Public Policy and Diet Quality: Impact of Prices on Nutrient Adequacy using French Expenditure Data from 1996 to 2005

By

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Abstract

This paper aims at simulating optimal prices satisfying public health recommendations in terms of nutrient adequacy. This implies to estimate a complete food demand system in order to compute price elasticities. Food consumption behaviors are described by an AI functional form [Deaton and Muellbauer(1980)] augmented to control for habit persistence. The demand system is estimated using the Iterated Least Square Estimator developed by Blundell and Robin (1999). We use French household expenditure data drawn from TNS Worldpanel covering 130 periods of 4 weeks from 1996 to 2005. Given the nature of our data, households are split into 8 cohorts based on two socio-demographic variables: date of birth and social status. A revised aggregation into 27 food groups is proposed in this paper. More precisely, commodities are grouped into homogeneous categories in terms of nutritional content and consumer preferences. Nutrient adequacy is defined using the MAR (Mean Adequacy Ratio), a nutrient only-based indicator. We calculate nutrient adequacy for 12 essential nutrients. Optimal prices are derived following Ramsey's approach to optimal taxation; Maximizing social welfare under nutritional constraints results in 27 optimal price variations or tax rates, each defined as a non-linear function of all direct and cross price elasticities and the above mentioned indicator for all food groups.

keywords: Household survey data, cohort, AI demand system, nutrient adequacy, diet quality and fat tax policy

jelclass: D12, C33

PRELIMINARY VERSION - DO NOT QUOTE

1 Introduction

Ensuring a healthy diet to most has become a matter of concern and public health over the last decade. Late trends in the prevalence of overweight, obesity and cardiovascular diseases have renewed efforts to understand the determinants of quality in consumers' diets. Part of these discussions have focussed on the prospect of potential "fat taxes" (and/or the subsidization of healthy food goods). The purpose of this study is to estimate price elasticities of demand and optimal commodity taxes/subsidizes with regard to improving overall diet quality and alleviating inequalities towards food consumption in France.

Nutritionists have long made nutrient adequacy recommendations and developed indicators assessing the diet quality of a consumer's food basket. They have set thresholds for nutrient necessary intakes and worked out general scores of compliancy to these recommendations, such as the MAR (Mean Adequacy Ratio). Assuming that the MAR gives a fair indication of nutrient adequacy, we aim at computing the optimal price levels, for each food group, satisfying a nutritional constraint expressed in terms of MAR level.

An analysis of fiscal policy effects on consumption and nutrition relies heavily on demand parameter estimates. To adjust the commodity composition of households food basket to meet the dietary recommendations, determinants of changes in food consumption have to be explained. As a first step, the object of this paper is to estimate price elasticities of demand for a complete food demand system. One major problem in demand parameter estimation is the choice of an appropriate functional form, both flexible and consistent with demand theory. During the last two decades, the AI model [Deaton and Muellbauer(1980)] has gained prominence in demand analysis and now appears to be the most popular functional form. We propose to incorporate a lagged dependent variable within the usual AI regression equation to account for habit persistence in consumption. We have used a pseudo-panel database reporting French households food purchases over the period 1996-2005 to estimate income, own-price, and cross-price elasticities for 27 food groups. While pseudo-panel data provide a mean to overcome data limitations, they have often yielded technical hitches in constructing variables.

As a second step, this paper attempts to address the fiscal policy issue of taxing/subsidizing food goods by using Ramseys approach to Optimal taxation in the case of nutritional objectives. Based on the factors identified as influencing the consumer demand, this paper develops modelling tools to simulate the impacts of food policy scenarios. Although caution should be taken in applying the model in practice, this approach might be important for providing guidelines to policy reforms on nutrition.

The paper is organised as follows: Part 1 provides a brief presentation of the AI demand system and the hypothesis of habit formation in consumption; Part 2 reviews the basic specification of the Ramsey model and present a theoretical application to nutritional policies; Part 3 discusses statistical and econometric issues involved in using the TNS Worldpanel database; Part 4 presents the empirical results of demand elasticity estimates and simulations of food policy intervention.

2 The Model

2.1 Estimating Price Elasticities

Choosing a functional form is an important issue in empirical studies. Different functional forms often result in very different elasticity estimates. We will use a variant of the Almost Ideal Demand System (AI) developed by Deaton and Muelbauer (1980) as it seems to be still one of the most used demand systems in empirical work.

The AI model has expenditure shares as dependent variables. It is given by:

$$w_{it} = \alpha_i + \sum_{j=1}^{n} \lambda_{ij} \ln p_{jt} + \beta_i (\ln M_t - \ln P_t) + \epsilon_t$$

where w_{it} is the consumption expenditure share of food commodity i in time t, α_i the intercept, β_t and λ_{ij} parameters, M_t total expenditures on food in time t, p_{jt} the price of the jth commodity in time t and ϵ a random disturbance term. lnP_t is the Translog price index in time t defined by:

$$\ln P_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j \ln p_{jt} + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \lambda_{ij} \ln p_{it} \ln p_{jt}$$

Equation ? is thus nonlinear in its parameters. To avoid complication with nonlinear estimation, [Deaton and Muellbauer(1980)] argue that if prices are highly collinear, the Stone's geometric index should be a good approximation of the Translog index. This substitution of Stone's price index will give rise to the Linear Approximate Almost Ideal demand System LA-AI.

$$\ln P_t = \sum_{i=1}^{n} w_{it} \ln p_{it}$$

The use of Stones price index has been questioned by several authors. Moschini (1995) notes that the Stone's price index is not invariant to units of measurement and therefore can affect the model properties. Pashardes (1993) shows that linearizing the model using the Stone's index can result in biases of the parameter estimates of the regression. Finally, the presence of the expenditure shares, w_{it}, on both sides of the equation give rise to simultaneity and endogeneity issues.

To avoid these problems, we follow one alternative suggested by Moschini (1995) using a modified Stone's price index where we lag the expenditure share, w_{it}, using instead a base-expenditure weighted index. Furthermore, prices are scaled by expenditure share sample means. This modified Stone price index can be defined as:

$$\ln P_t = \sum_{i=1}^{n} \overline{w}_{i0} \ln p_{it}$$

where $\overline{w}_{i0}$ is the mean budget share across households in the first period used as the base period.

Equation ? is a static model which assumes consumers adjust perfectly and instantaneously to changes in income or prices. It also implies that there is no differences between consumers' short-run and long-run behaviours. However, it is unlikely that consumers adjust their food behaviour instantaneously to shocks and changes in consumption determinants. When it comes to food consumption, one can realistically assume that habit persistence can prevent an immediate adjustment.

In the lines of Pollack and Wales (1969), Blanciforti and Green (1983) propose an *ad hoc* formalisation of habit formation within an AI type of demand model. To reflect habit persistence, the static AI was extended by specifying current budget share as a function of previous consumption levels. A lag term is thus linearly introduced in Equation ?.

$$w_{it} = \alpha_i + \eta_i w_{it-1} + \sum_{j=1}^{n} \lambda_{ij} \ln p_{jt} + \beta_i (\ln M_t - \ln P_t) + \epsilon_t$$

2.2 Deriving Optimal Prices

In this section, after a brief overview of the classical Ramsey taxation problem, we present a variant of this model applied to nutritional constraints.

The problem was first posed by Ramsey (1927): how to set commodity taxes so as to maximise social welfare subject to raising a given amount of revenue in a competitive equilibrium? Initially, the governments objective was assumed to finance a given level of expenditures.

Formally, this problem may be written as:

$$Max.V(p_g, I)$$
$$\text{s.t. } t.x(p_g) = R$$

where $V(.)$ is the indirect utility function, $p_g = p + t$ the gross price, $p = (p_1, p_2, ..., p_n)$ a n-dimensional vector of prices, $t = (t_1, t_2, ..., t_n)$ a vector of commodity taxes, $x = (x_1, x_2, ..., x_n)$ the vector of consumer demands and R the amount of revenue to be raised. In addition, we assume a lump-sum income, I.

By analogy, we develop a model whose objective is no longuer to raise tax revenues but to comply with Public Health recommendations in terms of nutrient adequacy. These recommandations can be summarized using the popular MAR indicator (Mean Adequacy Ratio) defined as a linear combination of Nutrient Adequacy Ratios (NAR)[1]

$$MAR_i = \frac{1}{12} \sum_{j=1}^{12} \frac{nutri_{ji}}{RNI_j}$$

with 12 selected nutrients for the MAR (See Appendix ? for a list of the nutrients.).

The MAR can be computed for a food good, a food group or a food basket understood as a "coktail" of nutrients (See Table 1 - Appendix 1 for MAR indicators per food group).

[1] $NAR_{ji} = \frac{nutri_{ji}}{RNI_j}$ with RNI standing for Recommended Nutrient Intakes.

$$MAR_f = \frac{1}{12}\sum_{i=1}^{n}\sum_{j=1}^{12} x_i(p_c)\frac{nutri_{ij}}{RNI_i}$$

with a food group made of n goods. It has to be noted that we assume that nutrient adequacy is strictly linear in the quantities consumed. Excesses in one nutrient can compensate lacks in another. For convience, we follow Darmon and Darmon (2008) on the SAIN and no upper bound is imposed on the NARs[2].

In an economy with a representative consumer and a social planner, our formulation of the problem gives[3]:

$$\begin{gathered} Max.V(p_g, I) \\ \text{s.t. } \textstyle\sum_{f=1}^{m} x_f(p_g).MAR_f = 1 \end{gathered}$$

where food groups are indexed by subscripts $f = 1, 2, ..., m$. Similary to Ramsey, household preferences are given by the indirect utility function.

However, a second constraint has to be added to control for the cost of the fiscal policy[4].

$$\begin{gathered} Max.V(p_g, I) \\ \text{s.t. } \textstyle\sum_{f=1}^{m} x_f(p_g).MAR_f = 1 \\ \text{s.t. } \textstyle\sum_{f=1}^{m} x_f(p_g).t_f = 0 \end{gathered}$$

where $t_f = p_f - p_f^{(0)}$ can either be understood as the price variations, $p_f^{(0)}$ being the market price, or the commodity taxes/subsidizes to be implemented, if these are assumed to be entirely passed on to the consumer ($\frac{\partial p_k}{\partial t_k} = 1$).

Thus we have a constrained optimisation problem with the Lagrangean:

$$L = V(p_g) + \lambda 1(\sum_{f=1}^{m} x_f(p_g).MAR_f - 1) + \lambda 2(\sum_{f=1}^{m} x_f(p_g).t_f)$$

Assuming that taxes or subsises are entirely passed on to the consummer, the first-order conditions of this new optimization problem lead to:

$$\forall k, \frac{\partial L}{\partial t_k} = \frac{\partial V(p_g)}{\partial p_k} + \lambda 1(\sum_{f=1}^{m} MAR_f\frac{\partial x_f}{\partial p_k}) + \lambda 2(x_k + \sum_{f=1}^{m} t_f\frac{\partial x_f}{\partial p_k}) = 0$$

[2]This assumption can be supported in our study by the fact that we use aggregate data. Compensation between nutrients is thus unlikely.

[3]Policy objective is set to full satisfaction of nutrient needs. It could be changed to $(1+po\%).MAR_f$ with po as the policy objective in terms of nutrient adequacy improvement.

[4]Government revenue is set to 0 for a balanced budget.

Using Roy's identity, and the uncompensated price elasticities e_{ij} and initial levels of price and quantity ($p_k^{(0)}$ and $x_k^{(0)}$), we have:

$$\forall k, x_k^* = \frac{\lambda 1}{\beta - \lambda 2}(\sum_{f=1}^{m} MAR_f.e_{fk}.\frac{x_f^{(0)}}{p_k^{(0)}}) + \frac{\lambda 2}{\beta - \lambda 2}(\sum_{f=1}^{m} t_f.e_{fk}.\frac{x_f^{(0)}}{p_k^{(0)}})$$

where β is the social marginal utility of income. $\lambda 1$ the social marginal utility of improving the nutrient adequacy indicator and $\lambda 2$ remains the usual marginal utility of raising an extra unit of revenu by taxing/subsidizing commodity k. More precisely, you have as many $\lambda 1_k$ and $\lambda 2_k$ as food groups. In particular, each $\lambda 1_k$ is the marginal utility induced by the price change in k necessary to increase the nutrient adequacy indicator, the MAR, of the food basket by one unit. At the optimum, all λ_k are equal. Otherwise, both consumer's utility and nutrient adequacy can be improved by changing relative prices.

Each x_k is bound with all own and cross prices by some differentiable demand function.

$$x_k^* = x_k^{(0)} + dx_k$$

$$dx_k = \sum_{f=1}^{m} \frac{\partial x_k}{\partial p_f} dp_f = \sum_{f=1}^{m} e_{kf}.\frac{x_k^{(0)}}{p_f^{(0)}}.t_f$$

Using equations ? and ?, we obtain a system of 29 non-linear equations (including the two constraints) with 29 unknowns (27 unknown price variations, t_f, and $\frac{\lambda 1}{\beta - \lambda 2}$ and $\frac{\lambda 2}{\beta - \lambda 2}$). Solving for this system, we compute the optimal price variations t_k.

3 Data, group aggregation and cohort construction

In this section, we first describe the data and how we have constructed consumption measures and household cohorts. We then present a first glimpse of household food consumption patterns based on these cohorts.

3.1 The Data

We have used data from TNS Worldpanel to estimate the augmented AI demand system [Deaton and Muellbauer(1980)] presented above. The database consists in a scanner panel dataset containing the weekly food shopping of approximately 5000 French households. The data covers 130 periods of 4 weeks from 1996 to 2005. Our justifications for using periods of 4 weeks were both to benefit from seasonal price and consumption variations, and to obtain cells, by food groups and cohorts, as large as possible to prevent any induced bias [Verbeek and Nijman(1992)].

All households are equipped with electronic scanning units and each member is expected to scan the Universal Product Code (UPC) bar code of every food purchases made for "at home" consumption across all outlet channels. Participants are recruited based on socio-demographic information to ensure sufficient representation of the whole population. We would like to stress that this database is a unique source of micro-data on French household food consumption behaviour.

We have removed outliers using Coulombe and McKay (2000) method appropriate with log-normally distributed data. Furthermore, we assume that the large size of our sample might arguably compensate for the underlying deficiencies.

To study food consumption reaction to price variations, we would ideally have needed panel data, where the same people are tracked over time and over the entire food bundle. However, the TNS panel divide food consumption into three sub-panels and, for convenience, participants are assigned in two groups. All households have to report general food purchases (GF) and then one group register its fruit and vegetable purchases (FV) when the others scan their meat, fish and wine acquisitions (MF). As such we are unable to track the entire "at home"' food consumption for a single household and, thus, to estimate a complete demand system. However, the three sets include all possible food goods at a very disaggregated level.

To circumvent this limitation, we suggest to construct a pseudo-panel database with synthetic cohorts following the method described in [Deaton(1985)] and [Verbeek and Nijman(1992)]. It implies spliting the sample into cohorts whose behaviour in terms of food consumption patterns can be assumed homogeneous. The average consumption of these clusters can then be tracked over time and over all the food groups, as long as the cells are continually representative of the underlying population.

3.2 Cohort construction

The pseudo-panel method requires that we form various cohorts defined according to relevant socio-economic variables. In the context of consumption behaviour, we selected two variables: date of birth and social status. Two conditions have to be satisfied for cohorts to give consistent measures of food consumption. First, cells have to be statistically significant samples of the underlying population. Verbeek and Nijman (1992) set a minimum of 100 individuals per cell. Furthermore, appartenance to one cohort has to be fixed over time.

Volatier (1997) showed the importance of generation and birth order on food behaviour and drew lines between age groups. The end of WWII represents generally a major demographic rupture and Babayou and Volatier (1997) demonstrated different behaviours in terms of food habits between seniors born before 1946 and baby-boomers. 1946 was thus selected as the appropriate splitting date of birth. Given the time range of our dataset (1996-2005), the cut results in two approximatively well balanced sub-panels. It is also assumed that the population has not been substantially affected by migration. Allais *et al* (2008) have shown that social status has an important effect on food consumption behaviour. Using similar data, Allais *et al* (2008) suggest including a composite income variable constructed by TNS WorldPanel, which offers a socioeconomic classication in four modalities. It was significant in their study in distangling cohorts according to social status.

One point should be noted about the use of cohort means; The aggregation process in the construction of cohorts may help overcome some potentially serious problems present at the individual level There shouldnt be as many biases due to measurement error [?], which should reduce the impact of idiosyncratic variability, a main drawback with data on individuals [Deaton(1985)]. Verbeek and Nijman

(1992) show that biases due to measurement errors can be minor when the number of individuals in each cell is sufficiently large (about 100 or more). As pointed out by Verbeek and Nijman (1992), there is a trade-off between increasing the number of cohorts to build homogenous clusters and statistical significance per cell, between reducing possible biases in estimates and degrees of freedom.

However, there are at least two practical problems with the use of pseudo-panels for studying consumption behaviour with the TNS database. Firstly, we do not have data on individual consumption but on households. This strong limitation has been often stressed as an important departure from the theory.

The second problem is that, given the overall sample size of the TNS (approximately 5000 households per year), some cells averages could be less than the 100 households recommended by Verbeek and Nijman (1992) if they are formed from the interaction of cohort and food groups. These small cell sizes may impair the statistical significance and precision of the estimates. We respond to this sample size problem by reducing the number of cohorts and using periods of 4 weeks rather than year as we observed more active households within each period than on the overall sample. Finally, the use of cohort also averages out unobserved heterogeneities at the cohort level.

3.3 Food Group Aggregation

In practice, consumers allocate their budget over a large number of goods with different relative prices. However, such a broad trade-off is too complex for empirical analysis. The literature offers alternative approaches to deal with this allocation problem.

The composite commodity theorem ([Hicks(1936)], [Leontief(1936)]) allows us to group commodities according to the behaviour of their relative prices. It asserts that a group of commodities whose prices move in parallel can be treated as a single good. However, as relative prices generally fluctuate considerably, it is hardly useful for commodity groupings in empirical analysis [Deaton and Muellbauer(1980)]. Lewbel (1996) proposes a generalized composite commodity theorem, which relaxes the assumption of perfect correlation among prices within a group. It assumes that the distribution of an individual goods price is independent of the composite group price, and tests for cointegration relationships between each prices and the price indice of group to which they belong.

In contrast, separability allows us to break consumers' decisions into multiple steps based on their preferences [Strotz(1957)]. If preferences are weakly separable, then commodities can be split into groups within which preferences can be described independently of consumption in other groups. This implies that a subutility function can be defined for each group and, in a utility tree, total utility results as the sum of each of these subutilities. Weak separability allows a two-stage budgeting, where consumers first allocate total expenditure to broad groups of commodities and then allocate each group expenditure to the individual goods in that group [Deaton and Muellbauer(1980)].

We will follow the « traditional » approach of maintaining the assumption of weak separability between foods and all other consumption goods. The food items that are closely related will then be grouped together into food groups, where a group comprises commodities that are closely substitutable. Food items were finally aggregated into 27 groups to allow estimation. Given the aim of this paper, these categories were constructed to distinguish two kinds of food products likely to be either taxed or subsidised. As such, an original taxonomy of food groups, homogeneous in terms of nutritional content and consumption preferences, is proposed (See table 1 - Appendix 1).

3.4 Price aggregation

An interesting feature of our dataset is the variable used as the price indicator. As market prices are not observed, we compute unit values following [Deaton and Muellbauer(1980)]. However, quality effects may result from the heterogeneity in commodity aggregates. To control for quality, Deaton and Tarozzi (2000) suggest estimating unit values at the most desaggregated level. In addition, Cox and Wohlgenant (1986) propose a correction method. It consists in reducing each household's unit values by its fraction explained by the household's caracteristics.

It adjusts the unit values in terms of household socio-demographic variables. The unit values of the aggregated commodity are estimated using the following equation (Cox and Wohlgenant, 1986):

$$p_{hk} - \overline{p}_k = \sum \beta y_i + \epsilon_k$$

where p_{hk} is the unit value of the kth aggregated commodity for household h, $\overline{p_k}$ the average unit value for group k (over the price cluster) and y household caracteristics.

Then, the quality-adjusted unit value can be obtained by:

$$p_{hkc} = \overline{p}_k + \epsilon_k$$

Given the household aggregation procedure necessary to estimate a demand system with our data, the correction for quality suggested by Cox and Wohlgenant (1986) is not relevant in our case. The aggregation of the error term is likely to tend towards 0 as $E(\epsilon_k) = 0$ (over the price cluster which might be different from the cohort).

Potential distortion for not adjusting for quality effects depend on the heterogeneity in commodity aggregates. As it has been said above, this problem can be partly resolved by disaggregating to the maximum extent (Deaton and Tarozzi, 2000). However, constructing price averages per food group and household, weighted by the quantities consumed, means ending up with prices estimated at the least dissagregated level and loosing information.

$$p_{hk} = \frac{\sum_{i=1}^{n} x_{hi} \cdot p_{hi}}{\sum_{i=1}^{n} x_{hi}}$$

Consequently, we suggest constructing price averages, per household and food group, using a Stone's index:

$$\ln p_k = \sum_{i=1}^{n} w_i \ln p_i$$

4 Results and discussion

This paper applies a LA-AI model augmented for habit formation to examine the impact of food price variations on diet adequacy. Since the system is expressed in budget shares, summing to 1, the estimation requires deleting one equation. The estimates are invariant to which equation is dropped (Barten, 1969). The homogeneity and symmetry conditions are imposed in the estimation. We apply Iterated Least Square Estimator developed by Blundell and Robin (1999) in Stata.

Table 1: Regression statistics

	LA/AI/HABIT				LA/AI			
	RMSE	R-sq	F-Stat	P	RMSE	R-sq	F-Stat	P
Equation1	.0046714	0.9299	208.37	0.0000	.0050293	0.9187	185.20	0.0000
Equation2	.0072536	0.8217	72.48	0.0000	.0075334	0.8084	69.39	0.0000
Equation3	.0030956	0.5821	23.23	0.0000	.0031642	0.5589	22.81	0.0000
Equation4	.0035268	0.7546	48.68	0.0000	.0036861	0.7300	45.34	0.0000
Equation5	.000541	0.7462	48.13	0.0000	.0006551	0.6619	37.07	0.0000
Equation6	.0036428	0.9177	172.79	0.0000	.0041378	0.8929	137.82	0.0000
Equation7	.001184	0.8555	90.58	0.0000	.0013118	0.8237	76.89	0.0000
Equation8	.0046522	0.9284	198.46	0.0000	.0056187	0.8944	139.03	0.0000
Equation9	.0011467	0.9329	217.47	0.0000	.0012414	0.9211	190.50	0.0000
Equation10	.0005153	0.8606	95.08	0.0000	.0005481	0.8411	86.19	0.0000
Equation11	.0007593	0.8895	127.06	0.0000	.0007709	0.8857	127.11	0.0000
Equation12	.003479	0.9531	317.57	0.0000	.0037562	0.9449	280.18	0.0000
Equation13	.0011509	0.8806	118.19	0.0000	.0011067	0.8893	131.61	0.0000
Equation14	.0012342	0.8928	124.37	0.0000	.001398	0.8618	99.53	0.0000
Equation15	.0022993	0.7753	51.80	0.0000	.0025625	0.7393	46.58	0.0000
Equation16	.0017167	0.9576	351.07	0.0000	.0022076	0.9307	220.56	0.0000
Equation17	.001774	0.9547	330.17	0.0000	.0019596	0.9450	280.27	0.0000
Equation18	.0012351	0.6299	25.59	0.0000	.0013538	0.5502	21.86	0.0000
Equation19	.0007291	0.8869	121.39	0.0000	.000762	0.8763	114.70	0.0000
Equation20	.0008263	0.8725	105.43	0.0000	.0009797	0.8204	74.71	0.0000
Equation21	.0044687	0.9584	362.04	0.0000	.0046094	0.9555	349.64	0.0000
Equation22	.0010958	0.9078	155.44	0.0000	.0011238	0.9034	152.84	0.0000
Equation23	.0009294	0.9185	179.13	0.0000	.0009443	0.9155	177.86	0.0000
Equation24	.0013919	0.8286	71.38	0.0000	.0016362	0.7612	51.93	0.0000
Equation25	.0015326	0.9510	305.35	0.0000	.0016122	0.9454	282.85	0.0000
Equation26	.0090991	0.8103	68.26	0.0000	.0092722	0.8021	68.28	0.0000

Implying that the conditional demand equations should be functions of prices and total expenditure on these goods, the assumption of weakly separable preferences raises the question of potential simultaneity bias of the demand model. Total food expenditure may be determined jointly with expenditure shares, making it endogenous. Furthermore, the lagged dependent variables included in the model to assess the hypothesis of habit formation are also endogenous by virtue of their correlation with the cohort-specific component within the error term. To control for endogeneity, we follow Blundell and Robin (1999) and apply their instrumental variable technique: the Two-Stage Least Squares (2SLS) estimator.

We proceed in two steps, using income as an instrument for household total food expenditure and all lagged prices and income for the lagged dependent variable. In a first step, the endogenous variables are regressed on the set of instrumental variables with all the other exogenous explanatory variables of the model included. The residuals from this first-stage regression are then included as additional explanatory variables in the budget share equations.

Table 1 reports basic statistics comparing both LA-AI models, with and without the inclusion of a lagged dependent variable. The estimated R2 for the 26 remaining equations of the system range from 0.7 to 0.9. The F-statistics reject the joint null hypothesis that all coefficients are equal to zero for both models. However, we observe higher goodness-of-fit estimates for the specification with habit formation and parameters for the lagged budget shares are statistically significant on most equations. Hence the LA-AI-HABIT model is prefered.

The parameters of the LA-AI equations do not have straightforward economic interpretation but are used to estimate elasticities. Table 1 - Appendix 2 reports the regression coefficients of the LA-AI-HABIT model. The estimated coefficients from the demand system were generaly statistically significant at the 10% level or better. Exceptions were essentially cross-price coefficients. The model incorporates socio-economic and demographic characteristics to account for differences in consumption behaviours accross cohorts. Most of the estimated coefficients associated with the temporal dummy variables and socio-economic and demographic characteristics were statistically significant, indicating that temporal and social effects are important in explaining food consumption patterns in France.

4.1 Food consumption patterns and elasticities

The general recent trend in the food consumption pattern of households seems to be an increase of the share of "already made food" in the French diet. Table ? (Appendix ?) shows the changes in budget-share purchased for major food groups in France from 1996 to 2005. Prepared meals, snacks and processed fruits and vegetables represent a larger part of French households' food expenditure. Conversely, it is observed that the share of fresh fruit and vegetable purchases within the household food basket have tend to decrease over the last 10 years.

Table 1 - Appendix 2 reports the coefficients for socio-economic and demographic variables from the LA-AI-HABIT model. Overall, educated households are likely to consume more meat, fish, dairy products, vegetables and fruits, and less grains, snacks and other salty goods. In addition, large families with children tend to have a higher vegetable and fruit budget share. Age (or the retirement status) has a strong and significant positive effect on the consumption of fish, meat and vegetables, and negative effects on snacks and processed fruits and vegetables. Although this study was not designed to assess the impacts of household characteristics on the composition of the food basket, there is evidence of such correlations.

Tables 2 shows the expenditure elasticity estimates from the LA-AI-HABIT model. The estimated expenditure elasticities are all positive, indicating normal goods for all food groups, and statistically significant at the 1% level. They range from 0.68 for *Poultry* to 1.66 for *Snacks*. More disaggregated data would have been necessary to isolate inferior goods.

It is interesting to note that meat has a higher expenditure elasticity than fish. This discrepancy might be partly explained by the fact that fresh meat is relatively costly. The expenditure elasticities of meat, delicatessen, processed fruits, prepared dishes, snacks, dairy products, soft drinks and coffee&tee are above 1, implying that these foods are luxury products in the household diet. Unexpectedly, the expenditure elasticities for fresh fruits and vegetables are relatively low. This result might be a reflection of the *"French paradox"* and show the importance of fruits and vegetables in the French diet.

Table 2: Expenditure elasticities

	Exp.
Fish	0.82***
Meat	1.02***
Poultry	0.68***
Deli meat	1.05***
Eggs	0.73***
Fresh veg	0.87***
Proc veg	1.00***
Fresh fruit	0.86***
Proc fruit	1.06***
Dried fruit	0.89***
Nuts	1.18***
Mixed dish	1.26***
Snack	1.66***
Yogurt	0.75***
Cheese	1.01***
Milk	1.30***
Cereals	1.12***
Potatoes	0.72***
Salty snack	0.80***
Sugar	0.91***
Sweets	1.18***
Animal fat	1.03***
Vegetal fat	1.10***
Water	0.81***
Non-Alcohol bev	1.47***
Alcoholic bev	0.76***
Coffee-tee	1.17***

Significance levels:
$*$: 10% $**$: 5% $***$: 1%

Table 3 reports the uncompensated price elasticities[5]. The estimated elasticities were computed at the sample means for each food group. The confidence intervals for the elasticity estimates were calculated using the Delta method. They generally conform with economic theory and their magnitudes are within usual ranges. All own-price elasticities have the correct negative sign and are statistically significant at the 1% level. They range from -0.63 for *Eggs* to - 1.04 for *Coffee and tee.* The Marshallian elasticities for *Coffee and tee* and *Meat* are slightly above 1, implying that a change in their price would lead to an almost exactly proportional response in demand. On the contrary, the uncompensated own-price elasticities of demand for *Eggs* and *Potatoes* are below 1 and amongst the weakest. These low elasticities were expected, in particular for eggs as it has very few substitutes. Conversely,

[5]Table 2 - Appendix 1 shows the compensated price elasticities

Table 3: Uncompensated price elasticities

	Fish	Meat	Poultry	Deli meat	Eggs	Fresh veg	Proc veg	Fresh fruit	Proc fruit	Dried fruit	Nuts	Mixed dish	Snack	Yogurt	Cheese	Milk	Cereals	Potatoes	Salty snack	Sugar	Sweets	Ani fat	Vegi fat	Water	NA bev	A bev	Coffee tee
Fish	-0,99***	0,06**	-0,02	-0,02	0,00	0,00	0,00	0,01	0,00	0,00	0,01**	0,01	0,00	-0,01	0,00	0,00	0,02*	0,01	-0,01	0,00	0,01	0,00	0,00	-0,01	0,00	0,01	0,09***
Meat	0,02*	-1,01***	0,00	0,01	0,00	0,00	-0,01**	0,00	0,01*	0,00	0,00	0,01	0,01	-0,01	-0,03**	0,01*	-0,02**	-0,01	0,00	-0,01**	-0,02	0,00	0,00	0,01**	0,02**	-0,02	0,02
Poultry	-0,02	0,03	-0,93***	0,07***	0,00	-0,01	0,01	0,00	0,00	-0,01	0,00	0,00	0,00	0,00	0,00	0,01	-0,01	0,00	0,00	0,01	-0,01	0,02*	0,01*	-0,01*	0,01	0,01	0,14***
Deli meat	-0,02*	0,01	0,03**	-0,77***	-0,01***	0,00	0,00	-0,01*	0,00	0,00	0,00	-0,01	-0,02**	-0,02**	-0,07***	0,00	-0,03***	0,00	-0,03***	0,01	-0,03*	-0,01	-0,02***	-0,01	0,00	0,01	-0,02
Eggs	0,02	0,00	0,01	-0,09***	-0,63***	-0,02	0,02	-0,01	-0,04	-0,01	-0,01	-0,04*	-0,03	-0,03	0,04	-0,01	0,00	-0,01	0,04	0,00	0,01	-0,02	0,02	-0,01	-0,02	-0,03	0,12***
Fresh veg	0,00	0,00	-0,01	0,01	0,00	-0,93***	0,01**	0,00	0,01	-0,01***	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,01**	0,00	0,00	-0,01	0,01	0,01*	-0,01	0,00	0,02	0,05*
Proc veg	0,00	-0,07**	0,01	0,00	0,01	0,02*	-0,98***	0,00	-0,02	0,00	0,00	0,00	0,01	-0,05***	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,02	0,03
Fresh fruit	0,02	0,01	0,00	-0,01	0,00	0,00	0,00	-0,95***	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,01	0,01	0,00	0,00	0,00	0,03**	0,00	0,00	0,01	0,00	-0,03*	0,06*
Proc fruit	0,00	0,07*	-0,01	-0,01	-0,03	0,01	-0,02	-0,01	-0,88***	0,01	0,01	0,05*	-0,02	-0,02	-0,16**	-0,02	0,00	0,00	0,00	-0,02	-0,01	0,03	-0,02	0,00	0,00	-0,01	-0,01
Dried fruit	-0,02	-0,1	-0,09*	-0,07	-0,03	-0,11***	0,03	0,02	0,06	-0,84***	-0,03	-0,05	0,04	0,11	-0,02	-0,01	-0,01	-0,02	0,03	0,02	0,09	-0,06	-0,01	0,02	0,01	0,05	0,09
Nuts	0,02	-0,02	-0,02	-0,02	-0,01	-0,02**	0,00	-0,02	0,01	-0,01	-0,98***	0,00	0,01	0,01	0,02	-0,01	-0,02*	-0,01	0,00	0,00	0,01	0,01	-0,01	0,00	0,01	-0,03**	-0,07***
Mixed dish	-0,01	0,01	-0,02*	-0,03*	-0,01***	-0,01	0,00	-0,01	0,01*	0,00	0,00	-0,97***	0,01*	0,00	-0,02	0,00	0,00	-0,01**	-0,01***	0,00	0,02	-0,01**	0,00	0,01**	0,00	-0,02	-0,17***
Snack	0,00	0,08	-0,02	-0,24***	-0,04	-0,02	0,01	-0,01	-0,05	0,02	0,01	0,08	-0,84***	0,07	-0,17	-0,01	0,02	0,02	0,04	-0,03	0,00	-0,1*	-0,05	0,02	0,03	-0,07*	-0,41***
Yogurt	-0,02	-0,01	0,00	-0,04	-0,01	0,00	-0,04***	-0,01	-0,01	0,02	0,01	0,01	0,03	-0,87***	0,00	-0,01	0,01	-0,01	0,02	0,00	0,00	0,01	0,01	0,00	0,01	0,01	0,15***
Cheese	-0,01	-0,04**	-0,01	-0,07***	0,00	0,00	0,00	-0,01	-0,03***	0,00	0,00	0,00	-0,01	0,00	-0,86***	0,00	0,01	0,00	0,00	0,00	-0,01	-0,01	0,01	0,00	-0,02**	-0,01	0,04***
Milk	-0,02	0,03	0,00	-0,02	-0,01	-0,01	0,00	-0,02**	-0,01	0,00	-0,01**	-0,01	0,00	-0,02**	-0,02	-0,98***	-0,02*	0,00	-0,01	0,00	-0,02	0,00	-0,01	0,00	-0,01	-0,02	-0,11***
Cereals	0,01	-0,05***	-0,02**	-0,07***	0,00	-0,01	0,00	0,00	0,00	0,00	-0,01*	0,01	0,01	0,00	0,01	-0,01	-0,96***	-0,01	0,00	0,00	0,00	0,02***	0,00	0,00	0,00	-0,02**	-0,03
Potatoes	0,05	-0,05	0,00	0,06	-0,01	-0,07**	0,01	0,00	0,01	-0,01	-0,02	-0,07*	0,03	-0,03	0,04	0,00	-0,03	-0,78***	0,00	0,00	-0,02	0,06**	0,01	-0,01	-0,03	0,03	0,15**
Salty snack	-0,03	0,02	0,01	-0,17***	0,03	-0,02	0,00	-0,01	0,00	0,01	0,00	-0,05**	0,03	0,04	-0,02	-0,01	0,02	0,00	-0,75***	0,01	-0,02	0,00	-0,01	-0,02**	0,05**	0,00	0,08***
Sugar	-0,03	-0,18**	0,06	0,11	-0,01	0,00	0,01	0,03	-0,05	0,01	0,01	0,00	-0,04	-0,01	0,07	0,00	0,01	0,00	0,02	-0,91***	-0,09*	-0,05	0,02	-0,01	0,00	0,00	0,11*
Sweets	-0,01	-0,03*	-0,02***	-0,03**	0,00	-0,01*	0,00	0,01	0,00	0,00	0,00	0,01	0,00	-0,01	-0,02*	0,00	0,00	0,00	-0,01**	-0,01**	-0,93***	-0,01***	-0,01**	0,00	0,00	-0,02*	-0,1***
Animal fat	-0,01	0,00	0,02	-0,02	-0,01	0,01	0,00	0,00	0,02	-0,01	0,01	-0,03*	-0,03*	0,01	-0,03	0,00	0,03***	0,02**	0,00	-0,01	-0,05**	-0,95***	-0,01	0,00	-0,02	0,00	0,03
Vegetal fat	-0,01	-0,02	0,03	-0,13***	0,01	0,02	-0,01	-0,02	-0,02	0,00	-0,01	0,01	-0,03	0,01	0,03	-0,01	0,01	0,00	-0,01	0,01	-0,05*	-0,02	-0,89***	0,01*	-0,01	0,00	-0,02
Water	-0,01	0,09***	-0,02	-0,01	-0,01	-0,02	0,00	0,02	0,00	0,00	0,00	0,06***	0,01	0,00	0,02	0,00	0,00	-0,01	-0,01**	0,00	0,05**	0,00	0,01*	-0,98***	0,01	-0,01	-0,01
Non-Alcohol bev	-0,03	0,07*	-0,01	-0,04	-0,01	-0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	-0,11***	-0,01	-0,01	-0,02	0,02**	0,00	-0,02	-0,03	-0,01	0,01	-0,95***	-0,06***	-0,27***
Alcoholic bev	0,01	0,00	0,00	0,02*	0,00	0,01	0,01*	-0,02	0,00	0,00	0,00	0,01	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,02	0,00	0,00	0,00	0,00	-0,9***	0,07**
Coffee-tee	0,07	0,11	0,04	-0,03	0,01	0,01	0,02	0,01	0,01	0,01	-0,01	-0,22***	-0,06***	0,07**	0,16***	-0,01	0,02	0,02	0,00	0,02	-0,17*	0,04	0,01	-0,06***	-0,08***	-0,09	-1,04***

Significance levels:
$*$: 10% $**$: 5% $***$: 1%

the high own-price elasticity of demand for meat can probably be explained by the existence of many substitutes and is usually regarded as a luxury food item.

As it is usually observed in complete demand system estimation, more that half of the cross-price elasticities are not statistically significant. Furthermore, most of the significant estimated cross-price elasticities are close to zero. The results clearly indicate complementarity between *Coffee and tee* and *Snacks* (-0.41), and reciprocaly (-0.22), while coffee is a substitute for prepared meals (0.15). The estimates of cross-price elasticities also show prevalence of complementarity between *Coffee and tee* and soft drinks (-0.27), and *Delicatessen* and *Snacks* (-0.24). In addition, moderate complementarity occur between *Meat* and *Sugar* (-0.18), *Delicatessen* and *Other salty snacks* (-0.17), *Delicatessen* and *Vegetal fat*, *Cheese* and *Processed fruits* (-0.16), *Fresh vegetable* and *Dried fruits* (-0.11), *Animal fat* and *Snacks* (-0.10) , *Alcoolic beverage* and *Coffee and tee* (-0.09). *Coffee and tee* appears thus highly complementary, even with prepared meal (-0.17), milk (-0.11) and sweets (-0.10), this versality suggesting both importance and uselessness. It is unexpectedly substituable with sugar (0.11).

4.2 Optimal food taxes and subsidizes

Following our theoretical model, our goal is to solve for the optimal price variations. We want to find the set of taxes/subsidizes that maximizes global welfare, under the constraints of improving the MAR score and maintaining a balanced budget. The calculation starts with initial value for taxes/subsidizes and then iterates on those variables until a convergence criterion is met. Table 4 reports the magnitude of these optimal price variations as a percentage of previous prices. Six scenarios are tested: 1%, 5%, 10%, 15%, 20% and 25% increases in the MAR[6].

As expected, the level of the optimal tax rates depend on the level of the price elasticities and of the nutritional indicators for each food group. It reveals that taxing/subsidising food goods according to nutrient adequacy recommendations requires setting high tax rates. Optimal tax rates are generally more than twice the size of the nutritional improvement target. These high rates reflect, in part, the fact that the price elasticities in the model are relatively low. *Vegetal fat*, which ranks first with regard to dietary recommandations for 100g, is reported as requiring the highest level of subsidization (-214.79% for an overall +10% increase in the MAR). These results might show how deceptive a straightforward application of the formula can be.

However, these tax rates do not only represent the optimisation of global welfare under nutritional constraints but also the interactions between the consumers utility and the price structure. Assuming price-taker households, preexisting distortions between optimal prices for the consumer to maximise utility and market prices are theoretically possible and likely. Such optimal prices would actually tend toward zero. The canonical microeconomic model of consumer behaviour states that individuals maximise utility according to a given set of prices. Therefore, it is possible to maximise global welfare by setting commodity taxes, whose magnitudes need to be counterbalanced by the fiscal constraint[7]. Because of these effects, the

[6] The overall MAR is observed to be 78.47%

[7] In our case, we impose that the cost of the policy is equal to zero

Table 4: MAR - Simulated optimal tax rates

	Nutritional objective						
	1%	5%	10%	15%	20%	25%	Baseline - 0%
Fish	83,62%	76,41%	64,64%	37,49%	37,25%	37,03%	85,22%
Meat	55,25%	49,99%	41,61%	23,09%	22,76%	22,45%	56,45%
Poultry	83,02%	74,84%	61,82%	33,52%	33,17%	32,86%	84,87%
Deli meat	58,55%	53,08%	44,34%	24,88%	24,57%	24,28%	59,79%
Eggs	15,29%	7,78%	-2,26%	-15,23%	-16,21%	-17,16%	17,12%
Fresh veg	6,01%	0,87%	-5,82%	-13,70%	-14,53%	-15,34%	7,27%
Proc veg	25,10%	20,44%	13,77%	2,44%	1,84%	1,27%	26,21%
Fresh fruit	32,55%	26,72%	18,31%	3,85%	3,22%	2,63%	33,93%
Proc fruit	-43,02%	-45,51%	-47,27%	-41,21%	-42,29%	-43,35%	-42,30%
Dried fruit	22,22%	17,23%	10,19%	-1,11%	-1,78%	-2,43%	23,42%
Nuts	-62,79%	-63,92%	-63,28%	-51,18%	-52,34%	-53,47%	-62,37%
Mixed dish	27,29%	24,04%	19,15%	9,35%	8,97%	8,60%	28,04%
Snack	20,17%	19,86%	18,96%	14,55%	14,44%	14,33%	20,22%
Yogurt	39,15%	32,73%	23,34%	6,64%	6,00%	5,39%	40,66%
Cheese	43,58%	38,52%	30,76%	14,95%	14,50%	14,06%	44,75%
Milk	-96,04%	-95,76%	-92,27%	-71,17%	-72,52%	-73,84%	-95,88%
Cereals	-35,22%	-37,43%	-39,07%	-34,30%	-35,27%	-36,23%	-34,59%
Potatoes	-77,30%	-81,47%	-84,35%	-73,31%	-74,95%	-76,55%	-76,09%
Salty snack	42,83%	36,06%	26,10%	8,20%	7,59%	7,00%	44,42%
Sugar	105,15%	97,45%	84,38%	51,99%	51,91%	51,85%	106,84%
Sweets	40,41%	36,49%	30,31%	16,76%	16,43%	16,11%	41,30%
Animal fat	56,83%	51,23%	42,36%	23,04%	22,68%	22,34%	58,11%
Vegetal fat	-227,09%	-224,85%	-214,79%	-163,33%	-165,88%	-168,40%	-227,15%
Water	72,31%	65,15%	53,78%	29,22%	28,92%	28,65%	73,94%
Non-Alcohol bev	55,48%	52,63%	47,36%	32,07%	32,05%	32,03%	56,08%
Alcoholic bev	100,76%	92,36%	78,50%	46,17%	46,01%	45,87%	102,63%
Coffee-tee	74,71%	72,38%	67,13%	47,34%	47,12%	46,91%	75,15%
Actual improvement	1%	5%	10%	14,87%	15,68%	16,46%	0%
Policy cost	0	0	0	-0,00026	-0,00856	-0,07257	0

optimal taxes are observed to be significantly different from zero in the absence of any nutritional objective.

Although the numerical results do not validate the general hypothesis of a feasible food commodity taxation policy, it identifies 5 food groups likely to be subsidized: *Eggs*, *Fresh vegetables*, *Processed fruits*, *Nuts*, *Milk*, *Cereal products*, *Potatoes* and *Vegetable fat*. Given the diet quality indicator chosen in this study, these groups were also amongst these considered as being healthier in terms of dietary intakes. Furthermore, the simulation shows how unelastic demand leads to much higher tax rates. Simulations setting higher demand elasticities show lower optimal rates of taxation, namely 81% instead of 163% was found for *Vegetable fat* if its elasticity was set to -3 instead of -0.89. Unexpectedly, increasing the policy's target leads to decrease in the simulated optimal taxes. This discrepancy can be a result of the above mentionned reason.

5 Conclusion

In this paper we have estimated a complete food demand system for 27 major food groups based on data from ten household expenditure surveys conducted from 1996 to 2005. Following Allais *et al* (2008), we have assumed that preferences are weakly separable. All calculated income elasticities are positive and significant, and all own-price elasticities are negative and significant. Results indicate that income elasticities are not higher for healthier food groups. This finding has implications for policy reform in France with regard to alleviating inequality towards nutritional deficiencies. Demands are price elastic for few food groups although estimates show that consumers are slightly more responsive to price than has been previously found ([Lecocq and Robin(2006)], [Amiot-Carlin *et al*, 2007]). Furthermore, the results support the hypothesis of habit formation in consumption.

Another contribution of this study was the calculation of optimal price variations. In conformity with our expectations, simulation results are very sensitive to estimated demand elasticities. Somewhat stronger linkages are established between price elasticties, food commodities' nutritional content and overall dietary intakes. However, caution should be taken in applying this model in practice. These results must be considered as a first attempt to understand the impact of price variations on the composition of households food bundle and diet quality.

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