and 2002/03. Except in the southern region, the share of winter wheat increased. Rye increased only in the eastern part of Germany, whereas rape was expanded the most in all regions. Compulsory set-aside was reduced, while in the North, Centre and South, the specific regulation for small farms has to be taken into account.



Source: FARMIS 2004, FADN Germany.

Figure 3-2: Land allocation in 1996/97 and 2002/03 by crop

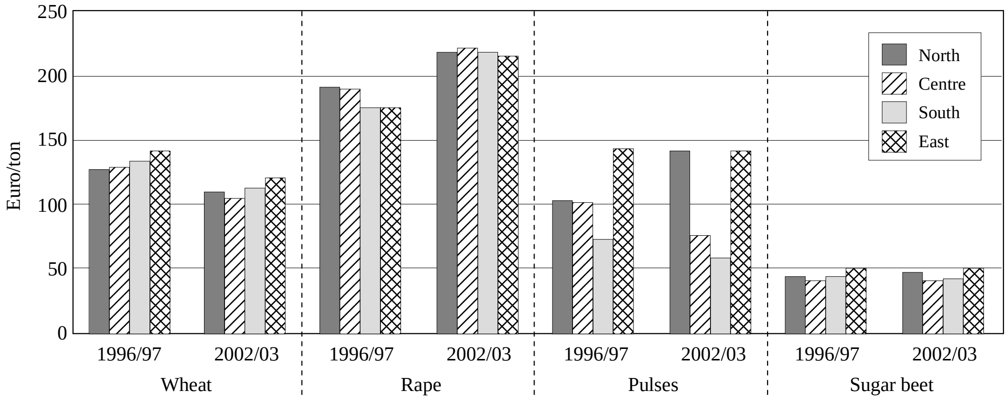
Under Agenda 2000, the levels of direct payments as depicted in Figure 3-3 for cereals, oilseeds and protein crops were harmonised. It becomes clear that the relative advantage of oilseed premiums declined to the level of cereals in 2002/03. The direct payments for protein crops are disturbed by vegetable peas, for which no payments are made.



Source: FARMIS 2004, FADN Germany.

Figure 3-3: Direct payments 1996/97 and 2002/03

Figure 3-4 shows the price change of the selected crops. The price for wheat decreased compared to the first year 1996/97, whereas the price for rape increased.



Source: FARMIS 2004, FADN Germany.

Figure 3-4: Price changes 1996/97 and 2002/03 by crop

3.3.3 Implementation of the calibration methods

To recover the cost function parameters of methods i) and ii), no further assumptions are needed besides the dual values of the constraint linear model (see equations (3.7) and (3.8)). For the method based on exogenous elasticity, two settings of elasticities, as presented in Table 3-1, are used. For *version II*, the elasticities for rape and for wheat were assumed to be 3.

Crops	Elasticities		Crops	Elasticities	
	version I	version II		version I	version II
Winter wheat	1.33	3.00	Pulses	1.50	
Spring wheat	1.33		Rape	1.99	3.00
Rye	1.33		Non-food rape	1.99	
Winter barley	1.33		Other oil seed	1.99	
Spring barley	1.33		Potatoes	0.40	
Oats	1.33		Sugar beet	1.33	
Grain maize	1.40		Set aside compulsory	1.50	
Other cereals	1.33		Set aside volunatry	1.50	

Table 3-1: Elasticities used for recovering the cost function parameter for scenario iii)

For the calibration method with *Maximum Entropy*, two different alternative support spaces are considered. For both versions, the support matrices of the entropy approach (equation (3.13)) are set as suggested in Paris & Howitt (1998)[5], whereas for *version I*, the vector of weights $\mathbf{W_l}$ is set with k=5 to (-2; -1, 0; 1; 2) and $\mathbf{W_d}$ is set to (0; 1; 2; 3; 4). In *version II*, $\mathbf{W_l}$ is set to (-1; -.5, 0; .5; 1) and $\mathbf{W_d}$ is set to (0; .66; 1.33; 2; 2.66). The alternative versions were chosen in order to test the impact of the support point setting with respect to the resulting simulation behaviour. The cost function parameters were estimated using ME.

Calibration methods i) to iv) are applied to the farm group supply models using the gross margin and production levels observed in 1996/97. Crop-specific costs are calculated with generation modules of the farm group model FARMIS. After estimation of the cost function parameters, the farm groups are tested for calibration to the observed production. Afterwards, the gross margins for 2002/03 are applied as shocks to the supply model, and differences between the observed and the simulated production for 2002/03 are evaluated by calculating the percentage absolute deviation (PAD):

$$PAD = N^{-1} \sum_i ABS\,|\,(\hat{x}_i - x_i\,)\,/\,x_i\,|, \qquad (3.24)$$

where N denotes the number of crops, x_i the observed land use in 2002/03 and $\hat{x}_i$ the calculated crop allocation.

The *FOC* Method is applied to one particular farm group using time series from 1996 to 2000 to estimate the cost function parameters. The support points for the error term (equation (3.18)) bound the support to within 5 standard deviations of the

5 See equation 29-33 in Paris and Howitt (1998).

land allocation, and prior information on supply elasticities in (3.19) is done analogously to the specification of the error term, where the $\mathbf{V}^{\varepsilon}$ Matrix with 2 support points for each prior information on elasticity bounds the support to within 2 standard deviations. The cost function parameters are estimated using GME. For the *FOC* method, observed gross margins from 2002/03 are applied to the calibrated farm group. For comparison, the *Original PMP* and the *Paris (1988)* methods are used, calibrated based on the average production from 1996 to 2000.

3.4 Results

Table 3-2 depicts the percentage absolute deviation for all farms groups for methods i) to iv). It is interesting to note that the mean PAD is relatively high for all scenarios.

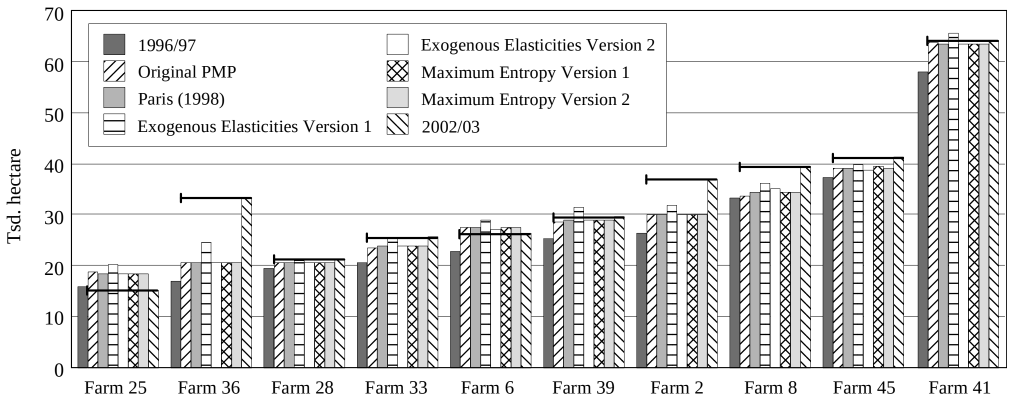
		Original PMP	Paris (1998)	Exogenous Elasticities		Maximum Entropy	
				Version 1	Version 2	Version 1	Version 2
Farm	1	82.2	69.1	76.9	82.9	69.1	69.1
Farm	2	101.6	99.2	99.9	85.5	99.0	99.3
Farm	3	134.2	119.0	116.4	119.5	118.9	118.4
Farm	4	72.8	49.5	47.5	40.9	49.5	49.6
Farm	5	29.0	27.3	26.1	24.6	27.3	27.3
Farm	6	85.8	76.1	43.7	38.6	60.9	44.9
Farm	7	90.4	55.3	55.7	51.1	56.5	57.7
Farm	8	91.2	78.3	72.7	65.3	78.4	78.4
Farm	10	36.4	32.0	35.7	39.4	32.0	32.0
Farm	11	99.1	65.8	67.5	63.6	66.8	65.8
Farm	12	32.3	27.1	31.4	33.2	27.1	27.1
Farm	13	84.1	80.6	56.8	56.5	80.6	80.6
Farm	14	16.8	15.7	15.1	16.3	15.7	15.7
Farm	15	73.7	73.1	77.6	75.6	73.1	73.1
Farm	16	83.0	70.2	63.5	58.9	70.2	70.2
Farm	17	74.6	56.4	60.0	60.7	56.4	56.4
Farm	18	39.5	33.8	32.2	30.8	33.9	33.9
Farm	19	169.0	104.7	103.7	101.0	104.7	104.7
Farm	20	108.6	108.5	106.0	100.9	108.5	108.4
Farm	21	93.4	67.2	63.0	53.5	67.2	66.9
Farm	22	93.1	30.5	30.5	28.7	30.5	30.5
Farm	23	109.5	96.1	93.8	91.7	96.1	96.1
Farm	24	110.5	35.3	33.7	31.8	35.3	35.3
Farm	25	141.4	83.1	83.4	82.1	83.1	83.1
Farm	26	58.7	31.8	29.3	30.8	31.7	31.7
Farm	27	96.8	95.8	77.5	69.7	95.9	95.8
Farm	28	160.3	152.3	143.3	136.5	152.3	152.3
Farm	29	26.4	24.6	26.8	22.7	24.6	24.6
Farm	30	51.7	46.7	51.5	53.1	46.7	46.7
Farm	31	146.3	138.0	144.9	114.4	128.4	113.4
Farm	32	100.5	103.3	53.7	39.4	103.3	103.3
Farm	33	156.1	129.0	137.8	120.0	129.1	129.1
Farm	34	137.4	141.3	141.9	125.4	141.3	141.3
Farm	35	78.1	82.1	75.8	65.2	82.1	82.1
Farm	36	183.0	196.0	186.2	184.4	196.0	196.0
Farm	37	170.2	174.2	174.0	167.1	174.2	174.2
Farm	38	44.2	43.3	35.6	43.5	43.3	43.3
Farm	39	72.5	74.0	72.2	63.7	74.0	74.0
Farm	40	126.9	114.8	129.2	138.0	114.7	114.4
Farm	41	109.6	126.7	154.8	155.4	126.7	126.7
Farm	42	82.2	96.9	93.0	79.2	96.9	96.9
Farm	43	61.6	49.8	46.2	48.4	46.0	38.6
Farm	44	97.4	95.5	97.8	92.6	95.6	95.6
Farm	45	47.2	43.1	45.7	39.1	42.7	43.1
Farm	46	124.7	96.5	102.7	103.4	96.5	96.5
Mean		93.0	80.2	78.1	73.9	79.6	78.8

Source: FADN, FARMIS

Table 3-2: Percentage Absolute Deviation (PAD) for the *ex post* experiment

One explanation could be the low crop yield in 2002 caused by the strong winter, the flood in August 2002 and the impact of Agenda 2000. The observed production of the farm groups seem to be not yet fully-adjusted to the new premium schemes, as shown in Figure 3-6 for rape seed. In addition, we have to take into account the fact that the PAD was obtained only for crops that were observed in the base year 1996/97. Therefore, the absolute value of the PDA should be interpreted with caution. Nevertheless, the relative differences of the percentage absolute deviation can be used to interpret the calibration methods with respect to the simulation behaviour. The *original PMP* scenario has the highest PAD value. Here, for the ‘marginal’ activities – crops with zero dual value on the calibration constraint – the cost function is linear. A price increase of the preferred production activity leads to a substitution away from marginal activities, but leaves the other preferred activities unchanged until the first marginal activity is replaced.

Two alternative exogenous own gross margin elasticities for rape and wheat were considered for the calibration scenario with *exogenous elasticities*. The results in Figures 3-5 and 3-6 show the sensitivity of this calibration approach (pillar 4-5). The second version benefits from the increase of the gross margin elasticity for wheat.

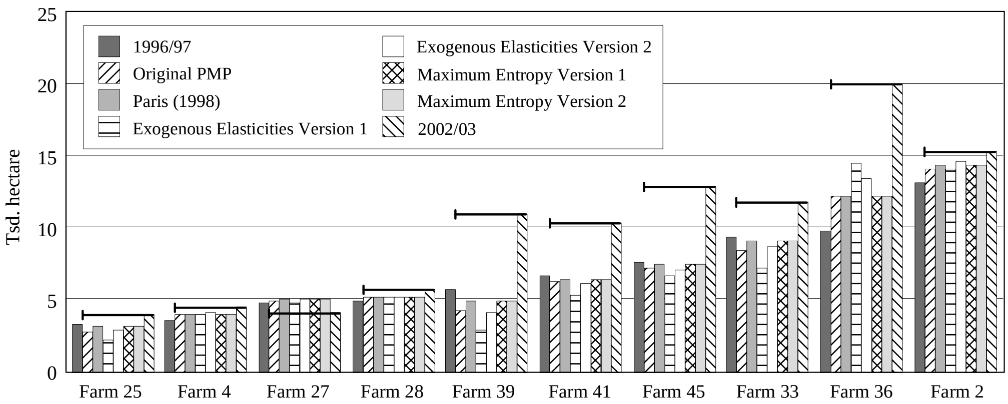


Source: FARMIS 2004, FADN Germany.

Figure 3-5: Allocation of wheat for large farms (>10,000 hectares)

The advantage of the *Maximum Entropy* method is the possibility of fully using any amount of sample information, no matter how scarce. The recovery of a fully-specified $\mathbf{Q}$ matrix for the cost function is no longer impossible. Moreover, the results for the ME approach are very similar to the calibration approach presented by *Paris (1988)* (see Figures 3-5 and 3-6). This behaviour can be explained if equation (3.8) and equation (3.11) are compared. For both approaches, the linear part of the cost function $\mathbf{d}$ was set to zero, whereas the ME approach recovering the full $\mathbf{Q}$ matrix and the *Paris (1988)* approach calculated the diagonal elements of the $\mathbf{Q}$ matrix. Furthermore, the difference between *versions I* and *II* of the *Maximum*

Entropy method is very small, which implies that the different support points for the simulation have only a marginal impact. The fully-specified **Q** matrix for one observation does not seem to contain more information on how the marginal incentives change if one moves away from the observed land allocation.

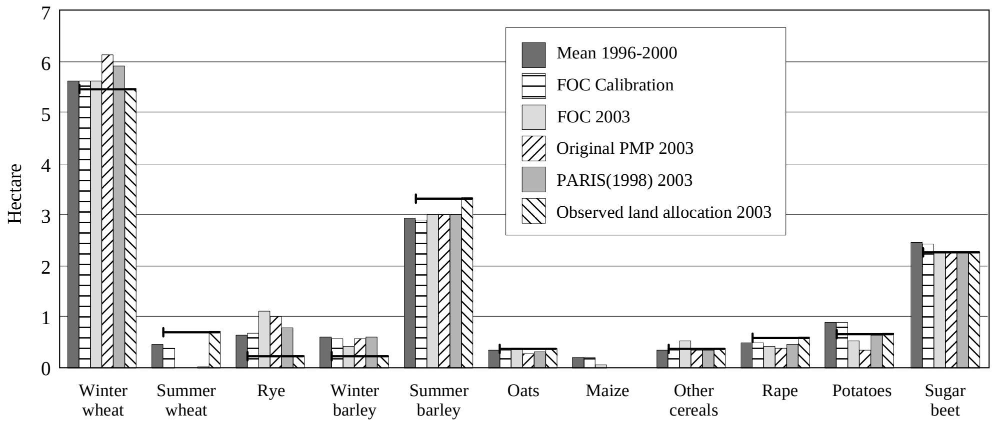


Source: FARMIS 2004, FADN Germany.

Figure 3-6: Allocation of rape for large farms (> 2000 hectares)

It appears that the support for the ME specification was defined without any additional prior information on the cost function, which causes a uniform distribution of probabilities, since the centres of the support ranges are already satisfied by the data constraints and, therefore, the resulting parameters from the ME approach are exactly the ones implied by the *Paris (1988)* method. These results coincide with findings from Heckelei & Britz (2000).

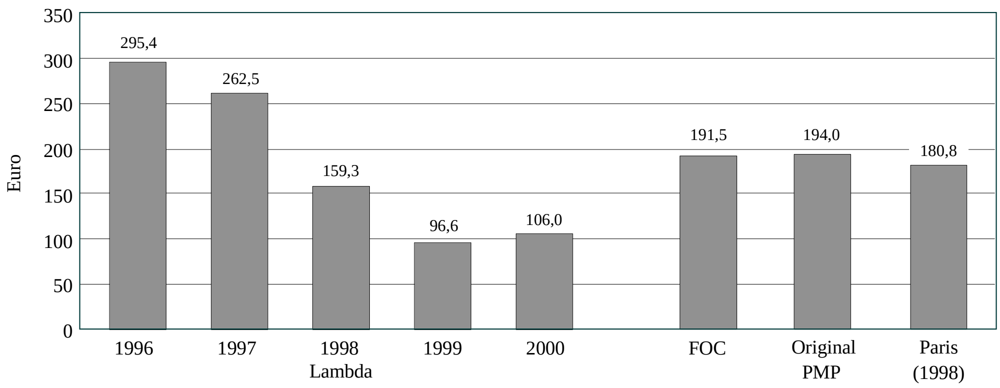
Apart from the methods above, Figure 3-7 shows the results for the explicit optimisation model based on five observations (1996-2000) over time. The mean of the land allocation from 1996 to 2000 is depicted in the first bar for each crop, the calibrated land allocation for the *FOC* method is presented in the second bar. The observed land allocation in 2002/03 and the different simulation scenarios are presented in the remaining pillars. The crop allocation in 2002/03 indicates that the *FOC* approach behaves differently. The total absolute bias for the *FOC* method of 2.78 outperforms the *original PMP* version, which has a bias of 3.6. However, the bias for the *Paris (1988)* method has almost the same value as the *FOC* approach. A possible explanation is that Agenda 2000 is mainly responsible for the gross margin changes, and the change in production in our observed target year is not considered during the *FOC* estimation (see Table 3-A1 and 3A-2, appendix). The recovered **Q** matrix of the method calibrates almost to the mean of land allocation over time, even in the case where crops were not observed for one year. Also interesting is the absolute deviation for winter wheat, where the method outperforms the other methods.



Source: FARMIS 2004, FADN Germany.

Figure 3-7: Crop allocations for farm groups from different calibration models

A distinctive difference of the approach is that it estimates duals of the land constraint endogenously. Lambda in Figure 3-8 denotes the estimated shadow prices for land obtained from the *FOC* model over the five years.



Source: FARMIS 2004, FADN Germany.

Figure 3-8: Dual values of land for the farm group

Alternatively, the shadow prices for the final model using the recovered **Q** matrixes are presented. The estimated shadow prices decrease from 1996 to 2000 due to the gross margin changes (see Table 3A-2, appendix). However, the resulting shadow prices for all three final models have only a small deviation. For completeness, we would like to mention that the *FOC* approach also provides an estimate for the elasticity matrix in Tables 3-A4 in the appendix and the fully specified cost matrix presented in Table 3-A3 in the appendix.

3.5 Conclusions

The paper investigates, using an *ex post* framework, the resulting simulation behaviour of different methods used to estimate the parameters of the cost function during supply model calibration. Four different methods proposed in the literature are evaluated using 45 farm group models for the year 1996/97. Observed gross margins for the year 2002/03 are applied to the calibrated supply model. We then assessed the deviation as the percentage absolute deviation between observed and simulated production. The *ex post* framework shows that, as long as the condition in equation (3.13) is satisfied, the calibration of the resulting model is guaranteed, but different specification of $\mathbf{d}$ and $\mathbf{Q}$ results in different simulation behaviour, as also reported by Cypris (2000).

If we want to discriminate between the PMP approaches based on the findings of the *ex post* experiment, we would have to prefer the calibration method with *exogenous elasticities* (*version II*). The PAD outperformed all other methods. The resulting simulation behaviour is defined by the given elasticities and reduces the role of PMP to all it is: a calibration method.

The PMP approach, where *Maximum Entropy* (Paris and Howitt, 1998) was applied could not improve the supply response compared to the observed values in the target year. This leads to the conclusion that the specifications (support point settings) to recover cost function parameters seemed unfavourable. However, the applied methodology offers potential for further development. The ME framework has the possibility to introduce additional out of sample information such as elasticities and can, superior to the *exogenous elasticity* method, account for cross-effects between crops and incorporate multiple observations.

The *original PMP* method has the highest PAD, resulting from the linear form of the cost function of the marginal activity. Hence, this PMP method should not be considered as a calibration method for MP models.

Apart from the *ex post* experiment with 45 farm groups, we could demonstrate that the suggested *FOC* approach introduced by Heckelei & Wolff (2003) can be applied to FADN data time series. The approach estimates the cost function parameter using the explicit optimisation model, offers the possibility to incorporate prior information and avoids the general misspecification of the PMP models. From the findings of the *FOC ex post* experiment, we could see that the approach outperforms the original PMP method but did not find that the method significantly outperforms *Paris (1988)*. One reason is probably the short time series of the estimation. From the methodological point of view, however, it should be mentioned that this method is the only approach where the response behaviour relies on real observations. Jansson (2007) used the *FOC* method with a Bayesian estimation technique and aggregated the single production activities into crop groups for the cost function, which reduced the dimension of the Q matrix and, hence, results in lower computational requirements and avoids support point-related complications. The approach could replace the current GME setup. More observation over time will improve the specification, but in contrast to the sector approach (Jansson, 2007), FADN time series are rare due to the random nature of the sample, in which farms can enter and leave the sample depending on the sampling plan.

We can conclude that the PMP calibration methods, as implemented, result in different response behaviour for the *original PMP*, the *exogenous elasticities*. The *Paris (1988)* and the *Maximum entropy* methods behaved similarly. Further, we can conclude that for all PMP methods[6], the fit to the observed values is very poor. To improve PMP approaches with respect to the simulation behaviour, additional information such as exogenous elasticities or observed farming pattern must be included during calibration. The estimation of the cost function parameters under the first order condition with prior information on elasticities and based on multiple observation is a promising method, but computational demands and numerical problems, as well the lack of sufficient time series from FADN, prevents this method from becoming a standard approach for farm group models.

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3.7 Appendix

	1996	1997	1998	1999	2000	2001	2002	2003
Winter wheat	788.1	535.5	457.1	479.5	485.1	805.2	915.0	750.2
Summer wheat	412.1	267.8	584.0	257.2	264.5	553.8	622.4	
Rye	562.4	428.3	452.6	328.3	473.4	850.1	822.7	773.6
Winter barley	782.8	487.2	341.2	365.7	462.1	968.5	845.7	646.9
Summer barley	759.1	613.0	502.9	477.9	485.9	893.3	814.4	748.0
Oats	825.9	554.7	967.1	677.5	341.9	849.0	1401.6	754.0
Maize	296.1	557.7	-79.5	1.9		901.3	879.7	718.8
Other cereals	769.8	607.2	576.1		247.7	1111.4	1319.7	927.1
Rape	1070.1	1133.7	862.3	801.7	978.9	356.6		859.4
Potatoes	641.0	2122.1	2509.4	1414.5	1568.6	1111.1	1881.2	954.9
Sugar beet	1877.3	2478.2	2276.4	2154.4	2160.4	2503.3	2153.3	2342.1

Source: FADN, FARMIS

Table 3-A1: Gross Margins for the farm group

	1996	1997	1998	1999	2000	2001	2002	2003
Winter wheat	5.78	5.55	5.81	5.53	5.57	5.46	5.08	5.49
Summer wheat	0.25	0.26	0.39	0.65	0.68	0.75	0.77	0.72
Rye	0.88	0.83	0.52	0.55	0.39	0.32	0.24	0.24
Winter barley	0.44	0.58	0.70	0.74	0.52	0.58	0.54	0.23
Summer barley	2.61	2.97	2.89	2.88	3.30	2.76	3.60	3.34
Oats	0.34	0.40	0.30	0.30	0.36	0.24	0.31	0.38
Maize	0.37	0.21	0.19	0.10		0.45	0.48	0.39
Other cereals	0.38	0.31	0.33		0.34	0.55	0.34	0.61
Rape	0.49	0.45	0.62	0.56	0.39	0.11		0.09
Potatoes	0.80	0.94	0.93	0.80	0.92	0.79	0.85	0.68
Sugar beet	2.41	2.30	2.50	2.47	2.55	2.38	2.29	2.26

Source: FADN, FARMIS

Table 3-A2: Observed land allocation for the farm group

	Winter wheat	Summer wheat	Rye	Winter barley	Summer barley	Oats	Maize	Other cereals	Rape	Potatoes	Sugar beet
Winter wheat	114	-169	-77	87	43	-79	-149	-153	-4	-121	-200
Summer wheat	-169	1148	409	-84	-140	485	-161	572	-200	-82	152
Rye	-77	409	853	136	-200	-200	-200	-58	-139	-90	166
Winter barley	87	-84	136	1193	-200	-200	199	35	-200	-112	-191
Summer barley	43	-140	-200	-200	261	-101	-159	77	-200	-106	-181
Oats	-79	485	-200	-200	-101	2000	-200	170	-200	-74	167
Maize	-149	-161	-200	199	-159	-200	882	94	123	-121	396
Other cereals	-153	572	-58	35	77	170	94	2000	56	-87	-90
Rape	-4	-200	-139	-200	-200	-200	123	56	1478	-65	287
Potatoes	-121	-82	-90	-112	-106	-74	-121	-87	-65	2000	75
Sugar beet	-200	152	166	-191	-181	167	396	-90	287	75	1203

Source: Own calculation.

Table 3-A3: Recovered Q Matrix for the farm group

	Winter wheat	Summer wheat	Rye	Winter barley	Summer barley	Oats	Maize	Other cereals	Rape	Potatoes	Sugar beet
Winter wheat	1.317	0.011	-0.119	-0.255	-0.857	-0.117	0.005	0.131	-0.392	-0.034	0.444
Summer wheat	0.217	1.325	-0.984	0.123	-0.027	-0.687	-0.006	-0.593	0.173	-0.070	-0.284
Rye	-1.299	-0.552	1.326	-0.196	0.484	0.436	0.114	0.052	0.225	-0.052	-2.233
Winter barley	-2.714	0.068	-0.192	1.327	1.707	0.100	-0.210	-0.323	0.814	-0.101	0.428
Summer barley	-1.596	-0.003	0.083	0.298	1.330	0.085	-0.029	-0.210	0.428	-0.073	-0.481
Oats	-1.579	-0.479	0.541	0.127	0.615	1.330	0.062	-0.082	0.417	-0.058	-1.909
Maize	0.351	-0.022	0.764	-1.440	-1.130	0.337	1.399	-0.337	-0.717	0.096	-8.215
Other cereals	2.169	-0.507	0.079	-0.503	-1.869	-0.101	-0.076	1.333	-0.935	-0.038	1.584
Rape	-2.490	0.057	0.131	0.486	1.462	0.196	-0.062	-0.359	1.988	-0.074	-1.777
Potatoes	-0.074	-0.008	-0.010	-0.020	-0.084	-0.009	0.003	-0.005	-0.025	0.866	-0.271
Sugar beet	0.257	-0.008	-0.119	0.023	-0.150	-0.082	-0.065	0.055	-0.162	-0.073	1.320

Source: Own calculation.

Table 3-A4: Recovered Elasticity Matrix for the farm group with the “First Order Condition” approach with multiple data points

Chapter 4. Estimating a farm group model and input allocations using accountancy data*

Abstract

This paper proposes and applies an innovative estimation approach for farm group programming models using Generalised Maximum Entropy. The proposed set-up simultaneously determines calibrating cost function parameters and input allocations to production activities. The methodology is applied to Belgium Farm Accountancy Data Network (FADN) data of arable farms for which available input allocations allow to validate the estimation approach. Results outperform separate estimates of input allocations previously applied in the literature and this finding is robust with respect to support point design.

Keyword: Input allocation, Accountancy data, Generalised Maximum Entropy

4.1 Introduction

Agricultural farms typically produce more than one product in different enterprises. For environmental and economic impact analyses, the knowledge on physical or monetary input costs per enterprise is often very important but typically not available. One way to circumvent this problem was to allow for jointness in outputs and only estimate relationships between multi-output and aggregated multi-input levels (for example in Mittelhammer et al., 1981; Just et al., 1983; Hasenkamp, 1976).

Increasing public and political interest focuses on externalities from agriculture such as nutrient concentration in ground water or pesticide residues. In this context, approaches which do not represent enterprise specific input intensities are of limited usefulness. Consequently, the use of Mathematical Programming (MP) models for agri-environmental policy assessment expanded. The formulation based on production activities defined by output and input coefficients enables an explicit representation of technologies and their adjustments to policy constraints. However,

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the necessary information on input coefficients is often not available in farm accountancy data. To generate the required data, the input use at enterprise level was generally determined prior to MP specifications either through *ad hoc* approaches or regressions of total input use on output quantities.

For policy relevant simulations, the specification of MP models should be based on observed behaviour. Positive Mathematical Programming (PMP, Howitt 1995a and 1995b) contributed to improvements in this respect, but empirical content and theoretical consistency was limited. Heckelei & Wolff (2003) show how to specify MP models based on optimality conditions using multiple observations (time series or cross sectional data) and, if required, how to incorporate prior information on parameters and shadow prices. However, most specifications of this sort require information on enterprise specific input cost.

Here we propose a methodology for specifying a farm group model while simultaneously estimating input allocations to enterprises instead of using the typical two step approach with input allocation prior to MP model specification. We hypothesize that this will improve upon the quality of the input allocation results compared to previous approaches. At the same time, we estimate the farm group model with a non-linear cost function using multiple observations from single farm accountancy data and prior information on shadow prices. This contributes to a better empirical foundation for PMP type models.

The reminder of the paper is organised as follows. In the next section a short introduction to the PMP literature and its variants as well as to input allocation approaches is given. Section 4.3 introduces the concept of the farm group model. This is followed by the empirical approach with the statistical model, GME estimation approach, data, and non-sample information in Section 4.4. Section 4.5 presents and discusses results on estimated input allocations and variables of the farm group model, including a sensitivity analysis of different support point designs. The final section concludes.

4.2 Literature Background

PMP was introduced to agricultural supply modelling by Howitt (1995a and 1995b). This methodology, specifying a calibrating non-linear objective function based on observed activity levels, promised to solve a difficult problem previously encountered by analysts working with linear farm programming models: how to calibrate the model without “polluting” it by poorly justified constraints. The advantages of PMP seemed especially large for policy relevant simulation analysis and a considerable strand of literature developed with methodological enhancements and applications of PMP and variants. For an overview see Heckelei & Britz (2005) or Henry de Frahan et al. (2007). One of the key criticisms of the original PMP approach was that it lacked a sufficient empirical base for the specification of the objective function and thereby also for the resulting supply behaviour. Consequently, approaches have been suggested to estimate PMP parameters using multiple observations and/or prior information on behavioural parameters (Heckelei & Britz, 2000; Heckelei & Wolff, 2003; Helming et al., 2001; Buysse et al., 2007; Jansson, 2007). A limited theoretical base for the PMP approach also lead to argue for alternative approaches to the estimation of explicit optimisation models without any PMP elements (Heckelei & Wolff, 2003; Jansson & Heckelei 2009).

One common characteristic of PMP type approaches for the specification of farm programming models in the literature is that information on input allocations to the different farm enterprises is available beforehand. As this type of information is rarely recorded, the allocations are often derived from aggregate data using *ad hoc* or statistical methodologies prior to the specification of the PMP parameters.

There is a long history of allocating inputs to production activities in agriculture. Apart from *ad hoc* approaches inferring the allocation from published 'industry standards', agronomic field trials and expert opinions, a system of linear multiple regression functions is frequently used (e.g. Ray, 1985; Errington, 1989; Midmore, 1990; Moxey & Tiffin, 1994; Dixon & Hornbaker, 1992; Léon et al., 1999). In its general form, one observation of an $M \times 1$ vector of total input use in monetary terms, **b**, is explained by a linear function of the monetary output vector $N \times 1$ **x** in the form of

$$\mathbf{b} = \mathbf{A}\mathbf{x} + \mathbf{u}\,, \tag{3.25}$$

where **A** is an $M \times N$ matrix of unknown technological coefficients with its elements a_{ij} representing the amount of input i required per unit of output and **u** is an $M \times 1$ vector of random disturbances.

Errington (1989) proposed a single equation estimation of this type. However, the employed Ordinary Least Squares (OLS) estimation technique did not guarantee positive estimated input coefficients. In some cases the sum of the input coefficients across the M input categories were larger than one, prompting the author to conclude negative profits associated with the corresponding products. Ray (1985) discussed several alternative estimation procedures based on mathematical programming. He emphasised that in view of the non-negativity property of the input coefficients, the OLS method may lead to unacceptable estimates. Midmore (1990) pointed out that farm specific input coefficients can be estimated from regional farm business survey data if a common commodity technology can be assumed[1] and a correction for heteroscedasticity resulting from the size effect in production is considered, further he noticed that accounting identities implying revenue exhaustion, i.e. equality of the sum of monetary inputs us across all categories to monetary output values, violate standard assumptions on the error distribution rendering least squares techniques problematic.

An alternative Bayesian estimation approach for the linear regression was offered by Moxey & Tiffin (1994). He argued that the use of Bayesian priors is a natural mean of conducting inequality constrained estimation and suggested to use additional prior information based on information from other studies. In the same direction Léon et al. (1999) proposed the use of Generalised Maximum Entropy (GME) estimation to introduce non-sample information on the estimated coefficients. Apart from non-negativity constraints on input coefficients they also imposed cross equation restriction on the coefficient matrix **A** to ensure adding up. They compared the Entropy results of the different model designs with those from classical estimation techniques, namely minimizing absolute deviations, OLS, and Bayesian estimation methods using accounting data from dairy/beef farms from France. Furthermore they tested the sensitivity of the GME outcomes to different designs of prior information implemented by the setting of support points. They concluded that standard estimation techniques are no real alternative due to the problems identified in the literature before and stated that it is difficult to discriminate between the Bayesian and the GME approach.

This paper contributes to the two strands of literature just described by combining the estimation of PMP parameters using multiple observations with the estimation of input allocations. It is hypothesised that the incorporation of a behavioural model will improve estimation results on input allocation.

4.3 Conceptual farm group model

Farm supply models to be specified in this exercise shall be suitable for policy relevant simulation analyses and therefore comply with the following requirements:

i) The implied simulation response should be based on observed behaviour leading to the estimation of parameters with multiple observations.

[1] This commodity technology assumption implies that the input structure of a commodity is the same, regardless of the industry (farm type in the context of agriculture) where it is produced Midmore (1990).

ii) The estimated supply model should reproduce the observed practice. In other words, we should obtain a calibrated model.

iii) The model should be able to explicitly represent technologies and policy constraints.

The first two points are strongly related to the PMP literature. Heckelei & Wolff (2003) critically review the rationalisation of the non-linear term and pointed out the inconsistent estimation of the dual values in the standard PMP approach. They proposed a conceptually simple but general alternative to overcome the problem and to calibrate and estimate the programming models by directly employing the optimality conditions. Their suggestion allows to simultaneously estimating parameters of the behavioural functions and the dual values of the constraints. The proposed model in this paper builds upon this approach. To start let us assume farmers maximize profits solving the following optimization problem:[2]

$$\max_{\mathbf{x}} \; f(\mathbf{x}) = [\mathbf{p}' \odot \mathbf{y}' + \mathbf{s}' - \mathbf{1}'_M \mathbf{A}]\mathbf{x} - [\mathbf{d}' - 0.5\mathbf{x}'\mathbf{Q}]\mathbf{x} \qquad (3.26)$$

subject to

$$\mathbf{R}\,\mathbf{x} \leq \mathbf{c} \;\; [\boldsymbol{\lambda}] \qquad (3.27)$$

$$\mathbf{x} \geq 0 \qquad (3.28)$$

where **x** now represents the $N \times 1$ vector of acreages. The vector **y, p,** and **s** are $N \times 1$ dimensional vectors of expected yields, expected prices, and subsidies, respectively. $\mathbf{R}$ a $2 \times N$ matrix of coefficients of a land and a sugar quota constraint. Furthermore, $\mathbf{c}$ is a 2×1 vector of available resources and $\boldsymbol{\lambda}$ the corresponding vector of shadow prices. The second summand of the profit function is a quadratic cost function with an $N \times 1$ parameter vector $\mathbf{d}$ and an $N \times N$ parameter matrix $\mathbf{Q}$.

Assuming that land and quota constraints are binding, the first order optimality conditions are given by:

$$\mathbf{p} \odot \mathbf{y} + \mathbf{s} - \left(\mathbf{1}'_M \mathbf{A}\right)' - \mathbf{d} - \mathbf{Q}\mathbf{x} - \mathbf{R}'\boldsymbol{\lambda} = \mathbf{0} \qquad (3.29)$$

---

[2] The symbol $\odot$ indicates and element-wise multiplication operator and $\mathbf{1}_M$ is an M-dimensional column vector of ones.

$$\mathbf{R}\,\mathbf{x} - \mathbf{c} = \mathbf{0} \tag{3.30}$$

In the next section, we will use these first order conditions together with equation (3.25) in order to estimate the unknown technology matrix for variable inputs $\mathbf{A}$, the parameters for the non-linear cost function $\mathbf{d}$, and $\mathbf{Q}$, and the dual values on land and quota, $\boldsymbol{\lambda}$, using multiple observations and prior information.

4.4 *Empirical approach*

This section develops the empirical model based on the aforementioned discussion, introduces the data, and describes the estimation approach.

4.4.1 *Estimated model*

Applying farm indices as $f = 1,...,F$ and indicating all observed data by the subscript '*o*', the first order condition from (3.29) can be written as:

$$\mathbf{0} = \mathbf{p}_f \odot \mathbf{y}_f + \mathbf{s}_f^o - \mathbf{1}^{M\prime}\mathbf{A}_f - \mathbf{d} - \mathbf{Q}\mathbf{x}_f - \mathbf{R}_f^{o\prime}\boldsymbol{\lambda}_f \;\; \forall \; f \tag{3.31}$$

We assume additive, iid errors for the endogenous variable of the optimisation model, acreages $\mathbf{x}_f$, so that

$$\mathbf{x}_f = \mathbf{x}_f^o + \mathbf{e}_f \;\; \forall \; f \,. \tag{3.32}$$

Furthermore, producers are considered to have naïve price expectations of the form

$$\mathbf{p}_{f,t} = \mathbf{p}^{o}_{f,t\text{-}1} + \mathbf{e}_f^p \quad \forall \; f \tag{3.33}$$

where the $\mathbf{e}_f^p$ is a vector of measurement errors.[3] Naïve expectations also apply to the yields but without error term.

Second order optimality conditions require that the $\mathbf{Q}$ matrix has to be symmetric positive semi-definite, which can be ensured by adding a Cholesky factorisation of $\mathbf{Q}$ as a constraint to the equations:

$$\mathbf{Q} = \mathbf{L}\mathbf{L}' \quad \text{with} \quad \mathbf{L}_{ij} = 0 \;\; \forall \; j > i \tag{3.34}$$

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[3] One reason for the likely existence of a measurement error is that implicit prices derived from sales accounts of farm records are not the prices obtained for the production of the same accounting year as this generally does not coincide with the production cycle. Alternatively, one might interpret the error as a random deviation from the naïve expectation hypothesis across the different farms.

We now re-parameterise the farm specific matrix of monetary input coefficients $\mathbf{A}_f$ in terms of a equally dimensioned matrix of cost shares for each variable input category i of the output category j per ha, $\tilde{\mathbf{A}}$, which is constant across farms. Let $\mathbf{T}_f$ be a $M \times N$ matrix of total revenue per ha of a crop with N identical columns $\mathbf{T}_{j,f} = \left(\mathbf{y}_f^o \odot \mathbf{p}_f + \mathbf{s}_f^o\right) \forall\ j$. Then we write $\mathbf{A}_f = \tilde{\mathbf{A}} \odot \mathbf{T}_f\ \forall\ f$ such that we can now include a farm specific version of equation (3.25) into our estimation setup as

$$\mathbf{b}_f = \left(\tilde{\mathbf{A}} \odot \mathbf{T}_f\right)\mathbf{x}_f + \mathbf{u}_f\ \forall f \tag{3.35}$$

Note that this formulation implies equality of total cost to total revenue if the elements of $\tilde{\mathbf{A}}$ add up to one across input categories. This is achieved by introducing a residual input category 'value added' as suggested by Leon et al. (1999) with corresponding monetary input coefficients equal to the difference between crop revenue plus subsidies and the observed variable input cost per ha (sum of all other monetary input coefficients across input categories). At estimation stage we have to guarantee the adding up condition of the shares by including the N equations

$$\tilde{\mathbf{A}}'\mathbf{1}^M = \mathbf{1}^N\ . \tag{3.36}$$

In order to achieve a farm group model calibrating to aggregate observed acreages we impose

$$\sum_{\mathrm{f}=1}^{\mathrm{F}} \mathbf{x}_f^o = \sum_{\mathrm{f}=1}^{\mathrm{F}} \mathbf{x}_f \tag{3.37}$$

and this concludes the model with equations (3.31) to (3.37) to be estimated. Note again that this model allows to simultaneously estimating the parameters **d** and **Q** of the PMP-type cost function, the shadow prices $\boldsymbol{\lambda}$ and input cost shares $\tilde{\mathbf{A}}$.

4.4.2 Data

The developed estimation approach is applied to a set of year 2000 FADN accounting data (1999 for price and yield data) from 56 Belgium farms. The Belgium dataset has a distinct advantage, input cost per production activity are additionally collected[4] compared to the other FADN datasets in Europe. The farms are classified using the type of farming definition (European Commission, CD 85/377/EEC, Article 6). Farms in the class 'specialist cereals, oilseed and protein crops' (FT13) and 'general field cropping' (FT14) and above a threshold of 60 economic size units are considered for estimation. The data distinguishes the five input categories

[4] J. Buysse from University of Gent provided the data for the estimation.

depicted in Table 4-1 and a ‘value-added’ category obtained residually. The inputs are used to engage in seven production activities.

	Unit	Winter Wheat	Winter barley	Chicory	Vegetables in open air	Potatoes	Green peas for tin	Sugar beet	Land
Inputs	(€/ha)								
Contract work		124 (73)	130 (59)	346 (130)	560 (285)	269 (215)	296 (128)	311 (136)	
Seeding		67 (23)	65 (25)	113 (2)	573 (285)	339 (99)	216 (58)	201 (28)	
Treatment		150 (41)	137 (39)	270 (96)	260 (84)	468 (112)	113 (47)	205 (74)	
Fertilizer		75 (29)	90 (63)	143 (79)	188 (88)	195 (78)	50 (0)	184 (109)	
Land	(ha)	27 (15)	10 (10)	9 (5)	8 (4)	14 (9)	8 (2)	14 (8)	58 (28)
Yield	(t/ha)	9 (1)	7 (1)	47 (6)	43 (18)	44 (7)	8 (1)	71 (10)	
Price	(€/t)	118 (8)	119 (10)	46 (4)	119 (102)	47 (26)	231 (26)	41 (5)	
Observations		54	26	27	8	28	6	56	

Note: standard deviations of variables are given in parenthesis

Table 4-1: Farm group sample

The available land resources and sugar quotas are not directly observed but instead calculated for each farm as the total sum of acreages planted and sugar production quantity, respectively.

4.4.3 Estimation

In order to incorporate valuable prior information we employ a GME estimator as introduced by Golan et al. (1996). For this purpose, we re-parameterise the unknowns of the model in terms of probabilities and support points. This applies to the input allocation matrix, $\tilde{\mathbf{A}}$, the vector of dual values for land and quota constraints, $\boldsymbol{\lambda}$, the linear term of the quadratic object function **d**, and the various error terms related to acreages, prices and input cost shares. Starting with the input cost shares we have

$$\tilde{\mathbf{a}}_{ij} = \mathbf{sa}'_{ij}\mathbf{pa}_{ij} \forall i, j \tag{3.38}$$

where $\mathbf{sa}_{ij}$ and $\mathbf{pa}_{ij}$ are $W\times 1$ vectors of support points and corresponding probabilities, respectively. Similarly, the elements of all other re-parameterised vectors are expressed as

$$\boldsymbol{\lambda}_{cf} = \mathbf{sl}'_{cf}\mathbf{pl}_{cf} \quad \forall\, c, f \tag{3.39}$$

$$\mathbf{d}_j = \mathbf{sd}'_j\mathbf{pd}_j \quad \forall\ j \tag{3.40}$$

$$\mathbf{u}_{if} = \mathbf{su}'_{if}\mathbf{pu}_{if} \quad \forall\ i, f \tag{3.41}$$

$$\mathbf{e}_{jf} = \mathbf{se}'_{jf}\mathbf{pe}_{jf} \quad \forall\ j, f \tag{3.42}$$

$$\mathbf{e}^{\mathrm{p}}_{jf} = \mathbf{sp}'_{jf}\mathbf{pp}_{jf} \quad \forall\ j, f \tag{3.43}$$

where $\mathbf{sl}_{cf}$ $(G\times1)$, $\mathbf{sd}_j$ $(D\times1)$, $\mathbf{su}_{if}$ $(K\times1)$, $\mathbf{se}_{if}$ $(P\times1)$, $\mathbf{sp}_{if}$ $(H\times1)$ are vectors of support points and $\mathbf{pl}_{cf}$, $\mathbf{pd}_j$, $\mathbf{pu}_{if}$, $\mathbf{pe}_{if}$, and $\mathbf{pp}_{if}$ are the corresponding vectors of probabilities.

We also need to introduce the following adding-up constraints on the probabilities:

$$\mathbf{1}^{W\prime}\mathbf{pa}_{ij} = 1 \ \forall\ i, j\ ; \tag{3.44}$$

$$\mathbf{1}^{G\prime}\mathbf{pl}_{cf} = 1 \ \forall\ c, f\ ; \tag{3.45}$$

$$\mathbf{1}^{D\prime}\mathbf{pd}_{j} = 1 \ \forall\ j\ ; \tag{3.46}$$

$$\mathbf{1}^{K\prime}\mathbf{pu}_{if} = 1 \ \forall\ i, f\ ; \tag{3.47}$$

$$\mathbf{1}^{P\prime}\mathbf{pe}_{jf} = 1 \ \forall\ j, f\ ; \tag{3.48}$$

$$\mathbf{1}^{H\prime}\mathbf{pp}_{jf} = 1 \ \forall\ j, f\ ; \tag{3.49}$$

The GME objective function following from this re-parameterisation is given by

$$\max_{\mathbf{pa}_{ij},\mathbf{pl}_{cf},\mathbf{pd}_j,\mathbf{pu}_{if},\mathbf{pe}_{jf},\mathbf{pp}_{jf}} \mathrm{H}(\mathbf{pa}_{ij},\mathbf{pl}_{cf},\mathbf{pd}_j,\mathbf{pu}_{if},\mathbf{pe}_{jf},\mathbf{pp}_{jf}) =$$

$$-\sum_{j=1}^{N}\begin{bmatrix}\sum_{i=1}^{M}\mathbf{pa}_{ij}\,'\ln\mathbf{pa}_{ij}\\ +\mathbf{pd}_j\,'\ln\mathbf{pd}_j\\ +\sum_{f=1}^{F}\mathbf{pe}_{jf}\,'\ln\mathbf{pe}_{jf}\\ \sum_{f=1}^{F}\mathbf{pp}_{jf}\,'\ln\mathbf{pp}_{jf}\end{bmatrix}-\sum_{i=1}^{M}\sum_{f=1}^{F}\mathbf{pu}_{if}\,'\ln\mathbf{pu}_{if}-\sum_{c=1}^{2}\sum_{f=1}^{F}\mathbf{pl}_{cf}\,'\ln\mathbf{pl}_{cf} \tag{3.50}$$

and is optimised subject to the model equations (3.31) to (3.37) and the GME constraints (3.38) to (3.49). After the optimal solution is obtained, the estimated values of the unknown parameters and error terms can be recovered by equations (3.39) to (3.43) using the optimal probability values.

4.4.4 Non-sample information

Non-sample or prior information in the GME estimation approach is defined via the support point settings. They are potentially highly relevant for the estimation results and will therefore be subjected to sensitivity analysis later on. We first introduce here an ‘initial’ or ’base’ support point setting in terms of bounds, spacing and the implied prior expectation. The 11 discrete support points for the elements of the matrix of input cost shares, $\tilde{\mathbf{A}}$, is defined taking prior information on the magnitude and range of the specific total input cost shares across all crops into account.[5] For the residual category ‘value added’, the support space is bounded between zero and one and support points are equally spaced with a distance of 0.1. This implies a prior expectation equal to 0.5 noting that this category can easily account for up to fifty percent of the total revenue for each product as in incorporates the remuneration to all fixed factors. Furthermore the prior information on seeding costs is introduced with equally spaced support points between 0 and 0.2 because the average seeding costs per hectare accounts for around ten percent of total revenue and this share is rather stable. For all other input categories, i.e. fertilizer, contract work, and plant protection, the support space is symmetrically distributed around an expectation of 0.15 with bounds 0 and 0.3.

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5 Following Léon et al. (1999), who used 11 support points.

All support spaces for error terms are symmetrically defined around zero with three support points. The support space for the noise related to total cost for each input category (equation (3.35)) follows the widely accepted three-sigma rule by Pukelsheim (1994) with support $(-3\hat{\sigma}_u, 0, 3\hat{\sigma}_u)$, where $\hat{\sigma}_u$ is the standard deviation of the total cost associated with each input category in the sample. The same approach is not suitable for the error term on land allocation, because they differ between farms (equation (3.32)). Also noting that acreages are likely observed with little measurement error, we have defined a range of 20 percent around observed activity levels. The support space for the noise term on expected prices (equation (3.33)) is again defined using the three-sigma rule for the prices observed in the farm group sample.

The support for the dual values on land and sugar quota constraints are also symmetrically defined over three discrete support points. The expected value – equal to the middle support point – for the dual on land is set to the land rent information available in the FADN data for each farm and the support space was defined as plus /minus one sample standard deviation of land rent. Estimates for the sugar quota rents for this sample were available from Buysse et al. (2007) for this sample and taken as the expected value. Because this information was not directly observed, the support space was defined by plus /minus 20 percent of the expected value. The expected values of the linear cost terms in **d** are defined as the sample average of corresponding total gross margins minus the expected dual values of land and sugar quota with a symmetrical support point setting of plus /minus ten times the expected value to account for the uncertain nature of the prior information.

4.5 Results

First we evaluate how the simultaneous estimation of input allocations and behavioural model compares to a separate linear regression as previously employed in the literature. For this assessment we use observed values on monetary input coefficients as presented in Table 1 that were not used in estimation. Then we look at the fit of the behavioural model with respect to the endogenous variables. Finally, the sensitivity of the results with respect to alternative support point designs is presented.

4.5.1 Input allocation

We estimated the farm group optimisation model simultaneously with the variable input allocation (FOC-LR-Model) as introduced in the previous section using the FADN data. For comparison, we also estimated independently the linear regression model represented by equation (3.35) similar to Léon et al. (1999) with GME using the same support points for the input cost shares as for the simultaneous approach (LR-Model). Both resulting input allocations are used to calculate Pearson's correlation coefficient with out-of-sample observed input allocations across farms (see Table 4-2). In line with our expectations, the FOC-LR model performs slightly better measured by the sum of the correlation coefficients over all input categories. But its performance is not dominant as the occurrence of the largest correlation coefficient switches between models when moving from one input category. Only with respect to the estimation for the input category *treatment,* the inclusion of the behavioural model in the estimation exercise seems to significantly improve upon the LR-model results.

	FOC-LR-Model	**LR-Model**
Contract Work	0.88	0.81
Seeding	0.73	0.87
Treatment	0.4	0.01
Fertilzer	0.35	0.49
Value added	0.88	0.77
Sum	3.24	2.95

Table 4-2: Pearson's correlation coefficient for input allocations of the FOC-LR and LR model with observed values

Table 4-3 depicts the deviation of estimated input cost shares from the observed averaged across all farms (bias) by input category and production activity. The bias measures are smaller for the FOC-LR model in 20 out of the 35 cases and the aggregate bias over all input categories and products to this model is smaller by about 5%).

		Contract work	**Seeding**	**Treatment**	**Fertilizer**	**Value-added**
Winter Wheat	LR	-0,019	-0,004	0,035	0,005	-0,014
	FOC-LR	0,017	-0,006	0,033	0,019	-0,065
Winter barley	LR	0,010	-0,024	0,009	-0,052	0,057
	FOC-LR	-0,024	-0,023	0,011	-0,070	0,106
Chicory	LR	0,053	-0,024	0,029	0,005	-0,062
	FOC-LR	-0,057	-0,024	0,010	-0,010	0,080
Vegetables in open air	LR	-0,103	0,046	-0,047	-0,033	0,138
	FOC-LR	-0,069	0,055	-0,023	-0,020	0,057
Potatoes	LR	0,049	0,005	0,037	0,011	-0,102
	FOC-LR	0,004	-0,032	-0,013	-0,014	0,054
Green peas for tin	LR	-0,029	0,042	-0,048	-0,057	0,092
	FOC-LR	0,008	0,035	-0,072	-0,081	0,111
Sugar beet	LR	0,047	0,004	-0,040	0,004	-0,016
	FOC-LR	0,036	0,003	-0,038	-0,004	0,003

Table 4-3: Bias of estimated input shares for the LR and the FOC-LR model

Despite mixed results on single input categories and products, we can infer a consistently superior performance by the FOC-LR model regarding the estimation of input allocations for the aggregate measures considered.

4.5.2 *Fit of behavioural model*

Although the comparison of input allocations between the two approaches already points at a potential benefit of the simultaneous estimation approach, the actual estimation of the farm group model is of considerable interest by itself. Table 4-4 shows correlation coefficients of crop acreage allocations, prices as well as land and quota rents with their 'observed' counterparts.[6] We see that in most cases the fit for acreage is high, above 0.9. Exceptions are vegetables in open air and Green peas for tin. This is, however, not surprising as Table 4-1 indicates that for those two production activities only very few observations for the farm group were available rendering the estimation generally more challenging. The fit for expected prices is low for winter wheat, potatoes and green peas due to the larger total price variation (see Table 4-1 and Figures 4-A1 to 4-A5 in the appendix).

Crop	**Land allocation**	**Price**
Winter Wheat	0.966	0.299
Winter barley	0.989	0.747
Chicory	0.753	0.638
Vegetables in open air	0.636	0.969
Potatoes	0.917	0.466
Green peas for tin	0.408	0.340
Sugar beet	0.999	0.643
Dual values		
Land	0.922	
Sugar Quota	0.907	

Table 4-4: Pearson's correlation coefficient between "observed" and fitted values of model variables

Observed values and corresponding estimates from the FOC-LR Model for the dual values of the land and sugar beet constraints are shown in Figure 4-1 and Figure 4-2, respectively, ordered by size of the observed values. A reasonably good fit with the observed values can be inferred. This is not a trivial result in the context of PMP literature, because many published approaches along the standard PMP approach

[6] 'Observed' refers to estimates from the Buysse et al. (2007) in the case of sugar quota rents as described in the previous section.

recover rather unrealistic dual values of resource constraints.[7] Nevertheless, there is some recognisable downward bias of the estimator, especially for the sugar beet case.

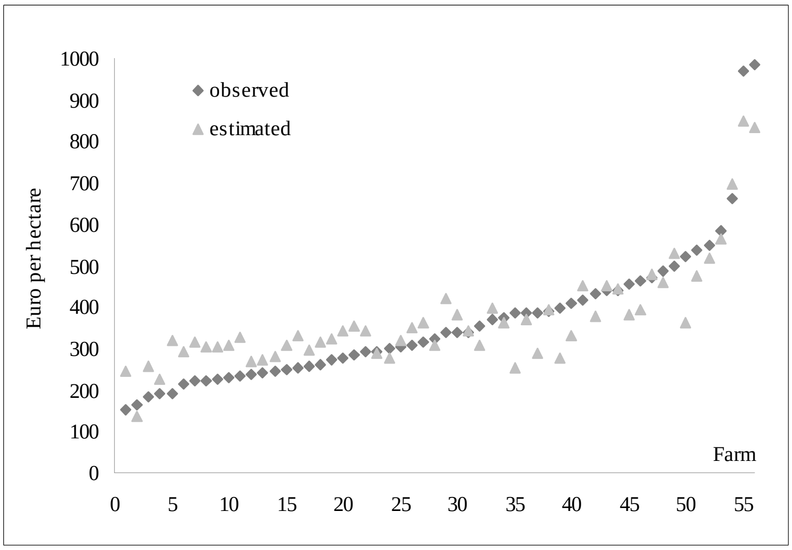

Figure 4-1: Observed and estimated values for land rent in Euro per hectare

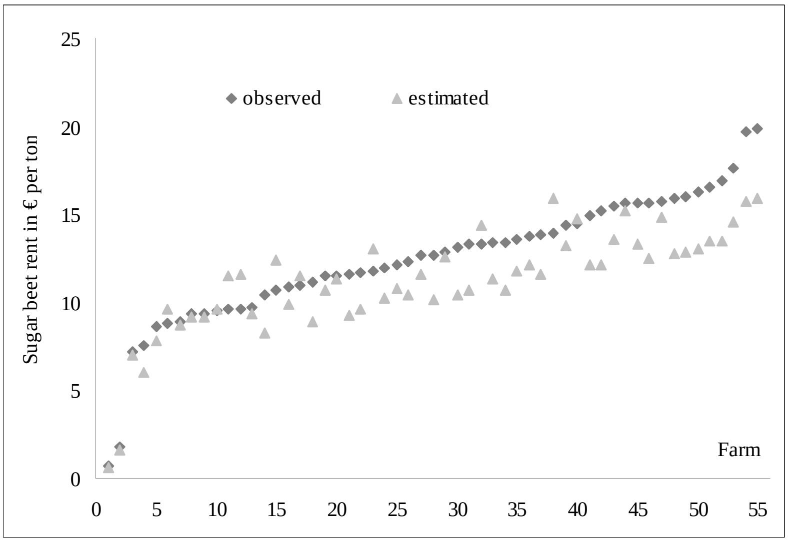

Figure 4-2: Observed and estimated values for sugar beet rents in Euro per ton

[7] See Heckelei and Wolff (2003) for a theoretical reasoning and, for example, Júdez et al. (2001) for a counter-example.

A possible explanation is our data induced assumption that observed sugar production equals the sugar quota, whereas the ‘observed’ values on sugar beet rents estimated by Buysse et al. (2007) were applied to the real quota quantity. This would also explain the downward bias of the estimated mixed sugar beet price presented in Figure 4-A2 in the appendix.

For completeness, we would also like to mention again that the approach also provided estimates of the quadratic cost function parameters (see Table 4-A1 in appendix) thereby offering a fully specified simulation model of a farm group based on single farm records.

4.5.3 Sensitivity of results to support point design

To shed some light on the robustness of the estimation results regarding the implementation of the prior information, we finish this result section with a sensitivity analysis with respect to the number of support points and their form of distribution. Because we have used well defined prior information from FADN for the dual values of the resource constraints, the land allocation and expected prices, we will focus here on the input allocation matrix $\tilde{\mathbf{A}}$. For this purpose we introduce six additional support point designs similar to those used in Léon et al. (1999). They are presented in Table 4-A2 in the appendix. The first three designs are defined again with eleven discrete support points, the first one symmetric, the second left-skewed, and the third right-skewed.

The support designs 4-6 have six support points and the general form of the distribution with the same set-up as the first three designs. Apart from the estimated input cost shares, Table 4-5 also presents percentage deviations from the base design no. 1 in parenthesis. Generally, the estimates are sensitive to the support point design. Somewhat surprising, the number of support points is also relevant even though the deviations of the symmetric distribution design no. 4 with 6 support points shows the smallest deviations to the base design.[8] Skewed distributions show overall larger deviations. Given that the prior expected values associated with these designs differ from the base case, we conclude that prior information on input allocation matters here for this sample. However, we can also see that it matters most for those products that have little data information, i.e. a low number of observations in the sample, such as green peas. This phenomenon of decreasing relevance of prior information with increasing data information and vice versa is well known - at least in Bayesian statistics - and highly desirable.

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[8] Golan et al. 1996, pp. 139-140, indicated that increasing the number of support points beyond 5 will not decrease the mean estimation error much anymore. However, that does not imply that the estimates might not differ for a specific sample.

Table 4-6 presents the correlation coefficients of estimated input allocations with observed input allocations for the six support designs, for both, the FOC-LR- and the LR-model. The superior performance of the FOC-LR model seems to be robust across all support point designs looking at the sum of the correlation coefficients for both approaches.

Input	Crop	Design No. 1	Design No. 2		Design No. 3		Design No. 4		Design No. 5		Design No. 6	
Contract work	Winter wheat	0.0503	0.0548	(-9)	0.0577	(-15)	0.0535	(-6)	0.0566	(-13)	0.0574	(-14)
	Barley	0.1052	0.0926	(12)	0.1119	(-6)	0.1058	(-1)	0.0934	(11)	0.1055	(0)
	Chicory for sugar	0.2066	0.2057	(0)	0.2294	(-11)	0.2173	(-5)	0.2147	(-4)	0.2298	(-11)
	Vegetables in open air	0.2194	0.2152	(2)	0.2381	(-9)	0.2265	(-3)	0.2274	(-4)	0.2422	(-10)
	Potato	0.0642	0.0605	(6)	0.0682	(-6)	0.0662	(-3)	0.0594	(7)	0.0649	(-1)
	Green peas for tin	0.1777	0.1646	(7)	0.2187	(-23)	0.1932	(-9)	0.1855	(-4)	0.2175	(-22)
	Sugar beet	0.0589	0.0576	(2)	0.0486	(17)	0.0545	(7)	0.0542	(8)	0.0493	(16)
Seeding	Winter wheat	0.0574	0.0563	(2)	0.0601	(-5)	0.059	(-3)	0.0565	(2)	0.058	(-1)
	Barley	0.0705	0.0587	(17)	0.0913	(-30)	0.0744	(-6)	0.0621	(12)	0.0812	(-15)
	Chicory for sugar	0.0748	0.0652	(13)	0.0992	(-33)	0.0808	(-8)	0.0713	(5)	0.0905	(-21)
	Vegetables in open air	0.1163	0.0916	(21)	0.1277	(-10)	0.1095	(6)	0.1004	(14)	0.1198	(-3)
	Potato	0.1539	0.1567	(-2)	0.1614	(-5)	0.1582	(-3)	0.1605	(-4)	0.1648	(-7)
	Green peas for tin	0.0922	0.0764	(17)	0.1305	(-42)	0.1035	(-12)	0.089	(3)	0.1215	(-32)
	Sugar beet	0.064	0.0646	(-1)	0.0559	(13)	0.0607	(5)	0.0619	(3)	0.0566	(12)
Treatment	Winter wheat	0.0846	0.0843	(0)	0.0799	(6)	0.0839	(1)	0.0823	(3)	0.0794	(6)
	Barley	0.123	0.1093	(11)	0.1447	(-18)	0.127	(-3)	0.1162	(6)	0.1352	(-10)
	Chicory for sugar	0.1026	0.0903	(12)	0.123	(-20)	0.1049	(-2)	0.0933	(9)	0.1115	(-9)
	Vegetables in open air	0.1039	0.0887	(15)	0.1195	(-15)	0.1045	(-1)	0.0911	(12)	0.1083	(-4)
	Potato	0.1724	0.1665	(3)	0.1783	(-3)	0.1717	(0)	0.1704	(1)	0.1762	(-2)
	Green peas for tin	0.1384	0.1203	(13)	0.1847	(-33)	0.1517	(-10)	0.1355	(2)	0.1732	(-25)
	Sugar beet	0.1034	0.1079	(-4)	0.1012	(2)	0.1041	(-1)	0.1072	(-4)	0.1038	(0)
Fertilizer	Winter wheat	0.0411	0.0428	(-4)	0.0296	(28)	0.0369	(10)	0.0355	(14)	0.0309	(25)
	Barley	0.1567	0.1492	(5)	0.1805	(-15)	0.164	(-5)	0.161	(-3)	0.1757	(-12)
	Chicory for sugar	0.0651	0.0585	(10)	0.0801	(-23)	0.0668	(-3)	0.0591	(9)	0.0717	(-10)
	Vegetables in open air	0.0775	0.0691	(11)	0.0837	(-8)	0.0766	(1)	0.068	(12)	0.0774	(0)
	Potato	0.0804	0.0747	(7)	0.08	(0)	0.0774	(4)	0.0748	(7)	0.0777	(3)
	Green peas for tin	0.0851	0.071	(17)	0.1106	(-30)	0.0886	(-4)	0.0696	(18)	0.093	(-9)
	Sugar beet	0.0625	0.0646	(-3)	0.066	(-6)	0.0655	(-5)	0.0687	(-10)	0.0676	(-8)
Value-added	Winter wheat	0.7666	0.762	(1)	0.7727	(-1)	0.7667	(0)	0.7691	(0)	0.7742	(-1)
	Barley	0.5447	0.5901	(-8)	0.4715	(13)	0.5289	(3)	0.5673	(-4)	0.5024	(8)
	Chicory for sugar	0.5509	0.5804	(-5)	0.4683	(15)	0.5301	(4)	0.5616	(-2)	0.4966	(10)
	Vegetables in open air	0.4829	0.5354	(-11)	0.431	(11)	0.4829	(0)	0.5131	(-6)	0.4522	(6)
	Potato	0.5291	0.5416	(-2)	0.512	(3)	0.5264	(1)	0.5348	(-1)	0.5165	(2)
	Green peas for tin	0.5066	0.5678	(-12)	0.3555	(30)	0.463	(9)	0.5204	(-3)	0.3948	(22)
	Sugar beet	0.7112	0.7054	(1)	0.7283	(-2)	0.7151	(-1)	0.708	(0)	0.7226	(-2)

Note: the numbers in parenthesis are percentage deviations to the base design no. 1

Table 4-5: Average estimated input cost shares for different support point designs

Apparently, the simultaneous approach is able to better use the available data information. Interestingly, the left-skewed support point distributions show the best performance for both models. This ‘insight’ is of limited empirical relevance, however, because we only know by comparing with input allocations not employed in the estimation approach and normally not available.

Model	Input	Design No.					
		1	2	3	4	5	6
FOC-LR	Contract work	0.879	0.865	0.904	0.891	0.889	0.907
	Seeding	0.734	0.563	0.719	0.684	0.633	0.712
	Treatment	0.399	0.439	0.174	0.307	0.361	0.201
	Fertilizer	0.349	0.487	0.187	0.324	0.466	0.306
	Value-added	0.882	0.899	0.782	0.838	0.869	0.806
	Sum	**3.243**	**3.253**	**2.765**	**3.044**	**3.218**	**2.931**
LR	Contract work	0.806	0.793	0.83	0.811	0.791	0.817
	Seeding	0.873	0.838	0.812	0.884	0.88	0.876
	Treatment	0.011	0.098	-.11	-.,02	0.009	-.093
	Fertilizer	0.494	0.573	0.461	0.515	0.627	0.538
	Value-added	0.767	0.759	0.743	0.761	0.748	0.75
	Sum	**2.951**	**3.061**	**2.736**	**2.944**	**3.058**	**2.888**

Table 4-6: Correlation Coefficients for sensitivity designs

4.6 Conclusion

This paper offered an approach to estimate a non-linear farm group optimisation model simultaneously with unknown input coefficients using GME based on multiple observations. This approach combines the more recent PMP literature with the extensive one on allocating variable inputs to production activities using farm accountancy data. Using a sample of Belgium FADN accountancy records, the hypothesis that this simultaneous approach would outperform separate input allocation regressions introduced by Léon et al. (1999) was confirmed. The new approach showed better results for all considered aggregate measures across farms comparing estimated input coefficients with observed ones available for this sample.

Apart from input allocation results, the concept also offers a specification of a farm group supply model with a PMP-type objective function based on multiple farm level observations. This is itself a relevant contribution, because most models of this type are not based on a statistical estimation approach. The fit of model variables to the farm data and available prior information on resource shadow prices was overall very satisfactory. The ability to include prior information on resource shadow prices promise more realistic results compared to standard PMP specifications.

The result on the superior performance of the simultaneous estimation approach also held up when support point specifications of the GME approach were varied. It could be shown that support point designs matter for estimation results, especially if prior expected values on parameters differ and data information is limited. The number of support points had only limited impacts on the estimates.

The developed approach could be extended into different directions. More observations over time will probably improve the specification with respect to the price response behaviour of the resulting farm group model. Panel data typically show more price variation and will therefore likely result in more robust estimates in this respect. The focus of the current paper on evaluating estimates of input coefficients required observed input allocations. Another direction of further development could be the application of Bayesian approaches as in Jansson (2007) which promise a more straightforward and transparent implementation of prior information without support point related complications and less computational requirements.

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4.8 Appendix

	Winter Wheat	Winter barley	Chicory	Vegetables in open air	Potatoes	Green peas for tin	Sugar beet
Winter Wheat	0.22	0.00	0.41	0.32	0.00	-0.48	-0.46
Winter barley	0.00	0.06	0.00	0.37	-0.34	-0.16	0.07
Chicory	0.41	0.00	1.71	1.16	-0.97	-0.44	-1.87
Vegetables in open air	0.32	0.37	1.16	2.98	-2.56	-1.41	-0.86
Potatoes	0.00	-0.34	-0.97	-2.56	3.00	0.17	0.70
Green peas for tin	-0.48	-0.16	-0.44	-1.41	0.17	2.07	0.27
Sugar beet	-0.46	0.07	-1.87	-0.86	0.70	0.27	2.14

Table 4-A1: Estimated Q-Matrix of the quadratic cost function for farm group

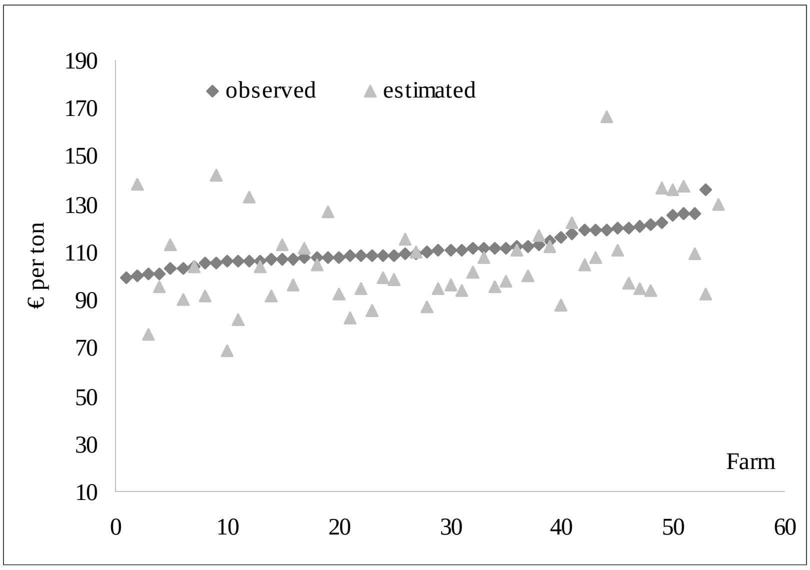

Figure 4-A1: Estimated and observed wheat prices

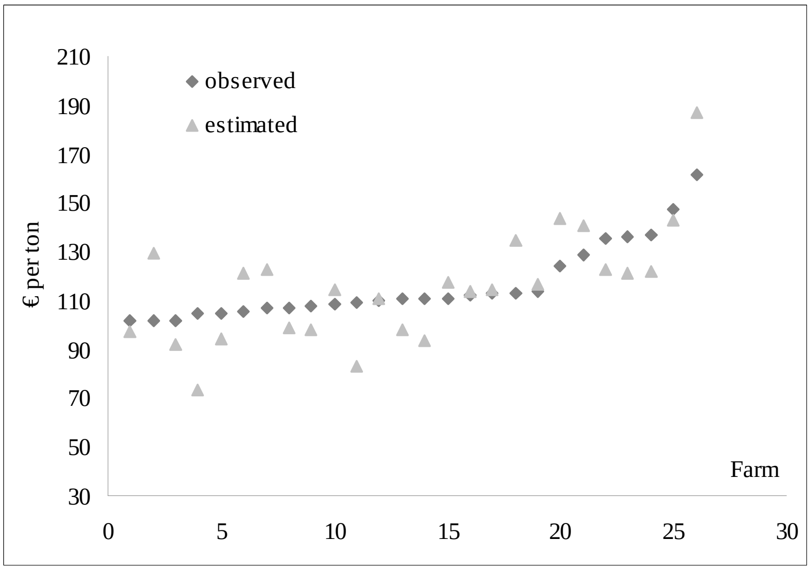

Figure 4-A2: Estimated and observed barley prices

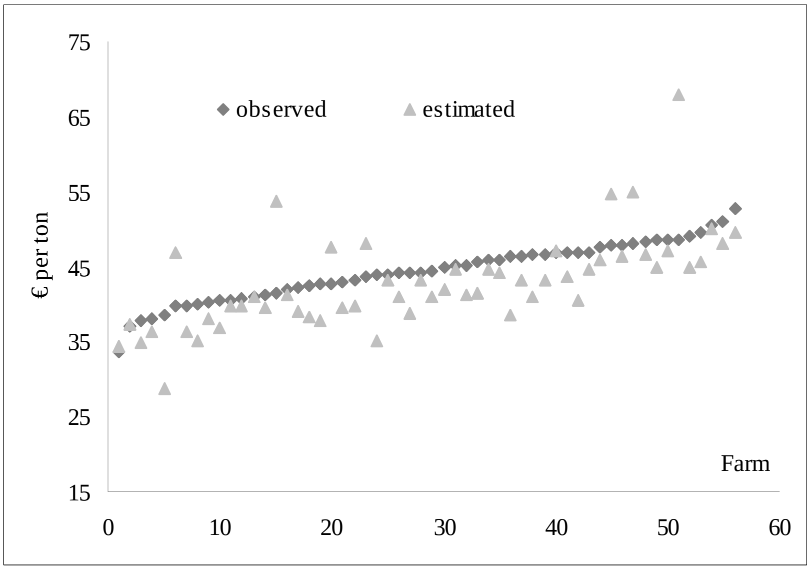

Figure 4-A3: Estimated and observed sugar beet price

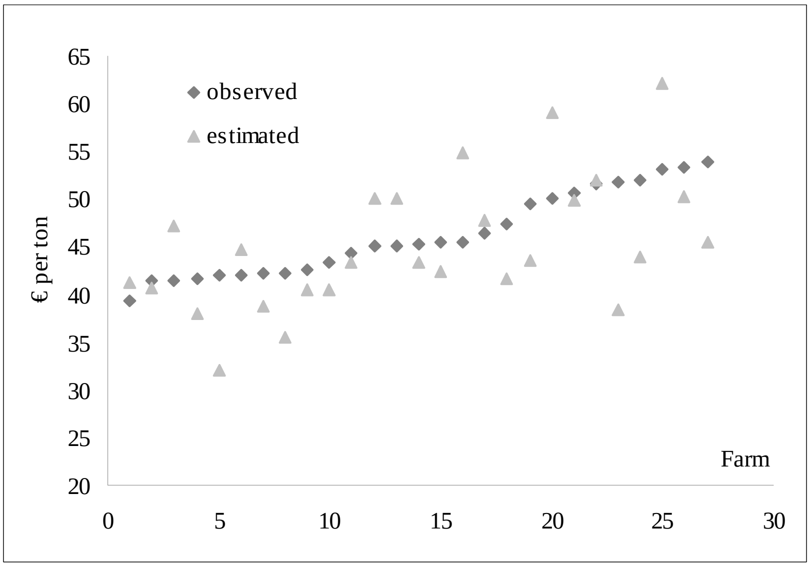

Figure 4-A4: Estimated and observed chicory prices

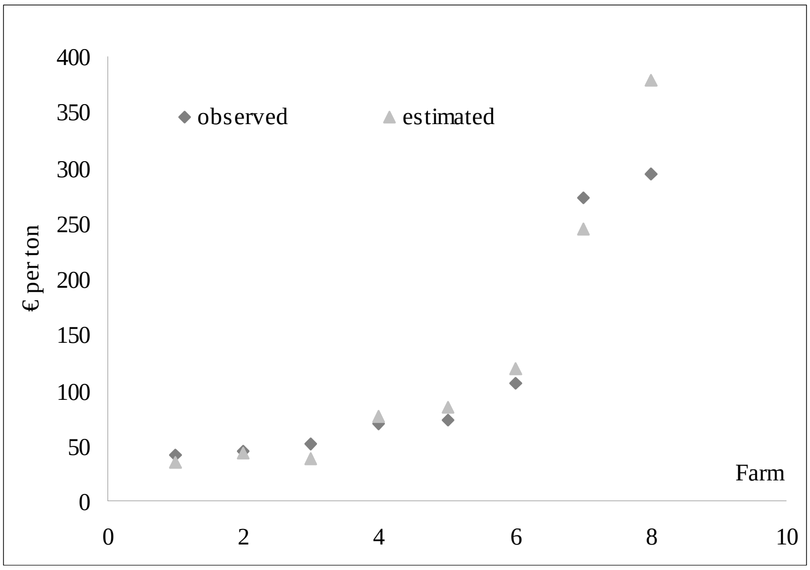

Figure 4-A5: Estimated and observed vegetable prices

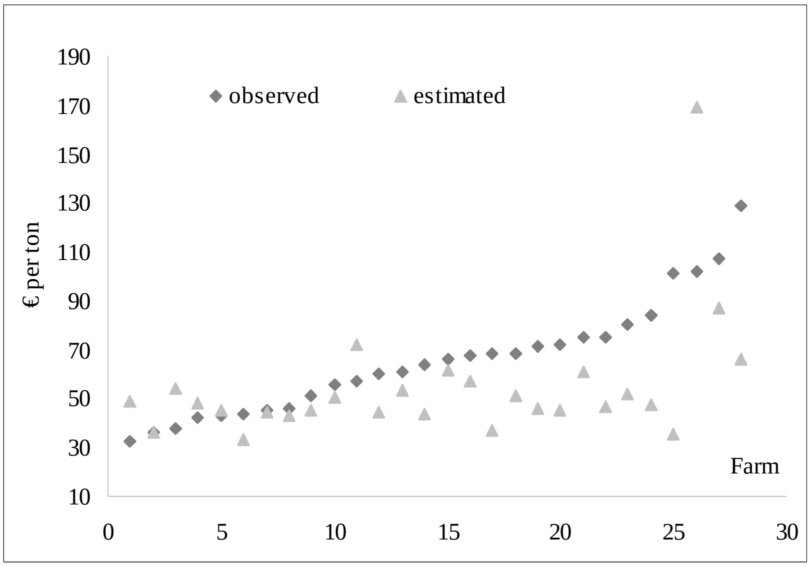

Figure 4-A6: Estimated and observed potato prices

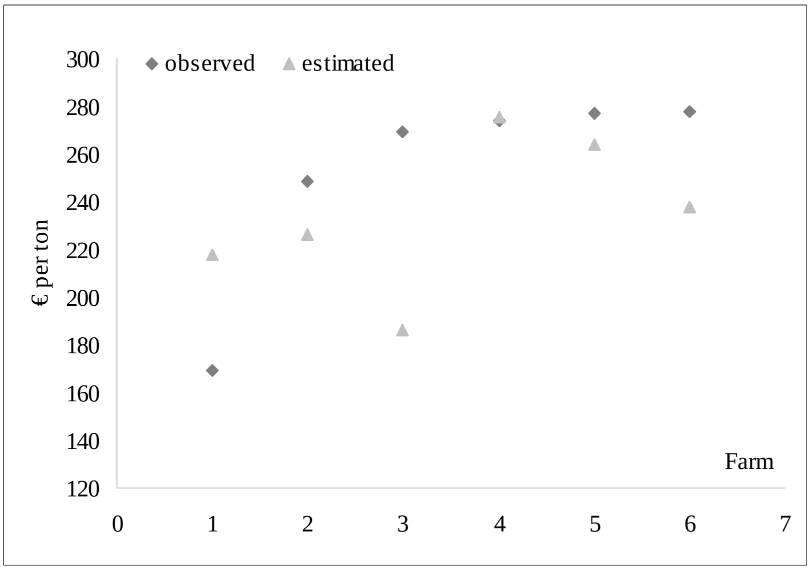

Figure 4-A7: Estimated and observed Green peas for tin prices

Design No.	Input Category	Number of Support Values	Type of Spacing	Selected Support space
Design No. 1	Seeding	11	Symmetric	0.0, 0.02 , 0.04 , 0.06 , 0.08 , 0.1 , 0.12 , 0.14 , 0.16 , 0.18 , 0.2
	all other			0.0, 0.03 , 0.06 , 0.09 , 0.12 , 0.15 , 0.18 , 0.21 , 0.24 , 0.27 , 0.3
	Value-added			0.0, 0.1 , 0.2 , 0.3 , 0.4 , 0.5 , 0.6 , 0.7 , 0.8 , 0.9 , 1
Design No. 2	Seeding	11	Non-Symmetric, left skewed	0.0, 0.008, 0.016, 0.025, 0.033, 0.041, 0.05 , 0.066, 0.1 , 0.133, 0.2
	all other			0.0, 0.012, 0.025, 0.037, 0.05 , 0.062, 0.075, 0.1 , 0.15 , 0.2 , 0.3
	Value-added			0.0, 0.041, 0.083, 0.125, 0.166, 0.208, 0.25 , 0.333, 0.5 , 0.666, 1
Design No. 3	Seeding	11	Non-Symmetric, right skewed	0.0, 0.066, 0.1 , 0.133, 0.15 , 0.158, 0.166, 0.175, 0.183, 0.191, 0.2
	all other			0.0, 0.1 , 0.15 , 0.2 , 0.225, 0.237, 0.25 , 0.262, 0.275, 0.287, 0.3
	Value-added			0.0, 0.333, 0.5 , 0.666, 0.75 , 0.791, 0.833, 0.875, 0.916, 0.958, 1
Design No. 4	Seeding	6	Symmetric	0.0, 0.04 , 0.08 , 0.12 , 0.16 , 0.2
	all other			0.0, 0.06 , 0.12 , 0.18 , 0.24 , 0.3
	Value-added			0.0, 0.2 , 0.4 , 0.6 , 0.8 , 1
Design No. 5	Seeding	6	Non-Symmetric, left skewed	0.0, 0.01 , 0.02 , 0.08 , 0.14 , 0.2
	all other			0.0, 0.015, 0.03 , 0.12 , 0.21 , 0.3
	Value-added			0.0, 0.05 , 0.1 , 0.4 , 0.7 , 1
Design No. 6	Seeding	6	Non-Symmetric, right skewed	0.0, 0.06 , 0.12 , 0.18 , 0.19 , 0.2
	all other			0.0, 0.09 , 0.18 , 0.27 , 0.285, 0.3
	Value-added			0.0, 0.3 , 0.6 , 0.9 , 0.95 , 1

Table 4-A2: Designs of the Support Set for the Input Allocation Matrix

Chapter 5. EU-wide farm types supply in CAPRI - How to consistently disaggregate sector models into farm type model*

Abstract

The aim of the paper is to motivate the introduction and characterisation of an EU-wide farm type model in the CAPRI (Common Agricultural Policy Regional Impact) model, partly based on a comparison with other farm model approaches. The proposed farm type disaggregation of the regional CAPRI supply models aims firstly at reduced aggregation bias. This is expected to allow for a more profound and robust impact assessment of farm and agri-environmental related policy changes and to help the linkage to bio-physical models. Secondly, the integration of the farm types in the overall CAPRI modelling framework allows for endogenous price feedback through CAPRI's global market model. The disaggregation is based on an estimation approach which smoothly integrates the information from the EU-wide Farm Structure Survey (FSS) into the CAPRI model database. Example results from Denmark show that this approach outperforms simple scaling by uniform factors by endogenously taking information about the type of farming and economic size into account during the estimation.

Keywords: EU-wide farm supply analysis, Highest posterior density estimator, CAPRI farm type layer

5.1 Introduction

The Common Agricultural Policy (CAP) is evolving quickly, shifting its focus to externalities of agricultural production, provision of public goods and the contribution of the farming sector to Rural Development. The legally required impact assessments (EC, 2002) of EU legislation need to take these aspects into account, and the research community supports and accompanies the process of redirecting the CAP by developing and applying tools for impact assessment. The CAPRI model (Britz & Witzke, 2008) provides a prominent example for such a tool used in

* The article was developed together with W. Britz (University of Bonn) and has been submitted for a special issue organized by EU Commission JRC-IPTS Seville for the *Journal of Policy Modelling*.

different projects, such as in SEAMLESS (van Ittersum et al., 2008), SENSOR (Jansson et al., 2007) or EURURALIS (van Meijl et al., 2006), and impact assessments, e.g., for the Mid-Term Review (Britz et al., 2003) or the Sugar Market Reform (Adenäuer, 2005, Adenäuer et al., 2007). The development of CAPRI responded to the demand for regionalized analysis of a CAP moving from price- to direct income-support in the nineties, in order to complement the analysis of multi-commodity models with a country or EU resolution such as ESIM (Banse et al., 2004) or AGLINK/COSIMO (OECD, 2007). Equally, environmental concerns were taken into account in CAPRI by integration of different environmental indicators such as nitrogen (Leip et al. 2009) and GHG emission (Perez, 2005) accounting or a Life Cycle analysis of energy use in agriculture (Kempen & Kränzlein 2008), recently improved by spatial downscaling (Leip et al., 2008) and links to bio-physical models (Britz & Leip 2009).

However, as in many other economic models for the agricultural sector, CAPRI simulates for each region only an aggregate over all farms. Such a territorial representation might lead to aggregation bias and does not allow analysis of impacts on specific farm groups. We motivate and discuss therefore in the following the development of a layer of farm type models for CAPRI, integrated in the overall model chain, and describe the development of a matching consistent data base. Section 5.2 motivates a disaggregation by farm types. It reviews existing farm type approaches and motivates and presents specificities of the CAPRI farm type layer. Section 5.3 discusses the definition of a suitable farm typology, where given regional data are disaggregated based on farm structural statistics. Section 5.4 introduces details of the disaggregation methodology and Section 5.5 presents data and data preparation. Section 5.6 shows results for an example region and conclusions are drawn and the approach critically discussed in Section 5.7.

5.2 The Farm Type Approach

5.2.1 Motivation of farm type models in the impact assessment of agricultural policies

Disaggregation by farm type mainly aims to capture heterogeneity in farming practises and farms within a region, in order to reduce aggregation bias in response to policy and market signals, with a focus on farm management, farm income and environmental impact. The argument is especially striking when policy instruments are either targeting specific farm types or are modulated depending on farm characteristics. The evolvement of the accompanying measures in the 1992 reform, and the introduction of premium schemes depending on farm characteristics, such as stocking densities and herd sizes, the small producer scheme and agri-environmental legislation such as the Nitrate and Water directives generated an incentive for tools and analysis disaggregated by farm types. Examples are the AROPAj system (Baranger et al., 2008; Jayet, 1990), FARMIS (Offermann et al., 2005) and LUAM (Jones et al., 1995) where aggregates of specific farm types for administrative regions at the sub-national scale are simulated based on mathematical modelling and sources by the European Farm Accountancy Data Network (FADN) database, so called bio-economic farm models such as the FSSIM model in SEAMLESS (Louhichi et al., 2005) or econometrically estimated farm-household models (see, e.g., Lansink & Perling, 1996).

Besides the reduced aggregation bias, a disaggregation by farm types in impact assessment contributes results regarding the distribution of impact in the farming community, e.g., regarding farm income distribution, environmental externalities or provision of public goods. It might also allow linkage to modules for farm structural change.

5.2.2 Review of existing approaches

The comparison presented in the following section aims at emphasizing differences between the three different approaches to farm type models, to better motivate the specific layout chosen for the CAPRI farm type layer. The first approach is based on linear or non-linear programming models representing either single farms or groups of farms defined from Farm Accountancy Data Network (FADN) or similar sources at national or regional level. FADN, based on micro-accounting data, provides output coefficients such as crop yields, the selection of production activities, and resource capacities such as land or family labour as well as output prices. Input coefficients, such as fertiliser application rates or feed requirements per production activity, are not provided by FADN, and therefore typically derived based on engineering approaches or are econometrically estimated. The input and outputs (I-O) coefficients, along with related prices define gross margins per production activity. The objective function maximizes the sum of these gross margins by choosing an optimal farm program, depending on the resource endowment and resource requirements at activity level. The basic methodology focuses on currently observed farming practices, as the production possibility set is derived from FADN. However, compared to CAPRI, where a non-linear cost function is introduced and where possible econometrically estimated (Jansson, 2007), AROPAj and LUAM, as many linear programming models, face well-known problems of Linear Programming (LP) such as overspecialization. Therefore, additional safeguards such as maximum cropping shares or bounds on the allowed changes of herd sizes are introduced in the framework. The calibration of the AROPAj model to the observed praxis (De Cara & Jayet, 2000), unlike in CAPRI or FARMIS, does not result in an exact but in approximated calibration by adjusting uncertain I-O parameters to reduce the gap between the observed cropping patterns and the computed solution. The approaches based on FADN will inherit its properties, specifically, its relatively low representation of less frequent farm types.

The *second* approach is more normative as a far wider range of potential activities defines the solution space of the model, derived from combining engineering knowledge with simulations by biophysical models. An example is provided by the farm models in the SEAMLESS modelling chain (Louhichi et al., 2005). The farm endowment, such as family labour, land or production rights might be taken from FADN, and the observed yields may serve as an indication of potential yields, but linking the potential choice set characterizing the farms to the observed one and the given endowment requires expert knowledge. The model set-up is hence far more resource-demanding than using solely observed practise from FADN. Primary data collection and link to GIS is necessary to source the bio-physical models, including location specific data relating to soil, topology, climate or the crop calendar. As a consequence, even a large-scale project such as SEAMLESS only populated some EU regions with models, supposed to be representative, and used statistical extrapolation to generate results for the whole EU. For a more detailed comparison of FSSIM and CAPRI, see (Britz et al., (forthcoming)). Calibration to the observed current state of the system, but even more, to observed responses of the farming systems to changes in its market and policy environment remains a challenge in bio-economic model and is a partially unresolved issue, as it is their application for forward looking analysis where technical progress need to be taken into account. Bio-economic models are however suitable to highlight which potential activities might be chosen by farmers under a different policy and market environment. And clearly, their detailed description of agricultural management eases linkage to environmental indicator calculators or bio-physical models, and allows simulation of such policy measures linked to very specific farm management practises.

The *third* approach rests in econometrically estimated farm-household models. Requiring panel data or even cross-sectional time series, they are mostly based on FADN or, again, based on often richer national and regional farm record data sets. Prominent examples are different variants of such models estimated by Lansink & Perling (1996). Based on duality theory, utility or profit maximization is assumed to derive behavioural functions representing first order conditions, where parameter restrictions and/or the choice of the functional form guarantee regularity. Their biggest advantage lies in their fully empirically based simulation behaviour, and their ability to test for the underlying behavioural assumptions. However, the often highly non-linear estimators restrict the size of the parameter space, leading typically to a far higher aggregation by activities/products compared to the programming approaches discussed above. A further serious disadvantage of these duality based models for integrated assessment is the missing explicit technology description where input demands can typically not be allocated to activities. That renders it difficult to link their results to bio-physical accounting approaches or models.

5.3 *Characteristics of the farm types in CAPRI*

Perhaps the most important characteristic of the CAPRI farm type module is its full integration in the CAPRI modelling chain, which ensures price feedback based on sequential calibration with the global, large-scale market model (Britz, 2008). All the other approaches discussed above are stand-alone supply models, where prices are exogenous. Linking these other farm models to existing market models is far from easy due to differences in product definitions, but also, due to the missing match to the data sets underlying market models, questions of IT integration notwithstanding. The strict and consistent top-down disaggregation approach in CAPRI discussed in the following ensures a harmonized data set across regional scales and farm types.

The farm type supply module in CAPRI consists of independent aggregate non-linear programming models for each farm type and each region, representing as an aggregate all activities of all farms falling in that type and a specific administrative regional unit at NUTS (Nomenclature des unités territoriales statistiques) II level. As templates, they share the structure of the regional programming models in CAPRI and thus provide a compromise between a pure LP approach and the fully econometrically estimated one. The latter is achieved by combining a Leontief technology for variable costs covering a low and high yield variant for the different production activities with an in part econometrically estimated non-linear cost function (Jansson, 2007), extending Positive Mathematical Programming (PMP) (Howitt, 1995). The cost function captures the effects of labour and capital on farmers' decisions and allows both for perfect calibration of the models and a smooth simulation response. The farm models capture, similar to the regional ones, in high detail, the premiums paid under the CAP, include NPK balances and a module with feeding activities covering nutrient requirements of animals. Constraints besides the feed block relate to arable land and grassland, set-aside obligations and milk quotas. Prices are exogenous in the supply module and provided by the market module, with whom they are solved sequentially until convergence. Grass, silage and manure are assumed to be non-tradable and receive internal prices based on their substitution value and opportunity costs.

CAPRI farm type index	Type of farming FSS	Long text for the CAPRI farm type
1	FT13	Specialist cereals, oilseed and protein crops (FT 13)
2	FT14_60	General field cropping (FT 14) + Mixed cropping (FT 60)
3	FT41	Specialist dairying (FT 41)
4	FT_42_43	Specialist cattle-rearing and fattening (FT 42) + Cattle-dairying, rearing and fattening combined (FT 43)
5	FT44	Sheep, goats and other grazing livestock (FT 44)
6	FT50	Specialist granivores (FT 50)
7	FT7	Mixed livestock holdings (FT 7)
8	FT8	Mixed crops-livestock (FT 8)
9	FT31	Specialist vineyards (FT 31)
10	FT32	Specialist fruit and citrus fruit (FT 32)
11	FT33	Specialist olives (FT 33)
12	FT34	Various permanent crops combined (FT 34)
13	FT2	Specialist horticulture (FT 20)
14	FT9	Non-classifiable holdings'

Table 5-1: Type of Farming groups in CAPRI

The CAPRI farm type module comprises a maximum of ten farm types per region, which always include a residual farm type to exhaust regional production as well as input and primary factor use. Each of the remaining up to nine farm groups is characterized by the "type of farming," see Table 5-1, defined by the relative contribution of different production branches to the gross margin of the farm (European Commission, CD 85/377/EEC, Article 6), and the "economic size class" based on "European size units" (ESU)[9], a concept defined in Chapter IV Article 8 in CD 85/377/EEC and Annex III. The EU classification scheme allows for a far more detailed characterisation of the farm's specialisation, but data confidentiality issues and reduced average weights when using more disaggregated types on regional aggregates render it suitable to stick to the classification shown below. Equally, resources for reporting and result analysis clearly depend on the level of disaggregation. Similar arguments hold to allow for solely three farm size classes, leading to 14*3=52 cells in overall typology.

9 The following size classes had been chosen: <1-<16 ESU (class 1), 16-<100 ESU(class 2), 100< ESU(class 3)

No. FSS groups	Type of farming	ESU class	Utilised agricultural area	Number of holdings	Livestock unit	Rank for farm types in CAPRI
			1,000 ha	1,000	1,000	
1	FT8	3	394	2.41	1,318	1
2	FT50	3	160	1.56	1,229	2
3	FT41	3	352	3.67	724	3
4	FT13	3	447	8.72	85	4
5	FT14_60	3	326	1.53	177	5
6	FT8	2	110	2.44	268	6
7	FT14_60	2	224	4.49	78	7
8	FT13	3	232	0.94	56	8
9	FT41	2	68	1.69	119	9
10	FT13	1	140	10.62	13	10
11	FT14_60	1	59	5.06	12	10
12	FT2	1	0	0.09	0.01	10
13	FT2	2	2	0.26	0.23	10
14	FT2	3	7	0.45	0.09	10
15	FT32	1	1	0.14	0.01	10
16	FT32	2	4	0.16	0.02	10
17	FT32	3	2	0.02		10
18	FT34	2	0	0.10		10
19	FT34	3	3	0.08		10
20	FT41	1	0	0.08	1	10
21	FT_42_43	1	6	0.67	16	10
22	FT_42_43	2	7	0.20	20	10
23	FT_42_43	3	2	0.02	5	10
24	FT44	1	25	2.50	5	10
25	FT44	2	14	0.17	6	10
26	FT44	3	11	0.01		10
27	FT50	1	0	0.06	3	10
28	FT50	2	5	0.34	79	10
29	FT7	1	0	0.05	1	10
30	FT7	2	4	0.11	14	10
31	FT7	3	28	0.20	106	10
32	FT8	1	33	2.77	32	10
Sum for Farm Types			2,312	27.45	4,054	
Sum Residual farm type			352	24.16	314	
Total			2,664	52	4,367	
Coverage %			**87**	**53**	**93**	

Table 5-2: Ranking of farm types based on the FSS farm group statistics for Denmark

The restriction to maximal ten farm groups per region is based on storage and computing time considerations, but also by the aim to keep database and model outputs at a manageable size for quality control and result analysis. Those farm groups, differentiated by the typology based on size and specialisation, which are represented explicitly in a region are selected according to their importance for the regional agriculture measured by Livestock Units (LU) and Utilised Agricultural Area (UAA). Compared to weights based on number of farms or economic indicators, area farmed and livestock numbers provide a compromise between economic, social and environmental aspects of farming. The approach is shown for Denmark[10] in Table 5-2.

In the chosen example of Denmark, the explicitly defined nine farming types cover more than 85 % of the UAA and more than 90 % of the LU recorded by FSS for this particular year, but account for only 53% of the agricultural holdings. All remaining FSS farming groups indicated with a "10" are aggregated to the residual farm type. Applying the same methodology to all NUTS II regions in the EU leads to the distribution as depicted in Table 5-3.

	No. of types in				
	EU-27	**EU-25**	**EU-15**	**EU-10**	**EU-02**
A Economic size					
< 16 ESU	541	464	321	143	77
≥ 16 ≤ 100 ESU	715	698	628	70	17
> 100 ESU	460	440	346	94	20
B Type of Farming					
Specialist cereals, oilseed and protein crops (FT 13)	237	212	149	63	25
General field cropping (FT 14) + Mixed cropping (FT 60)	290	271	212	59	19
Specialist horticulture (FT 20)	9	9	9		
Specialist vineyards (FT 31)	9	9	9		
Specialist fruit and citrus fruit (FT 32)	16	16	14	2	
Specialist olives (FT 33)	18	18	18		
Various permanent crops combined (FT 34)	13	13	13		
Specialist dairying (FT 41)	239	230	200	30	9
Specialist cattle-rearing and fattening (FT 42) + Cattle-dairying, rearing and fattening combined (FT 43)	168	168	152	16	
Sheep, goats and other grazing livestock (FT 44)	194	172	159	13	22
Specialist granivores (FT 50)	118	108	76	32	10
Mixed livestock holdings (FT 7)	103	89	56	33	14
Mixed crops-livestock (FT 8)	302	287	228	59	15
C Residual farm type					
Residue	225	211	170	41	14
Total (A+C or B+C)	1,941	1,813	1,465	348	128

Table 5-3: General overview of farm types selected for the CAPRI layer

[10] Denmark has no further sub-regions in CAPRI, which motivated its use as an example.

The map in Figure 5-1 (see also Figure 5-A1 to 5-A6) below shows where the specialized dairy farm type with an ESU class larger than 100 is explicitly modelled, coloured according to its share on regional UAA.

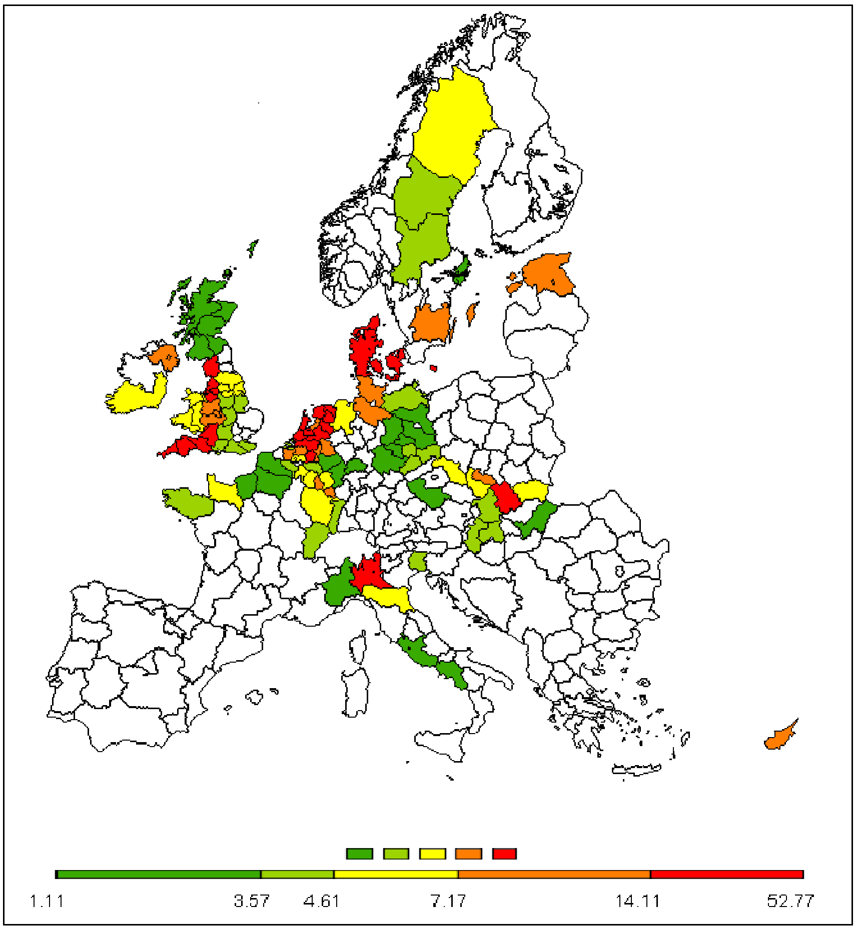

Figure 5-1: Share of UAA on the NUTS II region in % for the specialized dairying farm type with an ESU greater than 100 ESU

5.3.1 Disaggregation problem

The disaggregation of the regional data base of CAPRI to farm types delivers specific benefits, which relate to the existing infrastructure of CAPRI. The farm type module shares the structure and technical implementation of the regional database, allowing use of existing procedures to populate and calibrate the individual farm models, and to store and view results. Equally, all existing post-model reporting modules for the regional model can be applied, such as indicator calculators for nutrient balances and green house gases accounting. Once the results from the farm type are re-aggregated to the NUTS II level, they can be down-scaled to an 1x1 km resolution (Leip et al., 2008). The top-down data consistency integrates the farm type models smoothly in the overall system, ensuring also their inter-operability with the global market model.

For consistency, however, harmonization of the production levels found in the Farm Structure Survey (FSS) data with the regional data base of CAPRI is required, a major challenge, also from the methodological viewpoint, which is discussed in detail in the next section. We refrain here from discussing how a the full farm type data base is constructed, including mutually compatible I-O coefficients, see Gocht (forthcoming) for a discussion.

The FSS delivers data on production levels, providing a well-established statistical database, harmonized across Europe and featuring suitable coverage by farm type. Despite that fact that FSS underlies many of the regional statistics sourcing CAPRI, some inconsistencies to the regional data set in CAPRI remain. This is the case because:

- CAPRI considers a three year average (for the version discussed n here years 2001-2003) derived from regional time series, whereas FSS provides data for one specific year from the period 2003 – 2005, depending on the Member State.

- The regional CAPRI database is made consistent to national data sets such as market balances and economic accounts, completed such that data gaps have been filled in by means of econometric routines, and harmonized over time regarding product/activity classifications. As a consequence, regional data in CAPRI can differ slightly from annual FSS data.

- The economic thresholds for the FSS survey are different from those underlying the Economic Accounts for Agriculture (EAA). This can lead to inconsistencies for some selected activities such as nurseries where production quantities are not defined in physical units but in constant values.

- All figures in FSS are rounded to the first digit after the comma and those individual farm data which account for more than 80 percent of the aggregate are replaced by missing values, as outcome of EU legislation dealing with statistical confidentiality (Council Regulations (CE) No. 322/97, OJ No L 52/1, and EURATOM, EEC No. 1588/90, OJ No L 151/ 1).

One way to remove the data inconsistencies in acreage and herd sizes consists in multiplying each FSS value with a fixed correction factor, calculated from the given regional value in CAPRI and the sum over the farm types in that region in FSS. However, this can first lead to a correction of the activity levels which changes the farming pattern such that a different type of farming or a different economic size classification could result for some farm groups, so the data base might no longer represent the most important groups according to FSS. Secondly this approach could also result in a violation of political requirements for set-aside in the FSS groups[11]. Not least, the changes could generate unrealistic farm programs. In order to avoid reclassifications during the consistent top-down disaggregation, we propose a statistical estimator which ensures regional consistency and compliance with set-aside obligations while preventing changes in the type of farming and economic size class. The estimator treats the original FSS farm group data as a random variable comprising measurement errors, which seems reasonable given rounding, introduction of missing values and reporting thresholds. By assuming properties of the error distribution, the most probable crop levels and acreages for each farm type are estimated recovering the given regional data, in compliance with set-aside obligation while maintaining the type of farming and ESU class of each farm group.

5.4 The statistical disaggregation estimator

The following section we discuss in detail the layout of the disaggregation estimator, starting with the data constraints, before the definition of the Highest Posterior Density is motivated.

5.4.1 Data constraints

The estimator aims first at ensuring that each farm group keeps its "type of farming" (see Table 5-1) during estimation, which requires translation of tabular information in official documents (European Commission, CD 85/377/EEC, Annex II Section B) in numerical constraints. Specifically, the "type of farming" is defined by rules relating to the contribution of production branches, expressed by the partial standard gross margins (SGM) (**p**), in relation to the total SGM (**t**). Both, the partial and the total SGM are expressed in Economic Size Units (ESU). **t** and **p** of a farm group is determined by a set of standard coefficients (**s**) which can be used to value areas under crops and numbers of animals produced by the farm groups, where it is assumed that one ESU is worth 1.200 Euro.

During the estimation, these contribution of production branches shares are not allowed to violate a set of constraints, similar to crop rotation restrictions, which

[11] The farm type base year is referenced to a three year average around 2002. Therefore set-aside was still in place and had to be considered.

define the given farm type. The total standard gross margin (**t)** is a (1 x F) vector and therefore computed by

$$\mathrm{t} = (\sum_j \mathrm{s}_j \mathrm{x}_j) / (1200 \times N) \quad \forall \text{ f} \in \mathbf{F}$$

for each farm group (f) where N is the number of holdings represented by the particular farm group (f) and 1.200 indicates the value of one ESU. The matrix (**x**), for each region in CAPRI, consists of a farm type dimension with f=1,.., F and of a production activity dimension with j=1,.., J indicated in Annex Table 5-A1 and holds the production levels in hectare or animal heads to be estimated. The vector (**s**) is the activity specific gross margin in Euro given per hectare or animal head and provided by Eurostat[12] for each sub-region. Constraints had been defined for all types according the rules outlined in EU Commission (CD 85/377/EEC), and ensure during estimation of the production levels (**x**) that the selected types stay within their definition. To give an example the type of farming which comprises specialized cereals, oilseed and protein crops have two constraints which are implemented in the estimation problem as:

$$((\sum_{j \in \mathrm{P1}} \mathrm{s\,x}) / (1200 \times N)) / \mathrm{t} > 2/3 \quad \forall \mathrm{f} \in \mathbf{F}$$

$$((\sum_{j \in \mathrm{P13\_14}} \mathrm{s\,x}) / (1200 \times N)) / \mathrm{t} > 2/3 \quad \forall \mathrm{f} \in \mathbf{F}\,.$$

The constraints which ensure that the farm groups remain in the economic size class are for the smallest size class with less than 16 ESU

$$\mathrm{t} < 16 \quad \forall \mathrm{f} \in \mathbf{F}$$

for the size class greater equal than 16 and less than 100 ESU as

$$\mathrm{t} \geq 16 \quad \cap \quad \mathrm{t} < 100 \quad \forall \mathrm{f} \in \mathbf{F}$$

and for the large scale farm size class as

[12] The SGM are collected by Eurostat from the Member States and are downloadable from the official Eurostat webpage. The special treatment for grazing stock and fodder crops is implemented in the explained CAPRI farm type approach (see CD 85/377/EEC, Annex I, 5. treatment of special cases).

$t \geq 100 \quad \forall f \in \mathbf{F}$.

A further restriction defines the obligatory set-aside area as a function of the grandes cultures area as:

$$x_{oset} = \sum x\, q / (100 - q) \quad \forall f \in \mathbf{F}; \forall j \in \mathbf{A}.$$

The crop production activities for arable land are (A) with $A \subset J$. The set-aside rate (**q**) is given for each crop in percentage. The next constraint ensures that for each production activity, the sum of all farm types sums up to the regional levels indicated by (r)

$$\sum_{f \in F} x_f = x \quad \forall j \in J; \forall r \in R$$

and the last equation calculates the UAA (**u**) for each farm type.

$$\sum_{j \in J} x_j = u \quad \forall f \in F$$

5.4.2 Estimator

The data constraints alone do not allow a unique solution to be found, as there are the $F \times J$ unknown vectors of cropping hectares and animal herd sizes ($\mathbf{x}$) to be estimated, which by far exceed the number of linear (in)equality constraints. The FSS raw data on cropping acreages and animal herd sizes are therefore seen as random variables distributed around the true, but unknown observations which are characterised by the above defined data constraints. We assume that the error term is white noise with co-variance zero, and follow the approach in Heckelei et al. (2005, 2008) to derive a Highest Posterior Density estimator to recover the data with the highest posterior density. That leads to the following estimator

$$\min \mathit{vec}(\mathbf{x} - \mathbf{x}^{p}, \mathbf{u} - \mathbf{u}^{p}, \mathbf{p}^{n} - \mathbf{p}^{n,p}, \mathbf{t} - \mathbf{t}^{p})'$$
$$\times \Sigma^{-1} \mathit{vec}(\mathbf{x} - \mathbf{x}^{p}, \mathbf{u} - \mathbf{u}^{p}, \mathbf{p}^{n} - \mathbf{p}^{n,p}, \mathbf{t} - \mathbf{t}^{p})$$

where the partial standard gross margin (**p**) is defined as:

$$p^{n} = \sum_{j \in P_n} sx \quad \forall f \in \mathbf{F}; \; n \in 1..5$$

The estimation framework combining the estimator and the data constraints can be interpreted as the search for the production activity levels which minimize the deviation between the prior information on levels $\mathbf{x}^p$, on total standard gross margins $\mathbf{t}^p$, the partial standard gross margins $\mathbf{p}^p$ and the UAA $\mathbf{u}^p$ of each farm group with respect to the constraints for each farm type in the region for the Type of Farming and the Economic Size, the set-aside regulations (political constraints) and the consistency to regional data.

5.5 Data

5.5.1 Databases underlying the consistent EU-27 wide farm types approach

One outstanding attribute of the farm type layer in CAPRI is its EU-27 wide territorial coverage. Only two harmonized and standardized data sources provide information on farm types at the EU-27 level: FADN and FSS. FADN is the most often used database to source EU farm type models. It comprises single farm record data on production and sales quantities, production activity levels, yields for selected activities, input cost aggregated on the farm level; information about prices and positions of the gain and loss accounts of a farm plus some further elements. The definitions in FADN are harmonized by EU legislation which also requests yearly updates by the EU Member States. The FADN covers however only a sample of farms with aggregation weights attached, with a somewhat low representativity for less frequent farm types and production activities (see also table 5-4 below). The second data source, FSS, reports mainly data on production activities by region and farm type, based on a sub-survey each third year and a complete survey each tenth year. Both data sets exclude small farms based on minimum economic thresholds, with lower thresholds in FSS and a hence better representation compared to FADN. Equally, some enterprises, such as highly commercialised farms are not obliged to provide accountancy information to FADN, but are included in the FSS. The combination of differences in thresholds and definitions, and the sample nature of FADN leads to coverage differences; as shown in Table 5-4 for the FADN year 2004 at Member State level for those EU countries where groups from our CAPRI farm typology based on the FSS survey where completely missing in FADN. To give an indication about the size of the error, the number of missing hectares is shown.

	Specialist cereals, oilseed and protein crops (FT 13)			General field cropping (FT 14) + Mixed cropping (FT 60)			Specialist dairying (FT 41)			Specialist cattle-rearing and fattening (FT 42) + Cattle-dairying, rearing and fattening combined (FT 43)			Sheep, goats and other grazing livestock (FT 44)			Specialist granivores (FT 50)			Mixed livestock holdings (FT 7)			Mixed crops-livestock (FT 8)		
	ESC1	ESC2	ESC3	ESC1	ESC2	ESC3	ESC1	ESC2	ESC3	ESC1	ESC2	ESC3	ESC1	ESC2	ESC3	ESC1	ESC2	ESC3	ESC1	ESC2	ESC3	ESC1	ESC2	ESC3
Belgium and Luxembourg					15			38	5		30	4				0	6	1		11	2		16	12
Germany	94	24		15	46		67	49		20			4				3			24		88		
Greece				33									67	17			1	2	38	6		29		
Spain										29	4		51	20	59	0	44	28	97	33			92	
France		171			131			132			74		154				12	1		34				
Irland																		15		4				
Italy											4													
Austria										62	1		296			0			1					
Portugal				13									8				1	6	4					
Sweden	48			75	9					25							1		0			34	6	
Finland				3	7			4			2						3					1	2	
The United Kingdom										86			2,284					12						
Cyprus																	0							
Czech Republic	1	4	5			4				1			1			0	0	1						
Hungary																7			11					
Slovak Republic																		1						

Table 5-4: UAA in 1000 hectares without representation in FADN

For Germany, for example, almost 390,000 hectares are not represented in FADN. The table also illustrates that especially small farm types (<16) ESU are often poorly represented in FADN, due to exclusion thresholds. High deviations are also found for large farms specialized in granivores (FT50 + ESC2 and FT50 + ESC3), highlighting that commercial farms are not well represented in FADN, FSS draws, hence, a more complete picture of the agricultural production structure compared to FADN, and is a more inviting source in that respect for the farm type disaggregation. As FSS does however only cover data on acreages and herd sizes, yields and input coefficients have to be derived from FADN, for a thorough discussion see Adenäuer et al. (2006a, 2006b) and Gocht (forthcoming).

5.5.2 FSS Data preparation

Eurostat[1] aggregated and processed the single FSS records for all ~250 CAPRI regions for EU-27, according to the chosen typology, delivering a data set respecting the data confidentiality obligations mentioned above. Farm groups were deleted, where the UAA levels or the number of holdings were zero. The data set covers data on land use, livestock farming and labour force as well as number of farms for each farm type and region. The example results presented here refer to Denmark, with 32 farm non empty groups by specialisation and size class as Table 5-2 shows. Rounding and introduction of missing values due to statistical confidentiality obligations might lead to cases where the prior data are not in line with the type of farming and the ESU class shown in the data set. Therefore, the type of farming and the ESU class for each raw FSS group are re-calculated in order to apply the correct constraints of the raw data during estimation and to obtain the correct partial SGM and the TSGM.

[1] The work of Pol Marquer from EUROSTAT is gratefully acknowledged. He extracted different data selections for the new farm type layer and supported the whole data selection process with his knowledge and expertise.

	FSS			calculated				FSS			calculated		
No.	FSS Farm Group Name	Type of Farming	ESU group	Typ of farming	ESU Group	CAPRI farm type Rank	No.	FSS Farm Group Name	Type of Farming	ESU group	Typ of farming	ESU Group	CAPRI farm type Rank
1	DK000131	13	1	13	1	10	19	DK000414	41	4	41	4	**3**
2	DK000132	13	2	13	2	10	20	DK000421	42	1	42	4	10
3	DK000133	13	3	13	3	**4**	21	DK000422	42	2	81	2	10
4	DK000134	13	4	13	4	**8**	22	DK000423	42	3	81	3	10
5	DK000141	14	1	14	1	10	23	DK000424	42	4	81	4	10
6	DK000142	14	2	14	2	10	24	DK000441	44	1	44	1	10
7	DK000143	14	3	14	3	**7**	25	DK000442	44	2	44	2	10
8	DK000144	14	4	14	4	**5**	26	DK000443	44	3	44	3	10
9	DK000202	20	2	20	2	10	27	DK000444	44	4	80	4	10
10	DK000203	20	3	20	3	10	28	DK000502	50	2	50	2	10
11	DK000204	20	4	20	4	10	29	DK000503	50	3	50	3	10
12	DK000322	32	2	32	2	10	30	DK000504	50	4	50	4	**2**
13	DK000323	32	3	32	3	10	31	DK000702	70	2	81	2	10
14	DK000324	32	4	32	4	10	32	DK000703	70	3	81	3	10
15	DK000343	34	3	34	3	10	33	DK000704	70	4	72	4	10
16	DK000344	34	4	34	4	10	34	DK000802	80	2	81	2	10
17	DK000412	41	2	41	2	10	35	DK000803	80	3	61	3	**6**
18	DK000413	41	3	41	3	**9**	36	DK000804	80	4	80	4	**1**

Table 5-5: Farming types and ESU class recovered from the FSS raw data

Table 5-5 presents a comparison between identified type of farming and economic size class provided by Eurostat for the raw FSS data. It can be seen that for the nine most important farm types, which are retained exactly in the data base and model, only cell Nr. 35 was re-classified from an original mixed crop-livestock type to mixed crops.

5.6 Results

In order to analyse to what extent the proposed estimator leads to an improved presentation of the farming structure, the results are compared to a fixed number-scaling. Table 5-6 reports the results for the partial SGMs P1, P4 and P5[2] per farm type for Denmark. It can be seen that lower deviations from the prior shares in FSS could be achieved, compared to applying a uniform correction factor for each production activity.

[2] Partial SGM P2 and P3 are not identified or very small for the selected farm types because those partial standard gross margins belong to farming types not identified in the case of Denmark (see Table 5-A1, appendix).

Type of farming	Economic Size Class	partial SGMs														
		P1					P4					P5				
		FSS	Scaling	Deviation	Estimation	Deviation	FSS	Scaling	Deviation	Estimation	Deviation	FSS	Scaling	Deviation	Estimation	Deviation
	Unit	share	share		share		share	share		share		share	share		share	
Specialist cereals, oilseed and protein crops (FT 13)	≥ 16 and ≤ 100 ESU	0.94	0.93	-2%	0.94	0%	0.04	0.06	29%	0.04	0%	0.02	0.02	-1%	0.02	0%
Specialist cereals, oilseed and protein crops (FT 13)	> 100 ESU	0.94	0.94	-1%	0.94	0%	0.02	0.02	21%	0.02	0%	0.04	0.04	5%	0.04	0%
General field cropping (FT 14) + Mixed cropping (FT 60)	≥ 16 and ≤ 100 ESU	0.88	0.87	-1%	0.88	0%	0.06	0.08	24%	0.06	0%	0.03	0.03	-8%	0.03	0%
General field cropping (FT 14) + Mixed cropping (FT 60)	> 100 ESU	0.86	0.86	-1%	0.86	0%	0.02	0.03	30%	0.02	0%	0.06	0.07	6%	0.06	-1%
Specialist dairying (FT 41)	≥ 16 and ≤ 100 ESU	0.29	0.33	12%	0.29	-1%	0.71	0.66	-7%	0.71	0%					
Specialist dairying (FT 41)	> 100 ESU	0.27	0.30	11%	0.27	-2%	0.73	0.70	-5%	0.72	1%					
Specialist granivores (FT 50)	> 100 ESU	0.22	0.21	-5%	0.22	0%						0.78	0.79	1%	0.78	0%
Mixed crops-livestock (FT 8)	≥ 16 and ≤ 100 ESU	0.56	0.54	-4%	0.57	0%	0.17	0.22	22%	0.17	3%	0.26	0.24	-11%	0.27	-2%
Mixed crops-livestock (FT 8)	> 100 ESU	0.50	0.48	-4%	0.49	1%	0.04	0.05	16%	0.04	1%	0.46	0.47	2%	0.46	-1.6%

Table 5-6: Priors for and estimated partial SGMs (P1-P5) for all farm type in Denmark

Type of farming	Economic Size Class	ESU					UAA				
		FSS	Scaling	Deviation	Estimation	Deviation	FSS	Scaling	Deviation	Estimation	Deviation
	Unit	ESU	ESU		ESU		1,000 hectare	1,000 hectare		1,000 hectare	
Specialist cereals, oilseed and protein crops (FT 13)	≥ 16 and ≤ 100 ESU	36.7	35.1	-4%	36.4	-1%	446.7	433.8	-3%	459.5	3%
Specialist cereals, oilseed and protein crops (FT 13)	> 100 ESU	190.8	172.1	-11%	189.2	-1%	231.6	217.7	-6%	243.8	5%
General field cropping (FT 14) + Mixed cropping (FT 60)	≥ 16 and ≤ 100 ESU	43.7	45.2	3%	43.7	0%	223.9	234.9	5%	229.6	2%
General field cropping (FT 14) + Mixed cropping (FT 60)	> 100 ESU	225.5	205.3	-10%	222.8	-1%	325.7	312.2	-4%	331.4	2%
Specialist dairying (FT 41)	≥ 16 and ≤ 100 ESU	82.0	95.7	14%	84.1	2%	68.1	83.8	19%	67.0	-2%
Specialist dairying (FT 41)	> 100 ESU	249.0	283.1	12%	258.3	4%	349.8	451.8	23%	368.5	5%
Specialist granivores (FT 50)	> 100 ESU	328.7	319.7	-3%	331.1	1%	159.5	152.7	-4%	170.8	7%
Mixed crops-livestock (FT 8)	≥ 16 and ≤ 100 ESU	49.3	53.9	9%	50.3	2%	109.7	115.4	5%	115.1	5%
Mixed crops-livestock (FT 8)	> 100 ESU	244.0	229.3	-6%	236.1	-3%	394.5	376.2	-5%	410.7	4%
Aggregated residue							354.5	388.9	9%	371.1	4%

Table 5-7: Priors for and estimated UAA and ESU for all farm type in Denmark

Table 5-7 presents a comparison between the prior, the scaling method and the estimated values for the economic size of the farm type (ESU) and its land endowment (UAA). Again, the estimator outperforms simple scaling, leading to lower correction of total area and economic size of the farm groups.

Table 5-8 presents the deviation of crop groups for the different farm types in Denmark. Two aspects are worth commenting upon. Firstly, the deviation for the residual farm type is larger than for the other farm types. The reason is the missing rule for the residual farm type. The deviations of farm types with a clear definition regarding specialization and economic size are less prone to deviations as changes are restricted by the constraints which define farm size and farm specialization. Secondly, small observations are less robust and the percentage deviation can be higher, as for example, rounding has a far stronger effect.

5.7 Discussion and conclusions

The paper motivated the introduction of a farm type layer in the CAPRI model, compared it to alternative solutions and addressed the issue of a consistent disaggregation of regional agricultural data by farm supply. We will first discuss the latter issue.

Consistent disaggregation problems are frequent in economic analysis when working simultaneously on different spatial scales or combining different data sets. Our example provides a solution when structural relations at the lower level need to be maintained, here relating to the characterization of farm size and farm specialization. Examples for similar problems are the estimation of land cover or areas in a spatial disaggregation exercise, where one would like to keep cover and crop share relations in certain bounds at lower spatial scales, or the estimation of I/O coefficients consistent to national accounts while maintaining cost shares from the original micro records.

We propose the application of a Bayesian motivated estimation framework which treats the available disaggregated information, here the FSS data, as a random variable. Whereas the disaggregated data provide prior information, consistency and definition based conditions provide the data information. Their combination provides posterior estimates which fulfil the top-down disaggregation requirement while exhausting the information content of the raw data. In our example, the estimator ensures that the type of farming of each group, as well as the economic size of a farm group were not violated, allowing for a consistent disaggregation of the CAPRI regional data base based on the FSS database of Eurostat to source a layer of farm type models.

Type of farming	Economic Size Class	Ceareals					Pulses, Potato and Sugar Beet					Fodder Crops and Gras					Set-aside				
		FSS	Scaling	Deviation	Estimation	Deviation	FSS	Scaling	Deviation	Estimation	Deviation	FSS	Scaling	Deviation	Estimation	Deviation	FSS	Scaling	Deviation	Estimation	Deviation
	Unit hectare	1,000	1,000		1,000		1,000	1,000		1,000		1,000	1,000		1,000		1,000	1,000		1,000	
Specialist cereals, oilseed and protein crops (FT 13)	≥ 16 and ≤ 100 ESU	322	320	-0.6%	330	2.5%	13	15	15.1%	12	-3.9%	31	38	17.8%	67	53.7%	45	38	-17.8%	36	-26.1%
Specialist cereals, oilseed and protein crops (FT 13)	> 100 ESU	164	159	-2.7%	165	0.6%	7	8	10.7%	7	-7.4%	11	12	13.6%	24	55.9%	20	18	-7.2%	21	5.6%
General field cropping (FT 14) + Mixed cropping (FT 60)	≥ 16 and ≤ 100 ESU	105	106	0.6%	105	0.5%	19	19	0.7%	19	-1.4%	65	84	22.4%	77	15.3%	17	14	-22.3%	16	-9.4%
General field cropping (FT 14) + Mixed cropping (FT 60)	> 100 ESU	183	181	-0.9%	180	-1.4%	52	50	-2.8%	53	3.3%	28	35	18.9%	52	45.8%	28	22	-29.2%	22	-30.9%
Specialist dairying (FT 41)	≥ 16 and ≤ 100 ESU	16	17	2.9%	16	0.1%						47	63	25.5%	46	-1.9%	4	3	-23.4%	4	9.3%
Specialist dairying (FT 41)	> 100 ESU	73	74	0.3%	78	5.4%	3	3	-0.1%	8	59.0%	239	355	32.6%	265	9.9%	28	17	-70.2%	17	-67.2%
Specialist granivores (FT 50)	> 100 ESU	119	117	-1.7%	121	1.9%	2	2	2.4%	2	-11.4%	8	9	13.1%	14	41.5%	12	12	6.9%	15	22.6%
Mixed crops-livestock (FT 8)	≥ 16 and ≤ 100 ESU	66	66	-0.2%	67	2.0%	2	2	7.5%	2	-5.8%	29	37	21.8%	31	7.8%	7	7	0.5%	9	21.5%
Mixed crops-livestock (FT 8)	> 100 ESU	275	269	-2.3%	280	1.7%	15	15	2.2%	11	-35.7%	29	34	13.8%	64	54.2%	31	30	-3.9%	26	-18.1%
Aggregated residue		167	170	1.3%	135	-24.2%	4	4	9.1%	6	33.2%	140	169	17.3%	195	-20.9%	17	25	31.7%	21	-46.4%

Table 5-8: Estimates for selected crop activity level in Denmark

The main aim of introducing farm types into the CAPRI model was to improve policy impact assessments by considering farm structural characteristics such as farm size, crop mix, stocking density and yields, in order to considerably reduce aggregation bias and thus to improve the reliability of regional results. But equally, income effects as well as environmental and social impacts can be analysed in the context of farm specialization and size.

What are the down sides of the CAPRI farm type approach? First of all, the use of stylised and relatively simple template models which are structurally identical and express differences between farm type and regions solely by parameters alone might fall short of capturing the full diversity of farming systems in Europe. In particular, the evaluation of policy measures which impact on farm management decisions, such as manure handling or feeding practices, demand models which comprise these as decision variables. The relatively simple representation of agricultural technology in CAPRI compared to approaches parameterised based on biophysical models narrows down the scope of extensions in that direction, albeit the potential of the current template is not yet fully exploited in CAPRI. However, the dichotomy between increased detail for specific activities, regions and farm types, and a structurally identical template model remains. Updating and maintaining a regional data base with an additional breakdown by farm types requires more resources, as does the application of the enlarged simulation tool.

The CAPRI farm type layer provides a complementary approach to alternative farm type approaches. Its strength rests firstly in the fact that harmonized data sources and assumptions are applied across Europe; secondly, that the layer is transparently linked with a complex agricultural trade model so that the full range of CAP measures and their interactions can be analyzed; thirdly, that its maintenance and application are cheaper compared to alternative approaches should one aim at a full coverage of the EU.

A possible drawback of opting for a disaggregation by farm type instead of increasing the spatial resolution of the model is the fact that farm groups are not spatially explicit. That renders a link to bio-physical models challenging as, e.g., the soils on which the farm groups operate are not known. However, economic theory suggests that the distributional moments of bio-physical attributes as soil, slope, surrounding land cover or climate for each farm type will differ from the regional aggregated ones. Some approaches therefore try a spatial distribution of farm groups (see, e.g., Elbersen et al., 2006).

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5.9 Appendix

abbreviation	CAPRI activity long text	P1	P13_14	P2	P3	P4	P5	abbreviation	CAPRI activity long text	P1	P13_14	P2	P3	P4	P5
SWHE	Soft wheat production activity	x	x					TEXT	Flax and hemp production activity	x					
DWHE	Durum wheat production activity	x	x					TOBA	Tobacco production activity	x					
RYEM	Rye and meslin production activity	x	x					TOMA	Tomatoes production activity			x			
BARL	Barley production activity	x	x					OVEG	Other vegetables production activity			x			
OATS	Oats and summer cereal mixes without triticale	x	x					APPL	Apples pears and peaches production activity				x		
MAIZ	Grain maize production activity	x	x					OFRU	Other fruits production activity				x		
OCER	Other cereals production activity including triticale	x	x					CITR	Citrus fruits production activity				x		
RAPE	Rape production activity	x	x					NONF	Non food production activities on set aside	x	x				
SUNF	Sunflower production activity	x	x					FALL	Fallow land						
SOYA	Soya production activity	x	x					OSET	Set aside obligatory	x	x				
OOIL	Other seed production activities for oil industry	x	x					VSET	Set asice voluntary	x	x				
OIND	Other industrial crops production activity	x						BULL	Male adult fattening activity low final weight					x	
NURS	Nurseries production activity				x			BULH	Male adult fattening activity high final weight					x	
FLOW	Flowers production activity			x				SCOW	Suckler cows production activity					x	
OCRO	Other crops production activity	x						HEIR	Heifers raising activity					x	
MAIF	Fodder maize production activity	x						CAMF	Calves male fattening activity					x	
ROOF	Fodder root crops production activity	x						CAFF	Calves female fattening activity					x	
OFAR	Fodder other on arable land production activity	x						CAMR	Calves male raising activity					x	
GRAE	Gras and grazings production activity extensive					x		CAFR	Calves female raising activity					x	
GRAI	Gras and grazings production activity intensive					x		PIGF	Pig fattening activity						x
PARI	Paddy rice production activity	x	x					SOWS	Sows for piglet production						x
PULS	Pulses production activity	x	x					SHGM	Sheep and goats activity for milk production					x	
POTA	Potatoes production activity	x						SHGF	Sheep and goats activity for fattening					x	
SUGB	Sugar beet production activity	x						HENS	Laying hens production activity						x
								POUF	Poultry fattening activity						x

Table 5-A1: Cross set for calculating the partial SGM (P1-P5) for defining the type of farming and the total SGM

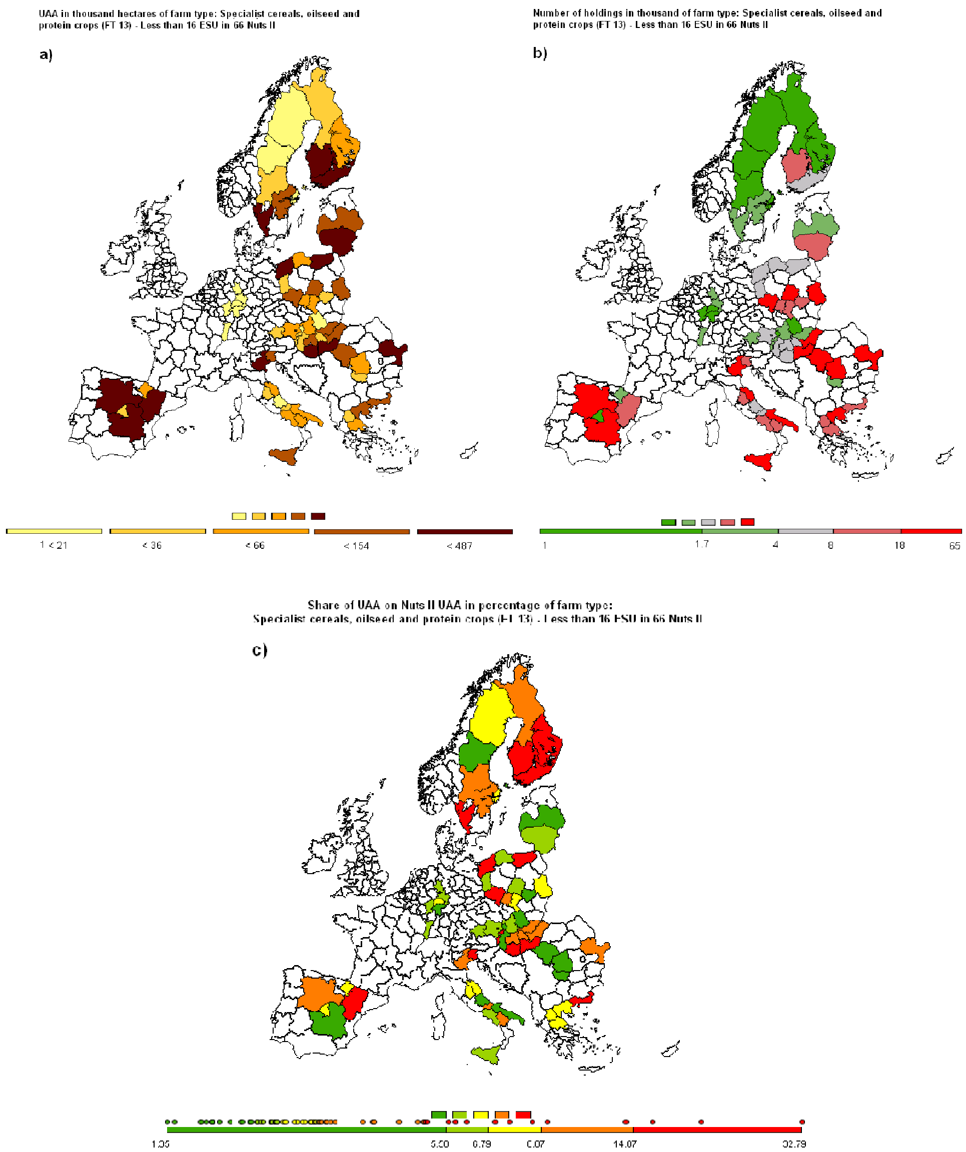

Figure 5-A1: Distribution of (a) total UAA in 1,000 hectares, (b) number of holdings in thousand and (c) share on NUTS II UAA in percentage of farm type of farm type: Specialist cereals, oilseed and protein crops (FT 13) - Less than 16 ESU in 66 NUTS II

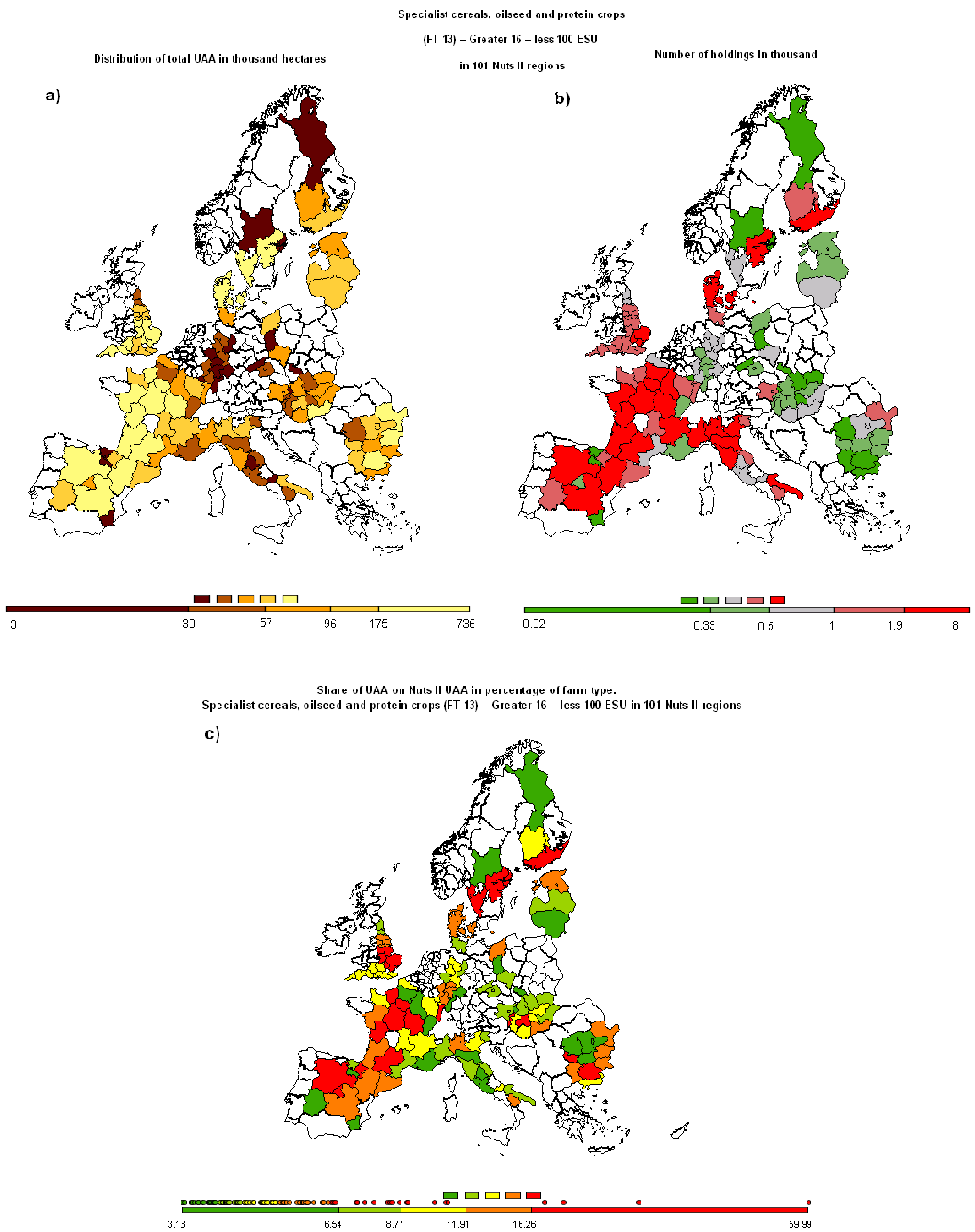

Figure 5-A2: Distribution of (a) total UAA 1,000 hectares, (b) number of holdings in thousand and (c) share on NUTS II UAA in percentage of farm type of farm type: Specialist cereals, oilseed and protein crops (FT 13) – Greater 16 – less 100 ESU in 101 NUTS II regions

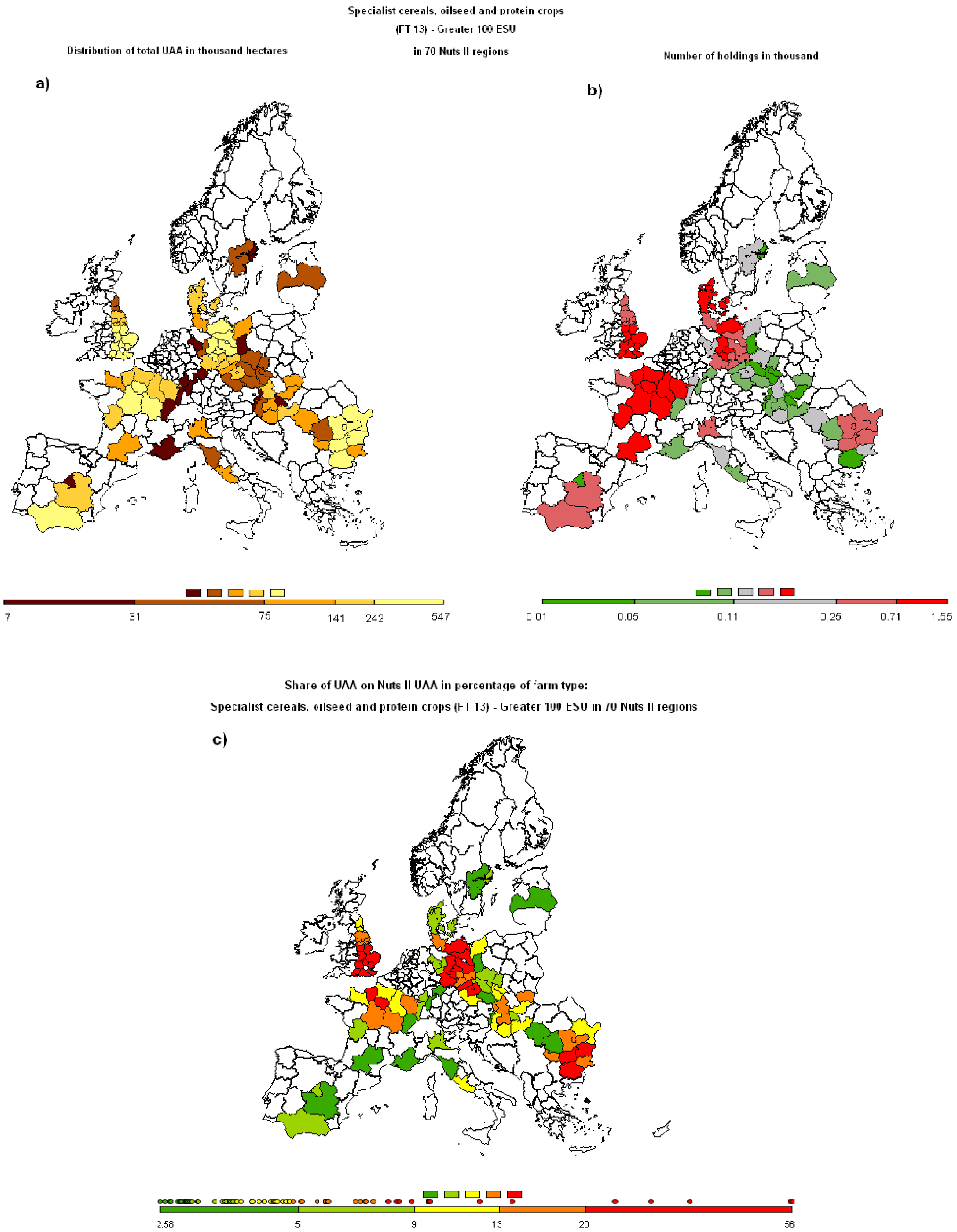

Figure 5-A3: Distribution of (a) total UAA 1,000 hectares, (b) number of holdings in thousand and (c) share on NUTS II UAA in percentage of farm type of farm type: Specialist cereals, oilseed and protein crops (FT 13) - Greater 100 ESU in 70 NUTS II regions

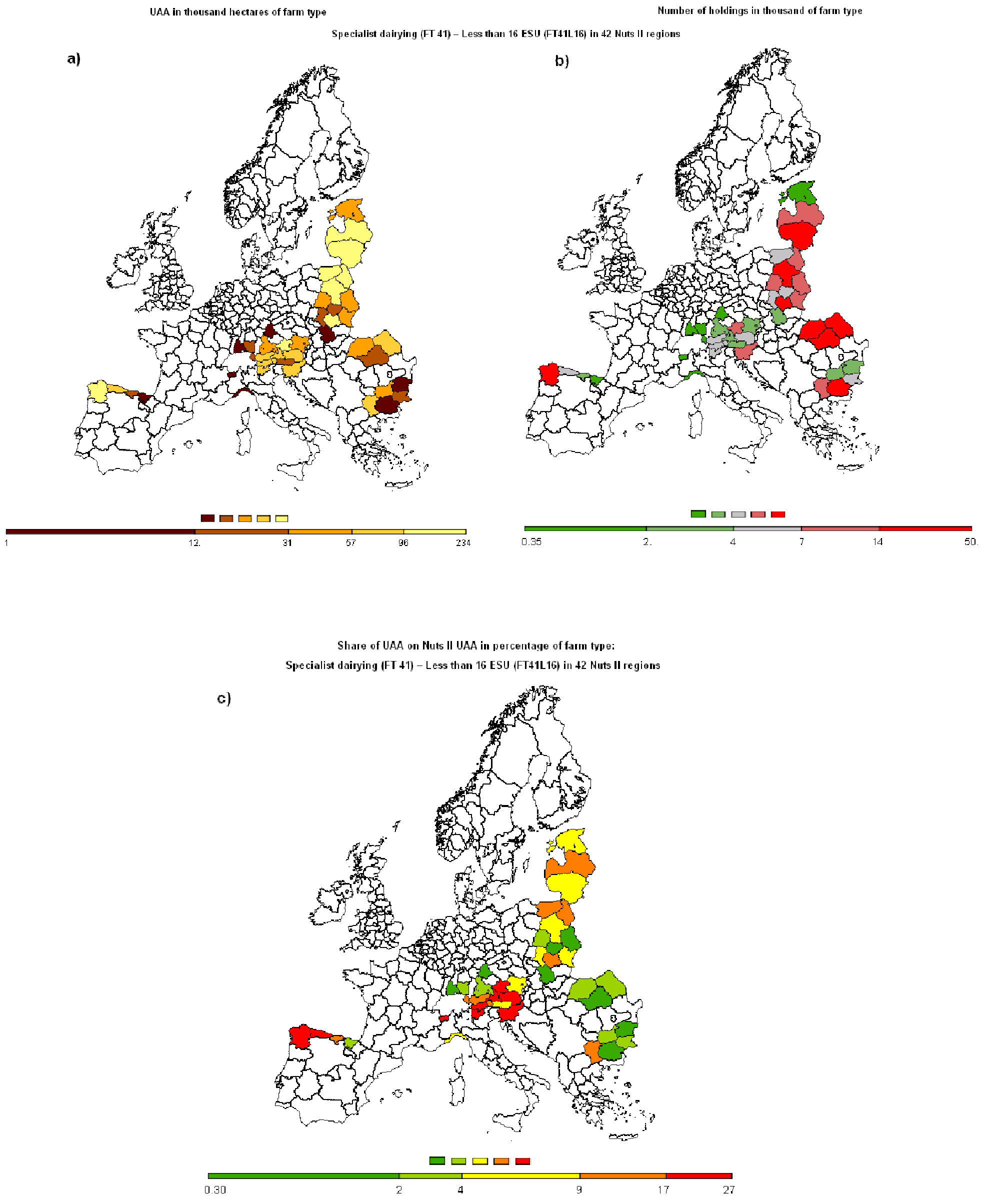

Figure 5-A4: Distribution of (a) total UAA 1,000 hectares, (b) number of holdings in thousand and (c) share on NUTS II UAA in percentage of farm type of farm type: Specialist dairying (FT 41) – Less than 16 ESU (FT41L16) in 42 NUTS II regions

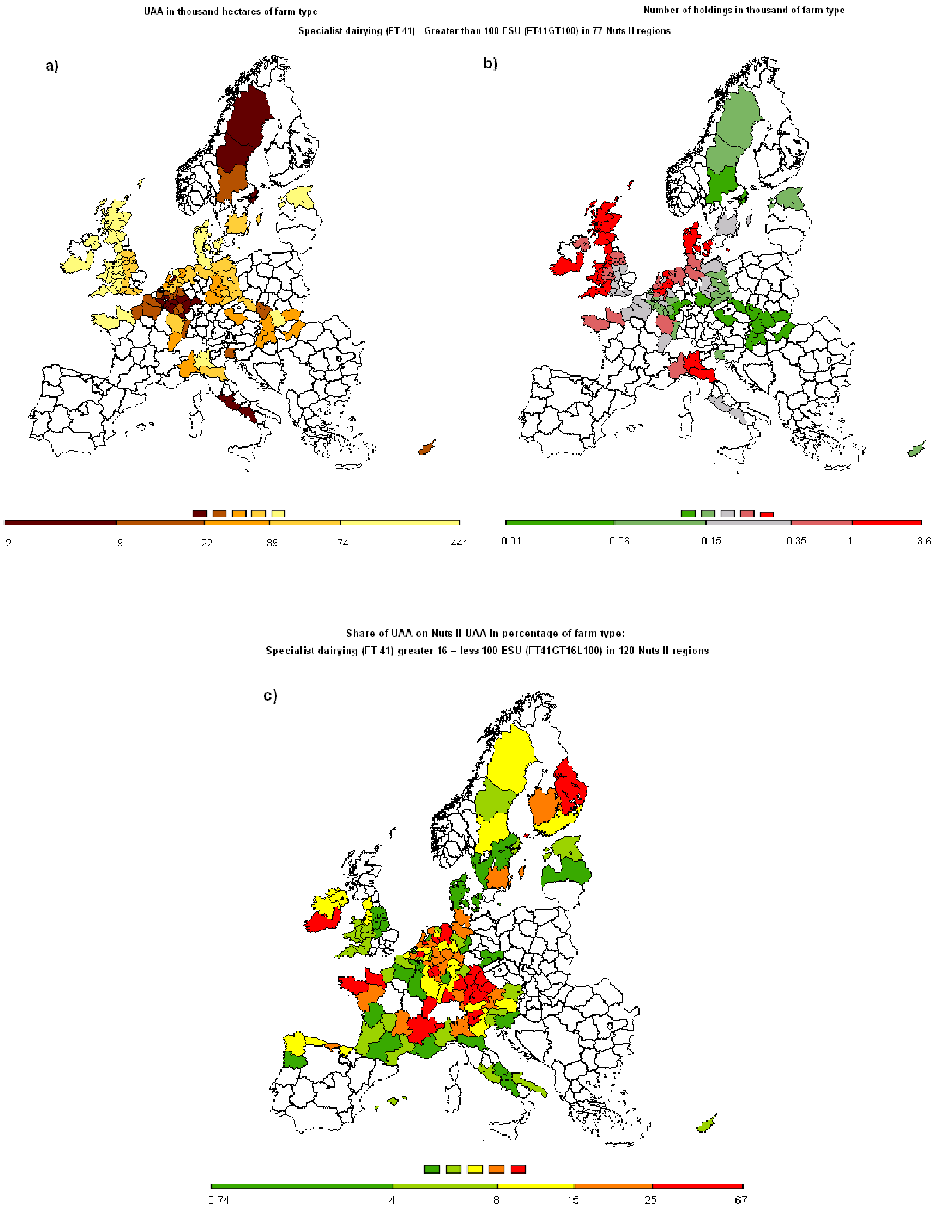

Figure 5-A5: Distribution of (a) total UAA 1,000 hectares, (b) number of holdings in thousand and (c) share on NUTS II UAA in percentage of farm type of farm type: Specialist dairying (FT 41) greater 16 – less 100 ESU (FT41GT16L100) in 120 NUTS II regions

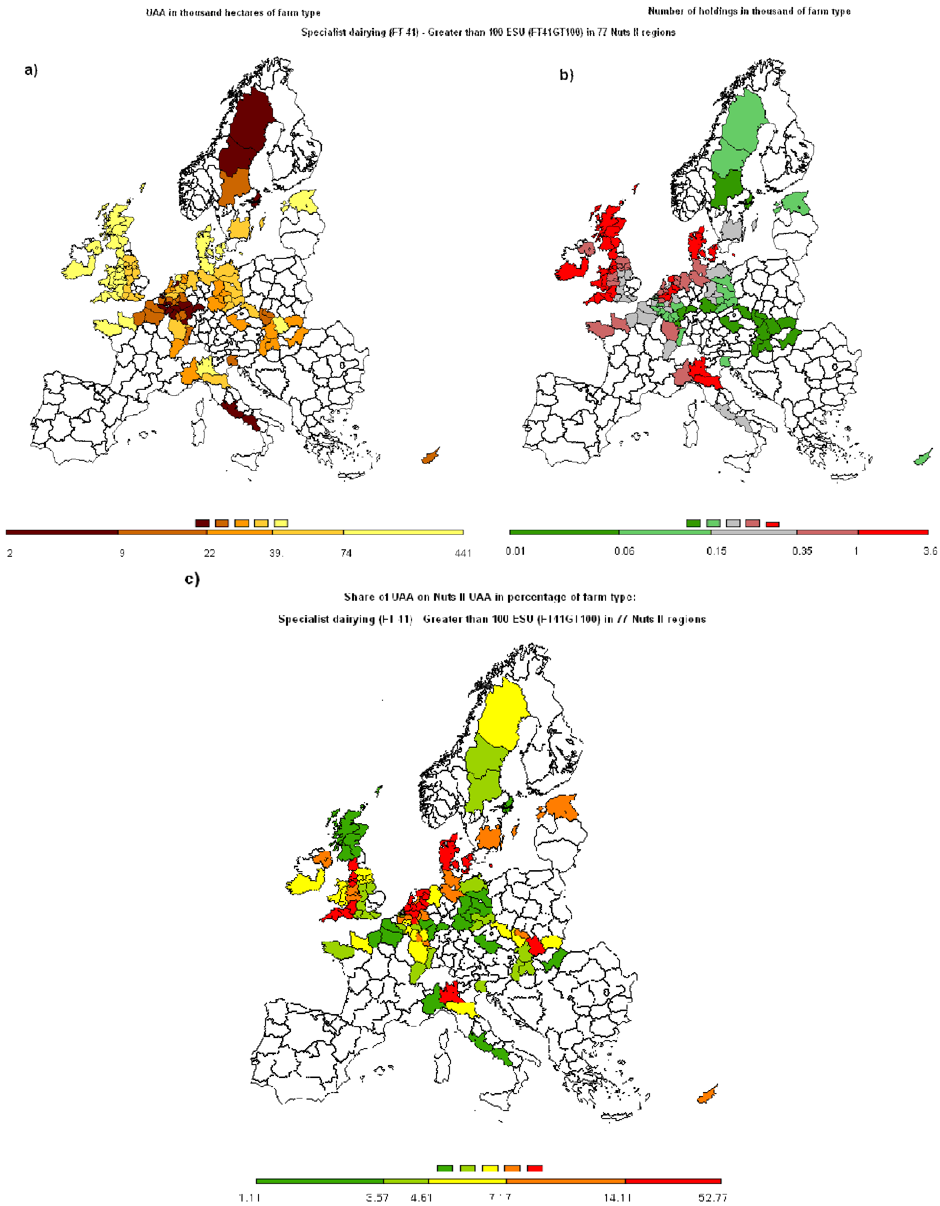

Figure 5-A6: Distribution of (a) total UAA 1,000 hectares, (b) number of holdings in thousand and (c) share on NUTS II UAA in percentage of farm type of farm type: Specialist dairying (FT 41) - Greater than 100 ESU (FT41GT100) in 77 NUTS II regions

Chapter 6. Discussion

6.1 Conclusion

This thesis contributes to the development of methods used for economic farm modelling. In Chapter 2, attention was given to a non-parametric method to measure technical efficiency. Most agricultural scientists have ignored sampling noise and often had little theoretical and empirical guidance on how to correctly conduct Data Envelopment Analysis (DEA). This chapter presented different model specifications using a bootstrap approach to derive confidence intervals. The results show that DEA without considering statistical properties can lead to erroneous conclusions. It follows that DEA results must be interpreted cautiously, and that further research is necessary before DEA can be accepted as a standard approach for the evaluation of input-output productivity. Apart from the model specifications, it was important to develop the computational framework for the convenient calculation of confidence intervals. Using the slice model in GAMS, we could show that the statistical properties of DEA estimates can be easily obtained.

In Chapter 3, the response behaviour of prominent Positive Mathematical Programming (PMP) variants is assessed, utilising *ex post* time series from the German Farm Accountancy Data Network (FADN) database. The results show that the response behaviour is strongly determined by the different PMP approaches recovering the parameters of the non-linear cost function. Furthermore, we find that the fit of the simulated farm group models to the observed values for all considered calibration methods is poor. We conclude that when time series or panel data are not obtainable, the use of exogenous elasticities to determine the cost function parameters is a convenient method to introduce out of sample knowledge. However, we should be careful because the calibration method with exogenous elasticities does not determine the cross relationships of the quadratic cost function parameter. Furthermore, the elasticities applied during calibration are unlikely to be the same as the ones in the final model, which results from the non-linear functional form, its parameter and the constraints of the model. If several observations are available but the parameters cannot be identified with normal well-posed estimation techniques, ill-posed estimation techniques such as Maximum Entropy (ME) offer a way to include prior beliefs on the estimated parameters and to estimate the observed relationship between the cropping pattern and the height of the received gross margins for the non-diagonal matrix elements of the cost function. Furthermore, it could be shown that an alternative cost function estimation under the first order condition of the model with time series and prior information can be used instead of a PMP approach for estimating the model. This approach is theoretically consistent and avoids the general misspecification of the traditional PMP approach. However, computational demands and numerical problems, as well the lack of sufficient time series from FADN, prevent this method from becoming a standard approach for farm group models.

Chapter 4 offers an approach to estimate a non-linear farm group optimisation model simultaneously with unknown input coefficients using Generalised Maximum Entropy (GME) based on multiple observations. This approach combines the more recent PMP literature with the extensive one on allocating variable inputs to production activities using farm accountancy data. The model was estimated using a cross-sectional sample of 58 FADN accountancy records. The special situation in Belgium was used, in which input costs per activity are collected to compare the findings. The hypothesis that this simultaneous approach would outperform separate input allocation regressions was confirmed. Apart from this, the concept also offers a specification of a farm group supply model with a PMP-type objective function based on multiple farm level observations. This is itself a relevant contribution, because most models of this type are not based on a statistical estimation approach. The result on the superior performance of the simultaneous estimation approach also held up when support point specifications of the GME approach were varied. It could be shown that support point designs matter for estimation results, especially if prior expected values on parameters differ and data information is limited. The number of support points had only limited impacts on the estimates.

Chapter 5 introduced the farm type layer in the Common Agricultural Policy Regionalised Impact (CAPRI) model and addressed the issue of a consistent disaggregation of regional agricultural data by farm supply. Our example provides a solution when structural relations at the lower level need to be maintained - in our case, the characterisation of farm size and farm specialisation. We propose the application of a Bayesian motivated estimation framework that treats the available disaggregated information, the Farm Structure Survey (FSS) data, as a random variable. Whereas the disaggregated data provide prior information, consistency and definition based conditions provide the data information. Their combination provides posterior estimates that fulfil the top-down disaggregation requirement while exhausting the information content of the FSS data. The estimator ensures that the type of farming of each group, as well as the economic size of a farm group, were not violated, allowing for a consistent disaggregation of the CAPRI regional database based on the FSS to source a layer of farm type models for the CAPRI model. The developed method was compared to a variable-wise linear scaling approach, and results show the superior performance of the proposed Bayesian approach compared with the results from normal scaling.

6.2 Outlook

This thesis gives special attention to different methods in economic farm modelling. Because each single chapter of the thesis already discusses further research directions, the focus here is on two specific topics that are turning out to be the most interesting and promising for further research from the author’s perspective.

The first topic relates to the specification and the estimation of farm group models. The approach in Chapter 4 with a simultaneous determination of input allocation under the first order condition should be extended to more observations over time to improve the specification with respect to the price response behaviour. Panel data typically show more price variation and will therefore likely result in more robust estimates in this respect. This extension is in line with the developments of Chapter 3, in which for a single farm group the calibration PMP approach was replaced by an estimation of the cost function parameters over time. However, the approach in Chapter 3 did not utilise single FADN farms for the estimation but used an aggregated farm group sample over time. Furthermore, the inclusion of prior information in the form of elasticities, also presented in Chapter 3, would further improve the specification of the farm group model presented in Chapter 4. Another direction for improvement is related to the estimation technique employed for the farm group model. Findings from other studies suggest that a Bayesian approach, rather than an ME or GME, promises a more straightforward and transparent implementation of prior information without support point related complications and with less computational requirements. Further research is also needed to solve the problem that arises when animal production activities are considered, because inequality constraints, caused by the relation between fodder production and fodder use, can lead to non-closed optimisation problems, which are difficult to solve.

A second research direction results from the developments in Chapter 5 and focuses on the farm type models in CAPRI. In contrast to Chapters 3 and 4, in which the farm group model was estimated based on a bottom-up approach using single farm records or groups of farms, farm models in Chapter 5 are developed top-down using the Farm Structure Survey (FSS) as information to disaggregate the regional sector models in CAPRI. The advantage is that the resulting farm groups are consistent with the sector approach. Although the farm type models use output coefficients derived from FADN, the input allocation coefficient is equal for all farm types and is based on information from the upper regional model. The current model can be extended by using the estimation model from Chapter 3 and would also lead to a better specification of the cost function parameter and therefore to a improved model response. Another extension is the inclusion of structural change in the “baseline” projection, which would imply estimating the changes of the representativeness factor (number of holdings in a farm type) over time. The development of such an approach has to be left for future research.