Combining Sample and Non-sample Information in a Mixed Generalized Maximum Entropy Approach:

Modeling the Primary Dairy Sectors of Hungary and Poland

Axel Tonini

Mansholt Graduate School,
Agricultural Economic and Rural Policy Group, Social Sciences Department,
Wageningen University, The Netherlands
Email: axel.tonini@wur.nl

Roel Jongeneel
Agricultural Economic and Rural Policy Group, Social Sciences Department,
Wageningen University, The Netherlands
Email: roel.jongeneel@wur.nl

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Abstract.

The EU dairy sector has undergone and is still facing important changes. The April 2004 accession of the new member states led to an increase in production and demand for dairy products in the EU. Therefore quantitative information concerning the likely response of dairy supply to changes in output prices for the new member states is an urgent need for reliable policy analysis. Our model, based on a microeconomic dual approach, is dynamic in its specification allowing gradual adjustments in stock variables. Cow milk and beef and veal productions are directly integrated in the model since in the new member states there is almost no specialized beef production. A mixed generalized maximum entropy estimator is developed coping with limited data by exploiting non-sample information. Non-sample information comes both from economic theory and agro-economic plausibility. Our estimates suggest overall an inelastic dairy supply response for Hungary and Poland. In addition we find medium-run complementarity between the production of cow milk and beef and veal.

Key Words: Dairy, Hungary, Poland, Normalized Profit Function, Mixed GME.

JEL Classification: C14, Q11.

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"…it is well known, but also well ignored, that exact probability statements can no longer be made if the maintained hypothesis is…rejected in the light of the evidence"
[Theil and Goldberger, 1961:65]

Outline

1. Introduction and Objective

The EU dairy sector has undergone and is still facing important changes. One of the most important concerns the EU enlargement with 10[1] new members states (NMS). The April 2004 accession of the NMS led to an increase in production and demand for dairy products in the EU. This is likely to further increase in the coming years with the (planned) accession of Romania and Bulgaria in 2007. At the same time the EU dairy sector has to cope with domestic policy reform (i.e. Luxembourg Reform) and the current round of World Trade Organization (WTO) negotiations. Therefore quantitative information concerning the likely response of dairy supply to changes in output prices for the NMS is an urgent need for reliable policy analysis. We focus on providing dairy supply elasticities for Hungary and Poland that are the third and first milk producers respectively in the CEECs.

Our model, based on a microeconomic dual approach (Chambers, 1988), is dynamic in its specification allowing gradual adjustments in stock variables. Implicit is the assumption that farmers will only partially adjust the quasi-fixed inputs or stock variables towards their desired levels. Beef and veal production in many CEECs is closely linked to dairying since there is almost no specialized beef and veal production in these countries (European-Commission, 2002). For this our model directly integrates cow milk and beef and veal productions, both as regard the underlying decision making model and in specifying the constraints and trade-offs between the two types of productions. The past literature analyzing dairy supply did not explicitly model the joint-production character of cow milk and beef and veal productions (Parton, 1992) with the exception of Burrell and Jongeneel, (2001).

Modeling the Central Eastern European Countries (CEECs), who faced the so-called transition from a centrally planned regime to a more free oriented economy, implies that one has to cope with data problems. Data issues do not often receive the necessary attention in applied analysis. For a general survey on economic data issues see Griliches, (1986) and Blangiewicz, et al., (1993) for data flaws related to Eastern

[1] Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovak Republic and Slovenia.

European countries. In modeling Eastern European countries there are serious problems with measurement error in variables, heterogeneity in the data and data unavailability. First, the error in variables bias is due to different methodologies and definitions in the data collection when referring to the central planned era and the subsequent liberalization period as well as to a systematic political bias. Econometric tools are available to treat random and unbiased measurement errors in variables issues, but little is known on the effect of systematic measurement error in variables. Second, it is difficult to find time series of desired length that respect homogeneity since reliable time series after the transition period are only sparsely available. Additionally the desired variables may be not available at all.

Given the peculiarities mentioned above, the required stable structure for economic and econometric modeling is often compromised creating an *ill-posed* and *ill-conditioned* inference problem. Being convinced that the best possible data should be used for an econometric investigation even though their quality may be arguable we develop and apply a mixed estimator relying on a generalized maximum entropy (GME) approach developed by Golan, et al., (1996), Mittelhammer, et al., (2000). In order to make our problem analytically tractable, our approach exploits both sample information (SI) and non-sample information (NSI).

The use of NSI in econometric analysis has a long history embracing the frequentist mixed estimation approach of Durbin, (1953) then extended by Theil and Goldberger, (1961), Theil, (1963), and Toutenburg, (1982, among others), and the Bayesian (Koop, 2003, Lancaster, 2004, Zellner, 1971, among others) and Entropy Econometrics (Golan, et al., 1996, Mittelhammer, et al., 2000) perspectives. Although the frequentist mixed estimation and the Bayesian and Entropy inferences are based on different methodologies they all share the possibility to exploit NSI. NSI is suitable in the presence of too few observations, multicollinearity problems, or simply in the presence of information-poor data set (Mittelhammer and Conway, 1980). Moreover if reliable NSI exists and is available, its inclusion is attractive because it increases the efficiency of the inference procedure, as well as the reliability of the obtained estimates (Dorfman and McIntosch, 2001). In our analysis NSI comprises theoretical restrictions on parameters coming from economic theory and prior knowledge on technical agro-economic relationships.

In Section 2, we describe the model presenting the theoretical model and then the empirical specification. We start Section 3 by briefly discussing the entropy concept and developing the mixed GME estimation. In Section 4, we discuss SI as well as NSI particularly focusing on the latter. Section 5 presents results. We conclude in Section 5.

2. The Model

2.1. Theoretical Model

Our model is based on the duality theory of production. A dual approach is particularly convenient for multiple-input and multiple-output technologies (i.e. cow milk and beef and veal productions). Related demand and supply functions can be easily recovered from the original profit function (Hotelling, 1932) as well as shadow prices and shadow price functions for the quasi-fixed inputs (Diewert and Wales, 1987, Moschini, 1988). Moreover, the advantage of following a dual framework is that it guarantees internal consistency between output supply and input demand equations. A short-run variable profit function is considered (Diewert, 1974, Lau, 1972) and defined as follows

$$\pi(\mathbf{n}^o, \mathbf{n}^i, \mathbf{f}) \equiv \max_y \{\mathbf{n}^o \mathbf{y}^o - \mathbf{n}^i \mathbf{y}^i \,|\, (\mathbf{y}^o, \mathbf{y}^i, \mathbf{f}) \in S\} \qquad (1)$$

where $\mathbf{n^o} \equiv (n_1^o, n_2^o, \ldots, n_I^o)$ is a positive *I*-dimensional vector of expected output prices, $\mathbf{n}^i \equiv (n_1^i, n_2^i, \ldots, n_V^i)$ is a positive *V*-dimensional vector of expected variable input prices $\mathbf{f} \equiv (f_1, f_2, \ldots, f_H)$ is a positive *H*-dimensional vector of quasi-fixed inputs, $\mathbf{y}^o \equiv (y_1^o, y_2^o, \ldots, y_I^o)$ is a positive *I*-dimensional vector of outputs quantities, $\mathbf{y}^i \equiv (y_1^i, y_2^i, \ldots, y_V^i)$ is a positive *V*-dimensional vector of variable input and *S* is the production possibility set representing all feasible combinations of inputs and outputs. Several regularity conditions for a profit function have to be satisfied in order to meet the duality between profit and production functions. The conditions are linear homogeneity in prices (a), symmetry (b), monotonicity (c) and convexity in prices (d) (Diewert, 1974, Mass-Colell, et al., 1995). Supply functions are derived for given output prices and quasi-fixed inputs through the Hotelling's lemma (Hotelling, 1932)

$$\partial\pi\left(\mathbf{n}^{o*},\mathbf{n}^{i*},\mathbf{f}^{*}\right)/\partial n_i = y_i\left(\mathbf{n}^{o*},\mathbf{n}^{i*},\mathbf{f}^{*}\right), \quad i = 1,\ldots, I \tag{2}$$

where $y_i\left(\mathbf{n}^{o*},\mathbf{n}^{i*},\mathbf{f}^{*}\right)$ is the profit maximizing amount of output *I* given the prices $\mathbf{n}^{o*},\mathbf{n}^{i*}$ and the quasi-fixed inputs $\mathbf{f}^{*}$. The shadow price of the quasi-fixed inputs (Diewert, 1974, Moschini, 1988) are given by

$$\partial\pi\left(\mathbf{n}^{o*},\mathbf{n}^{i*},\mathbf{f}^{*}\right)/\partial f_h = u_h\left(\mathbf{n}^{o*},\mathbf{n}^{i*},\mathbf{f}^{*}\right) = n_h^s, \quad h = 1,\ldots, H. \tag{3}$$

The short-run profit function approach with the associated supply functions is complemented by stock adjustment equations for the quasi-fixed inputs following Burrell and Jongeneel, (2001) taking into account adjustment dynamics. Rearranging equation (3) yields the optimal level for the quasi-fixed inputs as given by

$$f_h^{*} = f_h\left(n_h^s,\mathbf{n}^{o},\mathbf{n}^{i},\mathbf{f}_{H-h}\right), \; h = 1,\ldots, H \tag{4}$$

where $\mathbf{f}_{H-h} \equiv \left(f_1, f_2,\ldots, f_{H\text{-}h}\right)$ is the vector of all quasi-fixed inputs but f_h. It is assumed that the adaptation of the quasi-fixed inputs to their optimal or desired (long-run) levels does not occur instantaneously but rather adapt through a partial adjustment mechanism (Greene, 2002, Maddala, 1992). The partial adjustment mechanism is given by

$$f_{h,t} = \lambda_h f_{h,t}^{*} + \left(1-\lambda_h\right) f_{h,t-1} \quad \text{where } 0 < \lambda_h < 1 \text{ and } h = 1,\ldots, K. \tag{5}$$

2.2. Empirical Model

Our empirical model exploits a restricted normalized quadratic profit function and it directly considers the relationship between cow milk and beef and veal productions. The normalized quadratic profit function was first introduced by Lau, (1976). Of the four regularity conditions, homogeneity in prices (a) is embedded in the model specification through normalized prices. Symmetry (b) $\alpha_{ij} = \alpha_{ji}$ and $\beta_{hk} = \beta_{kh}$ for all *i* and *j*, monotonicity (c) and convexity (d) are treated as additional consistency constraints during estimation, see the estimation section. Global convexity is a necessary condition for the duality between production and profit. The fulfillment of curvature conditions is also required for partial and general equilibrium modeling. Diewert and Wales, (1987), show that the normalized quadratic retains its flexibility even when global convexity is imposed. The normalized quadratic profit function is specified as follows

$$\pi_t^n = \alpha_0 + \sum_{i=1}^{2}\alpha_i n_{i,t}^n + \sum_{k=1}^{3}\beta_k f_{k,t} + 0.5\sum_{i=1}^{2}\sum_{j=1}^{2}\alpha_{ij} n_{i,t}^n n_{j,t}^n + 0.5\sum_{h=1}^{3}\sum_{k=1}^{3}\beta_{hk} f_{h,t} f_{k,t} + \sum_{i=1}^{2}\sum_{h=1}^{3}\gamma_{ih} n_{i,t}^n f_{h,t} \quad (6)$$

where $n_{i,t}^n = n_{i,t}^o / n_{I,t}^i$ are normalized output prices by a feed price index ($n_{I,t}^i$) used as a numéraire with i = 1 (cow milk), 2 (beef and veal meats), $f_{h,t}$ are quasi-fixed inputs with h = 1 (dairy cow stock), 2 (permanent pasture) and 3 (time trend), and $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ are parameters to be estimated. The restricted normalized profit is computed from $\pi_t^n = \sum_{i=1}^{j-I} n_{i,t}^n y_{i,t} - y_{I,t}^i$. In order to take into account the farmers response to expected prices, the output prices are expressed as three years moving average (expected profit maximization). The supply equations[2] are obtained through Hotelling's Lemma from equation (6)

$$y_{i,t}^o = \alpha_i + \sum_{j=1}^{2}\alpha_{ij} n_{j,t}^n + \sum_{h=1}^{3}\gamma_{ih} f_{h,t}, \quad i = 1,2 . \quad (7)$$

Short-run price elasticities can be computed at any point in time and are given by

$$\eta_{ij}^S = \frac{\partial y_{i,t}^o}{\partial n_{j,t}} \cdot \frac{n_{j,t}^n}{y_{i,t}^o} = \tilde{\alpha}_{ij} \cdot \frac{n_{j,t}^n}{y_{i,t}^o}, \qquad i, j \neq I, \qquad \eta_{jI}^S = -\sum_l \eta_{jl} \quad (8)$$

[2] The demand equation for the numéraire variable input (animal feed) can be recovered from the linear homogeneity in prices of the profit function $y_{I,t}^i = \alpha_0 - 0.5\sum_{j=1}^{2}\alpha_{ij} n_{i,t}^n n_{j,t}^n$. The intercept term, if the profit function is not directly estimated, can be recovered by difference from the expected profit and the estimated parameters in the system of equations.

where $\tilde{\alpha}_{ij}$ is an estimated parameter. The quasi-fixed input optimal levels are derived by partially differentiating equation (6) with respect to the quasi-fixed inputs and bringing terms to the right hand side, as given by

$$f_{h,t}^{*} = \frac{1}{\beta_{hh}}\left(n_{h.t}^{s} - \beta_{h} - \sum_{k \neq h}^{3} \beta_{hk} f_{k,t} - \sum_{i=1}^{2} \gamma_{ih} n_{i,t}^{n} \right), \qquad h = 1,2\,. \qquad (9)$$

By assuming a partial adjustment mechanism the stock equations are given by

$$f_{h,t} = \frac{\lambda_{h}}{\beta_{hh}}\left(n_{h,t-1}^{s} - \beta_{h} - \sum_{h \neq k}^{3} \beta_{hk} f_{k,t-1} - \sum_{i=1}^{2} \gamma_{ih} n_{i,t-1}^{n} \right) + \left(1 - \lambda_{h}\right) f_{h,t-1} \quad h = 1,2 \qquad (10)$$

where the right hand side variables are introduced with one lag in order to reflect expectations and to decrease potential simultaneity issues with the derived supply equations. Depending on the assumptions made with the quasi-fixed inputs, the elasticities can be calculated for various length of time. We assume that in the medium-run only dairy cow stock can adjust whereas in the long run both dairy cow stock and permanent pasture stock adjust. Here we report the expression for the medium-run own price elasticity

$$\eta_{ij}^{M} = \frac{\partial y_{i,t}^{o}}{\partial n_{j,t}} \cdot \frac{n_{j,t}^{n}}{y_{i,t}^{o}} + \frac{\partial y_{i,t}^{o}}{\partial f_{h,t}} \frac{\partial f_{h,t}}{\partial n_{j,t-1}^{*}} \cdot \frac{\partial n_{j,t-1}^{n}}{y_{i,t}^{o}} = \tilde{\alpha}_{ij} \cdot \frac{\partial n_{j,t}^{n}}{y_{i,t}^{o}} - \tilde{\gamma}_{ii} \frac{\tilde{\lambda}_{i}}{\tilde{\beta}_{ii}} \tilde{\gamma}_{ii} \cdot \frac{\partial n_{j,t-1}^{n}}{y_{i,t}^{o}} \qquad (11)$$

where $\tilde{\alpha}_{ij}$, $\tilde{\gamma}_{ii}$, $\tilde{\lambda}_{i}$ and $\tilde{\beta}_{ii}$ are estimated parameters and it is assumed that lagged prices adjust to current prices in the medium-run so that $n_{j,t}^{n} = n_{j,t-1}^{n}$.

3. Estimation Approach

3.1. A Mixed Maximum Entropy Estimator

The maximum entropy formulation is based on the entropy measure of Shannon, (1948) and it is further developed in Jaynes, (1957a, b) and Levine, (1980). The entropy concept in information theory is developed in Theil, (1967) and its generalization to solve econometric problem are treated in Golan, et al., (1996) and Mittelhammer, et al., (2000). Shannon's formulation selects a criterion to find one of the infinite solutions measuring the uncertainty related to the appearance of a set of events. Considering x a random variable which can have several potential outcomes x_k, (k = 1,2,…, K) characterized by probabilities p_k, the Shannon's formulation defines the entropy measure as

$$H(\mathbf{p}) \equiv -\sum_k p_k \ln p_k \qquad (12)$$

where $\sum_k p_k = 1$ and $0 \cdot \ln(0) = 0$. The entropy measure H reaches a maximum for a uniform probability distribution of events for the random variable x.

In the ME approach, SI is processed in a deterministic fashion as a moments or consistency constraints. Lindley, (1956) introduced the idea for which a statistical sample could be viewed as a noisy channel in Shannon's terms that conveys a message about a parameter with a certain prior distribution. In a GME estimator each observation on the dependent variable of a linear regression model is considered as moment or consistency constraint allowing for stochastic deviations. Each piece of SI when introduced as moment or consistency constraint alters the uniform probability distribution in the entropy criterion. The entropy criterion selects the most uninformative or uncertain probability distribution consistent with the SI. As such it is a conservative estimation procedure[3].

Several advantages of a GME estimator in favor over the more traditional approaches for the problem at hand can be mentioned (Golan, et al., 1996). First a GME estimator is more efficient relative to traditional estimators because it considers the data

[3] Lindley, (1956:109), points out that the finite sample GME solutions are biased just as other Stein-like estimators. Still GME estimates exhibit high precision since the solution has to respect the moments or consistency constraints.

constraints for each observation rather than to rely on sample moment conditions. Second it is a more robust estimator because of the implicit weighting in the objective function between prediction and precision so that outlying observations become less influential on the parameter estimates. Third it can provide estimates even when the number of parameters exceeds the number of observation/data points. Finally it is a robust estimator if disturbances terms are not normal and the exogenous variables exhibit multicollinearity.

Our estimation is based on a mixed GME estimator. The traditional sampling theory approach to estimation uses SI on the dependent variable and the related explanatory variables. Still additional sources of information, beyond SI, can be utilized if it contributes to make the right decision during the inference procedure (Conway and Mittelhammer, 1986, Judge, et al., 1985). In several situations in applied work information about the unknown location parameter vector can be found in the literature and/or conjectured. Our mixed GME estimator combines during estimation external source of information in a form of NSI incorporated through (stochastic) constraints on parameters as additional moments or consistency constraints. At the same time, our approach deviates from the frequentist mixed estimation approach of Conway and Mittelhammer, (1986), Mittelhammer and Conway, (1988) and Jongeneel, (2000) because it relies on the GME criterion based on the probabilistic uniform distribution of the location parameter space. Therefore the NSI when incorporated alters the uniform probability of each parameter through its stochastic component in the entropy criterion.

The mixed GME estimator can be represented as follows. Consider a traditional set of E general linear models as given by $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$ where $\mathbf{y}$ is a $(ET \times 1)$ vector of observations on the dependent variable, $\mathbf{X}$ is a $(ET \times K)$ matrix on the k explanatory variables, $\boldsymbol{\beta}$ is a $(EK \times 1)$ vector of parameters to be estimated and $\mathbf{u}$ is a $(ET \times 1)$ vector of disturbance terms. Parameters and disturbance terms supports are reparameterized as required in a GME framework (Golan, et al., 1996). So that $\boldsymbol{\beta} = \mathbf{zp}$ and $\mathbf{u} = \mathbf{Vw}$, where $\mathbf{z}$ is a $(1 \times M)$ row vector of parameter supports, $\mathbf{p}$ is a $(M \times 1)$ column vector of proper parameter probabilities, $\mathbf{V}$ is a $(T \times TJ)$ matrix of disturbance term supports and $\mathbf{w}$ is a $(TJ \times 1)$ column vector of proper disturbance term probabilities. In the mixed GME estimator the general linear model is enriched by restrictions introduced as additional moment or consistency constraints. The restrictions are constituted of combinations between the elements of $\boldsymbol{\beta}$ (i.e. parameters) and of $\mathbf{X}$ (i.e. explanatory variables). The general structure of the mixed GME estimator is given by $\mathbf{R} \cdot (\boldsymbol{\beta} \otimes \mathbf{i}) + \mathbf{v} = \boldsymbol{\psi} \otimes \mathbf{j} + \boldsymbol{\omega}$, or more precisely

$$\begin{bmatrix} \mathbf{r}'_{111} & \mathbf{r}'_{112} & \mathbf{r}'_{113} & \mathbf{r}'_{114} & \cdots & \mathbf{r}'_{12K} \\ \vdots & \mathbf{r}'_{l1k} & \vdots & \vdots & \vdots & \vdots \\ \mathbf{r}'_{L11} & \vdots & \mathbf{r}'_{L13} & \vdots & \vdots & \mathbf{r}'_{L1K} \\ \mathbf{r}'_{L21} & \vdots & \vdots & \mathbf{r}'_{L24} & \vdots & \mathbf{r}'_{L2K} \\ \vdots & \vdots & \vdots & \vdots & \mathbf{r}'_{lek} & \vdots \\ \mathbf{r}'_{LE1} & \mathbf{r}'_{LE2} & \mathbf{r}'_{LE3} & \mathbf{r}'_{LE4} & \cdots & \mathbf{r}'_{LEK} \end{bmatrix} \cdot \left[\begin{bmatrix} \beta_{11} \\ \vdots \\ \beta_{1K} \\ \beta_{21} \\ \vdots \\ \beta_{EK} \end{bmatrix} \otimes \begin{bmatrix} 1_{11} \\ \vdots \\ 1_{1K} \\ 1_{21} \\ \vdots \\ 1_{EK} \end{bmatrix} \right] + \begin{bmatrix} \mathbf{v}_1 \\ \mathbf{v}_2 \\ \vdots \\ \vdots \\ \vdots \\ \mathbf{v}_L \end{bmatrix} = \begin{bmatrix} \psi_1 \\ \psi_1 \\ \vdots \\ \vdots \\ \vdots \\ \psi_L \end{bmatrix} \otimes \begin{bmatrix} 1_1 \\ 1_2 \\ \vdots \\ \vdots \\ \vdots \\ 1_T \end{bmatrix} + \begin{bmatrix} \boldsymbol{\omega}_1 \\ \boldsymbol{\omega}_2 \\ \vdots \\ \vdots \\ \vdots \\ \boldsymbol{\omega}_L \end{bmatrix} \quad (13)$$

where $\mathbf{R}$ is an $(LT \times EKT)$ information design matrix with L restrictions applied at each data point (T) for K parameters. Matrix $\mathbf{R}$ consists of column vectors $\mathbf{r}_{lek}$ of dimension $(T \times 1)$ (note that stochastic restrictions are applied at each observation in our problem). The column vectors $\mathbf{r}_{lek}$ can be constituted by a vector of time invariant scalars expressing the underlying combination of parameters and/or by a vector of time varying scalars such as explanatory variables of the $\mathbf{X}$ matrix. $\boldsymbol{\beta}$ is a $(EK \times 1)$ column vector of parameters belonging to the set of the general linear model. $\mathbf{i} = (1,1,\ldots,1)'$ is a $(ET \times 1)$ column vector. $\mathbf{v}_l$ is a $(T \times 1)$ column vector of disturbance terms taking into account the variance in the k $\mathbf{r}_{lk}$ vectors. $\boldsymbol{\psi}$ is a $(L \times 1)$ column vector of L estimates of NSI. $\mathbf{j} = (1,1,\ldots,1)'$ is a $(T \times 1)$ column vector. $\boldsymbol{\omega}_l$ is a $(T \times 1)$ vector of disturbance terms in the NSI information and is also reparameterized. It is assumed that $\mathbf{E}(\mathbf{u}) = 0$, $\mathbf{E}(\mathbf{v}) = 0$, and $\mathbf{E}(\boldsymbol{\omega}) = 0$, in order to have zero expectation in the disturbance terms. In addition we assume that $\mathbf{E}(\mathbf{uv}) = 0$, $\mathbf{E}(\mathbf{u}\boldsymbol{\omega}) = 0$ and $\mathbf{E}(\mathbf{v}\boldsymbol{\omega}) = 0$ implying that the two error components $\mathbf{v}$ and $\boldsymbol{\omega}$ are uncorrelated between each other and with the stochastic components $\mathbf{u}$.

The stochastic nature embedded in equation (13) is founded on both the frequentist approach and in the subjective approach to probability[4]. In the former $\mathbf{v}$ is related to the sample scale parameter of the $\mathbf{R}$ matrix. In the latter, $\boldsymbol{\omega}$ is the result of both statistical properties and introspection and/or interpretation of the researcher. The definition of $\boldsymbol{\omega}$ depends in fact from the uncertainty attached to the NSI that may either comes from previous statistical analysis being based on the sampling variance or rather comes from prior beliefs on its validity and based on subjective uncertainty.

3.2 Estimation of the Model based on Sample Information

The estimated system is composed by equations (7) and (10). Although it may be preferable to jointly estimate the profit function (6) together with the derived behavioral equations (7) and (10) by improving the efficiency of the inference procedure, the profit function was not directly estimated (see footnote 2). The direct estimation of the profit function due to its second order terms may frequently creates multicollinearity problems especially in our case when the available data series is particularly short[5].

The entropy criterion requires expressing all the parameters in a reparameterized form in terms of parameter supports and proper probabilities or convex weights. In order to reparameterize the parameter support space, the parameters α_{ij}, for example, need to be reparameterized in term of a proper parameter support space and related proper probabilities or convex weights. The parameter support space is defined as follows $\sum_m z_{ijm}\tau_{ijm} = \alpha_{ij}$, $\forall i, j$ where $\mathbf{z_{ij}} = [z_{ij1}, z_{ij2}, \cdots, z_{ijM}]'$ is a $M \times 1$ vector of parameter supports such that $z_{ij1} < z_{ij2} < \cdots < z_{ijM}$ and M is a fixed integer with dimension $M > 2$. The parameter support space spans up a uniform discrete space centered at zero which contains the expected parameter realization in the interval $[-a, a]$. During estimation we

[4] A cross-entropy (CE) approach for the problem at hand would have been an infeasible alternative to our mixed GME estimator for several reasons. First a CE method cannot easily model the case when NSI is incorporated involving non-linear combination of parameters as well as explanatory variables. Second it would have been impossible to explicitly define the uncertainty attached to the NSI through additional stochastic components.

[5] Additionally since the numéraire variable input is not specific to dairy the resulting profit may suffer of measurement errors.

set $|a| = 10^3$ indistinctly for each parameter[6]. The number of support points is fixed for $M = 5$ since Golan, et al., (1996:138-140) shows that the greatest precision is achieved for $M \geq 5$. The corresponding proper probabilities or convex weights associated with the parameter support space are defined as follows where $\mathbf{p_{ij}} = [p_{ij1}, p_{ij2}, \cdots, p_{ijM}]'$ is a $M \times 1$ vector of unknown probabilities or convex weights such that $\mathbf{p_{ij}} \in [0,1]$, $\sum_m p_{ijm} = 1$. A similar reparameterization is also used for the remaining parameters α_i, γ_{ik}, β_h, β_{hh}, β_{kk}, γ_{ih} and λ_h.

The stochastic components in equations (7) and (10) need also to be reparameterized. The disturbance terms e_i are also treated as an unknown parameter to be estimated and they therefore requires the specification of a proper disturbance term support space with associated proper probabilities or convex weights. The disturbance term for the supply equations is defined as follows $\sum_j v_{ij} w_{ij} = e_i$, $\forall i$ where $\mathbf{v_i} = [v_{i1}, v_{i2}, \cdots, v_{iJ}]'$ is a $J \times 1$ row vector of disturbance term supports such that $v_{i1} < v_{i2} < \cdots < v_{iJ}$ and J is a fixed integer, $\mathbf{w_i} = [w_{i1}, w_{i2}, \cdots, w_{iJ}]'$ is a $J \times 1$ vector of unknown probabilities or convexity weights such that $\mathbf{w_i} \in [0,1]$, $\sum_j w_{ij} = 1$. The disturbance terms e_h for the stock equations are specified in a similar way. The disturbance support spaces are specified following the three-sigma rule of Pukelsheim, (1994). The number of support points for the disturbance terms is set for $J = 5$. Reparameterizing the model according to a GME approach leads to transform equation (7) and (10) in the following equations

$$y_{it}^o = \sum_{m=1}^{5} z_{im} p_{im} + \sum_{j=1}^{2} \sum_{m=1}^{5} z_{ijm} p_{ijm} n_{j,t}^n + \sum_{h=1}^{3} \sum_{m=1}^{5} z_{ihm} p_{ihm} f_{h,t} + \sum_{j=1}^{J} v_{ij} w_{ij} \qquad i = 1,2. \qquad (14)$$

[6] The definition of the parameter location in a GME framework may depend on prior knowledge about the unknown parameters to be estimated. Still most of the time, when we are uncertain about the parameters to be estimated, Golan, (1996:137-142) shows that wide bounds may be selected without extreme risk. Wide support bounds attribute a higher impact to the SI decreasing the parameter support impact.

$$f_h = \frac{\sum_{m=1}^{5} z_{hm}^{\lambda} p_{hm}^{\lambda}}{\sum_{m=1}^{5} z_{hhm} p_{hhm}} \left(n_{h,t-1}^{s} - \sum_{m=1}^{5} z_{hm} p_{hm} - \sum_{h \neq k}^{3} \sum_{m=1}^{5} z_{hkm} p_{hkm} f_{k,t-1} - \sum_{i=1}^{2} \sum_{m=1}^{5} z_{ih} p_{ih} n_{j,t-1}^{n} \right) +$$

$$+ \left(1 - \sum_{m=1}^{5} z_{hm}^{\lambda} p_{hm}^{\lambda} \right) f_{h,t-1} + \sum_{j=1}^{J} v_{hj} w_{hj}$$

$h = 1,2$ and $i = 1,2.$ (15)

The entropy criterion is constituted by a dual-loss objective function in which equal weights are given to precision and prediction[7]. The GME criterion maximizes the cumulative joint entropy representing the parameters (α_i, α_{ij}, γ_{ih}, λ_h, β_{hh}, β_h, β_{hk}, γ_{ih}) and the stochastic disturbance terms e_i and e_h. By rewriting the proper probabilities or convex weights associated to each parameter using compact vector notation we obtain $\mathbf{p} = \left(\mathbf{p}_{im}, \mathbf{p}_{ijm}, \mathbf{p}_{ihm}, \mathbf{p}_{hm}^{\lambda}, \mathbf{p}_{hhm}, \mathbf{p}_{hm}, \mathbf{p}_{hkm}, \mathbf{p}_{ih} \right)$ and $\mathbf{w} = \left(\mathbf{w}_{ij}, \mathbf{w}_{hj} \right)$ so that we can write the GME objective criterion as given by

$$\max_{p,w} H(\mathbf{p}, \mathbf{w}) = -\mathbf{p}' \ln \mathbf{p} - \mathbf{w}' \ln \mathbf{w} \quad (16)$$

subject to the moments or consistency constraints given by equation (7) and (10) and the GME adding-up conditions with respect to the proper probabilities or convex weights as given by

$$\sum_{m=1}^{5} p_{im} = \sum_{m=1}^{5} p_{ijm} = \sum_{m=1}^{5} p_{ihm} = \sum_{m=1}^{5} p_{hm}^{\lambda} = \sum_{m=1}^{5} p_{hhm} = \sum_{m=1}^{5} p_{hm} = \sum_{m=1}^{5} p_{hkm} = \sum_{j=1}^{5} w_{ij} = \sum_{j=1}^{5} w_{hj} = 1 \quad (17)$$

and the required theoretical symmetry restrictions given by $\sum_m z_{ijm} p_{ijm} = \sum_m z_{jim} p_{jim}$ and $\sum_m z_{hkm} p_{hkm} = \sum_m z_{khm} p_{khm}$[8]. We also require zero expectation in the disturbance terms

[7] This can be relaxed during estimation attributing different weights to precision and prediction in the entropy criterion.
[8] Additionally since the GAMS program does not allow strict inequality restrictions we fix the bound for λ_h to be between $0 + \Delta$ and $1 - \Delta$, with (small number) Δ chosen to be 0.1. A time varying partial

as given by $\sum_{t=1}^{T}\sum_{\mathrm{j}=1}^{5}\mathrm{v}_{\mathrm{ij}}w_{ij}=0$ and $\sum_{t=1}^{T}\sum_{\mathrm{j}=1}^{5}\mathrm{v}_{\mathrm{hj}}w_{hj}=0$ following Golan, et al., (2001). The primal solution to the GME Lagrange problem yields the optimal values for the proper probabilities or convex weights related to signal and precision components ($\tilde{p}_{im}$, $\tilde{p}_{ijm}$, $\tilde{p}_{ihm}$, $\tilde{p}_{hm}^{\lambda}$, $\tilde{p}_{hhm}$, $\tilde{p}_{hm}$, $\tilde{p}_{hkm}$, $\tilde{w}_{ij}$, $\tilde{w}_{hj}$). From the estimated proper probabilities or convex weights and the parameter supports the estimates are recovered for all parameters. The empirical model constituted by the system of equations (7) and (10) is then enriched by adding NSI utilizing a mixed GME estimator, see next section.

4. Data and Mixed GME Estimation

4.1 Sample Information

Data on the Hungarian and Polish agriculture are obtained from mixed statistical sources based on FAO, (2005), OECD, (2004), and WIIW, (2004) and local National Statistical Offices. Summary statistics are provided in the Appendix. Two dairy outputs (cow milk and beef and veal), one variable input (animal feed) and two quasi-fixed inputs (dairy cow stock and permanent pasture) are considered. The data cover the period 1990-2002 and are indexed to the base year 1990.

The two dairy outputs are from OECD, (2004) and are measured in million of tons. For Poland we exclude from the national cow milk production the part coming from subsistence farming[9] (Banse and Grethe, 2005, European-Commission, 2002b). There are several motivations for this. First, it is not plausible in the near future to attach a commercial value to the cow milk belonging to subsistence farming since it does not comply with EU hygienic requirements. Second, it is expected that the fringe of subsistence farms may be characterized by a different price response than the one characterizing the rest of the national cow milk production (Deolalikar, 1981). For Hungary the cow milk production refers to the total national cow milk production since

adjustment coefficient was also estimated for two sub-samples. Still this did not show remarkable changes on the partial adjustment parameters underlying constancy in the adjustment over time.

[9] For convenience we estimated the cow milk belonging to subsistence farming as the cow milk coming from dairy farms with 1 or 2 cows.

their dairy production is mostly concentrated in specialized dairy farms (European-Commission, 2002a, Jongeneel and Tonini, 2003).

The output prices are from OECD, (2004) and expressed in local currency per ton. Output prices are averaged over the two past and the present years in order to reflect expected prices. With respect to the quasi-fixed input prices, the price of dairy cows for Hungary is based respectively on data coming from the Hungarian Agricultural Economics Research Institute (AKII) and the feed price index is used as a proxy variable for the permanent pasture price since no other information is available from official statistics. For Poland data are based on the National Statistical Office (GUS). The quasi-fixed input prices are deflated using an agricultural price index (WIIW, 2004). The animal feed input price is computed by creating a feed price index based on the major coarse grains feed ingredients and then averaged over the past two and the present years reflecting expected prices. For Hungary the feed price index is based on barley, maize, wheat and other grains whereas for Poland it is based on maize, wheat and other grains[10].

The two quasi-fixed inputs, dairy cow stock and permanent pasture are based on FAO, (2005) and are measured respectively in thousand of animals and thousands of hectares. For Hungary since the series for permanent pasture between 1990 and 2002 does not show significant variations over time and is of doubtful quality we use the productive agricultural land coming from the Hungarian National Statistical Office (KSH). This takes into account that animal feeding in Hungary is largely based on compound feed (European-Commission, 2002a).

4.2 Non-sample Information and Mixed GME Estimation

In our paper we exploit NSI capturing information coming from economic theory as well as agro-economic NSI beliefs. We will first discuss NSI coming from economic theory in order to respect the required theoretical properties and then we will turn in elaborating the NSI that concerns prior beliefs about dairying.

[10] Since dairy feed ingredient data were not available we relied on the coarse grains used for animal feeding for the overall agricultural sector.

4.2.1 Non-sample Information Coming from Economic Theory

In order to ensure that the estimated supply functions are deriving from a well-behaved profit function we first impose global convexity in prices. Convexity in prices of the profit function requires that the own price elasticities of the output supplies in equation (7) must be positive and that the Hessian matrix of price derivatives must be positive semi definite (Chiang, 1984:338-340). This translates in adding the following inequality restrictions on parameters

$$\begin{gathered}\alpha_{11} \geq 0,\ \alpha_{22} \geq 0 \\ \alpha_{11} \cdot \alpha_{22} - \alpha_{12} \cdot \alpha_{21} \geq 0\end{gathered} \qquad (18)$$

where α_{11}, α_{22} and α_{12} are coefficients associated respectively to the prices of cow milk, beef and veal meats and their cross products respectively. The first two inequalities ensure that the own price elasticities of the output supplies are positive and the last inequality comes from the imposition of a positive semi definite determinant for the Hessian matrix of the second order terms. Second we require that the estimated supply functions in equation (7) are increasing in quasi-fixed inputs through the following inequality restriction on parameters

$$\gamma_{ik} \geq 0, \qquad i, k = 1,2 . \qquad (19)$$

Third we ensure that the dairy cow and permanent pasture stock equations are decreasing in own prices as given by

$$\frac{\lambda_h}{\beta_{hh}} \leq 0, \qquad h = 1,2 . \qquad (20)$$

Fourth we impose that the cross price elasticities of cow milk and beef and veal with respect to feed price are negative. Since the cross price elasticity with respect to feed price is obtained by adding-up with a negative sign the own price and all cross price elasticities we get

$$-\alpha_{ii}\frac{n_{i,t}^{n}}{y_{i,t}}-\alpha_{ij}\frac{n_{i,t}^{n}}{y_{i,t}}\leq 0, \quad i, j = 1,2 . \qquad (21)$$

In addition we allow for the possibility of potential first-order autocorrelation in the estimated system. We then detect the possibility of contemporaneous correlation among the estimated equations. Under a GME framework the first-order autoregressive errors are specified following Golan, et al., (1996:147-149) as follows

$$e_{i,ht} = a_{i,ht} = \sum_{j} v_{i,hj} w_{i,h1j} , \qquad \text{for } t = 1 . \qquad (22)$$

$$e_{i,ht} = \rho_{i,h} e_{i,ht-1} + a_{i,ht} = \rho_{i,h} e_{i,ht-1} + \sum_{j} v_{i,hj} w_{i,h1j} , \quad \text{for } t = 2,3,\ldots,T. \quad (23)$$

Under this formulation the unknown parameters and unknown errors are simultaneously estimated together with the first-order autocorrelation coefficient $\rho_{i,h}$. The restrictions (22) and (23) are simply added during the estimation as additional moment or consistency constraints and do not require the reparameterization of the first-order autocorrelation parameter $\rho_{i,h}$ [11].

Since the level of sampling precision for a set of regressions can be improved by incorporating information on the contemporaneous correlations among the disturbance terms in the equations of the system we also consider the possibility of a seemingly unrelated regressions (SUR) estimation (Greene, 2002, Judge, et al., 1985, Zellner, 1962). We proceed by first estimating the model assuming an identity covariance matrix with respect to the contemporaneous correlation and estimate the GME residuals. Consistent estimates of the variances and covariances are computed by

[11] Additionally since the GAMS program does not allow strict inequality restrictions we fix the bound for $\rho_{i,h}$ to be between $-1+\Delta$ and $1-\Delta$, with (small number) Δ chosen to be 0.1.

$$\tilde{\sigma}_{ih} = \frac{1}{T}\sum_t \tilde{\mathbf{e}}_{it}\tilde{\mathbf{e}}_{ht} \qquad \text{for } i, h = 1, 2, 3, 4. \qquad (24)$$

If contemporaneous correlation is not present ($\tilde{\sigma}_{ih} = 0$) then the GME rule applies to each equation separately and full efficiency is achieved without the necessity to employ a SUR GME estimation. Since we are uncertain about the degree of potential contemporaneous correlation among the estimated equation, we first test if the contemporaneous covariances are zero, following Griffiths, et al., (1993:561). The test is structured as follows, where $H_0 : \sigma_{12} = \sigma_{13} = \sigma_{14} = \sigma_{23} = \sigma_{24} = \sigma_{34} = 0$ and $H_1 :$ *at least one covariance is non zero*, are respectively the null and alternative hypotheses of the test. The test statistic is given by $\theta = T\left(r_{12}^2 + r_{13}^2 + r_{14}^2 + r_{23}^2 + r_{24}^2 + r_{34}^2\right)$ where r_{ih}^2 is defined by $r_{ih}^2 = \tilde{\sigma}_{ih}^2 / \tilde{\sigma}_{ii}\tilde{\sigma}_{hh}$. Under the null hypothesis H_0 the test statistic θ has an asymptotic $\chi^2 -$ distribution with $C(C-1)/2$ degree of freedom, where C is the number of equations in the system. If the test rejects the null hypothesis it is then necessary to follow a generalized GME procedure in which the covariance matrix of the disturbance terms are modified taking into account the contemporaneous correlation[12].

4.2.2 Non-sample Information Coming from Agro-economic Relationships

The agro-economic source of information is related to knowledge coming from NSI information based on previous economic research as well as to knowledge coming from dairying. All the NSI coming from agro-economic relationships is introduced during estimation in a form of stochastic restrictions on parameters. This is necessary firstly because we want to express uncertainty around our prior beliefs on restrictions. Secondly because these restrictions involve (over time varying) sample data, a second error term is introduced to account for this variation. So that the explanatory variables embedded in

[12] In considering the set of our estimated equations we did not consider the one-step GME-SUR described in Golan, (1996:185-187). The approach of Golan, (1996) appears misleading since the consistency constraint numbered as (11.3.3) in their textbook only capture the contemporaneous correlation across disturbance terms without correcting the estimates for it. The consistency constraint (11.3.3) does not alter in fact the entropy criterion but only estimates ex-post the contemporaneous correlation across the equations in the system.

each restriction are taken into account through their scale parameter. In this sub-section we discuss the NSI related to the production of cow milk and beef and veal. We consider information concerning price supply elasticities, genetic progress, and the effect of a change in dairy cow stock on cow production. Also the cross price response between beef and veal and cow milk productions are considered.

Several cow milk supply elasticities are available from the literature particularly for the former EU-15 members. Here we consider only the studies that estimated cow milk supply elasticities before the introduction of a supply management system (Boots, et al., 1997, Colman, et al., 2005, Elhorst, 1990, Higgins, 1986, Oskam and Osinga, 1982, Thijssen, 1992). In Table 1 we report the estimated elasticities of cow milk supplies encountered in the literature.

Table 1: Estimated cow milk supply elasticities from the literature

Model		Country	Range of Estimates
Higgins	(1986)	Ireland	0.17
Oskam and Osinga	(1982)	The Netherlands	0.29
Elhorst	(1990)	The Netherlands	0.12
Thijssen	(1992)	The Netherlands	0.10
Boots et al.	(1997)	The Netherlands	0.26 - 0.43 [(a)]
Colman et al.	(2005)	United Kingdom	0.27 - 0.36 [(b)]

Note: [(a)] Estimates have to be considered as intermediate-term elasticities. [(b)] The data period for the estimation covers 1990-1991 and 1994-1995, during which the marketed milk was subject to a national marketing milk quota system. However the authors argue that milk producers had no prior fixed output constraints being free to buy or lease extra quotas.

The studies of Boots, et al., (1997), Elhorst, (1990), Oskam and Osinga, (1982), and Thijssen, (1992) focus on The Netherlands and a comparison of their elasticities indicates that cow milk supply elasticities have remained rather stable. This suggests that they are depending mainly on production structure or technological characteristics rather than on policy regimes. The estimates indicate an overall inelastic price response ranging from 0.10 to 0.43. The number of studies presenting beef and veal supply elasticities appears to the authors more limited than the one estimating cow milk supply elasticities. From Stout and Abler, (2004) and Tomek and Robinson, (1990) it appears that beef and veal supply elasticities range from 1.3 to 3.2 times the cow milk supply elasticities.

First we exploited the information found in the literature on cow milk and beef and veal price elasticities through a stochastic restriction on the medium-run elasticities.

Since in the short/medium-run an increase in cow milk yields is largely feed driven and considering that the feed technology is more limiting in the Eastern European countries than in the former EU-15 members it is reasonable to expect lower responses than those found in the aforementioned studies. The NSI on the medium-run cow milk elasticities (abbreviated in NSI1) is introduced during estimation by exploiting equation (7) and (10). The NSI1 restriction is specified as follow

$$\left(\alpha_{11} - \gamma_{11}\frac{\lambda_1}{\beta_{11}}\gamma_{11}\right)\frac{n_{1,t}^{n}}{y_{1,t}^{o}} + v_{NSI1,t} = \psi_{NSI1} + \omega_{NSI1} \tag{25}$$

where α_{11}, λ_1, β_{11}, and γ_{11} are parameters, $v_{NSI1,t}$ is the disturbance term that captures the sample scale parameter of the ratio $\frac{n_{1,t}^{n}}{y_{1,t}^{o}}$. ψ_{NSI1} represents the NSI estimates on the medium-run cow milk price elasticities. ω_{NSI1} is the disturbance term that captures the uncertainty in the NSI estimates. The disturbance terms in (25) and the system of equations (7) and (10) are assumed to be independent. v_{NSI1} is reparameterized so that $v_{NSI1,t} = v_{NSI1}^{v} w_{NSI1,t}^{v}$ where v_{NSI1} is the disturbance term support and $w_{NSI1,t}$ the set of proper probabilities or convex weights. The reparameterization follows the three-sigma rule of Pukelsheim, (1994) on the sample scale parameter of the ratio $n_{1,t}^{n} / y_{1,t}^{o}$. The NSI estimate ψ_{NSI1} is set to be equal to 0.28 for Hungary as well as for Poland in order to reflect the expected lower medium-run price response with respect to Western countries (see Table 1, last two rows). ω_{NSI1} is reparameterized by $\boldsymbol{\omega}_{NSI1,t} = V_{NSI1}^{\omega} w_{NSI1}^{\omega}$ in order to allow an expected medium-run cow milk price response ranging from 0.08 to 0.48. This results in a broad location parameter space definition compatible with the estimates found in the literature. The inclusion of the NSI estimate ψ_{NSI1} does not require unit of measure transformation because elasticity terms are unit and normalization free.

The NSI on the medium-run beef and veal elasticities (abbreviated in NSI2) was introduced similarly by the following elasticity-based restriction

$$\left(\alpha_{22} - \gamma_{22}\frac{\lambda_2}{\beta_{22}}\gamma_{22}\right)\frac{n_{2,t}^n}{y_{2,t}^o} + v_{NSI2,t} = \psi_{NSI2} + \omega_{NSI2} \tag{26}$$

where α_{22}, λ_2, β_{22}, and γ_{22} are parameters, $v_{NSI2,t}$ is the disturbance term that captures the sample scale parameter of the ratio $\frac{n_{2,t}^n}{y_{2,t}^o}$. The NSI estimate ψ_{NSI2} is set to be equal to 0.45 for Hungary as well as for Poland[13]. The higher price response for beef and veal in comparison to cow milk is usually connected to the lower level of fixed costs involved in beef and veal production. The disturbance terms in (26) and the system of equations (7) and (10) are assumed to be independent. v_{NSI2} is reparameterized so that $v_{NSI2,t} = v_{NSI2}^v w_{NSI2,t}^v$ where v_{NSI2} is the disturbance term support and $w_{NSI2,t}$ the set of proper probabilities or convex weights. The reparameterization follows the three-sigma rule of Pukelsheim, (1994) on the sample scale parameter of the ratio $n_{2,t}^n / y_{2,t}^o$. ω_{NSI2} is reparameterized in order to allow an expected medium-run beef and veal price response ranging from 0.0 to 0.9 reflecting high uncertainty. The inclusion of the NSI estimate ψ_{NSI2} does not require unit of measure transformation because elasticity terms are unit and normalization free.

Second we consider the inclusion of NSI on the autonomous annual cow milk and beef and veal yields increases (abbreviated respectively in NSI3 and NSI4). Relevant factors explaining the variation in yields increases are breed, the availability of breed programs (artificial insemination), and initial yield level. Moreover the actual yield increase depends on a combination of genotype and phenotype, or genetics and environmental conditions. In order to take into account the latter impact a number of regressions were done in which cow milk (beef and veal) yield was regressed on a cow milk feed price ratio (beef and veal feed price ratio) and a trend variable. This yields autonomous cow milk yields equal to 77Kg/cow/year and 90Kg/cow/year respectively for Hungary and Poland and autonomous beef and veal yields equal to -5 Kg/cow/year and 4

[13] This reflects a value equal to 1.6 times the cow milk medium-run supply elasticity.

Kg/cow/year respectively for Hungary and Poland[14]. In order to decompose the autonomous technical change on cow milk supply we first partially differentiated the cow milk supply in equation (7) with respect to the trend variable as given by $\partial y_1^o / \partial f_3 = \partial f_1 s / \partial f_3 = f_1 \partial s / \partial f_3 = \gamma_{13}$ where s represents cow milk yields and the dairy cow stock is assumed to not vary f_1 in the short-run. The restriction NSI3 on the expected value of the yearly autonomous cow milk yield is introduced through the following restriction

$$\gamma_{13} \cdot \frac{1}{f_{1,t}} + v_{NSI3,t} = \psi_{NSI3} + \omega_{NSI3} \qquad (27)$$

where γ_{13} is an estimated parameter from the system of equations (7) and (10), $v_{NSI3,t}$ is the disturbance term that captures the sample scale parameter of the ratio $\frac{1}{f_{1,t}}$ since the restriction is imposed at each data point. ψ_{NSI3} represents the NSI estimates on the autonomous cow milk yield annual increase. ω_{NSI3} is the disturbance term that captures the uncertainty in the NSI estimates. The disturbance terms in (27) and the system of equations (7) and (10) are assumed to be independent. $v_{NSI3,t}$ is reparameterized so that $v_{NSI3,t} = V_{NSI3} w_{NSI3,t}$ where V_{NSI3} is the disturbance term support and $w_{NSI3,t}$ the set of proper probabilities or convex weights. The reparameterization follows the three-sigma rule of Pukelsheim, (1994) on the sample scale parameter of the ratio $1/f_{1,t}$. The NSI estimate ψ_{NSI3} is set to be equal to 77 Kg/cow/year and 90 Kg/cow/year respectively for Hungary and Poland. ω_{NSI3} is reparameterized in order to allow a deviation of +/- 40 Kg/cow/ year around the expect cow milk yield (FAO, 2005). Similarly the expected value of the yearly autonomous beef and veal yield is introduced by

[14] Estimates are consistent with results found by genetic experts.

$$\gamma_{23} \cdot \frac{1}{f_{1,t}} + v_{NSI4,t} = \psi_{NSI4} + \omega_{NSI4} \tag{28}$$

The NSI estimate ψ_{NSI4} is set to be equal to -5 Kg/cow/year and 4 Kg/cow/year respectively for Hungary and Poland. ω_{NSI4} is reparameterized in order to allow a deviation of +/- 10 Kg/cow/ year around the expect beef and veal yield increase. The inclusion of the NSI estimates ψ_{NSI3} and ψ_{NSI4} requires unit of measure to have consistency between SI and NSI (see Table 2).

Third we consider the medium-run response of dairy production for a change in dairy cow stock (abbreviated in NSI5). The short-run response of total cow milk production to a change in the dairy cow stock is equal to the cow milk yield of the (marginal) cow, conditional on the fact that all other variables (prices and permanent pasture) remain fixed in the model. It is not trivial to estimate the contribution of the marginal cow. An approximation could be to rely on the average cow milk yield, maybe 'corrected' for the difference between 'marginal' and 'average' and the constancy of the quasi-fixed inputs other than dairy cow stock. However, in the medium-run the amount of permanent pasture might be assumed to fully adjust to the change in dairy cow stock. In that case it seems not a strong assumption to set the contribution of the marginal cow equal to the average cow milk yield. Average cow milk yields during the time period considered for Hungary and Poland are respectively 5200 Kg/cow and 3500 Kg/cow. By partially differentiating the system of supplies and stock equations in (7) and (10) with respect to the dairy cow stock we get $\partial y_1 / \partial f_1 = \partial y_1 / \partial f_1 + \partial y_1 / \partial f_2 \cdot \partial f_2 / \partial f_1 = \gamma_{11} - \gamma_{12} (\lambda_2 / \beta_{21}) \beta_{22}$ from this derives the NSI5 expressed in the following form

$$\gamma_{11} - \gamma_{12} \frac{\lambda_2}{\beta_{22}} \beta_{21} = \psi_{NSI5} + \omega_{NSI5} \tag{29}$$

where γ_{11}, γ_{12}, λ_2, β_{22} and β_{21} are parameters. ψ_{NSI5} represents the NSI estimates on the country specific cow milk yield. ω_{NSI5} is the disturbance term that captures the uncertainty in the NSI estimates. ω_{NSI5} is reparameterized in order to allow a deviation of +/- 500 Kg/cow around the expect cow milk yields. The inclusion of the NSI estimates ψ_{NSI5} requires unit of measure to have consistency between SI and NSI.

Finally[15] we introduce NSI information on the cross-price relationship between beef and veal and cow milk (abbreviated in NSI6). Since it is widely acknowledge that beef and veal production is a by-product of cow milk production for the former EU-15 members and particularly for the NMSs, it is also expected that in the medium-run an increase in the cow milk price, ceteris paribus, would lead to an increase in the size of dairy heard. Since dairy cows are an important and almost unique source for beef and veal supply in the country being analyzed this would lead to an increase in beef and veal supply (i.e. complementarity between beef and veal and cow milk productions). We therefore specify a restriction NSI6 on the medium-run cross price elasticity between beef and veal and cow milk production as follows

$$\left(\alpha_{22} - \gamma_{21}\frac{\lambda_2}{\beta_{22}}\gamma_{21}\right)\frac{n_{1,t}^{n}}{y_{2,t}} + v_{NSI6,t} = \psi_{NSI6} + \omega_{NSI6} \tag{30}$$

The NSI estimate ψ_{NSI6} is set to be equal to 0.14 for Hungary as well as for Poland in order to reflect a slightly higher degree of complementarity than the one encountered for the Former EU-15 members (Stout and Abler, 2004). ω_{NSI6} is reparameterized in order to allow an expected medium-run beef and veal price response ranging from 0.0 to 0.28.

[15] An additional restriction for Hungary is imposed since stock equations frequently provided a null response with respect to their own lagged prices because of the non-negative binding restrictions. In order to correct for this a series of regressions of stock variables on their lagged prices was estimated and the estimated price response substituted in the estimation through the following constraint $\frac{\lambda_h}{\beta_{hh}} \cdot \frac{f_h}{n_h^s} + v_{NSIh,t} = \psi_{NSIh}$ for h = 1,2.

No unit of measure transformation is required since the restriction is in term of elasticity. A summary of the NSI incorporated during estimation is presented in Table 2.

Table 2 Summary of non-sample information incorporated during estimation

NSI	Country	Unit of Measure	Non Sample Information	Prior Estimates (ψ_{NSIh})	Deviation (ω_{NSIh})
NSI1	Hungary, Poland	-	NSI1	0.28	+/- 0.20
NSI2	Hungary, Poland	-	NSI2	0.45	+/- 0.45
NSI3	Hungary	Kg/cow/year	NSI3	77	+/- 0.40
	Poland	Kg/cow/year	NSI3	90	+/- 0.40
NSI4	Hungary	Kg/cow/year	NSI4	-5	+/- 50
	Poland	Kg/cow/year	NSI4	4	+/- 50
NSI5	Hungary	Kg/cow	NSI5	5200	+/- 500
	Poland	Kg/cow	NSI5	3500	+/- 500
NSI6	Hungary, Poland	-	NSI6	0.14	+/- 0.20

The mixed GME criterion maximizes the cumulative joint entropies as given in equations (16) and (17) and in addition it incorporates the disturbances terms $v_{NSIl,t}$ (for *l = 1, 2, 3, 4, 6*) and ω_{NSIl} (for *l = 1, …,6*) attached to the NSI restrictions. We also require that $\sum_{t=1}^{T}\sum_{j=1}^{5} \mathrm{v}_{lj}^{v}\tilde{w}_{lj}^{v} = 0$ and $\sum_{j=1}^{5} \mathrm{v}_{\mathrm{lj}}^{\omega}\tilde{w}_{lj}^{\omega} = 0$ in order to have zero expectations. Also the theoretical restrictions given by equation (18) - (23) are incorporated during the mixed GME estimation. By rewriting the proper probabilities or convex weights associated to each parameters using compact vector notation we have $\mathbf{p} = \left(\mathbf{p}_{im}, \mathbf{p}_{ijm}, \mathbf{p}_{ihm}, \mathbf{p}_{hm}^{\lambda}, \mathbf{p}_{hhm}, \mathbf{p}_{hm}, \mathbf{p}_{kkm}, \mathbf{p}_{ih}\right)$, $\mathbf{w} = \left(\mathbf{w}_{ij}, \mathbf{w}_{hj}\right)$ and $\mathbf{w}_{NSI} = \begin{pmatrix} \mathbf{w}_{NSI1t,j}^{v}, \mathbf{w}_{NSI1,j}^{\omega}, \mathbf{w}_{NSI2t,j}^{v}, \mathbf{w}_{NSI2,j}^{\omega}, \mathbf{w}_{NSI3t,j}^{v}, \mathbf{w}_{NSI3,j}^{\omega}, \\ \mathbf{w}_{NSI4t,j}^{v}, \mathbf{w}_{NSI4,j}^{\omega}, \mathbf{w}_{NSI5,j}^{\omega}, \mathbf{w}_{NSI6t,j}^{v} \mathbf{w}_{NSI6,j}^{\omega} \end{pmatrix}$ so that we can write the mixed GME objective criterion as given by

$$\max_{p,w} H(\mathbf{p}, \mathbf{w}) = -\mathbf{p}'\ln\mathbf{p} - \mathbf{w}'\ln\mathbf{w} - \mathbf{w}_{NSI}'\ln\mathbf{w}_{NSI} \qquad (31)$$

subject to the moments or consistency constraints given by equation (7) and (10) and the GME adding-up conditions with respect to the proper probabilities or convex weights as given by equation (18) and

$$\sum_{j=1}^{5} w^{v}_{NSI1t,j} = \sum_{j=1}^{5} w^{\omega}_{NSI1,j} = \sum_{j=1}^{5} w^{v}_{NSI2t,j} = \sum_{j=1}^{5} w^{\omega}_{NSI2,j} = \sum_{j=1}^{5} w^{v}_{NSI3t,j} = \sum_{j=1}^{5} w^{\omega}_{NSI3,j} = 1$$
$$\sum_{j=1}^{5} w^{v}_{NSI4t,j} = \sum_{j=1}^{5} w^{\omega}_{NSI4,j} = \sum_{j=1}^{5} w^{\omega}_{NSI5,j} = \sum_{j=1}^{5} w^{v}_{NSI6t,j} = \sum_{j=1}^{5} w^{\omega}_{NSI6,j} = 1 \quad (32)$$

The normalized entropy index (*NEI*) taking into account the signal and noise parts of the system is used to assess the information content. The *NEI* presented in Golan, et al., (1996:93) is extended in order to accommodate the disturbance terms attached to the NSI as given by

$$NEI(\tilde{p},\tilde{w},\tilde{w}_{NSI}) = \frac{H(\tilde{p},\tilde{w},\tilde{w}_{NSI})}{\left[\varsigma \cdot \log(M) + T \cdot \left(\Phi + \Phi^{NSI}\right) \cdot \log(J)\right]} \quad (33)$$

where ς is the total number of estimated unknown parameters, *M* the dimension of the parameter support space, *T* the total number of observations, Φ the total number of disturbance terms attached to the estimated system of equations and Φ^{NSI} the total number of disturbance terms coming from the NSI. Thus, $H(\tilde{p},\tilde{w},\tilde{w}_{NSI})$ corresponds to the estimated values of the joint entropies (objective function) and the denominator of equation (34) corresponds to the maximum possible value of the joint entropies. The *NEI* is a relative normalized index bounded between zero (i.e. perfect certainty) and one (i.e. perfect uncertainty)[16]. An alternative measure increasing with the information content embedded in the estimated system is the so called information index (*II*) introduced by Soofi, (1992) and equal to $II(\tilde{p},\tilde{w},\tilde{w}_{NSI}) = 1 - NEI(\tilde{p},\tilde{w},\tilde{w}_{NSI})$. The *II* has to increase when adding valuable deterministic information to the model[17].

[16] It is important to remind that the *NEI* strictly depends on the definition of the support space with respect to the width and to the number of support points. Therefore it loses its proper interpretation when comparing situations in which the support spaces are defined in different ways. For a given set of moments or consistency constraints, larger support spaces will provide relatively higher *NEI* values, whereas narrow support spaces will provide relatively low *NEI*.

[17] When stochastic restrictions are added to the system the *II* may either decrease or increase depending on the problem at hand because of the augmented uncertainty related to the additional disturbance terms. This should be argument of further research.

5. Results

This section first presents the estimated dairy supply responses and subsequently moves to the model estimates and several qualifications. To the knowledge of the authors up to now there are no studies providing empirical estimates on the dairy supply response of CEECs. Few studies available in the literature analyze the impact of the EU enlargement on the dairy sector based on simulation exercises calibrated on conjectured supply elasticities (Banse and Grethe, 2005, Grethe and Weber, 2005). Since the main aim of this research is to provide empirical estimates of the price responses of cow milk and beef and veal outputs, the obtained price supply elasticities are summarized in Table 3. We consider the price responses related to Model 1 where none of the restrictions is enforced and the one related to Model 2 where all the NSI is exploited (i.e. theoretical restrictions as well as agro-economic restrictions on parameters). We calculate short-run as well as medium-run price elasticities where we allow adjustment in dairy cow stock.

Table 3.- Estimated price responses evaluated at sample means (Model 1 and 2).

	Hungary			
	Short-Run		Medium-Run	
Endogenous variables	*Cow milk*	*Beef and Veal*	*Cow milk*	*Beef and Veal*
Model 1 (unrestricted)				
Cow milk	0.0589	0.2298	0.1620	0.3723
Beef and veal	0.4564	-0.8341	0.6449	-0.5737
Model 2 (restricted)				
Cow milk	0.1724	-0.0331	0.2759	0.0710
Beef and veal	-0.0554	0.2236	0.1188	0.3988
	Poland			
Model 1 (unrestricted)				
Cow milk	-0.5954	-0.0675	0.6230	0.1541
Beef and veal	-0.8016	0.6123	1.0490	2.7385
Model 2 (restricted)				
Cow milk	0.1895	-0.0238	0.2835	0.0703
Beef and veal	-0.0422	0.2462	0.1246	0.5309

As can be seen from the estimated price responses in Model 1 not all estimates have proper sign (e.g. own price elasticity of beef for Hungary) and also their magnitude appear somehow questionable (e.g. beef and veal medium-run own price elasticity with respect to cow milk price for Poland). The introduction of NSI has a remarkable impact on the magnitude of the estimated elasticities particularly with respect to the own price response of beef and veal for Hungary and to the own price response of cow milk for Poland. In Model 2 all price responses are characterized by proper sign due to the enforcement of the required theoretical restrictions on parameters and of plausible agro-economic relationships. All own-price elasticities are smaller than one implying that for a given price change, the dairy supplies adjust less than proportionately. According to our results the short-run own-price elasticity for Hungary implies that a 10 percent change in the expected price of cow milk will induce about a 1.7 percent change in the supply of cow milk given *ceteris paribus* conditions. Our estimates seem to be rather conservative in comparison to what is found for other former EU-15 members (see Table 1). From the price homogeneity condition it is also possible to recover the cross price elasticities with respect to animal feed price by simply adding-up the own price and cross price elasticities. The cross price elasticities with respect to animal feed price, in the short-run range from -0.14 to -0.20 and in the medium run from -0.35 to -0.65.

Considering the joint character of cow milk and beef and veal productions, the signs of the cross-price elasticity for the supplies indicate the relationships between the outputs – a positive sign implies complementarity whereas a negative sign implies substitutability. From Table 3, all the short-run cross-price elasticities are estimated to be negative indicating short-run substitutability between cow milk and beef and veal productions. When the model allows for medium-run adjustment in dairy cow stock, all the medium-run cross-price elasticities are estimated to be positive indicating medium-run complementarity between cow milk and beef and veal productions. Our estimates for the medium-run suggest that for Hungary a 10 percent increase in the price of beef and veal will induce an increase in the supply of cow milk of about 0.7 percent. This indicates that when the investment decision on the dairy cow stock size is allowed to adapt cow milk and beef and veal productions are complement.

The effect of the dairy cow stock adjustment, as captured in the medium-run own price elasticities, is higher for beef and veal as compared to cow milk production, particularly for Poland. The medium-run adjustment in the cow milk own price elasticity leads to an increase in the price responsiveness of about 60 and 50 percent with respect to the short-run responses in Model 2 respectively for Hungary and Poland. Our estimates have important implications in view of the recent accession of the NMS to the EU and considering the planned reform agenda of the EU dairy policy. In other words it is expected that the national dairy production of Hungary and Poland is not likely to substantially increase its supply in response to the improved price conditions consequent to the EU accession. All this is based on the assumption that no other output or input prices change. Still the speed of the price responsiveness may also be affected by the extent to which these two countries are able to restructure (i.e. farm structure, ownership), specialize and modernize their dairy sectors.

Turning to the effects of the introduction of NSI in our estimates first we test for contemporaneous correlation among the estimated equations and then we discuss the main differences between Model 1 and Model 2. In Table 4 we present the results testing for contemporaneous correlation in the estimated system constituted by equations (15) and (16). For both countries and under the two different model specifications (i.e. Model 1 and 2), contemporaneous correlations seems to not constitute an issue at one per cent significance level.

Table 4.- Test for Contemporaneous Correlation

	Hungary	
	Model 1	**Model 2**
Lambda	7.493	8.354
Degree of Freedom (DF)	6	6
$\chi^2_{(DF) - (P = 0.001)}$	16.812	16.812
Test	Accept Null	Accept Null
	Poland	
	Model 1	**Model 2**
Lambda	14.6877$^{(*)}$	13.910$^{(*)}$
Degree of Freedom (DF)	6	6
$\chi^2_{(DF) - (P = 0.001)}$	16.812	16.812
Test	Accept Null	Accept Null

Note: Results derive from Model 1 and Model 2 where first-order autocorrelation is captured. $^{(*)}$ *at five per cent significance level we could reject the null hypothesis of zero contemporaneous correlation.*

Therefore we proceed by simply estimating the model allowing for first-order autocorrelation in each equation without correcting for contemporaneous correlation. The models were estimated using GAMS (Generalized Algebraic Modeling System) selecting the PATHNLP solver which is a nonlinear optimization solver. In Appendix 2 we present the GME estimates for the dairy supply system of Hungary and Poland without enforcing any restrictions (Table A2). The estimated models appear characterized by high condition indexes both for Hungary and Poland indicating severe problems of multicollinearity. This was rather expected given the limited number of observations in our sample compromising the sample scale among the explanatory variables. Given the short length of the available data series and the small variability in the variables the potential to have multicollinearity problems is increased. This underlines that the use of additional source of information external to sample data was necessary to make our ill-behaved problem analytically tractable. Rather surprising are the estimated negative price response of beef and veal production for Poland and the negative contribution of land to the dairy supplies. In the dairy cow stock equation there is an unexpected positive price response both for Hungary and Poland.

The parameter estimates for the models taking into account theoretical restrictions and all the NSI (Model 2) are presented in Table A3 (see Appendix 2). The inclusion of agro-economic relationships resulted in increasing the *II* of the model for Hungary whereas the *II* for Poland slightly decreased[18]. The inclusion of external source of information restored the contribution of several variables to the system especially for land that turned to positively affect the beef and veal supply. Table 7 lists the correlation between observed and predicted values across the different estimated equations in the system and the two model specifications. The in sample prediction of the model only slightly decreased after including the theoretical restrictions and the external agro-economic relationships.

Table 7.- Correlation between Observed and Predicted Values

	Hungary			
	Cow milk	*Beef and veal*	*Dairy Cow*	*Agricultural Land*
Model 1	0.9768	0.9811	0.9985	0.9966
Model 2	0.9419	0.9500	0.9263	0.9759
	Poland			
Model 1	0.9872	0.9783	0.9824	0.8029
Model 2	0.8656	0.9484	0.9786	0.7376

[18] This can be explained by the stochastic nature of the imposed restrictions during the estimation. This should constitute argument of further research.

6. Conclusions

In this paper we developed and applied a Mixed GME estimator. Given the limited data and their sometimes questionable quality, our empirical approach offered a feasible route to empirically estimate the price responsiveness of the Hungarian and Polish dairy-beef sectors, irrespective of the serious data problems. In this way an economic model was estimated fitting the available data through the moments or consistency constraints, satisfying theoretical consistency (economic point of view enforced through economic restrictions) and plausibility (i.e. being largely in accordance with agro-economic information about dairying).

Our results suggested overall an inelastic dairy supply response for Hungary and Poland. In addition we found complementarity between the production of cow milk and beef and veal in the medium-run where dairy cow stock can adjust. Further research should be done in order to take into account the following. First, we would like to more carefully analyze the error structure of the stock equations considering their partial adjustment specification. Second, we would like to apply an unambiguous measure assessing the information content of non-linear stochastic restriction on parameters. Finally, a computational issue that has to be solved is related to the computation of covariance matrixes when including non-linear stochastic restrictions on parameters.

Appendix 1: Descriptive Statistics

Table A1. – Summary Statistics

	Hungary		Poland	
	Mean	s.d.	Mean	s.d.
Cow milk production	0.758	0.093	0.791	0.081
Beef and veal production	0.621	0.256	0.587	0.186
Dairy cow	0.744	0.117	0.748	0.126
Land	0.961	0.022	1.003	0.009
Cow milk price	1.204	0.172	1.362	0.225
Beef and veal price	0.879	0.064	1.037	0.219
Dairy cow lagged price	2.298	1.284	1.004	0.180
Land lagged price	2.423	1.387	1.161	0.120

Appendix 2: Parameter Estimates

Table A2.- GME Estimates of Dairy Supply System (Model 1)

	Hungary		Poland	
	Cow milk	Beef and Veal	Cow milk	Beef and Veal
Intercept	1.9298	10.1940	4.4933	1.6069
	(2.986)	(18.381)	(0.534)	(4.870)
Cow milk price	0.0371	0.2354	-0.3458	-0.3451
	(0.011)	(0.068)	(0.004)	(0.039)
Beef and veal price	0.1981	-0.5893	-0.0515	0.3464
	(0.034)	(0.208)	(0.001)	(0.011)
Dairy Cow	1.4447	2.1639	1.7769	3.5558
	(0.017)	(0.104)	(0.021)	(0.189)
Land	-2.6553	-10.841	-4.9268	-4.2290
	(3.140)	(19.328)	(0.473)	(4.317)
Trend	0.0123	-0.0753	0.0621	0.0960
	(0.000)	(0.000)	(0.000)	(0.000)
Rho	-0.1948	-0.0686	-0.1082	
Condition Index	1252		750	
	Dairy Cow Stock	Land Stock	Dairy Cow Stock	Land Stock
Intercept	1.4831	-0.1478	0.3866	-0.7218
	(0.564)	(0.149)	(1.478)	(0.069)
Dairy cow price (L-1)	0.0433		0.0322	
	(0.000)		(0.007)	
Land price (L-1)		-0.0024		-0.0585
		(0.000))		(0.000)
Dairy cow (L-1)	0.4893	0.0250	0.9000	0.1838
	(0.002)	(0.000)	(0.170)	(0.004)
Land (L-1)	-1.7684	0.8748	-0.0582	0.5439
	(0.608)	(0.157)	(2.011)	(0.061)
Trend	0.0156	0.0002	0.0091	0.0045
	(0.000)	(0.000)	(0.000)	(0.000)
Cow milk price (L-1)	-0.0449	0.0096	-0.2241	0.0005
	(0.002)	(0.000)	(0.013)	(0.000)
Beef and veal price (L-1)	-0.0850	-0.0020	-0.0952	0.0236
	(0.005)	(0.000)	(0.006)	(0.000)
Rho	-0.5476	0.9376		
Condition Index	1769	2005	860	685
Information Index	9.35^{E} -04		4.44^{E} -03	

Note: (L-1) indicates lagged variables. In bracket are the standard errors computed using the method for OLS estimation described in Judge, et al., (1985)[19].

[19] Asymptotic standard errors were not recovered for Model 2 (see Table 6) because of the non-linear restrictions on parameters that require a specific treatment. This should constitute an element of further research.

Table A3.- GME Estimates of Dairy Supply System (Model 2)

	Hungary		Poland	
	Cow milk	Beef and Veal	Cow milk	Beef and Veal
Intercept	-0.4630	-0.4214	-1.1588	-0.7806
Cow milk price	0.1085	-0.0286	0.1101	-0.0182
Beef and veal price	-0.0286	0.1579	-0.0182	0.1393
Dairy Cow	1.0172	1.4024	1.0900	1.5636
Land	0.3472	-	0.8802	-
Trend	0.0111	-0.0148	0.0172	0.0112
Rho	0.9999	0.4076	0.1853	0.3459
	Dairy Cow Stock	Land Stock	Dairy Cow Stock	Land Stock
Intercept	0.0817	-0.0886	-0.2138	-0.3986
Dairy cow price (L-1)	-0.0629		-0.0421	
Land price (L-1)		-0.0151		-0.0457
Dairy cow (L-1)	0.9000	-0.0042	0.8205	0.1778
Land (L-1)	-0.0177	0.9000	0.1640	0.7707
Trend	-0.0171	-0.0046	0.0048	0.0065
Cow milk price (L-1)	-0.0640	-0.0052	-0.0459	-0.0402
Beef and veal price (L-1)	-0.0883	-	-0.0659	-
Rho	0.4222	0.4963	-0.1628	-0.3369
Information Index	1.56^{E}-03		3.37^{E}-03	

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