Analysing Impacts of Changing Price Variability with Estimated Farm Risk-Programming Models

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Abstract

We formulate and estimate a farm level simulation model of agricultural crop production, and apply it to a scenario with increasing yield variability. The objective function is of the mean-variance utility type with a positive mathematical programming (PMP) cost function, and it is estimated using the optimality conditions and a large panel data set obtained from the FADN. Special attention is given to the problem of separating the effect of the covariance matrix from that of the quadratic PMP terms. The model is applied in a partial analysis of impacts of climate change in Germany by exogenously changing yield patterns.

Key words: Climate change, positive mathematical programming, risk, Bayesian econometrics, FADN

1. Introduction

Farming is an inherently risky business, exposed to weather variations as well as unexpected market and policy changes. The role of risk and risk management in agriculture receives increased attention in recent years which may even further rise in the future. One consequence of the projected climate change may be increased crop yield variation due to a higher frequency of extreme events (Teixeira *et al.*, 2013) possibly calling for adaptations of cropping programs.[1] The opening of European agricultural market over the last two decades leads to an increase in variability of EU prices (Thompson *et al.*, 2000) despite little evidence on globally rising food price variability in the longer run (Gilbert and Morgan, 2010). In any case, increasing farmers' and political awareness lead to a substantial increase of risk management in the form of insurances and corresponding government support in the US over the last 20 years (Glauber, 2013) and has now also entered EU agricultural policy after long debates (European Commission (2013), Article 30).

However, many of the large scale applied agricultural economic models regularly used for policy impact analysis and market outlooks such as CAPRI and AgLink, do not explicitly consider risk as a factor influencing production decisions limiting their applicability in this respect. Modelling risk is certainly not new to agricultural economics[2], but due to the developments just mentioned it has recently also attracted increased attention from applied policy modellers (Cortignani and Severini, 2012; Petsakos and Rozakis, 2011), yet large scale applications at national or EU level are missing.

The purpose of this paper is to formulate, estimate and apply a robust model of agricultural crop production with explicit consideration of risk, suitable for large scale application to European agriculture. The proposed model resembles the one from Cortignani and Severini (2012) in extending a standard quadratic PMP objective function such that it represents an Expectation-Variance (EV) risk model. In contrast to their approach, our approach introduces farm specific relative risk aversion coefficients, estimates parameters using a more flexible and transparent Bayesian methodology and is designed for a large scale application based on an unbalanced panel data set obtained from FADN. Moreover, we also consider explicitly the estimation of the covariance matrix of gross margins using the same data set.

The paper contributes to analysing the question, raised by Heckelei (2002) (pp 40-43), as to what extent risk aversion is a valid micro economic explanation of PMP terms. In order to do so we develop a Bayesian econometric model allowing estimating objective function parameters

[1] Although inter-annual variability of major crops in important production countries did predominantly go down over the last 50 years and no positive impact of a changing climate signal could be identified (Osborne and Wheeler, 2013)

[2] For an overview and references see Moschini and Hennessy, 2001

econometrically and is a first step towards testing hypotheses concerning parameter values in the PMP functions (Jansson and Heckelei, 2010).

The applicability of the framework is demonstrated by the estimation of 323 farm type models in Germany based on a sample of 31 000 FADN farms observed 122 000 times in total. The models are applied and evaluated in a simulation where yield patterns are changed so as to represent possible effects of climate change. The present model contains only crop production, but it is extensible also to animal husbandry.

2. Microeconomic model

The key idea behind the model developed in this paper is to combine econometrically estimated positive mathematical programming models (Buysse *et al.*, 2007; Heckelei and Wolff, 2003; Jansson and Heckelei, 2011) with risk programming models such as those proposed by Freund (1956). Quadratic programming (QP) models have formed the basis of most PMP models (Heckelei *et al.*, 2012) since its formal introduction by Howitt (1995). The considered Expectation-Variance (EV) risk model considered here is also quadratic and can be written as

$$\max gm'x - \frac{\phi}{2}x'\Sigma x$$
$$\text{subject to}$$
$$Rx = v$$
$$x \geq 0$$

where

x is an n×1vector of agricultural production activity levels
gm is the n×1 vector of expected gross margins,
ϕ is the coefficient of absolute risk aversion,
Σ is the n×n covariance matrix of gross margins,
R is the $m \times n$ matrix of (fixed) resource use coefficients, and
v is the m×1 vector of endowments (e.g. land).

A quadratic PMP supply model can be formulated as

$$\max gm'x - c'x - \frac{1}{2}x'Qx$$
$$\text{subject to}$$
$$Rx = v$$
$$x \geq 0$$

where

c is a n×1 vector of linear PMP parameters and
Q is a n×n square, symmetric, positive definite PMP parameter matrix.

The linear constraint sets of the two models are identical, whereas the objective functions differ: the EV model contains a quadratic term representing the (dis-) utility of variance in profits, whereas the second model contains a general quadratic term that carries no particular economic meaning. Both the EV and the PMP models are quadratic in nature, and hence the conjecture is imminent that by merging the two, the importance of the PMP terms (the Q-matrix) in explaining model outcomes will be reduced as compared to a model without the variance terms (for example Jansson and Heckelei (2011)). Reducing the importance of the PMP terms is desirable, because their weak theoretical foundation impairs the interpretation of model results and constrains the possibility to create economically meaningful shocks.

Combining the EV and the PMP models above gives the quadratic supply model represented by equations (1) to (3).Since both terms enter the objective function in a quadratic way, the statistical identification of the parameters is cumbersome and is further discussed below.

$$\max gm'x - \frac{\phi}{2}x'\Sigma\mathrm{x} - c'x - \frac{1}{2}x'\mathrm{Qx} \qquad (1)$$

subject to

$$Rx = v \qquad (2)$$

$$x \geq 0 \qquad (3)$$

3. Data

The model (1)-(3) is assumed as a template model for a group of farms, all which are similar in terms of some selected attributes. Each farm group is thus represented by an instance of that model with its own unique parameterization. In order to estimate those parameters, we need to define a stochastic model relating observations to theory. The list of all permissible crops is shown in table 2.

The data set used in this exercise is the Farm Accountancy Data Network (FADN).The accounts are collected using a stratified sampling procedure (EU, 2008), which define the sample farms, to be selected in the network, to present the population. The population is clustered into grid cells using the type of farming (ToF), representing the specialisation, and the economic size of the holding (ESU). The network collects for each grid cell a certain number of FADN farms, which build up, finally the database. The total number of sampled farms divided by the total number of farms in the grid is the weighting factor. A factor describing how much of the population a FADN sample farm represents.

This approach forms an unbalanced panel data, where each farm in general participates in the sample several years, but where the composition of the sample changes over time. Overall 274,000 sample farms contributed in different years to the FADN network, between 1990 and 2008, representing a population of 4.15 million farms in 1990, which than increased due to the EU enlargement to a population of 4.95 million farms. Derived from national surveys, FADN is the only source of micro-economic data that is harmonised using bookkeeping principles. The accounting and recording principals of the FADN are specified under EU regulations, but the data is collected by MS organizations. The accounting positions are defined in several publications[3]. Generally the FADN sample contains primarily economic data on revenues, costs and assets, but also physical quantities such as mass of products produced, hectares planted with different crops and number of animals of different categories. Noteworthy is that inputs other than land are only measured in monetary terms and not allocated to the various products. For a detailed analysis of the underlying data and how the farm accountancy information is translated into the variable definition used in the estimation see Neuenfeldt and Gocht (2013). To define the groups for the estimation, we used the ToF and ESU classification as the sampling procedure in FADN, however, because the definition is too detailed we further aggregated as given in table **Fehler! Verweisquelle konnte nicht gefunden werden.**. This definition would result into 39 farm groups based on 13 specialisations and 3 farm sizes. This adjustment, unfortunately, doesn't prevent the existence of groups with little observations. Therefore, we apply a selection approach which first ranked the possible 39 farm groups of a region with respect to two equally weighted criteria: livestock units (LUs) and utilised agricultural area (UAA), and selects a

[3] RI/CC 1256 (REV. 7) (2011) and RI/CC 1256 (REV. 7) (2011) and RI/CC 882 (REV. 9) (2011)

defined number per region, across EU on average ~10 groups, as final farm group for the estimation. The remaining farms result, after aggregation, into the residual farm group (Gocht and Britz, 2011).

Using the above defined selection and considering only farms specialisation without animal production the data panel for the estimation consists of 323 farm groups with 122 000 observations in FADN for Germany.

4. Statistical model

4.1 Observable variables

We assume that the allocated hectares are measured without errors. This assumption seems reasonable in case of this variable and stabilizes the complex (bilevel programming) estimation problem. In contrast, gross output and input use is assumed to be observed with additive and normally distributed errors. At first glance, those variables may seem equally well known as land allocations. The motivation for assuming errors here is twofold. Firstly, the entries for gross production and use in FADN is the sum (and difference) of several positions (sales plus farm use plus closing stock minus opening stock). Secondly, realised values are likely different from optimal values as weather and other unexpected events will make an exact optimal choice unlikely. .

The error model used here is therefore different from the one in Jansson and Heckelei (2011), where land allocation is stochastic. In order to account for the possibility that the farmer in practice fails to exactly determine an optimal solution to the utility maximization problem, we add an optimization error also to the first-order condition itself.

Since the estimating equations contain three types of error terms (outputs, inputs and optimization error) it will not be possible to simultaneously estimate the variances of the error terms. The reason of the underlying identification problem is rigorously derived in the literature on Errors In Variables and Measurement Errors (Carroll *et al.*, 1995; Fuller, 1987). We make stronger assumptions on variances than necessary for identification by not only setting exact knowledge of their relative variances, but even making explicit assumptions of their values in terms of shares of the observed variables as reported in the section on priors below.

To summarize, we assume the following error models for the observable variable Z_{fit}, which is gross production (use) on farm f of output (input) j in year t:

$$Z_{fit} = \sum_i y_{fijt} x_{fit} + \varepsilon_{fjt}^{\mathrm{io}} \quad \forall j \in \text{outputs}$$

$$Z_{fjt} = \sum_i a_{ijt} x_{fit} + \varepsilon_{fjt}^{\mathrm{io}} \quad \forall j \in \text{inputs}$$

$$\varepsilon_{fjt}^{\mathrm{io}} \sim N\left(0, \sigma_{fjt}^2\right)$$

It is likely that some errors are correlated. That is ignored in this application, at the expense of efficiency of the estimator. A SUR estimator would be a feasible remedy, but would further increase the complexity of an already technically demanding estimation procedure.

4.2 Prior distributions

In order to render the estimator robust and also to utilize out-of-sample information about farm supply behaviour, we formulate prior distributions for selected parameters or hyper-parameters. The prior information is expressed as probability density functions to allow us to handle the information in a transparent and theoretically solid fashion in a Bayesian model. This is a suitable place to also discuss various parameter constraints that were introduced in order to restrict the number of free parameters to estimate.

The matrix Q is assumed to have a special block structure, where all crops are assigned to *crop groups*, and all crops within a crop group (see table   for the definition of groups) have exactly the same effect on all crops of another crop group. Furthermore, all farms belonging to the same farm group share the same Q matrix, scaled by a farm size index l_{ft} that is specified further below. Denoting crop group membership by the $n \times k$ indicator matrix G with k denoting the number of crop groups, we require that $Q_{ft} = l_{ft}(D + GBG')$, where B is the $k \times k$ matrix of unique cross-crop effects and D is an n-size diagonal matrix with only own-crop effects. The groups constructed are shown in table 4. Crops not belonging to any group will not have any direct effect on the marginal cost of other crops.

The farm size index l_{ft} is derived from the proposition that farms belonging to the same type should behave in a similar way. Similar supply behaviour is interpreted responding to a given price change by changing a similar share of their land allocation. We can imagine an exogenous price change, identical to all farms, and write the total differential of the first order conditions of the primal model in the following fashion:

$$dpY_f - \phi_f \Sigma dx_f - l_f Q dx_f - d\lambda_f' R = 0$$

Collecting terms gives

$$Q^{-1}\left(dpY_f - \phi_f \Sigma dx_f - d\lambda_f R\right) = l_f dx_f$$

Ignoring the risk component, i.e. the middle term of the bracket, for the time being and considering that changes in dual values $d\lambda_f$ are likely similar across farms. Then our definition of farms "behaving in a similar way" boils down to l_f being the inverse of the total farm land area, so that the right hand side becomes the change in the land use shares.

In our model, ϕ denotes the Pratt-Arrow measure *of absolute risk aversion*, defined as $\phi_{ft}^A = -u''(m_{ft})/u'(m_{ft})$. Is a local measure of risk preferences and may change over the level of income, m_{ft}. As the units of ϕ_{ft}^A and m_{ft} must always be reciprocal to one another(Raskin & Cochran, 1986), *relative risk aversion coefficient*, $\phi^R = \phi_{ft}^A m_{ft}$, is unitless. We assume that ϕ^R is similar across time and farms within a farm group. Therefore, we substitute $\phi^A = \frac{\phi^R}{m_{ft}}$ in the model, and formulate a gamma prior for ϕ^R with mode of 1 and the support $[0, +\infty]$.

For our priors we choose from four different families of (proper) density functions:

Family	**Description**	**Used for**
Spike	The parameter is fixed at a particular value.	Prior means and variances of (normally distributed) error terms of gross inputs, gross outputs and optimization errors.
Uniform	An upper and a lower bound is provided.	Parameters of the PMP cost function, in order to enforce curvature (the D matrix) and enable the solver to scale (avoiding infinity as upper limit).
Normal	Mean/mode and variance flexibly set, no bounds.	Optimization errors and error terms of activity levels.
Gamma	Only positive values permitted, but no upper bound. Distinct mode and flexible variance.	Positive parameters or hyperparameters: Variable input cost coefficients, supply elasticities, dual values (land rent), gross inputs, gross outputs and the relative risk aversion coefficient.

Parameterizing the gamma density is a bit more technical than for the other families. We compute the two parameters from more intuitive pieces of information: (i) the mode, and (ii) a subjective 'accuracy' defined from zero to infinity where the density goes towards a uniform density when accuracy goes to zero and 10 means "a fairly narrow peak" with a standard deviation equal to half of the mode. The key translation from accuracy to gamma-parameters was defined by linking accuracy to standard deviation via the formula[4] $\sigma = \frac{\text{mode}}{5\times\text{accuracy}}$. The graphs of some of the resulting density functions are shown in figure 1, together with the implied means and variances.

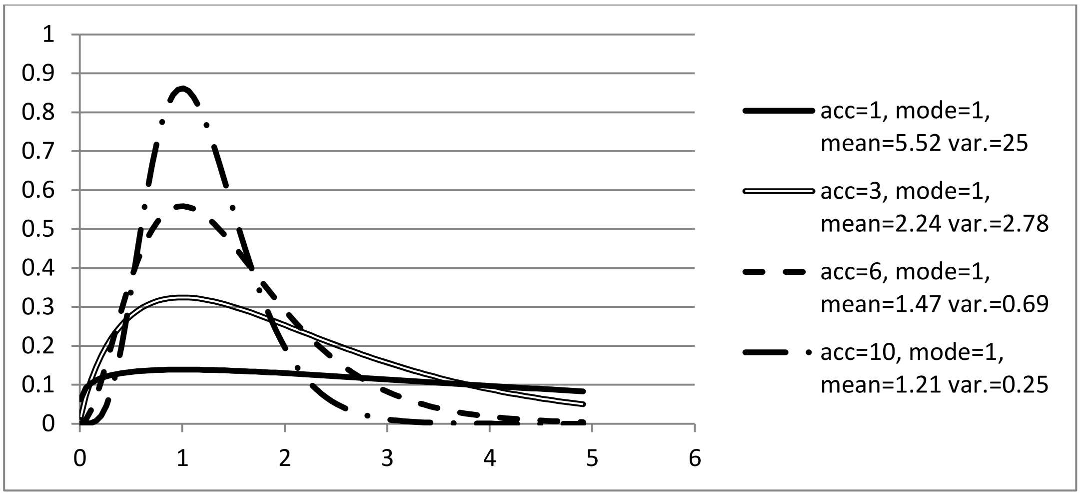

Figure 1: Graphs of gamma prior density functions for mode = 1 and various accuracies.

The matrix of input coefficients, A, is endogenously estimated, but assumed to be identical across farms belonging to the same farm group. For robustness of estimates we include a prior density for A obtained from the CAPRI model (Britz and Witzke, 2012). In particular, we use the average input coefficients for Germany as the prior mode for all farms of all farm groups, and assume a gamma density function with accuracy of three.

Regarding the parameters B and D of the PMP cost function, we force them in estimation to be such that the Q matrix is strictly positive definite (PD). That is accomplished by (i) requiring B to be positive semi-definite (PSD) via a Cholesky factorization and (ii) requiring that all the elements of the diagonal matrix D exceed an arbitrarily small positive number, for which we selected 10^{-6}. We also imposed an upper bound of 10^{6} divided by the average area of the crop on that farm, which should be well beyond the relevant range[5] for most crops. Finally, due to degrees of freedom considerations and identification, we fix one element of D to zero for each crop group[6].

The PMP cost function parameters have a direct impact on the supply elasticity of the primal model, and for that, we do have some fairly clear priors: the own-price supply elasticity for the

[4] This information is sufficient to derive the two parameters. Solving for the two gamma parameters requires solving a second degree polynomial where only the positive root is kept. The algebra is omitted in this paper due to space limitations.

[5] Note that the unit of D is "change in marginal cost in euro per hectare when acreage changes by one hectare", so that the upper bound implies that doubling the crop area increases the marginal cost per hectare by a million euro. An intensive perennial greenhouse crop might hit that bound in the short run, implying that the area is fixed, while any field crop should be well below that.

[6] If the expressions for the diagonal Hessian elements are written down *for all crops of a crop group* with n crop members it becomes evident that there are n equations but n+ 1 variable (the n diagonal elements of D plus the single diagonal own-crop-group effect element of B). One could alternatively fix the entire diagonal of B to zero, but that would make imposition of definiteness of the Hessian more demanding as we would need to consider the sum $H = D + GBG'$, which has higher rank than B.

farm group as a whole should be positive, typically in the magnitude of 1, and very large numbers, say beyond 10, are very rare in the literature. We computed an analytic expression for the own-price elasticity to include in the estimation equations, and imposed a gamma prior with mode 1.5 and an accuracy of 5.

Land rent λ is gamma distributed with mode derived from the land rental cost plus land asset values divided by 50 (equivalent to a 2% interest rate on own capital) divided by the land endowment. Accuracy is set to 3, which is fairly weak.

Optimization errors (the additive errors of the first order conditions) receive normal priors with zero mean and variance equal to the diagonal elements of the estimated covariance matrix Σ.

4.3 Estimation of the covariance matrix

The variance-covariance matrix of gross margins was estimated based on the (unbalanced) panel of FADN farm revenues. Since costs are arguably much less stochastic than revenues from the farmer's planning perspective, the variance of the gross margin will be approximated by the variance of revenues. To capture covariance of yields and prices, a feasible generalized least squares estimator was applied.

Each farmer knows whether her farm has systematically higher or lower revenues per hectare than the average, i.e. if the soil is good or bad, if she specializes in higher or lower quality crops, and so on. To avoid that such unobserved heterogeneity is interpreted as risk, a fixed effects model was estimated.

A particular problem is the computation of the covariance matrix from an unbalanced cube of error terms (i.e. error terms in the three dimensions of farms, crops and time with many missing values). The empirical covariance matrix often becomes indefinite, and missing values must be imputed somehow. A special *Hadamard weighted Frobenius norm shrinkage estimator*, similar to that proposed by Higham (2002), was developed in order to find the strictly positive definite covariance matrix that is closest (in the above norm) to the empirically estimated one. It is beyond the scope of this paper to describe that estimator in detail.

4.4 Bayesian posterior mode estimation

Putting together all the details provided above regarding sampling model we can follow Jansson and Heckelei (2010) and formulate the Bayesian posterior density function. Maximizing the posterior density provides a point estimate for the parameters of interest. The posterior density function is the product of many densities and will therefore be something highly nonlinear and numerically tiny. A logarithmic transformation of the posterior improves upon the numerical properties of the problem. Doing so and discarding constants, results in the following maximization problem:

$$
\begin{aligned}
\max -\sum_{fjt} n_{ft}\frac{1}{\tilde{\sigma}^2_{fjt}}\left(\varepsilon^{\mathrm{io}}_{fjt}\right)^2 - \sum_{fit} n_{ft}\frac{1}{\tilde{\tilde{\Sigma}}_{ii}}\left(\varepsilon^{\mathrm{foc}}_{fit}\right)^2 + \sum_{gijt}\left[\left(\tilde{\alpha}^{\mathrm{io}}_{gijt}-1\right)\log a_{gijt} - \tilde{\beta}^{\mathrm{io}}_{gijt}a_{gijt}\right] \\
+\sum_{gjt}\left[\left(\tilde{\alpha}^{\mathrm{ela}}_{gjt}-1\right)\log \eta_{gjt} - \tilde{\beta}^{\mathrm{ela}}_{gjt}\eta_{gjt}\right] + \sum_{ft}\left[\left(\tilde{\alpha}^{\lambda}_{ft}-1\right)\log \lambda_{ft} - \tilde{\beta}^{\lambda}_{ft}\lambda_{ft}\right] \\
+\sum_{g}\left[\left(\tilde{\alpha}^{\phi}_{g}-1\right)\log \phi^R_g - \tilde{\beta}^{\phi}_{g}\phi^R_g\right]
\end{aligned}
$$

Subject to the first (FOC)- and second-order condition (SOC) of the primal model,

$$
\left(Y_{ft}\widetilde{p_t} - A_t\widetilde{w}_t\right) - \frac{\phi^R}{\widetilde{m}_{ft}}\Sigma\tilde{x}_{ft} - c_f - \tilde{l}_{ft}D\tilde{x}_{ft} - \tilde{l}_{ft}\tilde{G}B\tilde{G}'\tilde{x}_{ft} - \lambda_{ft}\tilde{R} = \varepsilon^{foc}_{ft}
$$

$$B = U'U$$

and subject to the definition of errors on gross inputs and outputs (here observations are vertically concatenated into the matrix *z*).

$$\tilde{z}_{ft} = \begin{bmatrix} Y_{ft} \\ A_t \end{bmatrix} \tilde{x}_{ft} + \varepsilon_{ft}^{io}$$

and subject to the definition of the "hyper parameter" of supply elasticity η_f,

$$\eta_{ft} = \text{vec}\left(\text{diag}\left(Y_{ft}\left[H_{ft}^{-1} - H_{ft}^{-1}\tilde{R}\left(\tilde{R}H_{ft}^{-1}\tilde{R}\right)^{-1}\tilde{R}H_{ft}^{-1}\right]Y_{ft}\right)\right) \otimes \left[\tilde{p}_{ft} \oslash \tilde{z}_{ft}^{\text{out}}\right]$$

$$H_{ft} = \frac{\phi^R}{\widetilde{m}_{ft}}\Sigma + \tilde{l}_{ft}(D + GBG')$$

with H_{ft} for the Hessian matrix. The function diag(·) means that we consider only the diagonal of the square matrix argument[7], the vec(·) operator converts the diagonal matrix into a vector, the $\otimes$ operator is the binary element-wise multiplication operator, and $\oslash$ denotes the elementwise division operation.

5. Scenario

We simulate a scenario where the variances of all crop revenues increase by inflating the covariance matrix by a factor two. The results of the scenario are compared with a baseline representing the situation in 2007. More recent years than 2007 contain less complete data in the FADN dataset we used in this study.

6. Results

The impacts of the increased variance are very different across farm groups. Yet some general pattern emerges. Table 1 shows descriptive statistics of impacts on different farm groups for three major crop groups: cereals, oilseeds and other arable crops. The acreage of cereals goes down by 1.1% on average across farm groups, with a standard deviation of 4.5%. Oil seed production generally increases, by on average 4.2 percentage points and with large variation across farm groups (standard deviation of 21% change). The biggest impact in relative terms is found in "other arable crops", where the average acreage increase is close to 23%. One might hypothesize that the explanation is that sugar beet and potatoes (the major crops among "other arable crops"), and also oil seeds, more often are subject to fixed-term contracts and thus to less variation in the data set.

Looking at the details of farm groups, the tendency to decrease cereals production is quite general. The smallest specialist field crop farms show the strongest tendency to shift from cereals to other arable crops, whereas the larger specialist field crops farms rather tend to shift to oil seeds production. Among general field crops and mixed farms, there is a move away from other arable crops (-3.6%) and from cereals (-1%) towards oil seeds (+19%) among the smaller farms, whereas the larger farms increase their acreage of arable crops (+6.6%).

The move away from cereals towards other crops is found even for the animal farms, such as the specialist dairy farms of all sizes (-1% to -4%), despite them producing primarily for own consumption. In fact, only cattle rearing farms and the residual "rest" group tends to somewhat increase their own cereals production when facing the increased price variance pattern.

[7] The argument of the diag operator is in this case the matrix of derivatives $\left[\frac{\partial q_{fit}}{\partial p_{fjt}}\right]$ of the supply function implied by the FOC, as obtained using matrix algebra.

7. Discussion

The method is feasible as demonstrated in this paper. Much work remains before we can perform rigorous econometric tests for the values of the PMP-terms. The technical and numerical difficulties when handling the large unbalanced data set are considerable.

On the content side, we note that increased variability affects different farm groups in different ways. Part of the explanation is that the covariant matrices are different across farm groups. The model offers no insight into why that is the case. Another part of the explanation is in the risk aversion coefficients. In our model, the absolute coefficient of risk aversion is computed by dividing the relative risk aversion coefficient with total farm income. A farm that derives a large share of its income from crop production then becomes more sensitive to risk in crop production than a farm that derives a significant share of its income from other sources (animals, dairy). The remaining part of the explanation rests with the size of the B and D matrices, which in turn depend on the observed behaviour of the farms in the group in the sample.

The model estimated and applied in this paper opens up the possibility to simulate wealth effects of decoupled payments. In a traditional farm programming model, fully decoupled payments enter as a constant (lump sum) in the objective function. Changing a constant term has no effect on the location of the maximum. In our model, income enters as a scaling factor for the variance component of the objective function, affecting farm decisions.

The proposed model, finally, could be modified to simulate impacts of some income insurance support schemes as permitted under the current CAP.

Table 1: Descriptive statistics of simulation results for three major crop groups (percentage deviation from 2007 observation).

	Cereals	**Oil seeds**	**Other arable**
Mean	-0.01095	0.04212	0.22688
Standard Error	0.00271	0.01383	0.05009
Median	-0.00100	0.00240	0.02695
Standard Deviation	0.04473	0.21296	0.78568
Sample Variance	0.00200	0.04535	0.61729
Minimum	-0.26640	-1.00000	-1.00000
Maximum	0.19560	1.48900	8.53000
Count	273	237	246
Confidence Level(95.0%)	0.00533	0.02725	0.09867

Table 2: Crop groups and their member crops

Crop activities	**Crop group**
SWHE,DWHE,RYEM,BARL,OATS	CERE
MAIZ,OCER	CER2
RAPE,SUNF,SOYA,OOIL,OIND	OILS
PULS,POTA,SUGB,TEXT	OARA
MAIF,ROOF,OFAR	FARA

Table 3: Type of farming and economic size of the holding for the farm groups in the estimation based on SGM approach

Type of farming	Abbr.
Specialist cereals, oilseed and protein crops	FT13
General field cropping + Mixed cropping	FT14+ FT60
Specialist horticulture	FT20
Specialist vineyards	FT31
Specialist fruit and citrus fruit	FT32
Specialist olives	FT33
Various permanent crops combined	FT34
Specialist dairying	FT41
Specialist cattle + dairying rearing, fattening	FT42+FT43
Sheep, goats and other grazing livestock	FT44
Specialist granivores	FT50
Mixed livestock holdings	FT70
Mixed crops-livestock	FT80
Economic size class (ESC)	**Abbr.**
< 16 ESU	ESC 1
16 - 100 ESU	ESC 2
> 100 ESU	ESC 3

Table 2: Maximal set of crops in estimation

Abbr.	Descriptions
SWHE	"Soft wheat production activity"
DWHE	"Durum wheat production activity"
RYEM	"Rye and meslin production activity"
BARL	"Barley production activity"
OATS	"Oats and summer cereal mixes production activity without triticale"
MAIZ	"Grain maize production activity"
OCER	"Other cereals production activity including triticale"
RAPE	"Rape production activity"
SUNF	"Sunflower production activity"
SOYA	"Soya production activity"

OOIL	"Other seed production activities for the oil industry"
OIND	"Other industrial crops production activity"
OCRO	"Other crops production activity"
PARI	"Paddy rice production activity"
OLIV	"Olive production activity for the oil industry"
PULS	"Pulses production activity"
POTA	"Potatoes production activity"
SUGB	"Sugar beet production activity"
TEXT	"Flax and hemp production activity"
TOBA	"Tobacco production activity"
TOMA	"Tomatoes production activity"
OVEG	"Other vegetables production activity"
APPL	"Apples pears and peaches production activity"
OFRU	"Other fruits production activity"
CITR	"Citrus fruits production activity"
TAGR	"Table grapes production activity"
TABO	"Table olives production activity"
TWIN	"Wine production activity"

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