Estimating a farm group model and input allocations using accountancy data

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Introduction

For environmental and economic impact analyses, the knowledge on physical or monetary input use per production activity is often very important. However, input use at production activity level is typically **not available from accountancy data** and either *ad hoc* approaches or regressions of total input use on output quantities are applied to obtain the desired information. In a second step, the obtained coefficients are then used to specify Mathematical Programming (MP) models for agri-environmental policy assessment calibrated or fitted to observed choice in activity levels.

Here we propose a methodology for specifying a farm group model with a Positive Mathematical Programming (PMP) formulation while **simultaneously estimating** input allocations to enterprises instead of using a two step approach. As activity specific input costs are relevant for decisions on land allocation, we hypothesize that such an estimation approach will make better use of available information than the previously applied two-step approach.

A further contribution of this research is the real world example of estimating a non-linear cost function using multiple observations from single farm accountancy data and prior information on shadow prices. This generally serves a better empirical foundation for PMP type models.

Data

The developed estimation approach is applied to a set of year 2000 FADN* accounting data from 56 Belgium farms. The Belgium dataset we use has a distinct **advantage** as input cost per production activity are additionally collected and used to **validate** the results of the proposed approach.

The data distinguishes the five input categories and a 'value-added' category obtained residually. The inputs are used to engage in seven production activities.

Table 1: Farm group sample

	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
* FADN: European Farm Accountancy Data Network

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Methodology

Step 1: Starting point

Input allocation regressions (Léon et al., 1999)

$$\mathbf{b} = \mathbf{A}\mathbf{x} + \mathbf{u}$$

Farm group model (Howitt, 1995)

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

subject to

$$\mathbf{R}\mathbf{x} \le \mathbf{c} \; [\boldsymbol{\lambda}]$$

$$\mathbf{x} \ge 0$$

Step 2: Error model - simultaneous approach

Adjusted input allocation regression

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

$$\mathbf{T}_{j,f} = \left(\mathbf{y}_f^o \odot \mathbf{p}_f + \mathbf{s}_f^o\right) \;\forall\; j$$

First order optimality condition (farm group model)

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

$$\mathbf{x}_f = \mathbf{x}_f^o + \mathbf{e}_f \;\; \forall f$$

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

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

f	farm indices	'o'	observed data
i	variable input category	j	output category

- **A** matrix of unknown technological coefficients
- **b** vector of total input use in monetary terms
- **x** monetary output vector
- **u** vector of random disturbances
- **y, p, s** expected yields, expected prices, and subsidies
- **R** matrix of coefficients of a land and a sugar quota constraint
- **c** available resources and the corresponding
- **λ** vector of shadow prices
- **Q, d** quadratic cost function
- **Ã** cost shares for each *i* of *j* per ha - constant across farms

3. step: Estimation

- **Generalised Maximum Entropy (GME) estimator (Golan et al. 1997)**
- **Re-parameterize the unknowns of the model in terms of probabilities and support points for Input allocation matrix, the dual values for land and quota constraints, the linear term of the quadratic object function, and the various error terms related to acreages, prices and input cost shares**

Results

We evaluate how the simultaneous approach of input allocations and behavioral model compares to a separate linear regression (LR-model). Both approaches (LR-model and FOC-LR-model) are compared based on **observed values** on monetary input coefficients as presented in Table 1 that were **not used in estimation**. Then we also look at the fit of the behavioral model with respect to the endogenous variables.

Input allocation

Table 2: Pearson's correlation coefficient for input allocations

	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 3: Deviation of estimated input shares

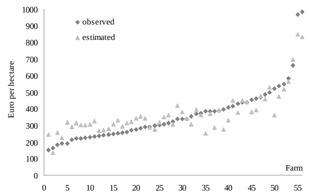
		Contract work	Seeding	Treatment	Fertilizer	Value-added
Winter Wheat	LR	-0,019	-0,004	0,035	0,005	-0,014
	FOC-LR	0,017	-0,006	0,033	0,019	-0,065
Winter barley	LR	0,010	-0,024	0,009	-0,052	0,057
	FOC-LR	-0,024	-0,023	0,011	-0,070	0,106
Chicory	LR	0,053	-0,024	0,029	0,005	-0,062
	FOC-LR	-0,057	-0,024	0,010	-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

Fit of the behavioral model

Table 4: Pearson's correlation coefficient "observed" and fitted values

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	

Figure 1: Observed and estimated values for land rent



Conclusions

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, but **not used in the estimation**.

The concept also offers a farm group supply model with a PMP-type objective function based on **multiple farm level observations**, a relevant contribution, because most models of this type are not based on a statistical estimation approach.

The ability to include **prior information on resource shadow prices promise more realistic results** compared to standard PMP specifications.

More observations over time will probably improve the specification with respect to the price response behavior 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. Another direction of further development could be the application of **Bayesian approaches** as in Jansson (2007, 2009) which promise a more straightforward and transparent implementation of prior information without support point related complications.

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For further information

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