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How did farmers act? An ex-post validation of normative and positive mathematical programming for an agent-based sector model

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Abstract.

This study evaluates normative (NMP) and positive (PMP) mathematical programming methods for the recursive dynamic agent-based sector model SWISSland, which determines production decisions for 3400 farm-level models for the ex-post period 2005 to 2012. This study clearly shows that PMP for crop production activities improves the forecasting performance of farm based agent-based models compared to NMP. It also shows that combining PMP and NMP could be a suitable approach for agent-based sector models. For short-term forecast PMP for all production activities and PMP combined with NMP lead to similar results. The results either show that PMP calibration based on revenues and PMP calibration based on the entropy approach lead to similar results. By combining PMP with NMP some limitations of PMP could be reduced. In branches where the adoption of new production activities is expected due to market, the NMP approach could be an appropriate solution.

Keywords: agent-based sector model, positive mathematical programming, ex-post validation

1. Introduction

Agricultural policy models apply either normative (NMP) or positive mathematical programming (PMP) to analyse the impact of policy changes. The main difference between the two is that NMP models are not calibrated to historical data, while PMP could reproduce observed data.

Studies evaluating the practice of PMP more than 15 years after the first paper on this subject published by Howitt in 1995 show that it has become very popular in aggregated policy-decision support models (Garnache et al., 2014; Heckelei et al., 2012). This is because it guarantees exact calibration to the base year and avoids predicting overspecialisation without adding weakly justified constraints to the model formulation (Kanellopoulos et al., 2010). The popularity of PMP is underscored by the fact that the majority of both European and non-European aggregated sector models[1] have used it for the calibration of crop and animal production since 2000.

All these studies show that PMP is less popular in farm-level models, however. To date, only a few farm-level models have used PMP for calibrating the crop activities of arable farms (Kanellopoulos et al., 2010) and both animal and crop production activities of dairy-farm models (Buysse et al., 2007). One of the reasons for the limited use of PMP in this context is that farm-level models generally only take account of activities observed during the reference period, even though new policies and market conditions allow farmers to undertake new production activities. Buysse et al. (2007) show that PMP is recommended for farm-level models when only modifications of existing policies are analysed, whilst NMP is preferred for modelling policy changes that are more radical. A review of the most popular agent-based models which apply mathematical programming to determine the production decisions of single farm agents leads to the same results. confirms this preference. To give several examples, the German AGRIPOLIS model (Happe 2004), the Italian RegMAS model (Lobianco and Esposti, 2010) and the agent-based software package MP-MAS (Schreinemachers et al., 2011) still use NMP.

The aim of this study is to assess the best mathematical programming method for the recursive dynamic agent-based sector model SWISSland, which determines production decisions for 3400 farm-level models based on mathematical programming, and extrapolates production results to sectoral scale. We analyse the forecasting performance of NMP and PMP for farm-level models. Because there is not only one PMP approach in practice, but rather several different mathematical

[1] Examples of PMP-based, aggregated models representing either farm-type groups or whole regions are the German FARMIS model (Offermann et al., 2005), the Italian FIPIM model (Arfini et al., 2011), the Spanish PROMAPA model (Júdez et al., 2008), the European CAPRI-FARM model (Gocht and Britz, 2011), the Swiss SILAS model (Mann et al., 2003), the German-Austrian Glowa-Danubia Decision-Support System model (Winter, 2005), the European CAPRI-REG model (Britz and Witzke, 2014), the Dutch DRAM model (Helming, 2005), the USDA REAP model (Johansson et al., 2007), the Californian SWAP model (Howitt et al., 2012) and the New Zealand model NZFARM (Daigneault et al., 2014).

versions of PMP which all influence the forecasting performance of the model, this study reviews the most frequently used approaches for application in the agent-based model SWISSland. Based on the finding of Buysse et al. (2007) we further investigate whether the forecasting performance of farm-level models could be improved by applying PMP for branches with minor policy changes, and by NMP for branches with further-reaching policy changes. This is why we are validating a combination of PMP for crop-production activities and NMP for animal-production activities for the ex-post period 2005 to 2012, in which policy changes in animal production (abolition of the milk quota in 2007, introduction of direct payments for dairy farms) in Switzerland were further-reaching than in the crop-production sector (tariff-rate decrease for cereals).

Section 2 of this paper gives a brief overview of the most relevant PMP versions considered for the evaluation. Section 3 gives an overview of the agent-based sector model SWISSland. In Section 4, we describe the different PMP and NMP modelling options tested within the SWISSland model for the ex-post period 2005 to 2012. By drawing a comparison with the historical pathway, Section 5 illustrates the forecasting performance of the single-farm models and Chapter 6 provides conclusions as to how PMP could be used in agent-based modelling.

2. NMP and the applied versions of PMP

NMP has been used in agricultural economics since more than 50 years now. A NMP model starts from a decision rule of the decision maker, which determines the levels of the different variables when aiming to optimise the objective set by the decision maker (Hazell and Norton, 1986). NMP farm models often maximize the profit in the objective function according to equation 1:

$$\max Z = \sum_i p_i x_i - c_i x_i \qquad (1)$$

In equation 1, parameter Z denotes the objective function value, p is the vector of product prices, c is the vector of variable costs, x the vector of production levels, and i is the index for the production activities. NMP models assuming constant marginal costs in the objective function become generally known as linear models (LP).

NMP does not guarantee the reproduction of the observed data. Positive mathematical programming models have been developed to overcome this normative character of NMP. The general idea of PMP is to use information contained in shadow values of an NMP model which is bound to observed activity levels by calibration constraints (Step 1). Based on these shadow values, a non-linear objective function is specified such that observed activity levels are reproduced by the optimal solution of the new programming problem without bounds (Step 2). For the mathematical details of this two-step procedure, see Heckelei et al. (2012), Sanders (2007), or Gocht et al. (2005).

PMP has been criticised for many years for a number of methodological and theoretical reasons. One of these is that arbitrary assumptions necessary for calibration will affect forecasting performance (Kanellopoulos et al., 2010). Another is the weak – or at least unclear – theoretical basis of PMP and the difficulties in justifying the functional forms used for PMP calibration (Doole and Marsh, 2013; Heckelei and Woolf, 2003). Several versions of PMP have therefore been developed which can either be differentiated by type of objective function and method for estimating the matrix coefficients of the objective function on the one hand, or by the calibration method on the other hand. Regarding the type of objective function and the calibration method this study uses an "extended variant" of PMP published by Kanellopoulos et al. (2010), which was developed for the simulation of single farm models. This variant assumes increasing marginal costs in the objective function whilst returns to scale remain constant (see Kanellopoulos et al., 2010):

$$\max Z = \sum_i p_i x_i - d_i x_i - \tfrac{1}{2} x_i Q_{ii} x_i \quad (2)$$

In equation 2, parameter d denotes the vector of the linear term of the quadratic objective function, whilst Q denotes the symmetric, positive (semi-)definite matrix of the quadratic cost term. For determining the coefficients d_i and Q_{ii} shadow values λ_i for both marginal and preferential activities need to be recovered from a primal LP model described in equation 1. Because such a LP-model is not able to recover shadow values for the marginal activities, increasing marginal costs are only assumed for the preferential activities while constant costs are applied for marginal activities. To overcome this problem the "extended variant" of PMP was developed. This variant is able to estimate a Q matrix either for marginal and preferential activities by using exogenous land rents g in the linear objective function for the available area y according to equation 3:

$$\max Z = \sum_i p_i x_i - c_i x_i - g * y \quad (3)$$

Most PMP models estimate the matrix coefficients Q and d of the quadratic cost terms based on exogenous supply elasticities from the literature. Due to the absence of empirical supply elasticities for Switzerland this study tests two different approaches. The first approach estimates the matrix coefficients

$$Q_{ii} = \frac{1}{\rho_{ii}} * \frac{revenue^*}{x_i^{\ *}} \quad (4)$$

and

$$d_i = c_i - \lambda_i - q_{ii} x_i^{\ *}, \quad (5)$$

based on revenues whilst all supply elasticities ρ_{ii} were set to the value of one. Parameter $x_i^{\ *}$ denotes the observed production levels of the base year and parameter λ the shadow values of calibration constraints. The second approach estimates the matrix coefficients based on maximum entropy

(ME), which was proposed by Paris and Howitt (1998). In this study, we use the maximum entropy approach to recover all the n*(n+1)/2 elements of the Q matrix as well as the Cholesky factorisation of this Q matrix to guarantee that the recovered Q matrix is symmetric, positive and semi-definite. The maximum entropy technique in combination with the PMP calibration allows recovering a quadratic activity variable cost function accommodating complementarity and substitution relations between activities. To estimate the parameter vector d and the matrix Q of the variable cost support points for the parameters were defined. As a starting point one could center the linear parameters d around the observed accounting cost per unit of the activity. For example, we could choose 5 support points for each parameter. The entropy problem is maximized using a support-space consisting of a Zd vector and a ZQ matrix. Because no cross cost effects are expected between crop and animal activities, the linear vector d of the quadratic activity cost function is partitioned into a vector including the crop activities and a second vector including the animal activities. Similarly, the quadratic matrix Q is partitioned into a matrix including the crop activities and a second matrix including the animal activities.

3. The SWISSland Model

The agent-based SWISSland[2] model ('SWISSland' being the German acronym for 'Structural Change Information System Switzerland') depicts 3400 FADN farms as realistically as possible in terms of their operational and cost structures as well as their social behaviour, as a representative sample of the approx. 50 000 family farms in Switzerland. The model allows us to assess the consequences of agricultural-policy measures, the impacts of both internal and external market influences, and the effects of heterogeneous site conditions specific to the alpine region on income trends, structural change and land management in the Swiss agricultural sector. At the same time, it is meant to enable us to make differentiated statements for regions and farm groups. SWISSland serves primarily as a policy advisory tool (Möhring et al., 2010).

The key objects of the model are agents representing real-life farms. We are dealing here with family farms operating year-round whose overall income is predominantly generated on the agricultural holding, or with alpine farms operating exclusively in the mountain region, primarily in the summer at an altitude of more than 1000 m.a.s.l. The model simulates a forecast period of up to 30 calendar years, corresponding more or less to a generational cycle of the farming family. The adaptive reactions of the individual agents and their behaviour when interacting with other agents are depicted in annual steps. The model flow described in Figure 1 applies for each time interval.

[2] A detailed technical description of the model can be found on www.swissland.org.

The annual iteration process is preceded by an initialisation step which is necessary for processing all input information for the model in the form required in each case.

The modelling of the behaviour of the agents substantially influences the manner in which the actors make their decisions. The behaviour of the individual agents is divided into fairly small, independent units ('microbehaviours'), individually parameterised, and modelled as an autonomous process (Kahn, 2007). Table 1 identifies the behavioural models previously modelled in SWISSland (categorised according to An (2012)). Also listed are the various data sources and the methods underlying the data survey.

The model is not spatially explicit. The FADN agents are distributed throughout Switzerland, and do not actually have neighbourly relationships with one another. Despite this, and to enable the simulation of the land market between the agents, the spatial structures of representative reference municipalities were implemented in the model (Mack et al., 2013). This allows both the home farms and the alpine farms to interact on the land market. These interactions are only possible within the lease regions and with (constructed) neighbouring agents, however. A lease algorithm enables the plot-by-plot allocation of the land of exiting farms to the remaining farms operating in the immediate vicinity. Exiting farms are those where the farm manager is not passing on the farm to a successor, or those where the potential successor decides against farm takeover on economic grounds. Income and farm-size criteria for farm-exits and farm entries were calibrated iteratively to the levels observed in the past period 2005 to 2012. A plot-by-plot bidding process models which neighbouring agent receives the freed-up land at what lease price. The neighbouring agent achieving the highest expected increase in income with the lease of the plot receives the lease plot.

Integrated into the iteration process is the SWISSland market module, which is, however, only used for ex-ante simulations. For ex-post simulations, the individual-farm prices and average sectoral price trends deduced from the FADN data are assumed. Exogenous variables ascribed to the model are 'technical progress', 'quota regulations', 'direct payments' and 'allowances', among others.

SWISSland calculates sectoral parameters via an extrapolation algorithm. Zimmermann et al. (2014) have compared various extrapolation alternatives for the model. Product quantities and prices, land-use and labour trend, income trend according to the Economic Accounts for Agriculture, the sectoral input and output factors for calculating environmental impacts, and important key structural figures such as number of farms, sizes and types of farm, or number of farms changing their farming system, are all sectoral output indicators.

Three different software components communicate with each other in the model via interfaces:

- A MySQL database organises all input and output data for depicting the behaviour algorithms for the decision-making of the individual agents (e.g. accounting data, group-formation data for forming population clusters, etc.) and manages the data for sequence- and data-transfer control.
- A Java platform models all heuristic behaviour models and rules, the interactions of the agents, program control, and control of the database interfaces, as well as paving the way for the transfer of information to the extrapolation module.
- A recursive-dynamic GAMS (=General Algebraic Modelling System) model optimises the production and investment decisions individually for each agent via a loop algorithm and ensures the PMP calibration.

Table 1: Behavioural and decision models and data-collection sources

Submodels	Behaviour	Data Collection					Decision Model					
		Sample survey (FADN)	Sample survey (representative)	Census data	GIS data	Bayesian network	Microeconomic	Heuristic rule-based	Space theory-based	Institution-based	Preference-based	Hypothetical rules
Agent rational decision module	Production decisions	x					x			x		X
Farm manager's life cycle	Farm takeover, Farm exit		x				x	x			x	
Land market	Lease decisions for land plots			x	x		x	x	x			X
Growth and investment	Investment decisions	x					x			x		X
	Entry or exit, year-round activities	x					x	x				X
	Strategy for shifts in labour input	x				x	x	x			x	
Alpine farming	Entry or exit, alpine activities	x	x		x		x		x		x	

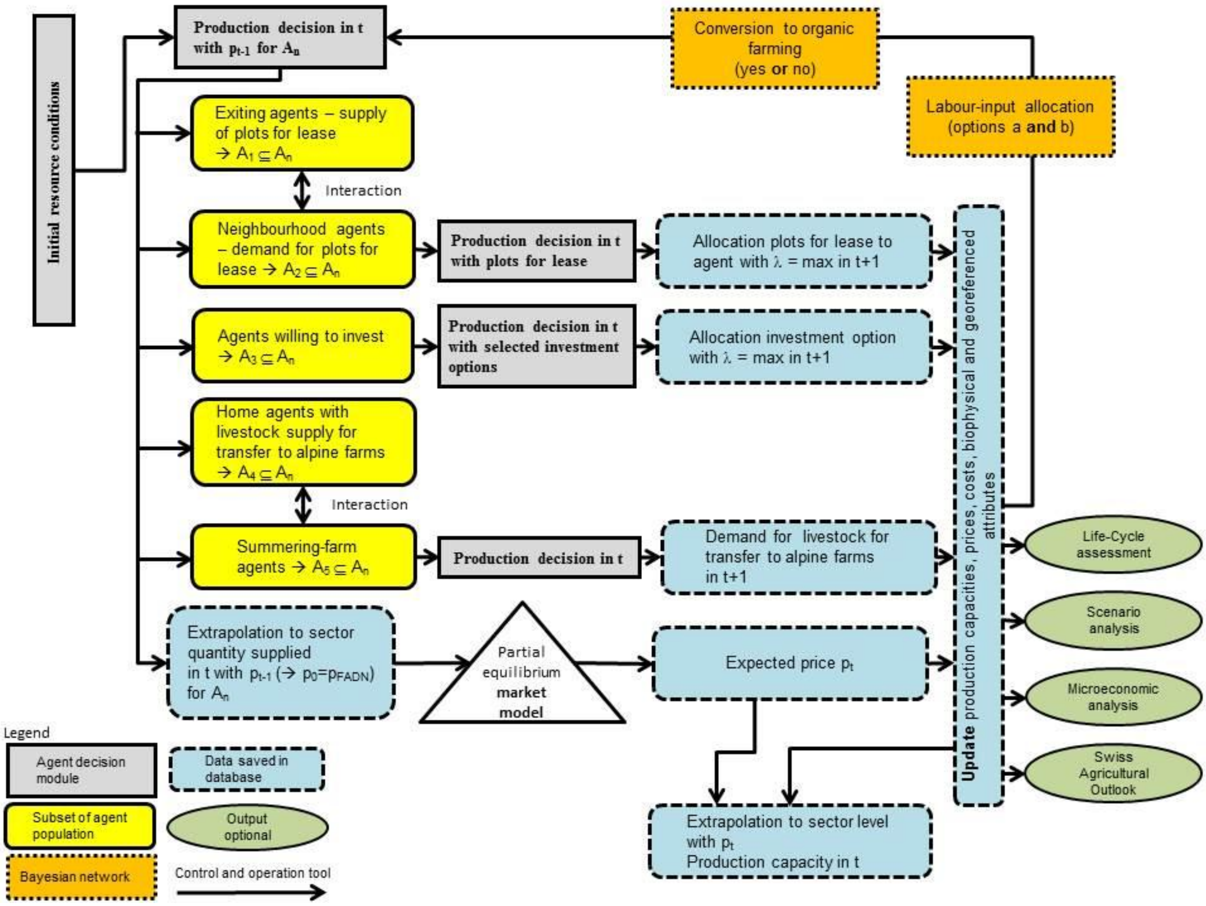

Figure 2: Design and process overview of SWISSland

The use of individual-farm FADN data ensures that various factors influencing the objective-function and production-coefficient matrix are also automatically taken into account, allowing the depiction of numerous management options that are typical for Switzerland. These management options are characterised by different arable, forage and animal-production systems within the various forms of agriculture, and thus by corresponding input/output intensity levels. The cost and output parameters of the production activities are therefore heterogeneous, and influence the decision-making scope of the agents.

The coefficients derived using the base year apply only for the current situation of the agents, however. Because future production and investment decisions can sometimes alter the ratios significantly, the individual-farm decision framework must be plausibly limited. For one thing, missing information from the base year must be added with the help of average values of other farms, or extrapolated using standard data. Here, it must be borne in mind that the given climatic or local conditions rule out certain production methods for some agents, and that high transaction and start-up costs would make inclusion in the agent's production programme fairly unlikely. For all agent activities occurring in the production programme of the forecast years rather than in the base year, the yield and price coefficients are estimated with the aid of a random distribution based on means and standard deviations of the values of all agents from the same region and form of agriculture.The following assumptions – explained in greater detail in the SWISSland ODD Protocol (Möhring et al., 2014) – therefore apply in the model.

Rational agent behaviour is taken as an important basic assumption of the model. Hence, each agent (Index a) maximises its annual household income (INCOME) for each time period (Index t).

In keeping with the theory of adaptive expectations, the agents (a) make their production decisions based on price (p) and yield (ε) expectations of the previous year for the various animal (Index l) and crop production activities (Index g). Prices and yields were estimated for each agent on an individual-farm basis from the FADN data of the base year, with the observed price trends and average annual yield changes (Δ) resulting from 2000 to 2012 being stipulated exogenously for every time period.

Household income (INCOME) results from the sale of agricultural products, from off-farm work (OFFFARM, Index o), and from the proceeds of the direct payments (PAYMENT, Index d) less the means-of-production costs. The level of the direct payments corresponds to the year-specific, production-dependent and production-independent approaches in each case, in accordance with current agricultural-policy provisions. Because this study tests various linear and PMP-based quadratic cost functions for plant- and animal-production activities they are described in Chapter 4.

$$\begin{aligned} Max\ INCOME_{a,t} = & \sum_g p_{a,g} * \Delta p_{t-1,g} * \varepsilon_{a,g} * \Delta\varepsilon_{t-1,g} * LAND_{a,t,g} + \sum_l p_{a,l} * \Delta p_{t-1,l} * \varepsilon_{a,l} * \Delta\varepsilon_{t-1,l} * ANIMAL_{a,t,l} \\ & + \sum_i p_{a,o} * \Delta p_{t-1,o} * OFFFARM_{a,t,o} + \sum_d p_{d,a} * \Delta p_{t,d} * PAYMENT_{a,t,d} - COSTFUNCTION_{a,t} \end{aligned} \tag{6}$$

subject to

$$\sum_g \omega_{a,g,w}^{LAND} * LAND_{a,t,g} + \sum_l \omega_{a,l,w}^{ANIMAL} * ANIMAL_{a,t,l} + \sum_f \omega_{a,f,w}^{LABOUR} * LABOUR_{a,t,f} \leq \beta_{w,a}$$

for all w $\notin$ g,l,f.

The resource endowment (w) of a farm consists of the available area (Index g), the animal places on the farm (Index l), the other capacities limiting animal and crop production (e.g. sugar-beet quota, milk quota up to 2007, provisions on the receipt of direct payments), and the labour force (Index f).

Information on the historically observed crop mix of the agents was derived from ten years of FADN-farm land-management data. The assumption is made that plant-production methods which were not observed in the base year, but which occur in the farm's historic crop mix, are taken into account in the agent's decision portfolio. This prevents over- or underestimates in the flexible extension of individual production methods, thereby limiting specialisation exclusively to base-year production decisions (cf. also Wiborg et al. (2005)).

The ex-post evaluation was carried out for the period 2005-2012 with the 2003-2005 three-year average as a base year. Over this period, Swiss agricultural policy changed decisively, particularly for milk and meat production. To cite an example, Switzerland concluded a free-trade agreement for cheese with the EU in 2007. The same year saw the country's gradual withdrawal from the milk quota system (FOAG, various years; Mack and Pfefferli, 2004), as well as the introduction of an RCLU payment for dairy cows. These and all further policy framework conditions decided on during this period form the exogenous bases for the agents' production decisions.

4. Method

4.1 Modelling options

Five different options for modelling animal- and crop-production decisions were analysed in this study (Table 2). Option 1 determines both crop- and animal-production decisions based on linear cost functions for 17 crops and 8 animal-production activities according to equation 7:

$$Max\ INCOME_{a,t} = REVENUE_{a,t} - \sum_l c_{l,a} * \Delta c_{t-1,l} * ANIMAL_{a,t,l} - \sum_g c_{g,a} * \Delta c_{t-1,g} * LAND_{a,t,g} \quad (7)$$

Option 1 does not calibrate the production activities to base-year levels. Since policy changes in the animal sector were greater than those in the crop sector from 2004 to 2012, option 2a and 2b apply linear cost functions for animal-production activities only while PMP-based quadratic cost functions are used to determine crop-production decisions (equation 8):

$$Max\ INCOME_{a,t} = REVENUE_{a,t} - \sum_g c_{g,a} * \Delta c_{t-1,g} * LAND_{a,t,g} - \sum_g d_{a,g} * LAND_{a,t,g} - 0.5 \sum_g Q_{a,g} * LAND^2_{a,t,g} - \sum_l c_{l,a} * \Delta c_{t-1,l} * ANIMAL_{a,t,l} \quad (8)$$

Option 2a estimates the matrix coefficients Q of the non-linear cost term based on revenues and uses supply elasticities equal to one owing to the lack of empirical data (equation 9).

$$Q_{g,a} = \frac{revenue_{g,a}{}^*}{LAND_{g,a}{}^*} \quad (9)$$

For those production activities for which the output is used on the farm itself, Q is calculated based on linear costs c and shadow values λ according to the German farm type model FARMIS (Schrader, 2009):

$$Q_{g,a} = (c_{g,a} + \lambda_{g,a})/LAND_{g,a}{}^* \quad (10)$$

The linear term d of the quadratic cost function is calculated according to equation 11.

$$d_{g,a} = \lambda_{g,a} - Q_{g,a} LAND_{g,a}{}^{*} \qquad (11)$$

Option 2b estimates the matrix coefficients of the quadratic cost functions for crop production activities on the basis of maximum entropy. Option 2a and 2b combine the advantages of both PMP and NMP modelling, with PMP calibrating crop-production activities to observed base-year levels taking into account the pedo-climatic conditions of the individual farms, and NMP enabling the modelling of the adoption of new animal production branches. In all models with a linear cost function in animal husbandry, the agents can invest in new barns, thereby considerably expanding their herd size even within a time period, provided that all other necessary resources are available in sufficient quantity. Moreover, a switch to new production activities in the animal husbandry sector is easily possible. In order to avoid an objective function with an integer formulation, however, individual barn construction variants (previously selected and evaluated according to plausibility) are tested iteratively with the aid of the loop process for each agent entitled to investment. Here, the annual external costs of the entire building (depreciation, repair, insurance and interest) are borne in mind, regardless of whether or not the barn can be fully utilised. If the agent is entitled to receive investment credits or investment aid, these lower the interest charges. Ultimately, the variant with the highest positive objective-function value is implemented. In the following year, all animal places resulting from the investment in the barn are available to the farmer. In this case, further use of the old barn is ruled out. Investment activities in new animal branches are taken into account when a farm successor takes over from his predecessor. Only for older agents it was assumed that investment was primarily in the animal branches pursued to date.

Option 3a and 3b test PMP-based quadratic production-cost functions for both animal- and crop-production activities: (12)

$$\begin{aligned} Max\ INCOME_{a,t} = REVENUE_{a,t} &- \sum_{g} c_{g,a} * \Delta c_{t-1,g} * LAND_{a,t,g} - \sum_{g} d_{a,g} * LAND_{a,t,g} - 0.5 \sum_{g} Q_{a,g} * LAND_{a,t,g}^{2} \\ &- \sum_{l} c_{l,a} * \Delta c_{t-1,l} * ANIMAL_{a,t,l} - \sum_{l} d_{a,l} * ANIMAL_{a,t,l} - 0.5 \sum_{l} Q_{a,l} * ANIMAL_{a,t,l}^{2} \end{aligned}$$

Because investments in new barns result in a complete change in the cost structure, the PMP-based cost function completely changes the function values derived in the base year. Since no methods were previously available to estimate the change in the PMP-based cost functions derived from the base year, a continuous model approach in which the agents continuously expand their barns by individual animal places was chosen for option 3a and 3b.

Table 2: Modelling options for determining production decisions

Option No.	Name	Cost function for crop production activities (g)	Cost function for animalproduction activities (l)	PMP calibration method	Estimate of matrix coefficients of quadratic cost function	Investments
1	Linear	Linear	Linear	-	-	Investment activities for new buildings
2a	Linear-Quad-Revenues	PMP-based; quadratic	Linear	Extended	Revenues	Investment activities for new buildings
2b	Linear-Quad-Entropy	PMP-based; quadratic	Linear	Extended	Maximum entropy	Investment activities for new buildings
3a	Quad-Revenues	PMP-based; quadratic	PMP-based; quadratic	Extended	Revenues	Continuous new-investment costs
3b	Quad-Entropy	PMP-based; quadratic	PMP-based; quadratic	Extended	Maximum entropy	Continuous investment costs for buildings

The criteria for farm take-overs and farm exits (household income, labour income and farm size) were calibrated iteratively to the observed number of farm exits in the period 2005 to 2012 using model option 3a.

4.2 Assessing forecasting performance

In this study, we assess the forecasting performance of the options on the basis of the average forecasting error AFE measuring the difference between forecasted and historical parameters at farm-scale and at sectoral scale. The farm-scale parameters assess the forecasting performance from those agents only, which remain over the whole simulation period 2005 to 2012 in the sample. In contrast sectoral parameters take into account farm sample changes due to farm exits and entries. Therefore simulation results from all agents were extrapolated to sectoral scale based on Zimmermann et al., 2014.

At farm-scale the forecasting error AFE measures the percentage difference between historical and forecasted average production levels for each production activity. The weighted forecasting error of crops WAFE aggregates the forecasting error AFE of each crop based on its average production share in the FADN farm sample. The forecasting error is calculated analogously for animals. Finally, the total weighted average annual forecasting error WAFE aggregates weighted forecasting error for crops and animals equally.

At sectoral scale we calculate the production changes from 2005 to 2012 in per cent: The forecasting error measures the deviation from historical values.

5. Results

Linear cost functions for both crop- and animal-production activities (option 1) lead at farm scale to the highest weighted forecasting error of almost 50% for crops and to the highest forecasting error for both animal and crop production in both time periods (Table 3). The results in table 3 also show that crop activities supported by direct payments such as extensive grassland, fallow land, oilseed rape, soya and sunflower are highly overestimated in the linear version, whilst PMP for crop-production activities significantly reduce the forecasting error in both time periods. The approach with quadratic production costs for crop activities and linear production costs for animal activities (option 2a and 2b) show a better forecasting performance in the long term than option 3a and 3b with quadratic production costs for both animal and crop production activities. The forecasting performance of option 2a and 2b improves in particular for the livestock categories of cattle, dairy cows, sucker cows, horses and hens, which showed a production increase above-average from 2005 to 2012 due to investment activities. Furthermore the forecasting error of fodder- and grassland-activities decreases in the versions with linear production costs for animals and PMP for crop production activities because these activities are highly influenced by the cattle production level. Only for marginal animal activities such as sheep and goats, which are underrepresented on Swiss FADN farms, the forecasting error is higher in the linear than in the PMP versions. For all aggregated crop activities as a whole, the entropy versions and the revenue versions lead to similar results in the short and long term. The results show that the method to estimate the coefficients of the non-linear cost term (revenue or entropy) does not influence the forecasting performance when PMP is only applied for crop production whilst linear production activities are used for animal activities. When PMP is used for both production categories, the entropy method leads to a slightly better forecasting performance in the long term.

Table 3: Results at farm scale: Average forecasting error for animal- and crop-production activities.

Production activity	Average ha/LU for all FADN Farms			Average forecasting error AFE (%)									
	2003-2005	2006-2008	2010-2012	No 1 Linear		No 2a Linear-Quad-Revenues		No 2b Linear-Quad-Entropy		No 3a Quad-Revenues		No 3b Quad-Entropy	
		S	L	S	L	S	L	S	L	S	L	S	L
Bread grain	1.39	1.40	1.46	50	52	10	13	8	12	8	10	6	10
Feed grain	1.07	1.13	0.92	84	80	14	5	14	6	12	12	9	12
Grain maize	0.22	0.20	0.21	28	21	8	2	8	2	4	6	11	4
Silage maize	0.88	0.91	1.00	9	17	7	3	7	3	2	6	3	6
Sugar beet	0.30	0.32	0.32	11	12	3	4	3	4	2	3	3	3
Potatoes	0.30	0.27	0.25	299	326	2	4	2	5	13	8	3	9
Oilseed rape	0.21	0.23	0.30	237	162	14	34	14	33	12	33	12	32
Sunflower	0.04	0.05	0.04	321	444	11	15	11	15	15	15	11	15
Legumes	0.07	0.08	0.05	130	236	19	18	18	19	12	24	15	24
Vegetables	0.09	0.10	0.11	237	224	13	16	13	16	11	15	12	15
Fallow land	0.04	0.05	0.03	73	148	13	25	15	23	2	29	14	24
Temporary grassland	2.86	2.92	3.34	10	22	5	8	3	10	1	11	0	13
Extensive grassland	1.30	1.30	1.31	68	64	1	1	3	5	20	1	3	5
Less-intensive grassland	0.69	0.68	0.65	8	13	16	21	17	23	2	25	18	24
Intensive grassland	8.66	8.79	8.92	9	11	1	2	0	2	14	3	1	2
Extensive pastures	0.21	0.25	0.25	20	21	11	13	7	9	3	16	8	9
Intensive pastures	1.77	1.78	1.69	2	3	2	3	5	0	3	2	6	1
LU (total)	26.98	27.65	29.83	10	13	5	5	4	6	5	11	5	13
Cattle (total)	21.60	22.07	24.00	13	16	7	8	6	8	7	14	8	14
Dairy cows	14.80	14.97	16.21	11	15	6	6	3	6	4	11	4	11
Suckler cows	1.28	1.57	1.86	15	5	1	2	7	5	22	34	22	35
Horses	0.19	0.22	0.20	16	2	1	11	10	2	6	27	4	34
Sheep	0.21	0.22	0.22	14	33	29	33	14	30	4	7	3	8
Goats	0.05	0.05	0.06	8	6	11	10	7	11	5	23	2	23
Sows	3.98	4.14	4.08	5	7	9	10	7	10	6	9	5	7
Fattening pigs	2.52	2.61	2.67	7	1	2	4	8	3	14	13	14	2
Hens	0.34	0.35	0.59	1	25	19	18	0	21	1	40	3	39
Poultry	0.60	0.60	0.67	1	11	13	23	6	12	0	10	0	12
Crop production				50	55	4	5	4	5	4	7	4	7
Animal production				10	14	6	10	6	10	7	13	7	11
Average				30	34	5	8	5	8	5	10	5	9

S= Short term; L=long term.

Because farm take-over and farm exit criteria were calibrated iteratively to the observed number of farm exits in the period 2005 to 2012 using the model option 3a this option shows the lowest average absolute deviation from historical values of around 3 %. Table 4 shows that all model options using PMP could reproduce the observed farm exits, whilst the linear version underestimates farm exits significantly. These results indicate that the linear version overestimates farm specialisation and farm income significantly. A comparison of the extrapolated production changes of all agents with the historical production changes of the agricultural sector shows that the option with linear cost functions for animals lead to better results, particularly in the production branches where the highest production increase were previously observed, such as suckler cows hens, horses, goats and poultry. In these animal sectors, above-average investments in new stables which overcompensate for the decrease in production owing to farm exits were observed in the past. The results show that modelling investments in new animal capacities based on linear cost functions leads to better results than using continuous investment activities combined with quadratic cost functions. The results also show that PMP for crop-production activities underestimates production increases above-average (such as rape seed, sugar beet, field vegetables etc). These results are caused by the characteristics of PMP. On the one hand the farm-level models only take account of activities observed during the reference period 2005, whilst an adoption of new crop production activities in the ongoing years could not be taken into account. On the other hand the quadratic cost functions prevent an overspecialisation and a production increase above-average for single activities.

Table 4: Results at sectoral scale: deviation from historical sectoral change (+/-%)

		Observed sectoral change from 2003/05 - 2010/12	No1 Linear	No 2a Linear-Quad-Revenues	No 2b Linear-Quad-Entropy	No 3a Quad-Revenues	No 3b Quad-Entropy
Farm exits			Deviation from historical sectoral change (+/-%)				
Total farms	Qty.	-11%	5%	1%	0%	2%	3%
Valley region	Qty.	-12%	5%	4%	2%	4%	6%
Hill region	Qty.	-9%	4%	-3%	-4%	0%	-1%
Mountain region	Qty.	-10%	3%	1%	1%	1%	1%
Farm size < 20 ha	Qty.	-18%	0%	-3%	1%	-1%	6%
Farm size 20-30 ha	Qty.	+4	8%	8%	-4%	6%	-2%
Farm size >30 ha	Qty.	+15%	9%	-4%	-13%	-4%	-19%
Crop production							
Bread grain	ha	-4%	-17%	-11%	-14%	-1%	-3%
Fodder crop	ha	-17%	-36%	-2%	-5%	12%	9%
Potatoes	ha	-17%	28%	-7%	-7%	-1%	1%
Rapeseed	Ha	35%	-52%	-48%	-50%	-41%	-43%
Sunflower	Ha	-32%	23%	12%	12%	18%	15%
Field vegetables	Ha	11%	173%	-14%	-17%	-9%	-10%
Silage maize	Ha	12%	2%	-6%	-5%	-14%	-6%
Sugar beet	Ha	6%	-23%	-12%	-12%	-11%	-7%
Open arable land	Ha	-6%	8%	-6%	-8%	0%	1%
Temporary ley	Ha	9%	2%	-3%	-7%	-15%	-13%
Total arable area	Ha	-2%	5%	-4%	-7%	-4%	-3%
Permanent grassland	Ha	-2%	5%	2%	-2%	3%	-2%
Total utilised agricultural area	Ha	-2%	5%	0%	-3%	1%	-2%
Total LU	LU	3%	1%	-3%	-5%	-9%	-11%
Dairy cows	LU	-6%	4%	2%	1%	-3%	-2%
Suckler cows	LU	55%	-6%	-17%	-20%	-60%	-60%
Pigs	LU	-3%	-1%	-6%	-6%	-3%	-34%
Fattening calves	LU	-13%	2%	1%	2%	12%	24%
Fattening bulls	LU	-6%	14%	5%	2%	2%	2%
Cattle total	LU	2%	0%	-4%	-4%	-11%	-9%
Sheep	LU	-1%	-19%	-21%	-21%	-5%	-3%
Goats	LU	25%	78%	78%	78%	-39%	-42%
Horses	LU	13%	93%	81%	-11%	88%	122%
Broilers	LU	31%	18%	13%	8%	-38%	-40%
Hens	LU	19%	10%	5%	2%	-20%	-20%
			Average of absolute deviation from historical sectoral change (%)				
All attributes			**20%**	**12%**	**10%**	**13%**	**16%**

6. Conclusions

This ex-post validation clearly shows that the use of PMP-calibration for selected production activities improves the forecasting performance of an agent-based farm model significantly comparing with NMP. The above results corroborate the study of Buysse et al. (2007), which has shown that PMP is recommended for farm-level models when it is only modifications of existing policies that are analysed, whilst NMP is preferred for modelling more-radical policy changes. In this study, we analysed model options which applied PMP for crop-production and NMP for animal-production activities. This study shows that combining PMP and NMP in farm models could be a suitable approach for agent-based sector models. Using PMP for farm activities with minor policy changes and NMP for activities with further-reaching policy changes could improve the forecasting performance of farm-level models, in particular in long-term forecasts. For short-term forecast PMP for both animal and crop production and PMP combined with NMP lead to similar results. The results either show that PMP calibration based on revenues and PMP-calibration based on the entropy approach lead to similar results. The results support other studies by Gocht (2005) and Winter (2005), both of whom discovered that the different PMP versions led to similar model results. Although all tested approaches lead to deviations in the actual observable trends, we may conclude that the PMP combined with NMP is preferable to full PMP when assessing the forecasting performance of production changes over time. These results also show that some limitations of PMP could be reduced by combining PMP with NMP. In branches where the adoption of new production activities is expected owing to market and policy changes, the NMP approach could represent an appropriate solution.

Moreover, the extent of the forecasting error of the extrapolated sectoral results could be influenced by the choice of extrapolation method. Zimmermann et al. (2014) have demonstrated that the choice of the extrapolation method in agricultural-sector models can strongly skew both the base-year results and the model results of the forecast years.

At the same time, the present paper shows that in general, an ex-post validation makes a valuable contribution to improving the accuracy of the model, but can also make a theoretical contribution to the methods used. On the other hand, the present example demonstrates that all of the calibration methods used have their strengths and weaknesses in individual areas. For this reason, the methodological considerations for improving the calibration of models should be continued. Not only will this improve the goodness of projection of the calibration; just as importantly, it will also have positive consequences for the acceptance of the calibration for use in policy advice.

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