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► **To cite this version:**

Nadine Herrard, Yves Le Roux, Yves Surry, . Département d'Economie Et de Sociologie Rurales, Rennes. A bayesian analysis of trade in agri-food products : an application to France. Ecole chercheurs d'économie internationale, Nov 1996, Rennes, France. 14 p. hal-02354663

HAL Id: hal-02354663

<https://hal.science/hal-02354663>

Submitted on 7 Jun 2020

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INRA - Département d'Economie et Sociologie Rurales
ECOLE CHERCHEURS D'ECONOMIE INTERNATIONALE
Rennes, 13-14-15 novembre 1996

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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 developed 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 leaned towards 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 from 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 homogeneously 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 assumptions: (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, homogeneously and weakly separable consumer preference structure where each good q_i for $i = 1, 2, \dots, n$ can be supplied by a set of m geographically differentiated products q_{is} from $s = 1, 2, \dots, m$. 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:

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

where $v_i(\cdot)$ 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 $q_i = v_i(\cdot)$. $U[\cdot]$ and $v_i(\cdot)$ satisfy the usual conditions of monotonicity, quasi-concavity and differentiability. Due to the linear homogeneity of the sub-utility functions $v_i(\cdot)$, it is possible to derive subgroup conditional demands of the form, for all s belonging to group i :

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

The optimization procedure behind the utility function [1.] may be viewed as occurring 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:

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

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. α_{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:

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

The subscript i is now omitted for reasons of convenience.

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

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

where δ_{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 σ can be derived by setting all the b_s equal to a constant b . The elasticity of substitution σ is then equal to $\alpha = 1 - b$.

The system of demand share equations formed by expression [3.] and with stochastic residuals μ_s could be estimated by an appropriate system estimation technique such as iterative seemingly unrelated estimation (ITSUR) or maximum likelihood (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 form¹. Then, iterative three stage least squares estimation is applied to this new system 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 rearrangement 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:

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 μ_s follows a logistic distribution.

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

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

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

where $dy/y = (dS_s/S_s) - (dS_m/S_m)$; $d(\cdot)$ designates the symbol "first-difference"; and ε_s is a vector of stochastic residuals which follows a multivariate normal distribution with zero means and a variance/covariance matrix Σ . 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 differences².

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

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 conditions³ - 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:

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

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 $f(\cdot)$ expressed as:

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

where y is the sample data set and $L(\cdot)$ 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 distribution over the the domain D , that is⁴:

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

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

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 expected loss.

with the (global or local) validity conditions, we would only retain the replications for which such conditions are satisfied 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.]:

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

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:

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

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.

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

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:

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

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 Σ , the resulting posterior density function for b is given by:

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

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 parameters⁵, 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 $f(\cdot)$ 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 associated 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,

⁵ Even in Zellner's case, the posterior distribution function of the structural 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:

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

for $s = 1, 2$

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 products⁶ 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

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 substitutability 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 small⁷, 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 substitutability relationships among sources:

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, substitutability 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.

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. Second, we propose the use of bayesian estimation procedures in agricultural trade modelling. The application to this Generalized Armington 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 methods 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 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).

References

- Chalfant, J. A., R. S. Gray and K. J. White (1991). **Evaluating prior beliefs in a demand system: the case of meat demand in Canada.** *American Journal of Agricultural Economics*. 73: 476-490.
- Chevassus-Lozza E., and Gallezot J. (1993). **L'intégration des marchés agro-alimentaires européens.** *Economie Prospective Internationale*. 53: 81-94.
- de Frahan, B. and P. Libert (1996) **Le commerce intra-branche dans l'industrie agro-alimentaire européenne: une nouvelle forme de globalisation.** *Economie rurale* (forthcoming).
- Geweke, J. (1988). **Antithetic acceleration of Monte Carlo integration in bayesian inference.** *Journal of Econometrics* 38: 73-89.
- Geweke, J. (1989). **Bayesian inference in econometric models using Monte Carlo integration.** *Econometrica*, 57: 1317-1340.
- Gordon, S. and G. Bélanger (1996). **Echantillonnage de Gibbs et autres applications économétriques des chaînes markoviennes.** *L'actualité économique - Revue d'analyse économique* 72: 27-49.
- Hanoch, G. (1975). **Production and demand models with direct or indirect implicit additivity.** *Econometrica*, 43(3): 395-419.
- Hazilla, M. and R. J. Kopp (1986). **Testing for separable functional structure using temporary equilibrium models.** *Journal of Econometrics*. 33: 119-141
- Hayes, D. J., T. I. Wahl and G. Williams (1993). **Testing restrictions on a model of Japanese meat demand.** *American Journal of Agricultural Economics*. 72: 556-566.
- Heckelei, T. and R.C Mittelhammer (1996). **Bayesian bootstrap analysis of systems of equations.** Discussion Paper 96-02, Agricultural and Resource Economics, University of Bonn.
- Monceau, C. (1995). **Trente ans d'échanges agro-alimentaires.** *INSEE-Résultats*, Economie Générale. n° 417-418. Paris: INSEE.
- Rossi, P. (1985). **Comparison of alternative functional forms in production.** *Journal of Econometrics*, 30: 169-179.
- Ruttan V. (1978) **Structural retardation and the modernisation of French agriculture: a skeptical view.** *Journal of Economic History*. 38: 714-728.
- Shumway, R. C., W. P. Alexander and H. Talpaz. (1990) **Texas field crops: estimation with curvature.** *Western Journal of Agricultural Economics*. 15: 45-55.
- Theil , H. (1969). **A multinomial extension of the linear logit model.** *International Economic Review* 10: 251-259.
- Tiffin, R. and A. Moxey (1992). **The imposition of curvature restrictions in a model of UK agriculture: a bayesian approach.** Discussion paper 3/92. Department of Agricultural Economics, University of Newcastle.
- Van Dijk, H. K., and T. Kloek (1990). **Further experience in Bayesian analysis using Monte Carlo integration.** *Journal of Econometrics* 14: 307-328.
- Zellner, A. (1971). *An introduction to Bayesian inference in econometrics*. New York: John Wiley & Sons.

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
		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		
		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		
		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		
		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
		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		
		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		
		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		
		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		
		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	-4,0662		
			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	Miscellaneous 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						
			σ_{12}	σ_{13}	σ_{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
	Local validity		Standard error	14,0588	0,0512	0,0547
	Bayesian estimation	Global validity	Posterior mean value	-2,7568	-7,5472	-8,0984
Local validity		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
	Local validity		Standard error	8,6153	0,1870	0,0466
	Bayesian estimation	Global validity	Posterior mean value	-0,1154	-3,8384	-2,6495
Local validity		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
	Local validity		Standard error	0,0000	0,0000	0,0000
	Bayesian estimation	Global validity	Posterior mean value	0,0301	-3,9783	-3,7859
Local validity		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
	Local validity		Standard error	19,8249	0,0322	0,0828
	Bayesian estimation	Global validity	Posterior mean value	4,3361	-0,4647	0,2065
Local validity		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
	Local validity		Standard error	2,5464	0,2092	0,3383
	Bayesian estimation	Global validity	Posterior mean value	0,0652	-2,9672	-2,9783
Local validity		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
	Local validity		Standard error	1,0040	0,3700	0,1413
	Bayesian estimation	Global validity	Posterior mean value	2,0996	1,6271	2,4863
Local validity		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
	Local validity		Standard error	231,3109	0,1605	0,0757
	Bayesian estimation	Global validity	Posterior mean value	-14,2572	-31,4910	-30,7889
Local validity		Standard error	112,6905	0,0667	0,2188	

Table 5: Allen elasticities of substitution

Processed food products						
			σ_{12}	σ_{13}	σ_{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
		Local validity	Standard error	31,4512	0,4402	0,9898
			5,6438	12,1857	12,7324	
			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
		Local validity	Standard error	220,7673	0,5121	0,3127
			-9,8885	-22,4580	-22,5226	
			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
		Local validity	Standard error	2,9006	0,0471	0,0624
			-2,3024	-6,9674	-6,7214	
			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	6,3350	7,5800	8,5888
		Local validity	Standard error	5,2604	0,2264	1,3936
			4,1379	4,3850	4,9266	
			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
		Local validity	Standard error	0,0000	0,0000	0,0000
			2,0000	2,0000	2,0000	
			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
		Local validity	Standard error	33,2911	1,2113	1,0445
			7,5584	15,5134	16,7712	
			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
		Local validity	Standard error	0,6531	0,3087	2,0203
			1,2256	1,0659	0,2322	
			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
		Local validity	Standard error	40,5377	1,2555	2,2606
			7,9695	12,3127	15,6732	
			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
		Local validity	Standard error	3,7929	0,0487	0,1049
			1,6038	4,2556	4,6209	
			1,6892	0,0683	0,6783	

			σ_{12}	σ_{13}	σ_{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
		Local validity	Standard error	61,3022	0,5263	2,1086
			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
		Local validity	Standard error	6,1221	0,0989	0,1483
			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
		Local validity	Standard error	10,9645	1,3902	0,5137
			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
		Local validity	Standard error	58,4037	4,4063	3,1703
			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
		Local validity	Standard error	4,9388	0,3488	0,1293
			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
		Local validity	Standard error	6,6912	0,4209	0,1199
			Posterior mean value	1,6478	-0,4092	0,3968
			Standard error	130,0161	0,1837	0,5952
4037	Miscellaneous 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
		Local validity	Standard error	1,1025	0,0429	0,1614
			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
		Local validity	Standard error	16,7386	0,3899	0,4311
			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
		Local validity	Standard error	90,9213	0,6145	1,8830
			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
		Local validity	Standard error	0,1591	0,0463	0,1237
			Posterior mean value	0,7097	1,0110	0,2150
			Standard error	0,9509	0,3644	0,0894