# A bayesian analysis of trade in agri-food products : an application to France

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# A BAYESIAN ANALYSIS OF TRADE IN AGRI-FOOD PRODUCTS: AN APPLICATION TO FRANCE (*)

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(*) This paper follows up and complements the findings and content of a presentation made at the VIIIth Congress of the European Association of Agricultural Economists, Edinburgh, 3-7 September 1996, and entitled ***"Modelling trade in processed food products: a generalized Armington approach"***. This paper presents the results of ongoing research. Comments are welcome.

# 1 - Introduction

Expansion in French total agricultural output over the last four decades has been accompanied by an equally, if not more, significant increase in France's trade for agri-food products. Thus, the volume of French agri-food exports increased more than six-fold between 1961 and 1990 (Monceau, 1995). France which was a net importer of food products in the sixties became a net exporter in 1970. This net exporting position in agri-food products was steadily consolidated over the 70's and 80's so that France is now the second world exporter of agri-food products behind the USA and before Netherlands.

Although French imports of agri-food products did not experience the same expansion as agri-food exports during the same period, they have steadily increased to reach in value terms 150 billion french francs in 1994, among which 2/3 represented import shipments of processed food products. Such a pattern is not surprising and is associated with a gradual integration of the EU agri-food sectors, and the development of intra-trade in this kind of products (Chevassus-Lozza and Gallezot, 1993; de Frahan and Libert, 1996). French imports of agri-food products originating from the rest of the EU are now representing about 70% of the total. Given this situation, it is interesting to know how the various competing import supplies of a given agri-food product interact between each other but also with the production of home-produced agri-food products.

The objective of this paper is to explain the patterns of imports and home-produced supplies for raw and processed agricultural products, using a differentiated product model. For this purpose, we propose a generalization of the Armington model based on an homogenous, indirect and implicitly additive structure of consumer preferences from which demand for imported and home-produced products are derived. Its empirical implementation is facilitated by the use of an homogenous 'Constant Difference of Elasticities' (CDE) functional form developed by Hanoch (1975). Relative to the Armington model, this proposed differentiated product model offers the advantage of computing varying elasticities of substitution among sources of import and domestic supplies.

When estimated econometrically, the CDE functional form must satisfy certain conditions (in the form of inequality restrictions on its parameters) to be globally or locally valid over its regularity domain. If conventional econometric estimation techniques were used, these conditions are not imposed and are usually tested "ex-post". On the other hand, in order to

ensure that the estimated parameters of the CDE function are globally or locally valid, constrained estimation techniques similar to those developped by Shumway *et al.* (1990) or Hazilla and Kopp (1986) for flexible functional forms could have been applied. We did not follow this route in estimating the CDE functions but rather leant towards an another alternative bayesian-like approach developed by Geweke (1988, 1989). In fact, imposing inequality constraints on parameters can be viewed as supplying prior information before we proceed to the econometric estimation of the functional form with a data sample, and then to infer the posterior distribution of the parameters. Such an estimation strategy which has been employed recently by Chalfant *et al.* (1991), Hayes *et al.* (1990), and Tiffin and Moxey (1992) for input and consumer demand and output supply systems derived form flexible functional forms has never been applied to agricultural trade modelling. It is also our intent to fill this gap by adapting the Geweke's procedure to the estimation of CDE demand functions.

The rest of the paper is structured in the following manner. The next section develops the conceptual model used to explain the imports and home supplies of goods. The estimable version of this model is also presented in this section. This is then followed in section 3 by a presentation and explanation of the bayesian estimation procedure employed in this study. In section 4, we report and discuss econometric results for twenty six agri-food products consumed in France, using annual data from 1977 to 1994. Concluding remarks are provided in the last section.

## 2 - Conceptual and empirical models

The proposed differentiated product model framework retains two essential characteristics from the Armington specification. First, we distinguish commodities that are differentiated by kind as "goods" and "goods" that are differentiated by origin as "products". Second, we assume that the utility function is homogenously and weakly separable. This proposed framework is however more general than the Armington model in the sense that we allow for imperfect substitution between various import and domestic sources of a given commodity but we also make the following additional asumptions: *(i)* varying elasticities between any two products of a good in a given market; *(ii)* distinct elasticities of substitution between any two pairs of products in a given market; and *(iii)* imports and domestic production are viewed as final good supplies entering the decision process of the consumers.

Given these assumptions, it is then possible to define a direct, homogenously and weakly separable consumer preference structure where each good $q_i$ for $i = 1,2,..,n$ can be supplied by a set of $m$ geographically differentiated products $q_{is}$ from $s= 1,2,..., m$. The products $q_{is}$ can

be ordered into a set of $n$ separable and mutually-exclusive groups. The utility function corresponding to this separable structure is homogenously weakly separable and is defined as follows:

$$U[q] = U[v_1(q_{11}, q_{12}, \ldots q_{1m}),\ v_2(q_{21}, q_{22}, \ldots q_{2m}),\ \ldots,\ v_n(q_{n1}, q_{n2}, \ldots q_{nm})] \quad [1]$$

where $v_i(.)$ are viewed as homogenous sub-utility functions which depend upon a set of geographically differentiated products $q_{is}$. Linear homogeneity of the sub-utility functions also implies that $q_i = v_i(.)$. $U[.]$ and $v_i(.)$ satisfy the usual conditions of monotonicity, quasi-concavity and differentiability. Due to the linear homogeneity of the sub-utility functions $v_i(.)$, it is possible to derive subgroup conditional demands of the form, for all $s$ belonging to group $i$:

$$q_{is} / q_i = g_i[p_{is}] \quad for\ \ s = 1, \ldots m\ \ and\ \ i = 1, \ldots n \qquad [2]$$

The optimization procedure behind the utility function [1.] may be viewed as occuring in two stages. The consumer determines first the product aggregates of each good $i$ subject to an income constraint and then allocates them among competing suppliers. Because the utility function is homogenously separable, we can define aggregate price indices $p_i$ which depend upon each $p_{is}$ through an explicit price function. In the Armington model, these price functions are represented by CES price aggregators of all import source prices.

The proposed differentiated product model expresses these prices functions (indices) in an implicitly additive fashion through the use of a CDE functional form. Hence implicit CDE price functions are defined and expressed as:

$$\sum_{s=1}^{m} H_{is}(p_{is}, p_i) = \sum_{s=1}^{m} B_{is} z_{is}^{\ b_{is}} \equiv 1 \qquad [3]$$

where each $H_{is}$ is approximated by a CDE functional form, $z_{is}$ is the product price $p_{is}$ normalized by the aggregate price of good $i$. In [3.], $B_{is}$ is called the distribution parameter. $b_{is}$ or $\alpha_{is} = 1 - b_{is}$ are the price parameters. $\alpha_{is}$ is also called the substitution parameter. The CDE price function is globally valid if $B_{is} > 0$, $b_{is} < 1$, and either $b_{is} \leq 0$ for all $s$ or $0 < b_{is} < 1$ for all $s$ (Hanoch, 1975, p 411). Weaker conditions can be obtained and consist of *(i)* one $b_{is} > 1$ and *(ii)* some $B_{is}$ and $b_{is}$ being of different signs. By applying Roy's identity, we derive the CDE demands for various (import and domestic) supplies:

$$S_{is} = \frac{z_{is} \dfrac{\partial H_{is}}{\partial z_{is}}}{\sum_{s=1}^{m} z_{is} \dfrac{\partial H_{is}}{\partial z_{is}}} = \frac{b_{is} B_{is} z_{is}^{\ b_{is}}}{\sum_{s=1}^{m} b_{is} B_{is} z_{is}^{\ b_{is}}} \qquad [4]$$

The subscript *i* is now omitted for reasons of convenience.

Allen elasticities of substitution can be derived using the following expression:

$$\sigma_{sl} = \alpha_s + \alpha_l - \sum_{k=1}^{m} S_k \alpha_k - \delta_{sl} \frac{\alpha_s}{S_s} \qquad [5]$$

where $\delta_{sl}$ is the Kroenecker sign equal to 1 for $s = l$ and 0 elsewhere.

From expressions [4.] and [5.] it can be seen that the Armington model characterized by a constant elasticity of substitution $\sigma$ can be derived by setting all the $b_S$ equal to a constant $b$. The elasticity of substition $\sigma$ is then equal to $\alpha = 1 - b$.

The system of demand share equations formed by expression [3.] and with stochastic residuals $\mu_S$ could be estimated by an appropriate system estimation technique such as iterative seemingly unrelated estimation (ITSUR) or maximum lilkelihood (ML) approach, which takes into account the adding up conditions associated with the budget shares ($S_s$). However, due to the highly nonlinear structure of the CDE demand equations, it is probable that non convergent and/or local optimum estimation solutions will occur. Furthermore, the existence of a right hand side endogenous variable implies a simultaneous estimation bias problem that needs to be taken into consideration. One way to overcome the nonlinearity of the CDE demand equations is to linearize and transform all of them in a log-ratio form[1]. Then, iterative three stage least squares estimation is applied to this new sytem of linearized CDE demand equations in order to ensure that, first, the estimated parameters are invariant with respect to the share equation dropped, and second, that the simultaneity bias problem is taken into account.

As it will be explained later, the above estimation procedure is not feasible in our study because the bayesian estimation procedure that we are using requires all the explanatory variables in the CDE share equation system to be **exogenous**. As a result, we adopt a two-step approach to estimate the parameters of the CDE demand equations. First, the system of log-linearized CDE demand equations is transformed in first differences. Therefore, the explanatory variables are expressed in a rate of variation form. We approximate the rate of variation of the price aggregator $p$ by a Stone's geometric price index of all import and domestic sources. This transformation is justified through a total differentiation and a re-arrangement of the implicit CDE price function. To show this, let us differentiate expression [3.] and express $dp/p$ as a function of all the $p_S$. The rate of change $dp/p$ is then given by:

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[1] This transformation which was first suggested by Theil to estimate multinomial logit model and then used by Rossi for system of cost share equations ensures that the estimated shares are always positive and smaller than one. Consequently, the monotonicity conditions are automatically satisfied. From an econometric estimation perspective, it means that the stochastic residual $\mu_S$ follows a logistic distribution.

$$\frac{dp}{p} = \sum_{s=1}^{m} \frac{B_s b_s \left(\frac{p_s}{p}\right)^{b_s}}{\sum_{s=1}^{m} B_s b_s \left(\frac{p_s}{p}\right)^{b_s}} \frac{dp_s}{p_s} = \sum_{s=1}^{m} S_s \frac{dp_s}{p_s} \qquad [6]$$

Then, substituting $dp/p$ in the first-difference, log-linearized CDE equations yields the final estimable econometric model specification (which we designate LA-CDEH):

$$\frac{dy_s}{y_s} = b_s \frac{dp_s}{p_s} - b_m \frac{dp_m}{p_m} + (b_m - b_s)\left(\sum_{s=1}^{m} S_s \frac{dp_s}{p_s}\right) + \varepsilon_s \quad for\ s = 1, \ldots m-1 \qquad [7]$$

where $dy / y = (dS_s / S_s) - (dS_m / S_m)$ ; $d(.)$ designates the symbol "first-difference"; and $\varepsilon_s$ is a vector of stochastic residuals which follows a multivariate normal distribution with zero means and a variance/covariance matrix $\Sigma$ . Note that in expressing the CDE demand share equations in first difference, the parameters $B_S$ vanish and are not identifiable. It is also worth pointing that this two-stage estimation of the CDEH demand equations is somewhat similar in spirit to the estimation procedure of the LA-AIDS model within which the aggregate translog price index (common to all AIDS share equations) is replaced by a Stone's geometric price index. It differs however from the LA-AIDS approach in the sense that the CDE demand equations are expressed in first differences[2].

## 3 - Econometric implementation

Given the proposed empirical model, the objective is to obtain bayesian estimates of the parameters $b$, incorporating (global or local) vailidity conditions. This section describes the bayesian estimation procedure used to estimate the coefficients $b$, and explains a practical method to generate posterior distributions that satisfy the validity conditions of the CDE function.

### *3.1 - Bayesian approach*

Bayesian estimation consists of combining prior information (prior density functions) with sample information (sample likelihood function) to obtain a posterior density of the parameters. Prior information that can be used for the parameters can be either informative (based on existing data or knowledge of the phenomen under study by the investigator) or non-informative or diffuse. In the former case, a prior density function can be well defined and incorporated into the bayesian approach. In the latter, diffuse priors are characterized by a flat

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[2] This link with the LA-AIDS approach justifies the use of the acronym LA-CDEH for the above estimable CDE equations.

density function approximated by a constant. In this study, we assume that prior information is diffuse, consisting of validity conditions imposed on the LA-CDE model. This means that in either cases - local or global validity conditions[3] - the vector of parameters ($b$) will satisfy the inequality constraints defined earlier. We also consider that this prior information on the parameters $b$ is known with certainty, so that a prior density function can be defined by a single indicator function:

$$p(b) = \begin{cases} 1 & for\ all\ b \in D \\ 0 & otherwise \end{cases} \qquad [8]$$

where $D$ is the region of the parameter space for which global or local validity conditions are satisfied. Then, through the Bayes rule, we obtain a posterior density function $f(.)$ expressed as:

$$f(b|y) = p(b).L(b|y) \qquad [9]$$

where $y$ is the sample data set and $L(.)$ is the likelihood function based on observed data. As the prior density function is a simple (unitary) indicator function, the posterior probability distribution is no more than a truncated density function generated from the sample likelihood function in expression [9.]. A point estimate of the parameters $b$ which does not violate the regularity conditions is then obtained by taking the mean of the posterior distibution over the the domain $D$, that is[4]:

$$E(b) = \int_{b \in D} b\, f(b|y) db \qquad [10]$$

Expression [10.] is the conceptual tool that serves to derive point estimates of the parameter $b$. Its implementation is only feasible in simple cases where the number of parameters is scant (in general no more than three). Beyond this, it is impossible to integrate expression [10.] analytically, and we must have recourse to Monte Carlo integration procedures.

### *3.2 Monte Carlo integration with importance sampling*

At first glance, the most logical way to use Monte Carlo integration to approximate expression [10.] is to draw a large number of random drawings from the posterior distribution and then take the sample means as a "proxy" for $E(b)$. To find a posterior distribution of $b$ consistent

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[3] It should be reminded that there is no need to worry about monotonicity conditions since they are built in the empirical CDEH specification.

[4] It should be pointed out that several estimates of $b$ can be formed, depending upon the investigator's objective function (see Chalfant *et al.*, 1991, p. 479). In our case, the adoption of the means of the posterior distribution implicitly implies that the loss function is quadratic. Then, the mean of the posterior distribution for $b$ minimizes the expectec loss.

with the (global or local) validity conditions, we would only retain the replications for which such conditions are satisifed and then compute the means of the parameters $b$. In so doing, these "restricted" means approximate the truncated posterior density function defined by expression [10.].

In cases where random numbers cannot be easily generated from the posterior distribution, it is possible to use Monte Carlo integration techniques with importance sampling. This alternative procedure involves drawing from a density function known as the importance function and then taking weighted averages across draws. Put more formally, consider $g(b)$ to be the importance function, from which random numbers are generated. Assume that the $b_i$ is the $i$th random draw from $g(b)$ and $w_i = f(b_i|y)/g(b_i)$. Then, the weighted means can be shown to approximate the integral appearing in expression [10.]:

$$\bar{b} = E(b) = \int_{b\in D} b \frac{f^R(b|y)}{g^R(b|y)} g^R(b|y)db = \frac{\sum_{k=1}^{n} b_{(k)} \frac{f^R(b_{(k)}|y)}{g^R(b_{(k)}|y)}}{\sum_{k=1}^{n} \frac{f^R(b_{(k)}|y)}{g^R(b_{(k)}|y)}} \qquad [11]$$

where $f^R$ and $g^R$ are the truncated posterior density functions, $b_{(k)}$ is a draw of parameter $b$ for which the validity conditions hold, and $n$ is the number of draws for which the validity conditions hold.

At the same time as the means is generated, it is possible to compute other relevant indicators. The first one is the probability that the validity conditions are satisfied. This probability is given by the following expression:

$$\bar{p}_D = \frac{\sum_{k=1}^{n} \frac{f^R(b_{(k)}|y)}{g^R(b_{(k)}|y)}}{\sum_{k=1}^{N} \frac{f^R(b_{(k)}|y)}{g^R(b_{(k)}|y)}} \qquad [12]$$

where $N$ is the total number of draws. Another useful indicator is the variance (and then the standard deviation) of the posterior distribution which is obtained by taking the estimated variance of the posterior distribution. The latter is computed taking into account the importance density function.

$$V(b) = E\left[(b_{(k)} - \bar{b})^2\right] = \frac{\sum_{k=1}^{n} (b_{(k)} - \bar{b})^2 \frac{f^R(b_{(k)}|y)}{g^R(b_{(k)}|y)}}{\sum_{k=1}^{n} \frac{f^R(b_{(k)}|y)}{g^R(b_{(k)}|y)}} \qquad [13]$$

Finally, to check whether the selected importance density function behaves well, the numerical standard error (*nse*) proposed by Geweke (1989) can be used for the indicators previously defined. The numerical standard error is given by the following formula:

$$nse(b) = \left( \frac{\sum_{k=1}^{n} (b_{(k)} - \bar{b})^2 \left(\frac{f(b_{(k)}|y)}{g(b_{(k)}|y)}\right)^2}{\left(\sum_{k=1}^{n} \frac{f^R(b_{(k)}|y)}{g^R(b_{(k)}|y)}\right)^2} \right)^{1/2} \qquad [14]$$

In our case of estimating the LA-CDEH, the method of Monte Carlo integration with importance sampling is well justified because the posterior distribution of the parameters $b$ has a complex form, thus hindering to generate a well behaved truncated density function through simulation. To show this, the results obtained by Zellner for a set of regression equations is applied to the parameters $b$ of the LA-CDEH. Assuming diffuse priors for $b$ and $\Sigma$, the resulting posterior density function for $b$ is given by:

$$f(b|y) \propto |A|^{-T/2} \qquad [15]$$

where $\propto$ denotes "is proportional to", $T$ is the number of observations and $A$ is a matrix of size $m$-1 by $m$-1 formed by the following elements:

$$a_{ij} = [e_i(b)' e_j(b)]$$

where $e_i(b)$ is the vector of residuals for the $i$th CDEH equation.

Although the above posterior density function is "unfamiliar", it is much easier to work with than the corresponding posterior probability distribution associated with an estimable CDEH model expressed in levels. In this latter case, the CDE demand equations include a right hand side (RHS) endogenous variable (i.e. the price aggregator $p$) which should be accounted for. To incorporate this RHS variable in the bayesian estimation of the parameters of the CDE model specification expressed in level form would have required to undertake a full system analysis of the CDE model including the demand equations and the CDE implicit price function given by expression[3.]. This would have resulted in a highly nonlinear model structure from which it would have been impossible to generate a posterior distribution of the parameters. Furthermore, a review of the literature on bayesian econometrics reveals that, apart from Zellner's study of systems of linear simultaneous equations which derives the posterior

distributions of the parameters[5], no work has been conducted over the last two decades on the bayesian estimation of nonlinear simultaneous equations. Given this situation, we had side-stepped this simultaneity bias problem by exogenizing the price aggregator and then by expressing the CDE demand functions in first difference form.

### *3.3 - Estimation strategy*

To implement Monte Carlo integration with importance sampling for the parameters of the LA-CDEH model, we follow closely the multi-step procedure proposed by Chalfant *et al* (1991). First the system of LA-CDEH demand equations given by expression [7.] and estimated by ITSUR estimation method produces estimates $\hat{b}$ and its variance/covariance matrix $V(\hat{b})$. Then, the random draws for the parameters $b$ are generated with the importance density function which is assumed to follow a multivariate Student-$t$ distribution. The random number generator used for the $t$-distribution is based on random drawings from the multivariate normal distribution which are then adjusted to the $t$-distribution using the various relationships existing between the normal, chi-squared and Student $t$-distributions. This procedure suggested by Van Dijk and Kloek (1990) included several steps which are easily implementable. To expand the number of drawings and also to improve convergence (Geweke, 1988), antithetic replications are also obtained and included into the bayesian estimation procedure. Once the random drawings for the parameters $b$ have been generated, the corresponding values of the posterior density functions $f(.)$ are computed using expression [11.]. The third step of the estimation procedure consists of checking whether each replication satisfies the global or local validity conditions. Then, the means and the variance of the posterior distributions and the assoicated probability distributions for which validity conditions hold are estimated using expressions [12.] and [13.]. Finally, *n.s.e.* of the estimated parameters $\hat{b}$ are derived to check the accuracy and the stability of the econometric results.

## 4 - Application to France

The generalized Armington model developed in the previous section is estimated for import and home produced supplies of agri-food goods in France. For each of the goods considered,

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[5] Even in Zellner's case, the posterior distribution function of the strucutural parameters is even more "unfamiliar" than the one found for a set of regression equations.

we distinguish three sources of competing supplies, namely imports from the Rest of the EU ($s$=1) and from the Rest of the World (RoW) ($s$=2) and consumption of home-produced products ($s$=3). A time trend is also incorporated to capture non-price effects. The empirical CDEH demand specification (expressed in first differences) that will be used with the French data has the following form:

$$\frac{dy_s}{y_s} = A_s + b_s\left(\frac{dp_s}{p_s} - (\sum_{s=1}^{3} S_s \frac{dp_s}{p_s})\right) - b_m\left(\frac{dp_m}{p_m} - (\sum_{s=1}^{3} S_s \frac{dp_s}{p_s})\right) + \varepsilon_s \qquad [16]$$

$$for \quad s = 1,2$$

where $A_S$ is a constant term standing for the autonomous effect of the trend variable.

### *4.1 - Data*

Data used to estimate the system of CDEH demand equations stem from two reference sources. Import data by origin were obtained from the French Customs trade data base while the prices and quantity consumed of home-produced goods are aggregates from the French national accounts developed by the Institut National des Statistiques et des Etudes Economiques (INSEE). Before we proceeded with the bayesian estimation, both data sources had to be harmonized to generate comparable price and quantity aggregates on the various supplies of agri-food products. Such a task is difficult, if not impossible, to perform at the aggregate level (3 SITC digit levels for instance). On the other hand, it is possible to obtain satisfactory and comparable data if we develop all these quantity and price aggregates at a more detailed and disaggregated level. For this purpose, we used the "NAP 600" level of the French National Accounts nomenclature (about 700 products) and matched it with the corresponding nomenclature of the French Customs data base. There are about 80 agri-food products[6] at the NAP 600 level but we only retain the ones for which each of the three import and home-produced supplies represent at least 1% of the total consumption. This selection resulted in a set of 26 (7 agricultural and 19 processed food) products, the consumption of which represents over 300 billion FF in 1994. Imports of the retained products represent 60% of total imports of French agri-food products on average (1990-94).

Data for all the dependent and explanatory variables are available on an annual basis over the period 1977-1994 and are all expressed in rate of variation. The rate of change for the Stone's

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[6] There are respectively 30 and 50 raw agricultural and food processed products in the NAP 600 nomenclature.

geometric price index was computed using an arithmetic average of current and past year budget shares.

### *4.2 - Econometric results*

Table 1 reports results on the structure of consumer preferences, including results obtained with the conventional econometric approach on the one hand, and those based on the bayesian approach on the other hand. Tables 2 and 3 give the associated parameter estimates of the generalized Armington model under the three assumptions: the unrestricted case, the global validity case, and the local validity case. With the traditional econometric (unrestricted) estimation, global validity conditions are satisfied for only three products, and local validity conditions for eight products (column (2) of Table 1). For the other products, estimated parameters should not lead to any interpretation, due to the non-validity of the demand equations. This can be seen through the signs of Allen partial elasticities of substitution (columns (3) to (5) of Table 1).

*(insert Table 1)*

*(insert Tables 2 and 3)*

These difficulties to interpret substituability and complementarity relationships among the various import and home-produced sources can be overcome by using results of the bayesian approach, which imposes local or global validity conditions on the parameters. First, it can be seen (column (6)) that the posterior probability for the global validity is frequently small, except for products such as "flowers and plants" (16%), "milk industry by-products" (23%), "baby food and dietetic foods" (15%), "brandies" (63%), "wine aperitives" (15%), and "fruit and vegetable juices" (21%). Nevertheless, it can be noticed that the posterior probability for global or local validity is greater than 30% for about two-thirds of the set of agri-food products (this probability is greater than 20% for 85% of the products). Moreover, the standard deviations computed for these posterior probabilities are always very small[7], and such a finding ensures the robustness and the stability of derived results.

The examination of posterior probabilities on the signs of Allen elasticities of substitution under the global validity restriction (columns (7) to (11) of Table 1) gives the following information on the substituability relationships among sources:

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[7] These standard deviations are not reported in Table 1 due to lack of space.

- The posterior probability that there exists at least one complementarity relationship between two sources is generally small (see column (8) of Table 1). Cases where the posterior probability that all Allen elasticities are positive is greater than 50%, are the most common (see column (7) of Table 1). Exceptions are for "canned vegetables", "prepared feed", "coffee, tea and other herbs", "soup mixes", and "brandies". In all these cases, the complementarity occurs between French products and imports from the Rest of the EU.

Conditionnally upon the existence of at least one complementarity relationship among sources (columns (9) to (11) of Table 1), this complementarity can be characterized as follows:

- The elasticity of substitution is negative with a high posterior probability, between imports from the Rest of the EU and imports from the RoW for all raw agricultural products, except: "fresh vegetables" and "dried vegetables", and for all processed food products, except: "canned fruit and jam" and "fruit and vegetable juices".

- The elasticity of substitution is never negative, with a significant posterior probability, between imports from the Rest of EU and home-produced products, for any product.

- The elasticity of substitution is significantly negative between imports from the RoW and home-produced products for only one product among processed food products ("fruit and vegetable juices").

As a result, imposing global validity conditions on the CDEH demand equations in the case where at least one complementarity relationship occurs, allows us to conclude to a high tendency to complementarity between the two kinds of imports (from the Rest of the EU and from the RoW) for a very large majority of goods. Otherwise, substituability is the rule between French products and imports from the Rest of the EU on the one hand, and between French products and imports from the RoW on the other hand. Such a result clearly runs counter the *"preference communautaire"*[8].

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[8] This result must be qualified when only weak conditions are imposed on parameters (local validity). Recall that these conditions are associated with a posterior probability which is largely greater than the one of the global conditions.In this case of local validity, complementarity between French products and imports from the Rest of the EU can be observed for several raw agricultural products and for some processed food products. But in the case of local validity, complementarity between French products and imports from the RoW remains the exception for raw agricultural products, but can be encountered with a significant posterior probability for a few processed food products (see columns (9) to (11) of Table 1).

## 5 - Concluding remarks

The objectives of this paper are two-fold. First, we develop an alternative product differentiation model which is more general than the Armington specification. econd, we propose the use of bayesian estimation procedures in agricultural trade modelling. The application to this Generalized Arminton model to French trade in agri-food products yields mixed results which are however superior to those obtained with a conventional estimation procedure.

These mixed econometric results may lead readers to question the usefulness of bayesian estimation methods to agricultural trade modelling. We do not think so and opt for a more optimistic outlook in suggesting that this first attempt in applying bayesian mehtods can be improved in several respects. First, the adoption of an homogenous consumer preference structure is too restrictive and should be relaxed towards more general non-homogenous structures. Second, the use of of Monte Carlo integration with importance sampling is one procedure among a set of simulation methods to generate random numbers. Hence, there have been some recent applications of Monte Carlo method based on the use of Markov chains to econometric modelling (Gordon and Bélanger, 1996). We could perhaps employ this latter approach in estimating the Generalized Armington model developed in this paper. Finally, a third direction to improve the econometric performance of this trade model would be to select other bayesian estimation procedures which are not necessarily based on the approximation of integrals of posterior distributions. In this vein, we are especially thinking of bayesian bootstrap analysis of systems of equations similar to the one proposed by Heckelei and Mittelhammer (1996).

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**Table 1: Results on the structure of the consumer preferences**

| | | Conventional approach | | | | | Bayesian approach | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Trend (1) | Validity cond. (2) | All Allen elast. >0 (3) | At least one Allen last. <0 (4) | Direct Allen elast. >0 (5) | Posterior probability (6) | Posterior probability that all Allen elasticity >0 (7) | Posterior probability that at least one Allen elasticity <0 (8) | Posterior probability that Allen elasticities between products 1-2 <0 (9) | Posterior probability that Allen elasticities between products 1-3 <0 (10) | Posterior probability that Allen elasticities between products 2-3 <0 (11) |
| **Agricultural raw products** | | | | | | | | | | | | |
| **111** | **Potatoes** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,0249 | 0,8861 | 0,1139 | 0,8696 | 0,0000 | 0,1304 |
| | Local validity | | | | | | 0,4137 | 0,4159 | 0,5841 | 0,0070 | 0,0000 | 0,9930 |
| **112** | **fresh vegetables** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,0015 | 1,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,3860 | 0,3172 | 0,6828 | 0,0125 | 0,9875 | 0,0000 |
| **113** | **Drioed vegetables** | x | | | | x | | | | | | |
| | Global validity | | | | | | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,9798 | 0,9353 | 0,0647 | 0,0000 | 0,9702 | 0,0298 |
| **114** | **Fruit** | | | x | | | | | | | | |
| | Global validity | | | | | | 0,0004 | 1,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | Local validity | | x | | | | 0,9937 | 0,8212 | 0,1788 | 0,0000 | 1,0000 | 0,0000 |
| **122** | **Non tropical oilseeds** | | | | | x | | | | | | |
| | Global validity | | | | | | 0,0007 | 0,5714 | 0,4286 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,2143 | 0,0046 | 0,4043 | 0,5957 | 0,0000 | 0,7857 |
| **142** | **Flower and plants** | x | | x | | | | | | | | |
| | Global validity | | | | | | 0,1596 | 0,7265 | 0,2735 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,2270 | 0,6692 | 0,3308 | 0,9663 | 0,0199 | 0,0138 |
| **143** | **Other vegetable products** | x | | | | x | | | | | | |
| | Global validity | | | | | | 0,0084 | 0,8861 | 0,1139 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,4068 | 0,7085 | 0,2915 | 0,0628 | 0,9115 | 0,0257 |
| **Processed food products** | | | | | | | | | | | | |
| **3502** | **Fresh meat** | | | | | | | | | | | |
| | Global validity | | | | | | 0,0130 | 0,6154 | 0,3846 | 0,9500 | 0,0000 | 0,0500 |
| | Local validity | | x | | | | 0,1940 | 0,0748 | 0,9252 | 0,8665 | 0,0021 | 0,1315 |
| **3505** | **Game and poultry meat** | | | x | | | | | | | | |
| | Global validity | | | | | | 0,0084 | 0,8542 | 0,1458 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,2838 | 0,7305 | 0,2695 | 0,0329 | 0,6859 | 0,2812 |
| **3614** | **Cheese** | | | x | | | | | | | | |
| | Global validity | | | | | | 0,0597 | 0,9510 | 0,0491 | 0,9032 | 0,0000 | 0,0968 |
| | Local validity | | | | | | 0,2309 | 0,8592 | 0,1409 | 0,1871 | 0,1710 | 0,6419 |
| **3616** | **Milk industry by-products** | | | | x | | | | | | | |
| | Global validity | | x | | | | 0,2314 | 0,6831 | 0,3169 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,2329 | 0,5344 | 0,4656 | 0,8405 | 0,0046 | 0,1550 |
| **3701** | **Canned fruit and jam** | x | | | | x | | | | | | |
| | Global validity | | | | | | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| **3702** | **Canned vegetables** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,0200 | 0,3710 | 0,6290 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | x | | | | 0,1784 | 0,0769 | 0,9231 | 0,9762 | 0,0204 | 0,0034 |
| **3703** | **Canned fish** | | | x | | | | | | | | |
| | Global validity | | | | | | 0,0417 | 0,9407 | 0,0593 | 0,9546 | 0,0000 | 0,0455 |
| | Local validity | | x | | | | 0,1971 | 0,5937 | 0,4063 | 0,3342 | 0,1146 | 0,5512 |
| **3902** | **Cookies and bakery products** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,0999 | 0,7475 | 0,2525 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | x | | | | 0,6006 | 0,3504 | 0,6496 | 0,8217 | 0,0070 | 0,1712 |
| **3907** | **Starch products** | | | | | x | | | | | | |
| | Global validity | | | | | | 0,0367 | 0,6491 | 0,3509 | 0,8938 | 0,0000 | 0,1062 |
| | Local validity | | | | | | 0,0659 | 0,0203 | 0,9797 | 0,9689 | 0,0000 | 0,0311 |
| **3908** | **Prepared feeds** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,0317 | 0,1283 | 0,8717 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,2167 | 0,5218 | 0,4782 | 0,6316 | 0,0154 | 0,3531 |
| **4031** | **Chocolate and confectionery products** | | | x | | | | | | | | |
| | Global validity | | | | | | 0,0000 | 0,9475 | 0,0525 | 0,9091 | 0,0000 | 0,0909 |
| | Local validity | | x | | | | 0,0000 | 0,3860 | 0,6140 | 0,0048 | 0,0000 | 0,9952 |
| **4032** | **Coeffee, tea and other herbs** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,0002 | 0,2500 | 0,7500 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,3420 | 0,0000 | 1,0000 | 0,9997 | 0,0000 | 0,0003 |
| **4033** | **Seasonings and salad dressings** | x | | | | x | | | | | | |
| | Global validity | | | | | | 0,0033 | 0,9655 | 0,0345 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,0268 | 0,5068 | 0,4932 | 0,3611 | 0,3241 | 0,3148 |
| **4034** | **Baby food and dietetic foods** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,1527 | 0,6449 | 0,3551 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,1189 | 0,0034 | 0,9966 | 1,0000 | 0,0000 | 0,0000 |
| **4036** | **Soup mixes** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,0805 | 0,4452 | 0,5548 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,5374 | 0,6849 | 0,3151 | 0,9696 | 0,0233 | 0,0071 |
| **4037** | **Miscallemous food products** | | | | x | | | | | | | |
| | Global validity | | | | | | 0,0753 | 0,6626 | 0,3374 | 0,8602 | 0,0108 | 0,1290 |
| | Local validity | | x | | | | 0,1788 | 0,0106 | 0,9894 | 0,9915 | 0,0032 | 0,0053 |
| **4101** | **Brandies** | | | x | | | | | | | | |
| | Global validity | | x | | | | 0,6294 | 0,4205 | 0,5795 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | | | | | 0,1364 | 0,9738 | 0,0262 | 0,1765 | 0,8235 | 0,0000 |
| **4104** | **Wine aperitives** | | | x | | | | | | | | |
| | Global validity | | | | | | 0,1461 | 0,6459 | 0,3541 | 1,0000 | 0,0000 | 0,0000 |
| | Local validity | | x | | | | 0,7378 | 0,8805 | 0,1195 | 0,0000 | 0,0010 | 0,9990 |
| **4108** | **Fruit and vegetable juices** | | | x | | | | | | | | |
| | Global validity | | x | | | | 0,2122 | 0,9633 | 0,0367 | 0,1136 | 0,0114 | 0,8750 |
| | Local validity | | | | | | 0,0933 | 0,3078 | 0,6922 | 0,4499 | 0,0281 | 0,5220 |

**Table 2: Parameter estimates of the generalized Armington model**

| Agricultural raw products | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | $b_1$ | $b_2$ | $b_3$ | $a_1$ | $a_2$ |
| 111 | Potatoes | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,0253 | ***0,5377*** | *4,2422* | | |
| | | | Standard error | 0,2824 | 0,2647 | 2,3769 | | |
| | Bayesian estimation | Global validity | Estimates | 0,3180 | ***0,8136*** | 0,5884 | | |
| | | | Standard error | 0,3200 | 0,2958 | 3,6637 | | |
| | | Local validity | Estimates | -0,1679 | ***0,3833*** | ***5,1737*** | | |
| | | | Standard error | 0,2357 | 0,2195 | 1,7415 | | |
| 112 | Fresh vegetables | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,7213 | ***-0,7240*** | 2,8552 | | |
| | | | Standard error | 0,4592 | 0,3919 | 1,8156 | | |
| | Bayesian estimation | Global validity | Estimates | ***0,8787*** | 0,0692 | 0,2984 | | |
| | | | Standard error | 0,1748 | 0,7945 | 2,5699 | | |
| | | Local validity | Estimates | 0,4531 | ***-0,7357*** | ***2,9873*** | | |
| | | | Standard error | 0,4016 | 0,3136 | 1,3834 | | |
| 113 | Dried vegetables | | | | | | | |
| | Conventional estimation | LSQ | Estimates | ***-0,2159*** | ***-0,4060*** | ***3,6334*** | ***-0,1060*** | -0,0987 |
| | | | Standard error | 0,0992 | 0,2134 | 0,8056 | 0,0425 | 0,0665 |
| | Bayesian estimation | Global validity | Estimates | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | | | Standard error | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | | Local validity | Estimates | ***-0,2150*** | ***-0,4075*** | ***3,6010*** | ***-0,1059*** | ***-0,0985*** |
| | | | Standard error | 0,0765 | 0,1614 | 0,5921 | 0,0316 | 0,0499 |
| 114 | Fruit | | | | | | | |
| | Conventional estimation | LSQ | Estimates | *-1,2735* | ***-1,9525*** | ***2,8301*** | | |
| | | | Standard error | 0,7257 | 0,6707 | 0,7788 | | |
| | Bayesian estimation | Global validity | Estimates | 0,5447 | 0,1512 | 0,4604 | | |
| | | | Standard error | 1,8407 | 2,1130 | 2,3794 | | |
| | | Local validity | Estimates | *-1,2877* | ***-1,9589*** | ***2,8419*** | | |
| | | | Standard error | 0,7080 | 0,6564 | 0,7518 | | |
| 122 | Non tropical oilseeds | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,5533 | *0,8076* | ***2,6601*** | | |
| | | | Standard error | 0,5054 | 0,4805 | 0,9858 | | |
| | Bayesian estimation | Global validity | Estimates | ***0,7574*** | ***0,8647*** | 0,7075 | | |
| | | | Standard error | 0,2599 | 0,0992 | 1,9615 | | |
| | | Local validity | Estimates | -0,0582 | -0,0470 | ***2,9854*** | | |
| | | | Standard error | 0,6754 | 0,9092 | 0,7187 | | |
| 142 | Flowers and plants | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,2685 | ***-0,5112*** | -1,4594 | ***0,0677*** | ***0,0824*** |
| | | | Standard error | 0,5875 | 0,1400 | 2,6958 | 0,0268 | 0,0304 |
| | Bayesian estimation | Global validity | Estimates | -0,2861 | ***-0,5527*** *** | | 0,0677 | 0,0817 |
| | | | Standard error | 0,5999 | 0,1273 | 1,2969 | 0,0230 | 0,0266 |
| | | Local validity | Estimates | 0,3504 | -0,5087 | -0,0363 | 0,0665 | 0,0806 |
| | | | Standard error | 0,7635 | 0,1382 | 3,3403 | 0,0236 | 0,0263 |
| 143 | Other vegetable products | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,4056 | -0,1016 | 15,3918 | 0,0507 | -0,0039 |
| | | | Standard error | 0,2508 | 0,3748 | 12,2898 | 0,0386 | 0,0629 |
| | Bayesian estimation | Global validity | Estimates | ***0,5421*** | 0,3162 | 0,3245 | 0,0347 | -0,0286 |
| | | | Standard error | 0,2715 | 0,4941 | 15,1194 | 0,0480 | 0,0730 |
| | | Local validity | Estimates | 0,3093 | -0,3928 | 16,8410 | 0,0476 | -0,0058 |
| | | | Standard error | 0,3019 | 0,4406 | 10,6159 | 0,0455 | 0,0754 |

**Table 3: Parameter estimates of the generalized Armington model**

| Processed food products | | | | $b_1$ | $b_2$ | $b_3$ | $a_1$ | $a_2$ |
|---|---|---|---|---|---|---|---|---|
| 3502 | **Fresh meat** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 1,3302 | ***0,6346*** | -5,5331 | ***0,0525*** | *-0,0410* |
| | | | Standard error | 0,8449 | 0,2753 | 4,5996 | 0,0146 | 0,0237 |
| | Bayesian estimation | Global validity | Estimates | 0,2888 | 0,3780 | -0,3882 | *0,0456* | -0,0404 |
| | | | Standard error | 1,1366 | 0,4544 | 5,5916 | 0,0239 | 0,0348 |
| | | Local validity | Estimates | 0,9315 | 0,3848 | -6,1570 | ***0,0510*** | -0,0352 |
| | | | Standard error | 1,1985 | 0,4406 | 7,0069 | 0,0232 | 0,0377 |
| 3505 | **Game and poultry meat** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,2294 | 0,0959 | ***15,5078*** | | |
| | | | Standard error | 0,2899 | 0,2521 | 7,7529 | | |
| | Bayesian estimation | Global validity | Estimates | 0,3202 | 0,3424 | 0,2813 | | |
| | | | Standard error | 0,2890 | 0,3424 | 15,2767 | | |
| | | Local validity | Estimates | -0,0678 | -0,0032 | *12,5663* | | |
| | | | Standard error | 0,4569 | 0,3193 | 6,6904 | | |
| 3614 | **Cheese** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,3362 | 0,2123 | 2,0250 | | |
| | | | Standard error | 0,2069 | 0,2857 | 3,3420 | | |
| | Bayesian estimation | Global validity | Estimates | *0,3946* | 0,3799 | 0,4606 | | |
| | | | Standard error | 0,2178 | 0,2981 | 1,6098 | | |
| | | Local validity | Estimates | 0,1740 | -0,0719 | 4,5930 | | |
| | | | Standard error | 0,3136 | 0,4186 | 3,6862 | | |
| 3616 | **Milk industry by-products** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | -0,0546 | -0,6559 | -3,1317 | | |
| | | | Standard error | 0,6026 | 0,9757 | 2,8076 | | |
| | Bayesian estimation | Global validity | Estimates | -0,4957 | -1,5045 | -2,7494 | | |
| | | | Standard error | 0,5728 | 1,2797 | 1,9209 | | |
| | | Local validity | Estimates | -0,3117 | -0,8533 | -1,1004 | | |
| | | | Standard error | 1,2245 | 1,1699 | 5,8944 | | |
| 3701 | **Canned fruit and jam** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | ***-2,6496*** | 0,2744 | ***7,6248*** | ***0,1077*** | 0,0408 |
| | | | Standard error | 0,9617 | 0,8147 | 1,7522 | 0,0391 | 0,0313 |
| | Bayesian estimation | Global validity | Estimates | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | | | Standard error | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | | Local validity | Estimates | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| | | | Standard error | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 |
| 3702 | **Canned vegetables** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | *1,3854* | 0,2800 | -7,6475 | | |
| | | | Standard error | 0,8432 | 0,8808 | 5,8135 | | |
| | Bayesian estimation | Global validity | Estimates | -0,1720 | -0,4078 | -3,8992 | | |
| | | | Standard error | 1,6157 | 0,9245 | 5,2482 | | |
| | | Local validity | Estimates | *1,0996* | -0,1581 | ***-8,1131*** | | |
| | | | Standard error | 0,6349 | 0,8834 | 5,7419 | | |
| 3703 | **Canned fish** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | -0,3186 | 0,6611 | 1,1703 | | |
| | | | Standard error | 0,3300 | 0,8088 | 2,2301 | | |
| | Bayesian estimation | Global validity | Estimates | -0,1036 | -0,0852 | -0,5393 | | |
| | | | Standard error | 0,2863 | 0,8682 | 1,9835 | | |
| | | Local validity | Estimates | -0,2959 | 0,5378 | 0,6974 | | |
| | | | Standard error | 0,2394 | 0,6890 | 1,3713 | | |
| 3902 | **Cookies and bakery products** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 1,5450 | ***-1,8141*** | *-7,2389* | | |
| | | | Standard error | 1,2864 | 0,8168 | 4,1986 | | |
| | Bayesian estimation | Global validity | Estimates | -0,7893 | *-2,5144* | -2,9751 | | |
| | | | Standard error | 2,4260 | 1,4223 | 4,8569 | | |
| | | Validité Locale | Estimates | 1,1625 | *-2,1980* | -6,5412 | | |
| | | | Standard error | 2,5919 | 1,3051 | 9,5597 | | |
| 3907 | **Starch products** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | ***0,8764*** | ***1,2698*** | -0,9366 | | |
| | | | Standard error | 0,3266 | 0,3098 | 0,9960 | | |
| | Bayesian estimation | Global validity | Estimates | 0,5708 | 0,7305 | 0,4364 | | |
| | | | Standard error | 0,3932 | 0,5794 | 1,4001 | | |
| | | Local validity | Estimates | ***1,0848*** | 0,7196 | -1,9323 | | |
| | | | Standard error | 0,3846 | 0,5952 | 1,6254 | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 3908 | **Prepared feeds** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,0967 | 0,9306 | -8,9296 | | |
| | | | Standard error | 0,6815 | 0,6488 | 14,9404 | | |
| | Bayesian estimation | Global validity | Estimates | -0,4267 | -0,4121 | -9,4210 | | |
| | | | Standard error | 0,6748 | 1,4158 | 8,0636 | | |
| | | Local validity | Estimates | -0,4060 | 0,0325 | 2,4812 | | |
| | | | Standard error | 1,1557 | 1,1007 | 25,3631 | | |
| 4031 | **Chocolate and confectionery products** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | -0,6727 | 0,3436 | 2,3545 | | |
| | | | Standard error | 0,5908 | 0,2611 | 1,6630 | | |
| | Bayesian estimation | Global validity | Estimates | 0,2224 | ***0,6034*** | 0,4425 | | |
| | | | Standard error | 0,9103 | 0,3026 | 1,9307 | | |
| | | Local validity | Estimates | *-0,8812* | 0,2704 | ***2,9765*** | | |
| | | | Standard error | 0,5132 | 0,2332 | 1,3869 | | |
| 4032 | **Cooffee, tea and other herbs** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,4019 | ***0,9958*** | ***-3,9132*** | | |
| | | | Standard error | 0,3387 | 0,1713 | 1,0350 | | |
| | Bayesian estimation | Global validity | Estimates | *0,7135* | ***0,8566*** | 0,4183 | | |
| | | | Standard error | 0,3778 | 0,1564 | 4,3331 | | |
| | | Local validity | Estimates | 0,2887 | ***1,0825*** | ***-4,0682*** | | |
| | | | Standard error | 0,4035 | 0,1388 | 1,1614 | | |
| 4033 | **Seasonings and salad dressings** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,7207 | 0,0154 | ***10,0214*** | ***0,2419*** | ***0,1980*** |
| | | | Standard error | 0,5461 | 0,1792 | 4,6359 | 0,0727 | 0,0756 |
| | Bayesian estimation | Global validity | Estimates | *0,5482* | 0,1517 | 0,4490 | 0,1540 | 0,1238 |
| | | | Standard error | 0,3326 | 0,1778 | 9,5893 | 0,1074 | 0,1003 |
| | | Local validity | Estimates | 0,2265 | -0,0100 | 2,2326 | *0,1795* | 0,1437 |
| | | | Standard error | 0,7987 | 0,1664 | 8,2010 | 0,0945 | 0,0949 |
| 4034 | **Baby and dietetic foods** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,3377 | 0,3190 | ***-2,4459*** | | |
| | | | Standard error | 0,5729 | 0,3866 | 0,9070 | | |
| | Bayesian estimation | Global validity | Estimates | -0,5393 | -0,2975 | -1,5224 | | |
| | | | Standard error | 0,9546 | 0,6556 | 1,2058 | | |
| | | Local validity | Estimates | 1,1609 | 0,5059 | ***-3,0430*** | | |
| | | | Standard error | 0,8826 | 0,3645 | 1,0622 | | |
| 4036 | **Soup mixes** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,2454 | *-0,7054* | -2,3627 | | |
| | | | Standard error | 0,9235 | 0,3766 | 9,7740 | | |
| | Bayesian estimation | Global validity | Estimates | -0,2906 | ***-0,8322*** | -3,3840 | | |
| | | | Standard error | 0,5838 | 0,2651 | 2,8744 | | |
| | | Local validity | Estimates | 0,0110 | ***-0,7950*** | 1,2621 | | |
| | | | Standard error | 1,0496 | 0,4000 | 11,1753 | | |
| 4037 | **Miscallenous food products** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 1,0885 | *0,8635* | -0,3882 | | |
| | | | Standard error | 0,6841 | 0,5222 | 1,9806 | | |
| | Bayesian estimation | Global validity | Estimates | 0,6632 | ***0,6649*** | 0,4917 | | |
| | | | Standard error | 0,4840 | 0,3068 | 0,9274 | | |
| | | Local validity | Estimates | ***1,2933*** | 0,5190 | -1,3915 | | |
| | | | Standard error | 0,3675 | 0,4435 | 1,3987 | | |
| 4101 | **Brandies** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | -0,3928 | ***-3,2646*** | -4,9442 | | |
| | | | Standard error | 0,4536 | 0,4481 | 5,7286 | | |
| | Bayesian estimation | Global validity | Estimates | -0,5511 | ***-3,2332*** | -6,6837 | | |
| | | | Standard error | 0,3899 | 0,4714 | 4,5436 | | |
| | | Local validity | Estimates | -0,4673 | ***-3,3452*** | 3,5377 | | |
| | | | Standard error | 0,4635 | 0,4231 | 8,8235 | | |
| 4104 | **Wine aperetives** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | ***-1,3696*** | ***-0,8566*** | 6,9518 | | |
| | | | Standard error | 0,6347 | 0,2909 | 6,8245 | | |
| | Bayesian estimation | Global validity | Estimates | -0,7329 | ***-0,8424*** | -2,9906 | | |
| | | | Standard error | 0,7344 | 0,2213 | 10,2322 | | |
| | | Local validity | Estimates | ***-1,4380*** | ***-0,8767*** | *8,1121* | | |
| | | | Standard error | 0,4669 | 0,2491 | 4,2501 | | |
| 4108 | **Fruit and vegetable juices** | | | | | | | |
| | Conventional estimation | LSQ | Estimates | 0,1789 | *0,6847* | 0,9674 | | |
| | | | Standard error | 0,2638 | 0,3576 | 1,2640 | | |
| | Bayesian estimation | Global validity | Estimates | 0,2999 | ***0,5966*** | 0,5231 | | |
| | | | Standard error | 0,2161 | 0,2499 | 0,5288 | | |
| | | Local validity | Estimates | 0,0063 | ***0,8023*** | 0,5010 | | |
| | | | Standard error | 0,2742 | | 1,1575 | | |

**Table 4: Allen elasticities of substitution**

| Raw agricultural products | | | | | |
|---|---|---|---|---|---|
| | | | $\sigma_{12}$ | $\sigma_{13}$ | $\sigma_{23}$ |
| 111 | Potatoes | | | | |
| | Conventional estimation | Sample mean value | 4,1840 | 0,4795 | -0,0329 |
| | Bayesian estimation | Global validity Posterior mean value | 0,2879 | 0,5131 | 0,0176 |
| | | Standard error | 14,0588 | 0,0512 | 0,0547 |
| | | Local validity Posterior mean value | -2,7568 | -7,5472 | -8,0984 |
| | | Standard error | 3,4998 | 0,0245 | 0,0175 |
| 112 | Fresh vegetables | | | | |
| | Conventional estimation | Sample mean value | 3,3283 | -0,2509 | 1,1944 |
| | Bayesian estimation | Global validity Posterior mean value | 0,7001 | 0,4708 | 1,2803 |
| | | Standard error | 8,6153 | 0,1870 | 0,0466 |
| | | Local validity Posterior mean value | -0,1154 | -3,8384 | -2,6495 |
| | | Standard error | 2,6765 | 0,0646 | 0,0254 |
| 113 | Dried vegetables | | | | |
| | Conventional estimation | Sample mean value | 4,2387 | 0,1994 | 0,3894 |
| | Bayesian estimation | Global validity Posterior mean value | 2,0000 | 2,0000 | 2,0000 |
| | | Standard error | 0,0000 | 0,0000 | 0,0000 |
| | | Local validity Posterior mean value | 0,0301 | -3,9783 | -3,7859 |
| | | Standard error | 0,2718 | 0,0215 | 0,0312 |
| 114 | Fruit | | | | |
| | Conventional estimation | Sample mean value | 5,1338 | 0,3513 | 1,0302 |
| | Bayesian estimation | Global validity Posterior mean value | 0,9070 | 0,5979 | 0,9914 |
| | | Standard error | 19,8249 | 0,0322 | 0,0828 |
| | | Local validity Posterior mean value | 4,3361 | -0,4647 | 0,2065 |
| | | Standard error | 1,8813 | 0,1566 | 0,0696 |
| 122 | Non tropical oilseeds | | | | |
| | Conventional estimation | Sample mean value | 1,7131 | -0,1394 | -0,3937 |
| | Bayesian estimation | Global validity Posterior mean value | -0,3749 | -0,2177 | -0,3249 |
| | | Standard error | 2,5464 | 0,2092 | 0,3383 |
| | | Local validity Posterior mean value | 0,0652 | -2,9672 | -2,9783 |
| | | Standard error | 2,5676 | 0,2088 | 0,2568 |
| 142 | Flower and plants | | | | |
| | Conventional estimation | Sample mean value | 0,2505 | 1,1988 | 1,9784 |
| | Bayesian estimation | Global validity Posterior mean value | 4,1872 | 5,3843 | 5,6509 |
| | | Standard error | 1,0040 | 0,3700 | 0,1413 |
| | | Local validity Posterior mean value | 2,0996 | 1,6271 | 2,4863 |
| | | Standard error | 8,4280 | 0,4353 | 1,0511 |
| 143 | Other agricultural products | | | | |
| | Conventional estimation | Sample mean value | 15,6363 | 0,1429 | 0,6501 |
| | Bayesian estimation | Global validity Posterior mean value | 0,8141 | 0,8058 | 1,0317 |
| | | Standard error | 231,3109 | 0,1605 | 0,0757 |
| | | Local validity Posterior mean value | -14,2572 | -31,4910 | -30,7889 |
| | | Standard error | 112,6905 | 0,0667 | 0,2188 |

**Table 5: Allen elasticities of substituion**

| Processed food products | | | | | | |
|---|---|---|---|---|---|---|
| | | | | $\sigma_{12}$ | $\sigma_{13}$ | $\sigma_{23}$ |
| 3502 | **Fresh meat** | | | | | |
| | Conventional estimation | | Sample mean value | -5,3437 | 0,824 | 1,5196 |
| | Bayesian estimation | Global validity | Posterior mean value | 1,6031 | 2,3693 | 2,2801 |
| | | | Standard error | 31,4512 | 0,4402 | 0,9898 |
| | | Local validity | Posterior mean value | 5,6438 | 12,1857 | 12,7324 |
| | | | Standard error | 43,1985 | 0,7401 | 1,9942 |
| 3505 | **Game and poultry product** | | | | | |
| | Conventional estimation | | Sample mean value | 15,4420 | 0,0301 | 0,1637 |
| | Bayesian estimation | Global validity | Posterior mean value | 1,0536 | 1,1147 | 1,0924 |
| | | | Standard error | 220,7673 | 0,5121 | 0,3127 |
| | | Local validity | Posterior mean value | -9,8885 | -22,4580 | -22,5226 |
| | | | Standard error | 40,5576 | 0,3809 | 0,1400 |
| 3614 | **Cheese** | | | | | |
| | Conventional estimation | | Sample mean value | 2,3260 | 0,5133 | 0,6372 |
| | Bayesian estimation | Global validity | Posterior mean value | 0,7709 | 0,6902 | 0,7048 |
| | | | Standard error | 2,9006 | 0,0471 | 0,0624 |
| | | Local validity | Posterior mean value | -2,3024 | -6,9674 | -6,7214 |
| | | | Standard error | 14,0610 | 0,0648 | 0,1706 |
| 3616 | **Milk industry by-products** | | | | | |
| | Conventional estimation | | Sample mean value | -0,7827 | 1,6932 | 2,2945 |
| | Bayesian estimation | Global validity | Posterior mean value | | | |
| | | | Standard error | 6,3350 | 7,5800 | 8,5888 |
| | | Local validity | Posterior mean value | 5,2604 | 0,2264 | 1,3936 |
| | | | Standard error | 4,1379 | 4,3850 | 4,9266 |
| | | | Standard error | 35,9890 | 0,2980 | 2,2938 |
| 3701 | **Canned fruit and jam** | | | | | |
| | Conventional estimation | | Sample mean value | 7,2473 | -0,1031 | -3,0272 |
| | Bayesian estimation | Global validity | Posterior mean value | 2,0000 | 2,0000 | 2,0000 |
| | | | Standard error | 0,0000 | 0,0000 | 0,0000 |
| | | Local validity | Posterior mean value | 2,0000 | 2,0000 | 2,0000 |
| | | | Standard error | 0,0000 | 0,0000 | 0,0000 |
| 3702 | **Canned vegetables** | | | | | |
| | Conventional estimation | | Sample mean value | -6,7213 | 1,2063 | 2,3116 |
| | Bayesian estimation | Global validity | Posterior mean value | 5,8052 | 9,2966 | 9,5324 |
| | | | Standard error | 33,2911 | 1,2113 | 1,0445 |
| | | Local validity | Posterior mean value | 7,5584 | 15,5134 | 16,7712 |
| | | | Standard error | 26,0938 | 1,0336 | 1,5727 |
| 3703 | **Canned fish** | | | | | |
| | Conventional estimation | | Sample mean value | 1,4959 | 0,9867 | 0,0070 |
| | Bayesian estimation | Global validity | Posterior mean value | 2,5352 | 2,9893 | 2,9709 |
| | | | Standard error | 0,6531 | 0,3087 | 2,0203 |
| | | Local validity | Posterior mean value | 1,2256 | 1,0659 | 0,2322 |
| | | | Standard error | 1,2099 | 0,7119 | 0,1989 |
| 3902 | **Cookies and bakery products** | | | | | |
| | Conventional estimation | | Sample mean value | -4,1295 | 1,2953 | 4,6544 |
| | Bayesian estimation | Global validity | Posterior mean value | 7,8354 | 8,2960 | 10,0211 |
| | | | Standard error | 40,5377 | 1,2555 | 2,2606 |
| | | Local validity | Posterior mean value | 7,9695 | 12,3127 | 15,6732 |
| | | | Standard error | 95,7296 | 0,6026 | 6,9001 |
| 3907 | **Starch products** | | | | | |
| | Conventional estimation | | Sample mean value | -1,7550 | 0,4514 | 0,0581 |
| | Bayesian estimation | Global validity | Posterior mean value | 0,2353 | 0,5294 | 0,3696 |
| | | | Standard error | 3,7929 | 0,0487 | 0,1049 |
| | | Local validity | Posterior mean value | 1,6038 | 4,2556 | 4,6209 |
| | | | Standard error | 1,6892 | 0,0683 | 0,6783 |

| | | | | $\sigma_{12}$ | $\sigma_{13}$ | $\sigma_{23}$ |
|---|---|---|---|---|---|---|
| 3908 | **Prepared feeds** | | | | | |
| | Conventional estimation | | Sample mean value | -8,5796 | 1,2805 | 0,4466 |
| | Bayesian estimation | Global validity | Posterior mean value | 11,8951 | 20,9040 | 20,8894 |
| | | | Standard error | 61,3022 | 0,5263 | 2,1086 |
| | | Local validity | Posterior mean value | 0,0033 | -2,4454 | -2,8838 |
| | | | Standard error | 670,4030 | 0,3603 | 1,0691 |
| 4031 | **Chocolate and confectionery products** | | | | | |
| | Conventional estimation | | Sample mean value | 3,0403 | 1,0294 | 0,0131 |
| | Bayesian estimation | Global validity | Posterior mean value | 0,7610 | 0,9219 | 0,5409 |
| | | | Standard error | 6,1221 | 0,0989 | 0,1483 |
| | | Local validity | Posterior mean value | 0,4623 | -2,2438 | -3,3954 |
| | | | Standard error | 2,5402 | 0,0601 | 0,0838 |
| 4032 | **Coffee, tea and other herbs** | | | | | |
| | Conventional estimation | | Sample mean value | -3,3898 | 1,5192 | 0,9254 |
| | Bayesian estimation | Global validity | Posterior mean value | -0,0593 | 0,3790 | 0,2360 |
| | | | Standard error | 10,9645 | 1,3902 | 0,5137 |
| | | Local validity | Posterior mean value | 3,7520 | 8,9027 | 8,1089 |
| | | | Standard error | 0,8908 | 0,2116 | 0,0658 |
| 4033 | **Seasonings and salad dressings** | | | | | |
| | Conventional estimation | | Sample mean value | 8,3713 | -1,6348 | -0,9295 |
| | Bayesian estimation | Global validity | Posterior mean value | 0,8582 | 0,5610 | 0,9574 |
| | | | Standard error | 58,4037 | 4,4063 | 3,1703 |
| | | Local validity | Posterior mean value | -0,0305 | -2,2731 | -2,0365 |
| | | | Standard error | 39,6363 | 4,0482 | 2,7069 |
| 4034 | **Baby and dietetic foods** | | | | | |
| | Conventional estimation | | Sample mean value | -1,5258 | 1,2391 | 1,2578 |
| | Bayesian estimation | Global validity | Posterior mean value | 4,1477 | 5,3725 | 5,1308 |
| | | | Standard error | 4,9388 | 0,3488 | 0,1293 |
| | | Local validity | Posterior mean value | 2,5248 | 6,0738 | 6,7288 |
| | | | Standard error | 2,5267 | 0,3859 | 0,1297 |
| 4036 | **Soup mixes** | | | | | |
| | Conventional estimation | | Sample mean value | -0,6934 | 0,9639 | 1,9147 |
| | Bayesian estimation | Global validity | Posterior mean value | 6,2468 | 8,7985 | 9,3401 |
| | | | Standard error | 6,6912 | 0,4209 | 0,1199 |
| | | Local validity | Posterior mean value | 1,6478 | -0,4092 | 0,3968 |
| | | | Standard error | 130,0161 | 0,1837 | 0,5952 |
| 4037 | **Miscallenous food products** | | | | | |
| | Conventional estimation | | Sample mean value | -0,7705 | 0,4812 | 0,7062 |
| | Bayesian estimation | Global validity | Posterior mean value | 0,1115 | 0,2847 | 0,2830 |
| | | | Standard error | 1,1025 | 0,0429 | 0,1614 |
| | | Local validity | Posterior mean value | 0,5776 | 2,4880 | 3,2624 |
| | | | Standard error | 0,7147 | 0,1585 | 0,9012 |
| 4101 | **Brandies** | | | | | |
| | Conventional estimation | | Sample mean value | 0,0969 | 1,7765 | 4,6483 |
| | Bayesian estimation | Global validity | Posterior mean value | 11,9070 | 15,3575 | 18,0396 |
| | | | Standard error | 16,7386 | 0,3899 | 0,4311 |
| | | Local validity | Posterior mean value | 2,8131 | -4,0699 | -1,1919 |
| | | | Standard error | 64,6972 | 0,9478 | 0,9431 |
| 4104 | **Wines aperitives** | | | | | |
| | Conventional estimation | | Sample mean value | 9,1324 | 1,3241 | 0,8111 |
| | Bayesian estimation | Global validity | Posterior mean value | 6,2804 | 8,4286 | 8,5381 |
| | | | Standard error | 90,9213 | 0,6145 | 1,8830 |
| | | Local validity | Posterior mean value | -2,5959 | -11,5847 | -12,1460 |
| | | | Standard error | 16,0684 | 0,2154 | 0,3406 |
| 4108 | **Fruit and vegetable juices** | | | | | |
| | Conventional estimation | | Sample mean value | 0,8928 | 0,6101 | 0,1042 |
| | Bayesian estimation | Global validity | Posterior mean value | 0,6039 | 0,6774 | 0,3807 |
| | | | Standard error | 0,1591 | 0,0463 | 0,1237 |
| | | Local validity | Posterior mean value | 0,7097 | 1,0110 | 0,2150 |
| | | | Standard error | 0,9509 | 0,3644 | 0,0894 |