# Organic Food Consumption Patterns in France 

## By

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#### Abstract

This research addresses two important issues for the future expansion of organic consumption in France. The first one is related to knowing whether the organic choice is a permanent feature of consumer's attitude or not: Do organic buyers occasionally pick one organic product or do they choose organic for "several" categories? The second issue concerns the impact of prices on buying organics which is revisited, distinguishing between capturing new consumers and increasing the demand coming from people already involved in organic markets. These questions are examined using the market basket approach; the price issue requires further estimations of demand models. The study relies on two staple food products, eggs and milk. The findings are : (i) choosing organic for one of the two items reinforces the probability of purchasing also the organic version of the second item; (ii) marginal reductions of the organic price have no impact on the decision of buying organic rather than conventional products; (iii) on the contrary, when people already purchase organic products, price elasticities are rather high; (iv) organic buyers' demographic profile is not related to income neither to age nor to family size, but to the educational level.


Key words: market basket approach, organic products, purchasing behavior, logit model.

JEL: C35, D12, Q13.
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In the recent years, in most developed countries, the demand for organic food has grown rapidly. In the USA, from 1997 to 2005, the annual growth rate has been $18.5 \%$ (Klonsky, 2007), almost ten times the rate in total food. In France, where the process is slower, we nevertheless record a two digit rate of expansion ( $10 \%$ per year from 1999 to 2005, according to the French Agency for the Development and the Promotion of the Organic Agriculture). As regards to supply, the International Foundation for Organic Agriculture states that, from 1999 to 2007, the world area devoted to organic food production has tripled. In 2007, the "green surfaces" were mainly located in Oceania (32\%), Europe ( $24 \%$ ) and Latin America (20\%), a region being mainly net exporter, specifically towards North America. ${ }^{1}$ In the rest of the world, organic expansion is clearly at its very beginnings. ${ }^{2}$ The French green area represents $8 \%$ of the European one, which positions France at the fifth rank on the continent, after Italy, $16 \%$, Spain, $14 \%$, Germany, $12 \%$, and the UK, $9 \%$. The objectives of the agreement concluded at the "Grenelle of the Environment", a meeting between the government and the green associations in 2008, are to reduce the use of pesticides by $50 \%$ and to increase the area devoted to organic productions up to $6 \%$ in 2010 , and $20 \%$ in 2020.

In spite of this recent development, no one can be sure about the future of organic consumption. Indeed, it remains a small segment, representing in most countries just a small percentage of the global food expenses ( $1.2 \%$ in France, $2.2 \%$ in the USA). Moreover, most of organic food purchases are occasional: in France, only $6 \%$ of the population is used to buy organic products each day. The question is thus whether such manifestations of interest towards the organic products are likely to transform into a regular purchasing habit. Economic research aims at understanding the mechanisms which can enforce the expansion of the demand for organics. A first concern is to measure the true willingness to pay (WTP) for organic and the motivations to pay for it. In a recent paper, Griffith and Nesheim (2008) compute, over 98 food groups, a global WTP for organic in the UK. They find that looking simply at the mean differences in price between organic and non-organic goods substantially over-estimates the mean premium for organic. Indeed, in this case, it represents $56 \%$ of the non-organic average price instead of being only $33 \%$ when controlling for all product characteristics. Hassan and Monier-Dilhan (2006) show the WTP for an organic label varies according to the brand it is associated with: The organic attracts more value when associated with store brands than with national brands. This can lead to an opportunity for retailers to develop organic food through store brands. Griffith and Nesheim also point that the reasons households are willing to pay vary, with quality being the most important, health concerns coming second, and environmental concerns lagging far behind. This statement contradicts Bellows et al.'s one (2008). According to them, demand for organic relying on environmental concerns is potentially larger than the one driven by personal health considerations.

A second concern is to measure the impact of a diminution of the organic prices on the corresponding demand. According to consumer surveys ${ }^{3}$, price leads the list of the barriers to purchasing organic products in France, more generally in Europe but also in the U.S. (Dimitri and Oberholtzer, 2005). The second main obstacle is the availability of organic products, and the third one is the small size of the organic product range. Thompson and Kidwell (1998) estimate a discrete choice model to assess the impact of prices and demographic characteristics on the choice of organic produce concerning fresh vegetables in the U.S. They find that marginal variations of the price difference between the organic and the conventional items have only a weak effect on the probability of buying organic. In a study relying on a demand model and concerning frozen vegetable, Glaser and Thompson (1999) find organic

[^0]products are unit price elastic. In the same vein, Bunte et al. (2005) estimate a demand model and find small own-price elasticity for organic products..

A third concern is the impact of the socio-demographic characteristics of consumers prone to purchasing organic food. Surveying studies about consumer demand for organic foods, Thompson (1998) concludes that neither age, nor income nor gender seem to influence the probability of buying organic products. Families with children under eighteen are more prone to make the organic choice and well educated consumers too.

This paper addresses two issues of first interest for the expansion of the demand for organics. The first one which, to our knowledge, has not been yet investigated for organics is whether organic purchases are or not additional. Indeed, we want to know if organic buyers occasionally pick one organic product or choose organic for "several" categories: Does an "organic consumer" potentially exist? The question has important implications for the future of organic markets: A positive answer means that, provided the industry and the retailers insure regular and easy supply, the demand for organics could extend to a large number of products.

If the organic choice is a permanent feature of consumers' attitude, buying the organic model in one category product should increase the probability of buying also organic when purchasing some other product. This hypothesis can be tested relying on discrete choice models. Indeed, during the last fifteen years, an increasing body of researches aims at adapting choice models to capture correlations between choices among different product categories (Russell et al., 1997). Interdependence between goods is often related to some common factors such as brand name or price as in Singh, Ansari and Gupta (2005)'s multicategory choice model which is applied to the demand for snacks. Interdependence can also rely on some product class complementarity as shown in Manchanda, Ansari and Gupta (1999) who assess complementarity within two pairs of goods (laundry detergent/fabric softener, and cake mix/cake frosting). It can also depend simply on the store traffic patterns as shown by Russell and Petersen (2000), who study the purchasing behavior for four grocery paper goods located in the same shop department.

Many recent empirical studies rely on the classical framework where a random utility model is specified with the distribution of the random parts of the utilities associated to the different products being assumed a multivariate normal. In this case, they obtain the multivariate probit model whose estimation uses hierarchical Bayes framework (see Rossi, Allenby, and McCulloch, 2005) and is computationally intensive. Russell and Petersen (2000) propose an alternative approach easier to implement but consistent with the random utility framework. We apply this approach to investigate for possible interdependences among organic purchases using purchases data of French households obtained from TNS Worldpanel.

The second issue addressed in this paper concerns the impact of prices. Russell and Petersen (2000)'s basket choice model opens into computing probability-price elasticities which measure the impact of price changes on the probability of buying organic rather than conventional. This question applies in particular to potential entrants into the organic markets. This aspect of the price issue is completed by the lessons drawn from the standard approach considering the global impact of price variations on the quantities. Indeed, this approach takes also into account the impact of price changes on the quantities, independently of their influence on the purchase frequency. This dimension is considered computing the price elasticities of a demand model.

We focus our analysis on the households' purchasing behaviour for two staple products, eggs and milk. The first section provides an overview of the organic market expansion for these products. The second section is devoted to the analysis of the association between organic and conventional product choices. The third section addresses the question of
the price impacts on the purchasing decisions in terms of probability of purchase as well as in terms of quantity purchased. The last section concludes.

## 1. Organic food demand for eggs and milk

In order of importance, the most consumed organic products in France are fruit and vegetables, dairy products and eggs. ${ }^{4}$ For this reason, we study eggs and milk, two staple food products, whose organic market share is $2.2 \%$ for milk and $3.2 \%$ for eggs (2005),. Table 1 presents the main features of the evolution the French annual consumption for the two categories, between 1998 and 2005. These figures are computed from the French TNS Worldpanel data (see section 2). ${ }^{5}$

Table 1: Evolution of French organic milk consumption from 1998 to 2005

| Year | Quantity per household |  |  | Consumers (\% of total buyers) |  | Prices |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Total | Organic | Organic | At least one organic purchase | $\begin{gathered} \text { Organic } \\ \text { purchases } \geq \\ 90 \% \\ \text { of total } \\ \hline \end{gathered}$ | Organic (€) | Organic/ <br> nonorganic |
|  | liter for milk, unit for egg |  | \% |  |  |  |  |
|  | Eggs |  |  |  |  |  |  |
| 1998 | 181 | 2.58 | 1.42 | 7.3 | 1.93 | 0.28 | 1.93 |
| 1999 | 146 | 3.44 | 2.36 | 9.2 | 2.61 | 0.29 | 1.87 |
| 2000 | 162 | 4.96 | 3.06 | 11.3 | 3.78 | 0.29 | 1.81 |
| 2001 | 166 | 4.86 | 2.96 | 11.2 | 3.78 | 0.31 | 1.94 |
| 2002 | 165 | 4.65 | 2.81 | 11.8 | 3.98 | 0.31 | 1.82 |
| 2003 | 186 | 5.12 | 2.75 | 12.6 | 4.50 | 0.35 | 2.06 |
| 2004 | 179 | 4.94 | 2.77 | 12.4 | 4.61 | 0.35 | 2.06 |
| 2005 | 181 | 5.82 | 3.21 | 13.3 | 4.91 | 0.34 | 2.00 |
|  | Milk |  |  |  |  |  |  |
| 1998 | 129. | 0.87 | 0.67 | 3.33 | 0.32 | 0.98 | 1,69 |
| 1999 | 105 | 1.01 | 0.96 | 4.73 | 0.46 | 1.15 | 1,92 |
| 2000 | 1174 | 1.43 | 1.22 | 5.45 | 0.68 | 1.16 | 1,90 |
| 2001 | 121 | 1.62 | 1.34 | 6.47 | 0.67 | 1.22 | 1,91 |
| 2002 | 127 | 2.07 | 1.62 | 7.15 | 0.87 | 1.11 | 1,66 |
| 2003 | 118 | 1.96 | 1.66 | 7.01 | 1.03 | 1.21 | 1,73 |
| 2004 | 108 | 2.01 | 1.86 | 8.08 | 1.25 | 1.22 | 1,69 |
| 2005 | 105 | 2.26 | 2.15 | 8.60 | 1.50 | 1.21 | 1,63 |

During the 1998-2005 period, the total demand per household remains stable (eggs) or decreases (milk), whereas the purchased quantities of the two organic versions double. At the beginning of the period, the organic market shares are $0.67 \%$ for milk and $1.42 \%$ for eggs; seven years later, they are respectively $2.15 \%$ and $3.21 \%$. At the same time the percentage of households buying organic products increases. This is true for all categories of consumers, for those buying organic at least once a year as well as for households buying more than $90 \%$ of

[^1]organic products in the category. During the period, prices (organic and conventional) raised regularly, at the rate of $15 \%$ (the inflation rate) for milk and $21 \%$ for eggs. The ratio between organic and non-organic prices remains stable, at a high level between 1.50 and 2.00).

## 2. Cross-category dependence among organic choices

In the present section, we deal with the issue of measuring the association between organic product choices in consumer baskets. We conduct a market basket analysis by concentrating on the composition of the basket of products, organic or not, purchased by a household during a single shopping trip. This analysis aims at quantifying the complementary or substitutional effects between the products, organic or not, that characterize the basket choice of a consumer. The analysis draws from the multivariate logit approach developed by Russell and Petersen (2000). As shown below, it can be estimated using classical maximum likelihood as its likelihood has a closed-form solution and does not need the computational effort involved in a multivariate probit approach. The main advantage of the multivariate logit approach is its closeness to the well-known and established conditional logit model (see Train, 2003) whose implementation can be done using standard econometric softwares such as Stata.

### 2.1 The Multivariate Logit Approach

When inspecting the market basket of consumers, we need to model the joint distribution of a vector of choice variables describing the presence or absence of the given products in the basket. If you assume that you have a basket with four products inside, we denoted by A, B, C , and D , then the choice process for the entire basket can be expressed in terms of a four multivariate distribution $\mathrm{P}[\mathrm{A}, \mathrm{B}, \mathrm{C}, \mathrm{D}]$ that defines the relative likelihood of each of the $2^{4}=16$ possible market baskets. For instance, a random utility model can be specified where the distribution of the random parts of the utilities associated to the different products is assumed to be a multivariate normal. Then, we obtain the multivariate probit model whose estimation uses hierarchical Bayes framework (see Rossi, Allenby, and McCulloch, 2005) and is computationally intensive. Another approach (Russell and Petersen, 2000) starts with modeling the choice behavior for one product conditional on the decisions made for the other products. You have several possibilities that arise from the specific order in which you place the products in the basket. In the example of a basket of four products, taking only the last choice into account, four last choices exist giving rise to four conditional probabilities: $\mathrm{P}[\mathrm{A} \mid \mathrm{B}, \mathrm{C}, \mathrm{D}], \mathrm{P}[\mathrm{B} \mid \mathrm{A}, \mathrm{C}, \mathrm{D}], \mathrm{P}[\mathrm{C} \mid \mathrm{A}, \mathrm{B}, \mathrm{D}]$, and $\mathrm{P}[\mathrm{D} \mid \mathrm{A}, \mathrm{B}, \mathrm{C}]$. This approach implicitly assumes that, although the true decision sequence between the products is not known, it is possible to develop a set of choice models that collectively describe the last decision in any possible decision sequence. Then, by specifying these conditional distributions, this approach allows to derive the properties of $\mathrm{P}[\mathrm{A}, \mathrm{B}, \mathrm{C}, \mathrm{D}]$ the probability that describes the relative likelihood of each possible bundle.
Now consider the Russell and Petersen (2000) approach in more details. Assume that a consumer k faces N products during a shopping trip. Then a market basket consists in a vector of product choices $\mathrm{B}(\mathrm{k})=(\mathrm{I}(1, \mathrm{k}), \ldots, \mathrm{I}(\mathrm{i}, \mathrm{k}), \ldots, \mathrm{I}(\mathrm{N}, \mathrm{k}))$ where $\mathrm{I}(\mathrm{i}, \mathrm{k})=1$ if consumer k buys product I , and 0 otherwise. Because each $\mathrm{I}(\mathrm{i}, \mathrm{k})$ can take only two values, there are $2^{\mathrm{n}}$ possible baskets, the null basket corresponding to non purchases across all products. In order to specify the probability that a product is chosen conditional upon the known choices of all the other products, we assume that the conditional utility of consumer k for product I is given by

$$
\begin{equation*}
\mathrm{U}(\mathrm{i}, \mathrm{k})=\alpha_{i}+\beta_{\mathrm{i}} \operatorname{Price}_{\mathrm{ik}}+\sum_{\mathrm{j} \neq i} \theta_{i j k}(\mathrm{j}, \mathrm{k})+\zeta(\mathrm{i}, \mathrm{k}) \tag{1}
\end{equation*}
$$

where Price $_{\mathrm{ik}}$ denotes the price of product $i$ faced by consumer $k . \alpha_{i}$ is a product specific constant. The term $\sum_{\mathrm{j} \neq i} \theta_{i j k} \mathrm{I}(\mathrm{j}, \mathrm{k})$ links the choice of the current product i to the actual choice decisions in all other products in the basket. It will be shown below that each cross-effect parameter $\theta_{i j k}$ possesses an interpretation in terms of the association between two products. More specifically, $\theta_{i j k}>0$ will imply a positive association between the two products i and j , while $\theta_{i j k}<0$ will imply a negative association. Moreover, we will see that logical consistency will require the cross-effect parameters to be symmetric, i.e. $\theta_{i j k}=\theta_{j i k}$. These parameters are also allowed to vary across consumers.
The conditional probability of purchasing product i given the choice outcomes in all other products is the probability that $\mathrm{U}(\mathrm{i}, \mathrm{k})>0$. Assuming that the random error $\zeta(\mathrm{i}, \mathrm{k})$ has a Gumbel distribution, this conditional probability can be expressed as the logit model

$$
\begin{equation*}
\operatorname{Pr}(I(i, k))=1 \mid I(j, k) \text { for } j \neq i=[1+\exp \{-\mathrm{Z}(\mathrm{i}, \mathrm{k})\}]^{-1} \tag{2}
\end{equation*}
$$

where $Z(i, k)$ denotes the deterministic part of the utility $U(i, k)$, i.e.

$$
\begin{equation*}
\mathrm{Z}(\mathrm{i}, \mathrm{k})=\alpha_{i}+\beta_{\mathrm{i}} \operatorname{Price}_{\mathrm{ik}}+\sum_{\mathrm{j} \neq i} \theta_{i j \mathrm{k}}(\mathrm{j}, \mathrm{k}) \tag{3}
\end{equation*}
$$

Intuitively, it means that the consumer's choice of the final product in the basket, the product $i$, is affected by the bundle of products already selected. In this way, the probability of choice for one product is dependent of the context created by previous choices.
Consider again the example with four products. Generally, the knowledge of all the conditional probabilities $\mathrm{P}[\mathrm{A} \mid \mathrm{B}, \mathrm{C}, \mathrm{D}], \mathrm{P}[\mathrm{B} \mid \mathrm{A}, \mathrm{C}, \mathrm{D}], \mathrm{P}[\mathrm{C} \mid \mathrm{A}, \mathrm{B}, \mathrm{D}]$, and $\mathrm{P}[\mathrm{D} \mid \mathrm{A}, \mathrm{B}, \mathrm{C}]$ does not allow recovering directly the joint distribution $\mathrm{P}[\mathrm{A}, \mathrm{B}, \mathrm{C}, \mathrm{D}]$. The factorization theorem developed in the framework of spatial statistics by Besag (1974) allows the derivation of the expression for the relative probabilities of two realizations of the vector ( $\mathrm{A}, \mathrm{B}, \mathrm{C}, \mathrm{D}$ ) as a function of the conditional probabilities (see Appendix). More structure must be imposed on these probabilities to get those of absolute probabilities. It can be shown that if the conditional probability distributions belong to the exponential family of distributions then an unique characterization of the joint probability exists (see also Besag, 1974). Moreover, the exponential family assumption implies that all the cross-effects parameters are symmetric. This result applies directly to the conditional probabilities we derive above as their distributions belong to the exponential family of distributions. Thus, let $\mathrm{B}(\mathrm{k})=(\mathrm{I}(1, \mathrm{k}), \ldots$, $\mathrm{I}(\mathrm{i}, \mathrm{k}), \ldots, \mathrm{I}(\mathrm{N}, \mathrm{k}))$ denote a basket where $\mathrm{I}(\mathrm{i}, \mathrm{k})$ has the same interpretation as above, and let $\mathrm{b}=$ $(\mathrm{X}(1, \mathrm{~b}), \ldots, \mathrm{X}(\mathrm{I}, \mathrm{b}), \ldots, \mathrm{X}(\mathrm{N}, \mathrm{b}))$ denote a realization of the basket $\mathrm{B}(\mathrm{k})$. In the example of four products, $\mathrm{B}(\mathrm{k})=(\mathrm{A}, \mathrm{B}, \mathrm{C}, \mathrm{D})$ and $\mathrm{b}=(1,0,1,0)$ is a realization of this basket where products A and C are present and not products B and D . Then, given equations $\ldots$ and the assumption that the cross-effect parameters are symmetric, the probability of selecting basket $b$ is

$$
\begin{equation*}
\operatorname{Pr}(\mathrm{B}(\mathrm{k})=\mathrm{b})=\frac{\exp \{(\mu(\mathrm{b}, \mathrm{k})\}}{\sum_{\mathrm{b}^{*}} \exp \left\{\mu\left(\mathrm{~b}^{*}, \mathrm{k}\right)\right\}} \tag{4}
\end{equation*}
$$

Where $\mathrm{b}^{*}$ denotes all possible $2^{\mathrm{N}}$ baskets and $\mu(\mathrm{b}, \mathrm{k})$ is the utility of basket b whose expression is given by

$$
\begin{equation*}
\mu(\mathrm{b}, \mathrm{k})=\sum_{\mathrm{i}} \alpha_{\mathrm{i}} \mathrm{I}(\mathrm{i}, \mathrm{~b})+\sum_{\mathrm{i}} \beta_{\mathrm{i}} \operatorname{Price}_{\mathrm{ik}} \mathrm{X}(\mathrm{i}, \mathrm{~b})+\sum_{i<j} \theta_{i j \mathrm{k}} \mathrm{X}(\mathrm{i}, \mathrm{~b}) \mathrm{X}(\mathrm{j}, \mathrm{~b}) \tag{5}
\end{equation*}
$$

The model in (5) has a noticeable feature: It looks like a standard conditional logit model with additional cross-effect terms $\theta$. It can thus be estimated using simple modifications of standard conditional logit estimation procedures in classical econometric softwares such as Stata. Indeed, each basket can be considered in the framework of a conditional logit model as a choice alternative. Its characteristics can then be easily derived from the expression of $\mu(\mathrm{b}, \mathrm{k})$. But it should be kept in mind that the model in (5) is not the result of the extension of a standard model, but it is derived using methods from spatial statistics (Besag, 1974).
Now, to explain the different outcomes of $\mu(\mathrm{b}, \mathrm{k})$ in (5), we present an example of a two product case. It is then easy to show that the cross-effect term $\theta_{12}$ obeys the relationship

$$
\theta_{12}=\log [\mathrm{P}[\mathrm{~A}=1, \mathrm{~B}=1] \mathrm{P}[\mathrm{~A}=0, \mathrm{~B}=0] /(\mathrm{P}[\mathrm{~A}=0, \mathrm{~B}=1] \mathrm{P}[\mathrm{~A}=1, \mathrm{~B}=0])]
$$

where the right hand side is the so-called log odds ratio used to measure the association in a two categorical variables table. Because the log odds ratio is symmetrical in the product indices, the cross-effect parameter must be symmetrical as well.

### 2.2 Data

Data concerning eggs and milk purchases are drawn from the French TNS Worldpanel, a micro-level database which contains information about every individual food purchase made by about 10000 French consumers (date of purchase, quantity, price, label, store where the purchase was made...). This dataset provides also information on the consumers' characteristics (income, age, education ...). The present analysis relies on the year 2005 where one can list 108,804 baskets containing eggs and /or milk. These purchases, $95 \%$ of which are made in mass distribution, were conducted by 12,890 households. Households’ socio-demographic characteristics are shown in the table 2.

Table 2: Household Data Summary

|  | Mean | Std. <br> Dev. | Min | Max |
| :--- | :---: | :---: | :---: | :---: |
| Household's size | 2.7 | 1.3 | 1 | 5 |
| Monthly income <br> per consumer unit <br> $(€)$ | 1203 | 653 | 90 | 5031 |
| Age <br> (year) | 48,4 | 15.5 | 18 | 98 |
| Educational level | Bachelor | - | Primary | $>$ Bachelor <br> +4 |

The market basket distribution is shown in table 3, where each of the 108,795 baskets is identified in terms of its contents: CE: Conventional egg, OE: Organic egg, SM: Conventional milk, OM: Organic milk.

Table 3: Basket Market Distribution

| Baskets with | Number of baskets |
| :---: | :---: |


| CE | 9768 |
| :--- | ---: |
| OE | 415 |
| CM | 24102 |
| OM | 310 |
| CE \& OE | 433 |
| OE \& OM | 77 |
| OE \& CM | 1497 |
| CE \& OM | 427 |
| CE \& CM | 63193 |
| CM \& OM | 959 |
| CE \& OE \& OM | 94 |
| CE \& OE \& CM | 3638 |
| OE \& CM \& OM | 242 |
| CE \& CM \& OM | 3052 |
| CE \& OE \& CM \& OM | 597 |
|  | 108804 |

As might be expected, baskets with organic products occur much less often than baskets with conventional products. Nevertheless, the number of baskets is never zero, whatever the combination of goods taken into account. Typically, a consumer scanner dataset such as the panel we use provides, for each purchased product, information for the unit price. However, it does not give any information on the brands for the other products that were on the shelves at the same time but that were not purchased. In other words, we observe only the prices for the products that belong to the basket selected by the household during his shopping trip and we must handle the problem of the missing prices. To get round that issue, we impute a value to each missing price in a given category of products by randomly sampling from a log-normal distribution ${ }^{6}$ whose characteristics are estimated using the average and standard deviation of the prices in the same category. We introduce a source of variability across prices by distinguishing the case of a purchase occurring in hard discounting store from the other cases.

### 2.3. Market Basket Analysis

First of all, we deal with a simple model without demographic shifters. Demographic variables are introduced in a second step. In this section we comment the results concerning the correlation between organic choices.

### 2.3.1 Benchmark Model

The basic model, used as a benchmark, is the one where in equation (5) the cross effect does not depend on consumer k: $\theta_{i j k}=\theta_{i j} \forall k$.

$$
\begin{equation*}
\mu(\mathrm{b}, \mathrm{k})=\sum_{\mathrm{i}} \alpha_{\mathrm{i}} \mathrm{I}(\mathrm{i}, \mathrm{~b})+\sum_{\mathrm{i}} \beta_{i} \operatorname{Price}_{\mathrm{ik}} \mathrm{X}(\mathrm{i}, \mathrm{~b})+\sum_{i<j} \theta_{i j} \mathrm{X}(\mathrm{i}, \mathrm{~b}) \mathrm{X}(\mathrm{j}, \mathrm{~b}) \tag{5.1}
\end{equation*}
$$

Table 4: Parameter Estimates for Benchmark Model

|  | Standard eggs | Organic eggs | Standard milk | Organic milk |
| :--- | :--- | :--- | :--- | :--- |

[^2]| Intercept | $.23^{* *}$ <br> $(.06)$ | $-2.94^{* *}$ <br> $(.10)$ | $1.04^{* *}$ <br> $(.05)$ | $-3.25^{* *}$ <br> $(05)$ |
| :--- | :---: | :---: | :---: | :---: |
| Price | .02 | 0.01 | $-0.08^{*}$ | .03 |
|  | $(.02)$ | $(.07)$ | $(.05)$ | $(.07)$ |
| Standard eggs $\theta_{1 \mathrm{j}}$ | - | $-.11^{* *}$ | $.78^{* *}$ | $.17^{* *}$ |
|  |  | $(.03)$ | $(.05)$ | $(.03)$ |
| Organic eggs $\theta_{2 \mathrm{j}}$ | $-.11^{* *}$ | - | $.18^{* *}$ | $1.33^{* *}$ |
|  | $(.03)$ |  | $(.04)$ | $(.04)$ |
| Standard milk $\theta_{3 \mathrm{j}}$ | $.78^{* *}$ | $.18^{* *}$ | - | .04 |
|  | $(.05)$ | $(.04)$ | - | $(.04)$ |
| Organic milk $\theta_{4 \mathrm{j}}$ | $.17^{* *}$ | $1.33^{* *}$ | .04 | - |
|  | $(.03)$ | $(.04)$ | $(.04)$ |  |

Standard errors of parameters are shown into brackets
Statistical significance is denoted as ** if .05 level or better, and as $*$ if .10 level or better.
The PseudoR ${ }^{2}$ reaches 0.51 . The intercepts for the standard products are positive. They are negative for the organic products. This result simply reflects that the probability of purchasing a standard product is higher than the probability of buying an organic product. Otherwise, all price effects are non significant.

There is no cross effect between the two varieties of a given product ( $\left.\theta_{12}=\theta_{21}=-0.11, \theta_{34}=\theta_{43} \simeq 0\right)$. In terms of utility, the purchase of organic eggs and conventional eggs or organic milk and conventional milk are independent. All other pairs of products act as demand complements. We can distinguish two kinds of complementarity. Between a conventional product and the organic variety of the other product (conventional milk and organic eggs, conventional eggs and organic milk), complementarity is weak $\left(0.18=\theta_{23}=\theta_{32} \simeq \theta_{14}=\theta_{41}=0.17\right)$. Between products belonging to the same variety (conventional eggs and conventional milk, organic eggs and organic milk) the complementarity is greater. For conventional products ( $\theta_{31}=\theta_{13} \simeq 0.78$ ), this medium level complementarity reflects their usual association in most shopping baskets. For organic products ( $\theta_{24}=\theta_{42}=1.33$ ) the complementarity, which is the highest one, translates an organic attitude.

### 2.3.2 Models with Demographic Variables

To take into account demographic variables, we use equation 5 with $\theta_{i j k}=\theta_{i j}+\gamma_{\mathrm{ij}} \mathrm{SD}_{\mathrm{k}}$, where $S D_{\mathrm{k}}$ denotes one of the four following variables: income per unit consumption, family head's age, household size, family head's education. We estimate thus four models, one for each demographic effect. For example, the equation considering the income per unit consumption effect is written as:

$$
\begin{equation*}
\mu(\mathrm{b}, \mathrm{k})=\sum_{\mathrm{i}} \alpha_{\mathrm{i}} \mathrm{I}(\mathrm{i}, \mathrm{~b})+\sum_{\mathrm{i}} \beta_{i} \operatorname{Price}_{\mathrm{ik}} \mathrm{X}(\mathrm{i}, \mathrm{~b})+\sum_{i<j}\left(\theta_{i j}+\gamma_{\mathrm{ij}} \mathrm{SD}_{\mathrm{k}}\right) \mathrm{X}(\mathrm{i}, \mathrm{~b}) \mathrm{X}(\mathrm{j}, \mathrm{~b}) \tag{5.2}
\end{equation*}
$$

Table 5 displays for each of the four estimated equations (5.2) only the results for the cross effects $\theta_{i j}$ and $\gamma_{i j}$. Indeed, constants and price coefficients do not change. The results are given at appendix 2.

Table 5: Results on cross effects and demographic shifters parameters

| Effects | $\begin{gathered} \text { Income } \\ (1000 €) / \\ \text { U.C. } \\ \hline \end{gathered}$ | Age | Family size | Educational Level |
| :---: | :---: | :---: | :---: | :---: |
| Cross effects |  |  |  |  |
| $\begin{aligned} & \text { CE \& OE } \\ & \theta_{12}=\theta_{21} \\ & \hline \end{aligned}$ | $\begin{gathered} \hline-0.27^{* *} \\ (0.05) \\ \hline \end{gathered}$ | $\begin{gathered} \hline-0.23^{* *} \\ (0.08) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.009 \\ & (0.06) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline-0.21^{* *} \\ (0.06) \\ \hline \end{gathered}$ |
| $\begin{aligned} & \text { CE \& CM } \\ & \theta_{13}=\theta_{31} \\ & \hline \end{aligned}$ | $\begin{aligned} & 0.96^{* *} \\ & (0.05) \\ & \hline \end{aligned}$ | $\begin{aligned} & 1.10^{* *} \\ & (0.05) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.51^{* *} \\ (0.05) \\ \hline \end{gathered}$ | $\begin{gathered} 0.84^{* *} \\ (0.05) \\ \hline \end{gathered}$ |
| $\begin{aligned} & \text { CE \& OM } \\ & \theta_{14}=\theta_{41} \end{aligned}$ | $\begin{gathered} \hline-0.14 * * \\ (0.06) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.04 \\ & (0.1) \end{aligned}$ | $\begin{gathered} \hline 0.31 * * \\ (0.07) \\ \hline \end{gathered}$ | $\begin{gathered} \hline-0.28^{* *} \\ (0.07) \\ \hline \end{gathered}$ |
| $\mathrm{OE} \& \mathrm{CM}$ $\theta_{32}=\theta_{23}$ | $\begin{aligned} & 0.30^{* *} \\ & (0.06) \\ & \hline \end{aligned}$ | $\begin{aligned} & 0.16^{*} \\ & (0.08) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.14 * * \\ (0.06) \\ \hline \end{gathered}$ | $\begin{gathered} 0.27^{* *} \\ (0.06) \\ \hline \end{gathered}$ |
| OE \& OM $\theta_{42}=\theta_{24}$ | $\begin{aligned} & 1.30^{* *} \\ & (0.07) \\ & \hline \end{aligned}$ | $\begin{aligned} & 1.49^{* *} \\ & (0.12) \\ & \hline \end{aligned}$ | $\begin{gathered} 1.23 * * \\ (0.09) \\ \hline \end{gathered}$ | $\begin{aligned} & 1.14^{* *} \\ & (0.09) \\ & \hline \end{aligned}$ |
| $\begin{aligned} & \mathrm{CM} \& \mathrm{OM} \\ & \theta_{34}=\theta_{34} \\ & \hline \end{aligned}$ | $\begin{gathered} -0.20 \\ (0.06) \\ \hline \end{gathered}$ | $\begin{gathered} -0.12 \\ (0.09) \\ \hline \end{gathered}$ | $\begin{gathered} 0.10 \\ (0.07) \\ \hline \end{gathered}$ | $\begin{gathered} 0.06 \\ (0.07) \\ \hline \end{gathered}$ |
| Demographic*cross effects |  |  |  |  |
| $\begin{aligned} & \mathrm{CE} \& \mathrm{OE} \\ & \gamma_{12}=\gamma_{21} \end{aligned}$ | $\begin{aligned} & \hline 0.02^{* *} \\ & (0.005) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.02^{* *} \\ & (0.005) \\ & \hline \end{aligned}$ | $\begin{aligned} & -0.03^{*} \\ & (0.02) \end{aligned}$ | $\begin{aligned} & \hline 0.025^{* *} \\ & (0.01) \\ & \hline \end{aligned}$ |
| $\begin{aligned} & \text { CE \& CM } \\ & \gamma_{13}=\gamma_{31} \end{aligned}$ | $\begin{aligned} & -0.02 * * \\ & (0.001) \\ & \hline \end{aligned}$ | $\begin{gathered} -0.006^{* *} \\ (0.004) \\ \hline \end{gathered}$ | $\begin{aligned} & 0.10 * * \\ & (0.005) \\ & \hline \end{aligned}$ | $\begin{aligned} & -0.014^{* *} \\ & (0.004) \\ & \hline \end{aligned}$ |
| $\begin{aligned} & \text { CE \& OM } \\ & \gamma_{14}=\gamma_{41} \end{aligned}$ | $\begin{aligned} & \hline 0.04 * * \\ & (0.006) \end{aligned}$ | $\begin{aligned} & \hline-0.002 \\ & (0.002) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.05 \\ & (0.02) \end{aligned}$ | $\begin{gathered} 0.11 \\ (0.01) \end{gathered}$ |
| $\begin{aligned} & \mathrm{OE} \& \mathrm{CM} \\ & \gamma_{32}=\gamma_{23} \\ & \hline \end{aligned}$ | $\begin{gathered} -0.01 * * \\ (0.005) \\ \hline \end{gathered}$ | $\begin{aligned} & 0.0006 \\ & (0.001) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.02 \\ (0.02) \\ \hline \end{gathered}$ | $\begin{aligned} & -0.02^{*} \\ & (0.01) \\ & \hline \end{aligned}$ |
| $\begin{aligned} & \text { OE \& OM } \\ & \gamma_{42}=\gamma_{24} \end{aligned}$ | $\begin{gathered} \hline 0.002 \\ (0.007) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.003 \\ & (0.002) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.03 \\ & 0.03 \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.044^{* *} \\ & (0.019) \\ & \hline \end{aligned}$ |
| $\begin{aligned} & \mathrm{CM} \& \mathrm{OM} \\ & \gamma_{34}=\gamma_{34} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.01^{*} \\ & (0.05) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.003^{* *} \\ (0.02) \\ \hline \end{gathered}$ | $\begin{gathered} -0.016 \\ (0.02) \\ \hline \end{gathered}$ | $\begin{gathered} \hline-0.002^{* *} \\ (0.01) \\ \hline \end{gathered}$ |
| Pseudo ${ }^{2}$ | 0.5137 | 0.5136 | 0.5139 | 0.5135 |
| Observations | 1570440 |  |  |  |

Standard errors of parameters are shown into brackets
Statistical significance is denoted as ** if .05 level or better, and as *if .10 level or better.
For these four models, the cross effect between goods is the sum of the simple cross effect and the demographic-cross one ( $\theta_{\mathrm{ij}}+\gamma_{\mathrm{ij}}$ ). Signs and values of cross-effects coefficients are similar to the benchmark model and the global fitness is the same as the benchmark model one. Introducing income or educational level provides a more accurate measure of the linkage between products. For example, the more consumers are well-off, the less they are prone to buy only conventional products ( $\gamma_{13}=\gamma_{31}=-0.02$ ).

Our main concern is the cross-effect between organic products. An important feature is that the only demographic variable which affects the strong positive cross-effect between the two organic products is the educational level. According to the educational level, the total cross effect ( $\theta_{24}+\gamma_{24}=\theta_{42}+\gamma_{42}$ ) is between 1.14 and 1.49. Loyalty to organics is not sensitive to income, though organic products are more expensive than conventional products, neither to age nor to household size. In other words, the "organic belief" is not linked to any particular socio-demographic profile but education.

## 3. Price effects

After having measured the impact of price variations on the frequency of buying organic instead of conventional (3.1), we evaluate the global impact of prices changes on the purchased quantities (3.2).

### 3.1. Probability-Price Elasticities

Discrete choice models allow computing price elasticities which measure the percentage change in the probability of choosing product i with respect to a change in the price of product j . These elasticities are related to the decision of buying each product (eggs or milk, organic or conventional). The direct price elasticities stemming for Russell and Petersen's choice model are computed using the following formulas:

$$
\begin{equation*}
e(i)_{k}=\partial \log \mathrm{P}(\mathrm{i})_{\mathrm{k}} / \partial \log \operatorname{Price}_{i k}=\beta_{i}\left[1-P(i)_{k}\right] \tag{6}
\end{equation*}
$$

$P(i)_{k}$ is the probability that basket k contains the product $\mathrm{i}: P(i)_{k}=\frac{\sum_{\mathrm{i}} \exp \{\mu(\mathrm{b}, \mathrm{k})\}}{\sum_{\mathrm{b}^{*}} \exp \left\{\mu\left(\mathrm{~b}^{*}, \mathrm{k}\right)\right.}$, at the numerator, the sum is over all baskets with product of category i , at the denominator, the sum is over all possible baskets.

The elasticities presented at table 6 are computed from the benchmark model. They are statistically non significant. This feature, which reflects the non significativity of the price coefficients $\beta_{i}$ in the expressions (6), is invariant to the introduction of demographic variables in the model. Clearly, it means that marginal variations of the organic price have no effect on the probability of purchasing organic instead of conventional, for milk as well as for eggs.

Table 6: Probability Price Elasticities

| Eggs |  | Milk |  |
| :---: | :---: | :---: | :---: |
| Organic | Conventional | Organic | Conventional |
| -0.056 | 0.001 | -0.063 | -0.042 |
| $(0.70)$ | $(0.005)$ | $(-0.075)$ | $(0.036)$ |

Standard errors of parameters are shown into brackets

### 3.2. Demand Price Elasticities

Demand model price elasticities are calculated using the parameters estimated from an AIDS demand system (Almost Ideal Demand System, Deaton and Muelbauer, 1980). This model has been widely used in research studies on the demand for food products (see among others Moschini, Moro and Green, 1994; Moschini and Mielke, 1989; Eales and Henderson, 2001; Eales and Unnevehr, 1988). We estimate a demand model for each product, which amounts to assuming that the decisions of purchasing eggs or milk are separable and preliminary to choosing organic or conventional for each product. The assumption of separability is generally strong; nevertheless, in the case of staple food goods like eggs and milk, one can consider that people use to buying them without balancing much with some other goods.

Since only a minority of households use to buy organic, we consider a representative consumer and observe his behavior for a weekly basis on the year 2005 (the period considered in the choice model). For each product there are 53 sets observations, including in particular the total expense spent on the product considered, its distribution between the two versions and the retail prices.

For each product, the demand model takes the form of a system of equations written in the following way for each product:

$$
\begin{equation*}
w_{i t}=\alpha_{i}+\sum_{j=1}^{5} \gamma_{i j} \log p_{i t}+\beta_{i} \log \left(Y_{t} / P_{t}\right)+\rho_{i t} \tag{7}
\end{equation*}
$$

The dependent variables $\left(w_{i t}\right)$ are the weekly market shares of each version in the budget of the representative household ( $w_{i t}$ with $i=1,2$ and $t=1, \ldots, 53$ ). The independent variables are the weekly prices of the 2 versions ( $p_{i t}$ ), the total expense for the product considered in the retail store studied $\left(Y_{t}\right)$, corrected by an index of average prices $\left(P_{t}\right)$ and $\rho_{i t}$ is the error term. ${ }^{7}$ Resulting from the additivity constraint, only one budget share equation is estimated. The direct price elasticities, calculated at the mean value (see Table 10), are computed using the following formulas tested by Green and Alston (1990) :

$$
\begin{equation*}
\varepsilon_{i}=-1+\frac{1}{\bar{w}_{i}}\left(\gamma_{i i}-\beta_{i}\right) \tag{8}
\end{equation*}
$$

Table 7: Demand Price Elasticities

| Eggs |  | Milk |  |
| :---: | :---: | :---: | :---: |
| Organic | Conventional | Organic | Conventional |
| $-2.38^{* *}$ | $-0.78^{* * *}$ | -0.38 | $-1.02^{* * *}$ |
| $(0.77)$ | $(0.12)$ | $(0.65)$ | $(0.02)$ |

Standard errors of parameters are shown into brackets
For the two categories, conventional demands are more or less unitary price elastic (0.78 for eggs and -1.02 for milk). On the contrary, on the organic market segments, the situations are contrasted, demand being price elastic for eggs ( -2.38 ) and price-rigid for milk (elasticity no statistically different from zero). These results underline that, contrary to what happens on conventional staple food goods, consumers do not react yet homogeneously to organic prices variations, even if they are already involved in organic markets. This heterogeneity may be related to the maturity of the organic markets, the eggs market being already more opened than the milk one (in 2005, the penetration rate is 13.3 for eggs and 8.6
${ }^{7}$ The translog price index $P_{t}$ (where $\log P_{t}=\alpha_{0}+\sum_{i} \alpha_{i} \log p_{i t}+\sum_{i}^{n} \sum_{j}^{n} \gamma_{i j} \log p_{i t} \log p_{j t}$ ) is replaced by the linear Stone index approximation $\left(\log P_{t}=\sum_{i} w_{i} \log p_{i}\right)$. To overcome the simultaneity problem related to the presence of $w_{i t}$ in both terms of equation (1), $w_{i t}$ in the Stone index, is substituted by the $w_{i}$ mean. Furthermore, the prices and expenses are normalized by their means (Ashe and Wessells, 1997). We impose the theoretical restrictions of additivity of budget shares $\left(\sum_{i} \alpha_{i}=1\right)$, of homogeneity and of symmetry $\left(\sum_{i} \gamma_{i j}=\sum_{j} \gamma_{j i}=\sum_{i} \beta_{i}=0\right)$.
for milk). More generally, these results confirm the information provided by the probabilityprice elasticities concerning the weak impact of prices variations on the organic demand.

## 5. Conclusion

In spite of its rapid growth during the last decade, the organic demand remains small and its development, important because of its positive impact on the environment, is not firmly established yet. This evolution relies on many factors related to supply as well as to demand. The objective of this research was to explore some aspects of the demand dimension. Does an "organic attitude" already exist, even for occasional purchasers, meaning that consumers interested in one organic good are likely to extend their organic purchases to other products? To what extent is the price gap between organic and conventional a decisive barrier to organic market enlargement?

Relying on the market basket analysis, we have shown that organic choices were "congruent", which means that consumers are prone to extend their demand for organics to a wide range of goods, provided that the industry and the retailers insure regular and easy supplying. As regards to the price aspects, our results mean that if the organic prices were to decrease, instead of increasing as during the 1998-2005 period, this would have, globally, no strong impact on the demand. Specifically, it would not lead to a significant enlargement of the organic markets to new consumers. This can be understood as simply reflecting that the marginal price decreases considered when computing price elasticities do not really affect the important price gap between organic and conventional product. Nevertheless, it is difficult to forecast a price decrease process for organics which would not be slow and progressive. Moreover, Bunte et al. have shown in their price experiment that strong price cuts in mass distribution do not move much the demand. It means that consumers are not waiting for such prices cuts to automatically and massively shift from conventional to organic products. This reflects that at the present time, organic markets enlargement is mainly a matter of consumer's conviction enforcement. Clearly, in the last decade, the organic conviction has been making progress. It is responsible of the organic demand increase which, as regards to the price evolution and the price elasticities computed in this study, should have remained stable or have decreased. The importance of personal conviction in the organic choice is underlined by our findings concerning the organic consumer's socio-demographic profile. Indeed, the probability of buying organic is no affected by any demographic variable excepted by the educational level. In particular, in spite of the huge price gap between the two kinds of product, wealthier households are not more prone to buy organics.

This investigation has several limits. One of them is related to the symmetry of the cross effect coefficients, necessary to apply Besag's decomposition theorem. There is, for example, no reason to assume that the additional utility of buying organic milk (for children, for instance) when having already bought conventional milk may be the same as the one drawn from buying, in the same shopping trip, conventional milk after organic milk, which may reflect a strong choice in favor of organics. Nevertheless, the main limit of the basket choice analysis is that too few products can be involved in the same framework. Indeed, the number of potential baskets grows exponentially with the number of categories and all possible baskets are not really available.

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[^0]:    ${ }^{1}$ North America's part of the organic agricultural world area is only $2.2 \%$ which is small compared to its national consumption.
    ${ }^{2}$ The African share of the area devoted to organic crops in the world is only $0.03 \%$.
    ${ }^{3}$ French National Organic Agency Report (2008).

[^1]:    ${ }^{4}$ Within the organic expense, fruit and vegetables represent $16 \%$, but micro-level data on organic purchases of fruit and vegetables are difficult to get. Eggs and milk account each for $6 \%$ of the total organic expense in France.
    ${ }^{5}$ In table 1, individual data are weighted according to some socio-economical parameters (income, age) to reflect the structure of the French consumption.

[^2]:    ${ }^{6}$ Price data are often approximated by a log-normal distribution, and our data on observed prices seems to be consistent with this assumption.

