Evaluating Changes in Cropping Patterns due to the 2003 CAP Reform. An Ex-post Analysis of Different PMP Approaches Considering New Activities

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Abstract

There is a growing interest on models able to anticipate farmers' response to agricultural and environmental policy changes. The Positive Mathematical Programming (PMP) method is being extensively used for evaluating the likely impacts of policy interventions. This paper evaluates the capability of three different PMP approaches to forecast changes in cropping patterns due to the 2003 CAP reform: the standard approach (Howitt 1995, Arfini and Paris 1995), the maximum entropy approach (Paris and Howitt 1998) and the Röhm and Dabbert approach (2003). However, neither of those approaches enables to model activities non-observed in the base situation. An additional approach is therefore suggested to consider new activities already introduced in the post-reform situation.

These approaches have been tested in an irrigated area of Central Italy. All models have been calibrated to the pre-reform situation and then the 2003 CAP reform has been simulated and model results have been compared with observed cropping patterns. Even if all models calibrate perfectly, response behaviour depends on the selected approach. Compared to the standard approach, the Röhm and Dabbert approach shows a too wide substitution between crops belonging to the same group; and the maximum entropy approach performs better only when prior information is considered. The extended PMP version proposed in this paper depicts a more realistic picture of post reform cropping patterns.

Key words: ex-post policy evaluation, positive mathematical programming, CAP reform

1. Introduction

There is a growing interest on models able to anticipate farmers' response to agricultural and environmental policy changes. Positive Mathematical Programming (PMP) is one of the methodological approaches that have been receiving much attention in recent years. Starting with the standard PMP approach (Howitt 1995a and 1995b), different PMP versions have been developed, including the maximum entropy calibration criterion (Paris and Howitt 1998; Heckelei and Britz 2000) and the Röhm and Dabbert approach (2003). Regional models based on PMP have been extensively used for evaluating the likely impacts of policy interventions (Bauer and Kasnakoglu 1990; Arfini and Paris 1995).

Several authors have pointed out the arbitrary response behaviour of PMP based models and have suggested ways to overcome some of the drawbacks of the PMP methodology (Gohin and Chantreuil 1999; Heckelei and Britz 2000) or proposed alternative methods (Heckelei and Wolff 2003). Gocht (2005) tested the response behaviour of several PMP versions illustrating the potentiality of the Maximum Entropy approach to incorporate extra information, which could result in improved simulation behaviour.

The scope of activities modelled is another relevant issue in agricultural supply modelling. The successive reforms of the Common Agricultural Policy (CAP) have led to significant changes in cropping patterns and farming practices throughout the European Union. However, agricultural supply models traditionally only consider activities observed in the pre-reform situation, that is, they do not take into consideration new crop or technology options, even when these might become plausible strategies under certain policy changes. Even if there have been some attempts to allow for more flexibility in model response (Paris and Arfini 2000; Blanco and Iglesias 2005), models based on traditional PMP approaches fail to model activities non-observed in the calibration period.

The aim of this paper is to evaluate the predictive capacity of several PMP approaches while modelling new activities non-observed in the base year. Three particular PMP approaches have been retained: the standard PMP approach, the Röhm and Dabbert approach and the maximum entropy procedure.

The performance of these PMP versions to anticipate the impacts of the 2003 CAP reform has been tested in an irrigated area of Central Italy. The focus has been mainly on winter cereals because the high level of policy support accorded to durum wheat in the pre-reform situation has radically changed with the introduction of decoupling. As a result, other winter cereals such as common wheat and barley have become relatively more profitable than before. However, these last two crops were almost not represented in the pre-reform conditions at least in some of the areas of the irrigation district. This represents a problem from the modelling point of view, because traditional PMP approaches do not consider the possibility of modelling new activities. To overcome this difficulty, here it is proposed a wide-scope PMP version allowing us to consider new activities that have been chosen by farmers in the post-reform situation even if these were not observed in the pre-reform situation in all sub-areas of the study area.

The remainder of the paper is organised as follows. In the second section, we address the main strong and weak points of selected PMP approaches. The suggested wide-scope PMP version is explained in section third and results of the simulation exercise are discussed in section fourth. Some concluding remarks are drawn in the last section.

2. The PMP methodology

The PMP methodology has first been developed to calibrate agricultural supply models (Howitt 1995a; Arfini and Paris 1995). This approach assumes a profit-maximising equilibrium in the base year situation and it recovers additional information from observed activity levels in the base year in order to specify a non-linear objective function such that the resulting non-linear model closely reproduces the observed farmers' behaviour. Most authors interpret PMP as the estimation of a non-linear cost function, partly because cost data is site-specific and official data sources are often lacking. Hence, we will focus on this particular formulation.

Conventional PMP approaches usually involve three steps: 1) Specification of a linear programming model – taking into account all available information – bounded to the observed activity levels by calibration constraints, in order to derive the differential marginal cost vector (μ); 2) Estimation of non-linear variable cost functions, assumed to capture all farming conditions non modelled in a explicit way; 3) Formulation of a non-linear programming model that exactly reproduces the observed behaviour in the base year.

Using a simplified notation, the constrained linear problem can be written in the following way:

$$\begin{aligned}
\max \quad & Z = r'\,x - c'\,x \\
\text{s.t.} \quad & A\,x \le b \qquad [\lambda] \\
& x \le x^0 + \varepsilon \qquad [\mu] \\
& x \ge 0
\end{aligned} \tag{1}$$

where **Z** denotes the objective function value; **x** is a (*n* x 1) vector or production activity levels; **r** and **c** are (*n* x 1) vectors of revenue and variable cost per unit of activity, respectively; **A** denotes a (m x n) matrix of coefficients in resource constraints; **b** and λ are (*m* x 1) vectors of resource availability and associated dual values, respectively; $\mathbf{x^0}$ is a (*n* x 1) vector of observed activity levels; ε denotes a (*n* x 1) vector of small positive perturbations, entered to prevent linear dependency between resource constraints and calibration constraints; and μ is a (*n* x 1) vector of dual values associated with the calibration constraints.

Once the bounded linear program has been solved, dual values μ are used in the second step to specify a set of non-linear cost functions such that the implied marginal costs equal the respective revenues in the base year situation. A quadratic variable cost function is commonly used, whose general formulation can be stated as follows:

$$VC = \alpha'\,x + \frac{1}{2}\,x'\,Q\,x \tag{2}$$

where α is a (*n* x 1) vector of parameters associated with the linear term, and **Q** is a (*n* x *n*) symmetric positive definite matrix of parameters associated with the quadratic term. The quadratic formulation implies increasing marginal costs with the level of the activity. Parameters α and **Q** are specified such that the solution of the non-linear program equals the solution of the constrained linear program. That is, the following condition on marginal costs holds:

$$MC = \alpha + Q\,x^0 = c + \mu \tag{3}$$

Several approaches have been developed to derive the parameters of the variable cost functions. We will focus in the three PMP approaches that will be tested later in this paper: the standard PMP approach (ST), the Röhm and Dabbert approach (R&D), and the Maximum Entropy criterion (ME).

2.1. Standard PMP approach

In the standard approach (Howitt 1995a, Arfini and Paris 1995) all off-diagonal elements of matrix **Q** are assumed null and then, the variable cost functions are independent from each other. Being **j** the index for the production activities, the function of average variable cost can be written:

$$AC_j = \alpha_j + \frac{1}{2}\beta_j \, x_j \tag{4}$$

And the problem consists on determining the parameters α and β that satisfy the following marginal conditions:

$$MC_j = \alpha_j + \beta_j \, x_j^0 = c_j + \mu_j \tag{5}$$

Given that multiple sets of parameters satisfy these conditions, in the standard PMP approach the value of α is fixed to the accounting cost **c**:

$$\alpha_j = c_j \, ; \quad \beta_j = \frac{\mu_j}{x_j^0} \tag{6}$$

This formulation implies that there will be some preferable activities with non-zero β values and some marginal activities with zero β values and, therefore, with associated linear cost functions. Furthermore, implied average cost will be higher than the observed one for preferable activities and marginal value for resources will be linked to marginal profit for marginal activities. Several options have been proposed to overcome these problems, including Paris's suggestion to fix a zero α value, addition of exogenous data on supply elasticities and incorporation of exogenous marginal values for land (Gohin and Chantreuil 1999). In this paper, the last option has been selected and exogenous land opportunity costs have been considered in all tested approaches.

2.2. Röhm and Dabbert approach

In the standard PMP approach, the parameters of the cost function for each activity are recovered separately from each other. In this way, different production technologies of the same crop (variants) are considered as separate activities and, consequently, in the simulation phase substitution among these variants is lower than expected. Röhm and Dabbert (2003) propose a different modelling approach to take into account the higher elasticity of substitution between crop variants than between different crops.

Denoting by *j* the crop and by *v* the variant, the non-linear programming model can be compactly written:

$$\begin{aligned} \text{Max} \quad & Z = \sum_j \sum_v \left(r_{j,v} - AC_{j,v} \right) x_{j,v} \\ s.t. \quad & \sum_j \sum_v a_{i,j,v} \, x_{j,v} \;\; \leq \;\; b_i \\ & x_{j,v} \;\; \geq \;\; 0 \end{aligned} \tag{7}$$

where **Z** denotes the objective function value; $\mathbf{x_{jv}}$ represents production activity levels (hectares allocated to crop *j* with variant *v*); $\mathbf{r_{jv}}$ and $\mathbf{AC_{jv}}$ denote average revenue and average variable cost per unit of activity, respectively; $\mathbf{a_{ij}}$ represents the matrix of coefficients in resource/policy constraints; and $\mathbf{b_i}$ is the vector of available resource quantities.

The R&D approach introduces a second slope parameter, which is common to all variants of the same crop. There will therefore be two sets of slope parameters, one for single crops and other for variants, so that the average cost functions take the following form:

$$AC_{j,v} = \alpha_{j,v} + \frac{1}{2}\beta_{j,v}\, x_{j,v} + \frac{1}{2}\gamma_j \sum_v x_{j,v} \tag{8}$$

Cost function parameters can be recovered solving the original linear problem with two additional calibration constraints:

$$\begin{aligned} \sum_v x_{j,v} &\le \sum_v x^0_{j,v}\,(1+\varepsilon_1) \qquad [\mu_j] \\ x_{j,v} &\le x^0_{j,v}\,(1+\varepsilon_2) \qquad [\mu_{j,v}] \end{aligned} \tag{9}$$

where ε_1 and ε_2 are small positive numbers ($\varepsilon_1 < \varepsilon_2$); μ_j are dual values associated with single crops; and μ_{jv} are dual values associated with crop variants. As for the standard PMP approach, multiple sets of cost function parameters satisfy the marginality conditions and one of the options to recover these parameters would be the following:

$$\alpha_{j,v} = c_{j,v} \;;\quad \beta_{j,v} = \frac{\mu_{j,v}}{x^0_{j,v}} \;;\quad \gamma_j = \frac{\mu_j}{\sum_v x^0_{j,v}} \tag{10}$$

The R&D approach considered in this paper does not distinguish crop variants because of lack of specific data. Instead, we have defined groups of similar crops in order to allow for a higher elasticity of substitution between closer activities. Specifically, a group of crops has been identified for winter cereals (durum wheat, common wheat and barley). Being g the subscript for crop groups, the model can be written in the following way:

$$\begin{aligned} \text{Max} \quad & Z = \sum_g \sum_j \left(r_{g,j} - AC_{g,j} \right) x_{g,j} \\ s.t. \quad & \sum_g \sum_j a_{i,g,j}\, x_{g,j} \le b_i \\ & x_{g,j} \ge 0 \end{aligned} \tag{11}$$

and the average variable cost functions take the following form:

$$AC_{g,j} = \alpha_{g,j} + \frac{1}{2}\beta_{g,j}\, x_{g,j} + \frac{1}{2}\gamma_g \sum_j x_{g,j} \tag{12}$$

Therefore, the slope of the average cost function is divided in two parts, one relative to the group and other relative to the crop. Cost function parameters are recovered in a similar way as in the original R&D approach.

2.3. PMP with Maximum Entropy

In order to recover the parameters of the cost function and to also capture the possible interactions among the various activities, Paris and Howitt (1998) suggested using the Maximum Entropy criterion[1]. In fact, the ME approach allows to recover a full **Q** matrix for the variable cost function, taking into account the possible cross effects among activities. The ME approach has proven useful for ill-posed problems, i.e. when the number of parameters to estimate is greater than the number of observations and there are a number of works combining PMP and ME (Paris and Howitt 1998; Paris and Arfini 2000; Heckelei and Britz 2000).

Paris and Howitt (1998) reparameterize the **Q** matrix based on LDL' (Cholesky) decomposition to ensure appropriate curvature properties of the estimated cost functions and they use only one observation on marginal costs. The work by Paris and Arfini (2000) is particularly interesting because it recovers the cost function of single farms relying on the cost function of the homogeneous farm group obtained by FADN data. Heckelei and Britz (2000) define priors directly on **Q** (not on the elements of a LDL' decomposition of Q as in Paris and Howitt 1998) and propose a method facilitating to use cross-sectional data and to incorporate prior information such as elasticity of substitution between crops.

In this analysis we refer to the method of Paris and Howitt (1998) with the definition of priors directly on **Q** as suggested in Heckelei and Britz (2000). Let us consider the general quadratic cost function with two unknown sets of parameters:

$$VC = \alpha' x + \frac{1}{2} x' Q x \tag{13}$$

Denote by α_j and $\beta_{jj'}$ the elements of vector α and matrix **Q**, respectively. These parameters need to be specified in such a way that the following conditions are respected:

$$\alpha_j + \sum_{j'} \beta_{j,j'} x_j^0 = c_j + \mu_j \tag{14}$$

Estimation of the cost parameters using the maximum entropy criterion implies solving the following ME problem:

$$\max \quad H(p\alpha, p\beta) = -\sum_k \sum_j p\alpha_{k,j} \ln p\alpha_{k,j} - \sum_k \sum_j \sum_{j'} p\beta_{k,j,j'} \ln p\beta_{k,j,j'} \tag{15}$$

$$\text{s.t.} \quad \alpha_j + \sum_{j'} \beta_{j,j'} x_j^0 = c_j + \mu_j \quad \forall j \tag{16}$$

$$\alpha_j = \sum_k p\alpha_{k,j} z\alpha_{k,j} \quad \forall j \tag{17}$$

$$\beta_{j,j'} = \sum_k p\beta_{k,j,j'} z\beta_{k,j,j'} \quad \forall j, j' \tag{18}$$

$$\sum_k p\alpha_{k,j} = 1 \quad \forall j \, ; \quad \sum_k p\beta_{k,j,j'} = 1 \quad \forall j, j' \, ; \quad \beta_{j,j'} = \beta_{j',j} \quad \forall j, j' \tag{19}$$

[1] The definition of entropy as information measure is due to Shannon (1948) and after Janes (1957) introduces the maximum entropy principle in order to obtain probability distribution that are consistent with the available information (Golan et al. 1996).

When the estimation is based in a single observation and no prior information is available, the ME optimal solution will imply a uniform distribution of probabilities and then the ME approach will respond in a similar way as the standard PMP approach.

In this approach, the choice of the support intervals is the only subjective aspect of the analysis. It is important to consider that the recovered parameters and the simulation results can be greatly influenced by support values when only one marginal cost vector is available (Heckelei and Britz 2000). The approach with only one observation on marginal costs could be applied in order to obtain a cost function based on prior information (for example a matrix of elasticities or exogenous production functions).

3. The proposed wide-scope PMP approach

Let us assume that we want to calibrate a regional model embracing several sub-areas. Even if these sub-areas are relatively homogeneous, not all production activities are found in all sub-areas in the reference period. However, if policy or market conditions change, some activities not present in the base year in a particular sub-area could be introduced. Therefore, we are interested in estimating non-linear cost functions for each potential activity in each sub-area; that is, including those activities not found in the reference period.

We suggest a method that owes much to the approach developed by Paris and Arfini (2000) to cope with the self-selection problem and we implement this method for each of the PMP approaches assessed in this paper (ST, R&D and ME).

The basic assumption is that, because of the relatively homogeneity of the different sub-areas, differences in cropland allocation across sub-areas can be explained by differences in farmers' preferences and local conditions. We could then hypothesize that, for each activity in the model, there will be a least-cost function characteristic of the region under study. Assuming a quadratic functional form, the average cost function for the sub-region producing with lower costs ($\mathbf{AC^L}$) can be expressed:

$$AC^L = \alpha + \frac{1}{2} Q\, x \tag{20}$$

The average cost function for the S-th sub-area ($\mathbf{VC_S}$) can then be interpreted as a positive deviation from this one:

$$AC_s = \alpha + \frac{1}{2} Q\, x_s + \delta_s \tag{21}$$

The cost parameter δ is supposed to capture site-specific characteristics (farmers' preferences and local conditions). For simplicity, it is assumed that accounting costs (vector **c**) are the same for all sub-areas.

This wide-scope version has been implemented for each of the modelling scenarios (standard PMP approach, Röhm and Dabbert approach and PMP with maximum entropy).

Considering first the standard PMP approach (ST), in the wide-scope version the average least-cost function for the *j*-th activity will have the following linear expression:

$$AC_j^L = \alpha_j + \frac{1}{2}\beta_j\, x_j \tag{22}$$

For each sub-area, the average cost function can then be formulated:

$$AC_{s,j} = \alpha_j + \frac{1}{2}\beta_j\, x_{s,j} + \delta_{s,j} \tag{23}$$

Cost function parameters can be recovered by solving the original linear problem with two additional calibration constraints, one for the total land allocated to the activity and another one for the land allocated to the activity in each sub-area:

$$\begin{aligned} &\sum_s x_{s,j} \le \sum_s x_{s,j}^0\,(1+\varepsilon_1) \qquad [\mu_j] \\ &x_{s,j} \le x_{s,j}^0\,(1+\varepsilon_2) \qquad [\mu_{s,j}] \end{aligned} \tag{24}$$

where ε_1 and ε_2 are small positive numbers ($\varepsilon_1 < \varepsilon_2$); $\boldsymbol{\mu_j}$ depict the dual values associated with total activity level; and $\boldsymbol{\mu_{s,j}}$ are dual values associated with sub-area activity levels.

Parameters $\boldsymbol{\alpha_j}$, $\boldsymbol{\beta_j}$ and $\boldsymbol{\delta_{s,j}}$ should satisfy the optimality conditions in the reference period:

$$MC_{s,j} = \alpha_j + \beta_j\, x_{s,j}^0 + \delta_{s,j} = c_j + \mu_j + \mu_{s,j} \tag{25}$$

Multiple sets of cost function parameters satisfy the marginality conditions. Assuming that $\boldsymbol{\delta_{s,j}}$ will be zero for the sub-area producing at the lowest cost, one of the options to recover these parameters would be the following:

$$\alpha_j = c_j \;;\; \beta_j = \frac{\mu_j}{x_j^{0L}} \;;\; \delta_{s,j} = \mu_{s,j} + \mu_j\left(1 - \frac{x_{s,j}^0}{x_j^{0L}}\right) \tag{26}$$

where $\mathbf{x_j^{0L}}$ depict the observed activity level for the least-cost sub-area.

Actually, this specification implies that the recovered MC is the lowest among those satisfying the optimality conditions[2]. In this way, even marginal costs for crops not grown in a particular sub-area in the reference period will be increasing in x because β_j is positive.

Considering now the R&D approach, a similar formulation can be used. For the least-cost sub-region, the two slopes β and γ are calculated by using the total area allocated to each group and each single crop. The resulting AC for each sub-area would be:

[2] This assumption is not necessary when using the ME approach.

$$AC_{s,j} = \alpha_{g,j} + \frac{1}{2}\beta_{g,j}\ x_{g,j,s} + \frac{1}{2}\gamma_{s,g}\ \sum_j x_{s,g,j} + \delta_{s,g,j} \tag{27}$$

Cost function parameters can be recovered solving first the original LP model with tree calibration constraints, one for the total land allocated to the activity, another one for the land allocated to each group in each sub-area and another one for the land allocated to the activity in each sub-area:

$$\begin{aligned} &\sum_s x_{s,g,j} \le \sum_s x^0_{s,g,j}\ (1+\varepsilon_1) && [\mu_{g,j}] \\ &\sum_j x_{s,g,j} \le \sum_j x^0_{s,g,j}\ (1+\varepsilon_2) && [\mu_{s,g}] \\ &x_{s,g,j} \le x^0_{s,g,j}\ (1+\varepsilon_3) && [\mu_{s,g,j}] \end{aligned} \tag{28}$$

Assuming $\alpha_{g,j} = c_{g,j}$, one of the set of parameters satisfying the optimality would be:

$$\beta_{g,j} = \frac{\mu_{g,j}}{x^{0L}_{g,j}} \quad ; \quad \gamma_{s,g} = \frac{\mu_{s,g}}{\sum_j x^0_{s,g,j}} \quad ; \quad \delta_{s,g,j} = \mu_{s,g,j} + \mu_{g,j}\left(1 - \frac{x^0_{s,g,j}}{x^{0L}_{g,j}}\right) \tag{29}$$

Also in this case, this assumption implies that the recovered MC is the lowest among those satisfying the condition and that β are positive.

To use this approach in the ME model, it is just needed to set the “central values” around the values shown above for the ST approach and to consider the optimality conditions that should apply. For the S-th model, the average cost function is given by the following expression:

$$AC_s = \alpha + \frac{1}{2}\ Q\, x_s + \delta_s \tag{30}$$

The value of δ will be specified depending on whether the j-th crop is grown or not in the reference period in the S-th sub-area. Cost parameters will be specified so as to respect the following conditions:

$$\alpha + Q\, x^0_s + \delta_s = c + \mu + \mu_s \quad \text{when} \quad x^0_s > 0 \tag{31}$$

$$\alpha + Q\, x^0_s + \delta_s \ge c + \mu + \mu_s \quad \text{when} \quad x^0_s = 0 \tag{32}$$

The ME procedure generates parameters α, Q and δ. These coefficients, when off-diagonal elements are zero, are the same as those derived by using the ST approach.

4. Results of the empirical analysis

The analysis has been conducted in an irrigation district of central Italy, where three sub-areas are distinguished (L1, L2 and L3). These sub-areas are similar in terms of soil quality, farm size and production technologies. Water is delivered by the irrigation board by means of three non-fully connected irrigation systems. For each area, data on production activity levels, input use per activity, water charges, variable costs per activity, expected crop prices and yields, irrigated area, water availability and agricultural policy subsidies and constraints have been collected in previous research (Cortignani and Severini, 2004). Each area is represented as a separate entity given by the sum of all farms located in that portion of the irrigation district.

Table 1 shows the cropping patterns in the three sub-areas in 2004 (pre-reform situation) and 2005 (first year after the implementation of the Single Farm Payment[3]). In 2004, most of the land was allocated to durum wheat; horticultural crops were also relevant, especially tomatoes for industry. Other winter cereals such as common wheat and barley were grown in a very limited zone and just in one of the three considered sub-areas. After the Fischler reform, the area allocated to durum wheat has fallen about 60% whereas this crop has been substituted by other winter cereals (such as common wheat and barley) and fodder crops.

Table 1. Observed activity levels (ha) for the three sub-areas and the total area.

Cropping activity	Pre-reform situation (2004)				Post-reform situation (2005)			
	L1	L2	L3	Total	L1	L2	L3	Total
Durum Wheat	1421	1351	1934	4706				1880
Soft Wheat	39	0	0	39				350
Barley	0	35	0	35				290
Maize	38	37	99	174	76	18	74	168
Asparagus	4	8	8	20	28	42	21	91
Artichoke	21	30	57	108	19	49	76	144
Cabbage	6	1	1	8	20	41	24	84
Sugar Beet	9	26	11	46	13	52	4	69
Tomato	193	384	437	1014	153	407	313	873
Melon	69	60	76	205	41	46	53	140
Watermelon	113	117	100	330	104	146	105	355
Fennel	89	150	186	425	24	62	169	255
Other Crops	319	171	397	887				3096

Source: Irrigation board.

We have assessed the capability of PMP based models for forecasting changes in cropping patterns due to the 2003 CAP reform. The three selected PMP approaches (ST, R&D and ME) have been tested in two different versions:

- Narrow-scope version: only activities observed in the base year are allowed in the post-reform simulation.
- Wide-scope version: new activities non-observed in the base year are allowed in the post-reform simulation.

The analysis has been carried out calibrating all models to the pre-reform situation (2004 data on cropland allocation) and then simulating the 2003 CAP reform. The post-reform scenario has been developed and used to simulate the response behaviour of the different PMP methods. The only changes considered in this scenario are agricultural policy changes, in particular decoupling of direct

[3] Unfortunately, for some crops data are available only for the whole study area and not for the three sub-areas.

payments for COP crops (including the special aid for durum wheat), the introduction of the partially coupled aid for the quality durum wheat, and modulation measures.

Model results have been compared to cropping patterns observed in the post-reform situation (2005 data on cropland allocation) by means of the Finger–Kreinin index. This index compares the simulated shares of each activity j (s_j^m) with the observed ones (s_j^0) and reaches its maximum value (100%) when model results math observed cropping patterns.

$$FK=\sum_j \min\{s_j^m ; s_j^0\}$$

Model response behaviour has proved dependent on the selected PMP approach. This is particularly true for some horticultural crops that have not been directly affected by the CAP reform. Also, significant differences are found on the level of COP crops and, in particular, on winter cereals. Table 2 compares observed cropping patterns in the post-reform situation with model results for the narrow-scope PMP version.

Table 2. Simulation results for each approach without new activities. Cropland allocation (ha) and Finger–Kreinin similarity index

	Simulated values (narrow-scope version)					**Observed values**
	ST	**R&D**	**ME I**	**ME II**	**ME III**	
Durum Wheat	2613	1604	2614	2603	2657	1880
Soft Wheat	87	706	87	87	85	350
Barley	69	607	69	149	92	290
Maize	118	109	118	119	119	168
Asparagus	21	21	21	23	23	91
Artichoke	109	109	109	75	109	144
Cabbage	8	8	8	8	8	84
Sugar Beet	55	52	55	54	54	69
Tomato	1025	1025	1025	1028	1021	873
Melon	206	206	206	206	206	140
Watermelon	332	332	332	332	331	355
Fennel	425	425	425	425	424	255
Other Crops	2732	2593	2731	2661	2666	3096
Similarity index	85.6	86.4	85.6	85.5	85.1	

As the choice of the support interval values may influence model behaviour in the ME approach, three different sets of support values have been used in order to illustrate this influence (Table 3).

Table 3. Support interval values considered in the ME models

	ME I					**ME II**					**ME III**				
α	-100	-10	0	10	100	-4	-2	0	2	4	-4	-2	0	2	4
Q_{jj}	0	0.5	1	1.5	2	0	0.5	1	1.5	2	0	0.5	1	1.5	2
$Q_{jj'}$	-2	-1	0	1	2	-2	-1	0	1	2	-3	-1	0	1	3

The spread of the support value for the parameter α is a very wide interval around the observed costs for model ME I and a more restricted interval for ME II and ME III. When no prior information on cost function is available, the ME problem will reach its optimum with a uniform distribution of the probability (ME I). As a result, parameter values equal those obtained with the standard approach and, therefore, model ME I responds in a similar way to model ST. When we reduce the interval for cost parameters (models ME II and ME III), response behaviour changes compared to the ST model. Nevertheless, we cannot state that the ME approach performs better than the ST approach.

Another factor that strongly influences model behaviour is the choice of crop groups in the R&D approach. In the considered case, there is a too wide substitution between durum wheat and common wheat, given that these crops belong to the same group. Under this approach, it is assumed that crop substitution effects will be stronger between similar activities than between different activities. In this case common and durum wheat are similar crops but cannot be considered as variants. Therefore, it seems important to create groups only with variant activities such as when the same crop is grown under two different production technologies.

Evaluation of model response behaviour for the wide-scope PMP version is presented in Table 4. The method suggested to model new activities depicts a more realistic picture of post reform cropping patterns. Compared to the narrow-scope version, the similarity index is greater in this case for all PMP approaches except for the R&D approach.

Table 4. Simulation results for each approach with new activities. Cropland allocation (ha) and Finger–Kreinin similarity index

	Simulated values (wide-scope version)					**Observed values**
	ST	**R&D**	**ME I**	**ME II**	**ME III**	
Durum Wheat	2272	401	2276	2168	2187	1880
Soft Wheat	168	2074	169	195	173	350
Barley	144	470	144	127	146	290
Maize	81	55	80	63	63	168
Asparagus	21	21	21	21	21	91
Artichoke	110	109	109	110	111	144
Cabbage	8	8	8	8	8	84
Sugar Beet	62	55	62	56	57	69
Tomato	1029	1028	1026	959	1019	873
Melon	206	206	206	207	207	140
Watermelon	332	332	332	327	324	355
Fennel	425	425	425	430	430	255
Other Crops	2946	2617	2943	3064	3048	3096
Similarity index	90.0	70.6	90.0	91.7	91.1	

5. Conclusions

Ex-post analysis of regional models behaviour, such as the one presented here, can prove useful to gain better insight into how mathematical models behave and which new developments are needed to improve the forecasting capacity of agricultural supply models. In fact, results show that, even if all models calibrate perfectly, model response depends on the selected approach. Therefore, the choice of the modelling approach can critically influence the outcome of the simulation exercise and should be considered carefully. Two of the most critical decisions regard the choice of the support interval values in the ME approach and the crop grouping in the R&D approach.

When no prior information about the cost function is considered, the ST and the ME approaches respond in a similar way. However, the ME approach could provide better results than those obtained by using the ST approach if prior information were available.

The choice of groups in the R&D approach strongly influences model results. The R&D approach shows a too wide substitution between durum wheat and common wheat (these activities make part of the same group). The performed simulation exercise suggests creating groups with variant activities (e.g. the same crop grown under different management practices) but avoiding to create groups involving different crops.

The extended PMP version proposed in this paper depicts a more realistic picture of post reform cropping patterns. This approach can be applied when areas or farms are relatively homogenous in terms of structural variables, land quality, production orientation and production technologies. Under these circumstances, this approach has been useful in getting better simulation results. Nevertheless, further research is still needed to investigate the theoretical soundness of the suggested approach.

6. References

Arfini, F.; Paris, Q. (1995). A positive mathematical programming model for regional analysis of agricultural policies. In Sotte, E. (Ed): *The Regional Dimension in Agricultural Economics and Policies*, EAAE, Proceedings of the 40th Seminar, June 26-28, Ancona, Italy, pp.17-35.

Bauer, S.; Kasnakoglu, H. (1990). Non Linear Programming Models for Sector and Policy Analysis. *Economic Modelling*, 7 (3) : 275-290.

Blanco, M.; Iglesias, E. (2005). Modelling new EU agricultural policies: global guidelines, local strategies. En Arfini, F. (Ed.): *Modelling agricultural policies: state of the art and new challenges*. Monte Università Parma Editore, Parma, Italy, pp. 831-843.

Cortignani, R.; Severini, S. (2004). Il Regime di Pagamento Unico: scelte produttive, partecipazione alle misure agro-ambientali e pressione sull'ambiente in un'area irrigua dell'Italia Centrale. *Rivista di Politica Agricola Internazionale*, 3-4: 97-110.

Gocht, A. (2005). Assessment of simulation behaviour of different Mathematical Programming approaches. En Arfini, F. (Ed.): *Modelling agricultural policies: state of the art and new challenges*. Monte Università Parma Editore, Parma, Italy, pp. 166-187.

Gohin, A.; Chantreuil, F. (1999). La programmation mathématique positive dans les modèles d'exploitation agricole. Principes et importance du calibrage. *Cahiers d'Economie et de Sociologie Rurales.*

Gohin, A.; Chantreuil, F. (1999). La programmation mathématique positive dans les modèles d'exploitation agricole. Principes et importance du calibrage. *Cahiers d'Economie et Sociologie Rurale*, 52: 59-77.

Heckelei, T.; Britz, W. (2000). Positive Mathematical Programming with Multiple Data Points : A Cross-Sectional Estimation Procedure. *Cahiers d'Economie et Sociologie Rurale*, 57: 27-50.

Heckelei, T.; Britz, W. (2005). Model based on Positive Mathematical Programming: state of the art and further extensions. Proceedings of the 89th European Seminar of the European Association of Agricultural Economists, Parma.

Heckelei, T.; Wolff, H. (2003). Estimation of constrained optimisation models for agricultural supply analysis based on generalised maximum entropy. *European Review of Agricultural Economics*, 30 (1): 27-50.

Howitt, R.E. (1995a). Positive Mathematical Programming. *American Journal of Agricultural Economics*, 77: 329-342.

Howitt, R.E. (1995b). A Calibration Method for Agricultural Economic Production Models. *Journal of Agricultural Economics*, 46: 147-159.

Paris, Q.; Arfini, F. (2000). Frontier Cost Functions, Self-Selection, Price Risk, PMP and Agenda 2000, Euro tools Working Papers Series, No. 20, May 2000.

Paris, Q.; Howitt, R. (1998). An Analysis of Ill-Posed Production Problems Using Maximum Entropy. *American Journal of Agricultural Economics*, 80:124-138.

Röhm, O.; Dabbert, S. (2003). Integrating Agri-Environmental Programs into Regional Production Models: An Extension of Positive Mathematical Programming. *American Journal of Agricultural Economics*, 85 (1): 254-265.