The Effects of a "Fat Tax" on the Nutrient Intake of French Households

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Abstract

This article assesses the effects of a "fat tax" on the nutrient intake of French households across different income groups. Since we would like to assess the global impact of a fat tax on nutrient intakes, we estimate a complete demand system. We find that a "fat tax" would have ambiguous and small effects on the nutritional intake of French households, and slight effect on body weight in short run. However, It generates substantial tax revenue, but at the expense of low income households' welfare.

Key words: Household survey data, cohort, demand system, nutrient elasticities, missing data, and fat tax policy

JEL classification: D12, C33

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Obesity and overweight have been recognized by the World Health Organization (WHO) as major worldwide public health concerns (WHO, NUT and Obesity, NCD 1997). In France, Paraponaris, Saliba, and Ventelou (2005) assess that the percentage of overweight or obese individuals has increased since 1980 from 32.9% to 37.5% for overweight and from 6.3% to 9.9% for obesity in 2003. In 1992, the medical cost of obesity in France was estimated by Detournay et al. (2000) and Levy et al. (1995) to be in the range 0.6–1.1 billion euros, which represented 0.7–1.5% of the country's total health expenditures. The growing obesity and the resulting economic externalities have conducted French health authority to explore market interventions, such as taxes and subsidies to impact on food consumption and consequently on body weight. In particular, French State policy makers, IGF-IGAS (2008), are questioning the efficacy of raising value added tax (VAT) for food items high in calories, fat, or sugar on household purchases and nutrient intake. This kind of tax is generally called the "fat tax" or "junk food tax". The objectives of this public policy measure are to decrease unhealthy food products, or at least function as a disincentive to unhealthy eating, and generate revenue earmarked to support health measures: improving diet by subsidizing healthful foods, increasing physical activity, obesity prevention, nutrition education, etc. The objective of this study is to quantify the relevance of a fat tax in France. This is done by answering to three sets of questions: (1) What are the impacts of a fat tax on household purchases and nutrient intakes? Although is quite intuitive that increasing the effective price of unhealthy foods should reduce their consumptions, the whole impact of this increase on nutrient intakes, and especially in calory and total fat intakes is not clear given that food purchases are highly interdependent.[1] What are the short and long run effects of this tax on body weight? (2) How many Euros would be raised? (3) How much a fat tax affects household economic welfare in the short term, and how regressive is the fat tax? To answer to these questions, we need to assess how food prices affect food demand. In other words, price and nutrient elasticities need to be estimated. This is done by estimating a complete food demand system using French household data collected by

TNS Worldpanel between 1996 and 2001. The study period was chosen to evaluate the effects of the fat tax before the implementation of the first national nutrition and health program in France.[2] Thus, the effects of informational programs are removed from our analysis.

Most of this kind of applied research, however, has been based on incomplete food demand systems using either some strong separability assumptions, as in Bertail and Caillavet (2008), or a methodology developed by LaFrance and Hanemann (1989), and thereby partly assess the price effects on consumption, in particular the trade-offs between various food items, and/or nutrients.[3] In this paper, a complete food demand system, which allows us to consider a very large set of interdependent demand relationships is estimated, to assess the *global* impact of a fat tax on households' nutrient intakes. To estimate a complete food demand model, we need to have complete information (prices, expenditures, budget shares etc.) over a large set of food items for all sampled households. However, expenditures, quantities, and supply prices for some food items for any given household are not recorded in TNS Worldpanel data. To solve the problem of data incompleteness, a cohort model obtained by aggregating the Almost Ideal Demand System (AIDS) over cohorts is proposed.[4] The crucial step in this approach is to estimate the unobserved variables using a pre-model over cohorts. One of the technical contributions of this paper is to show how the aggregation process leads to induced bias and heteroscedasticity.

In this study, we estimate nutrient elasticities for 32 nutrients in response to changes in 22 food category prices over cohort for the period 1996-2001. In particular, households are segmented into six regions of residence, and four income groups. Then, the methodology of Huang (1996), which consists of applying a nutrient conversion matrix to the price elasticities, is used to derive nutrient elasticities. Finally, the latter are used to see whether a fat tax reduces households' total energy intakes and quantify the associated trade-offs between nutrients. In similar works, Marshall (2000), and Mytton et al. (2007) for Great Britain, and Chouinard et al. (2007) for the U.S. assessed the impact of a fat tax on households' nutritional intake. But their analysis is restricted to a small set of nutrients, and trade-offs between nutrients are therefore partly assessed.

The household food acquisition data contained in the TNS Worldpanel database has advantages over individual food surveys more commonly used to study the relationships between food and health in France. Households respond over a longer period of time (an average of 4 years in the TNS Worldpanel survey), which enables the observation of long-term behaviors and avoids the well-known biases of individual food surveys. In the individual surveys, respondents may over- or under-report their consumption of certain foods of high or low nutritional value, respectively, either because they wish to lie or because they did in fact increase or reduce their consumption deliberately for the short period of the survey. However, these data do not take into account the effects of food purchased away from home and do not reach the level of individual choice. Chesher (1997) and Allais and Tressou (2008) developed non-parametric methods to decompose a series of household quantities into individual quantities. But, in light of the incompleteness of our database and the errors of approximation that follow from decomposition methods, as underscored by Allais and Tressou (2008), we do not chose to use these methods in the present study.

We find that cheese-butter, sugar fat products, and ready meals should be taxed to have the most effective impact on households' total energy, and taxing these goods do reduce households' calory intake, via, in particular, the decrease of households' saturated fat intake. But taxing these food categories involves ambiguous and small effects on households' nutrient intake. The effects are ambiguous because increasing the price of a food to reduce calory and/or fat intakes generally reduces intakes of other nutrients deemed good for health. For example, increasing cheese and butter prices decreases calory, saturated fat, and sodium intakes but also reduces intakes of vitamin D, calcium, iron, and magnesium. Even more importantly, we find nutrient price elasticities to be remarkably inelastic, as in Huang and Lin (2000) and Beatty and LaFrance (2005). These results call into question the effectiveness of tax policies intended to alter nutritional intakes, as it was also highlighted by Mytton et al. (2007) and Chouinard et al. (2007), and are consistent with the conclusions of Kuchler, Tegene, and Harris (2005) and Kuchler et al. (2005) for household food purchases. Regarding the impact of a fat tax on weight, we estimate that a 10% fat tax on food categories high in calory leads to quite small impacts, in the short run, but non negligible changes in the long run, on body weight. However, in some cases, it could take more than 8 years to reach the long term effects. Given that the taxed products are inelastic, fat tax policies raise substantial revenues. However, as Chouinard et al. (2007), we show that this political instrument can be extremely regressive.

This paper is organized as follows. First, the data and the cohort construction are presented. Second, the estimation over cohort of the unobserved data is described. Then, we lay out the aggregation procedure for the AIDS and highlight the resulting estimation problems. Fourth, the estimation results and the demand and nutrient elasticities are presented. Fifth, the fat tax policy is assessed based on changes in the intake of 32 nutrients, and short and long run variation in weight; the level of revenue raised by the tax; and household welfare costs. Finally, we conclude on wondering how would the food industry would respond to a fat tax policy, and whether a fat tax could be rather used as a threat to urge on *voluntary* approaches by food industry to reduce calory, via decreasing saturated fat content, in food products.

Data and Cohort Construction

This section begins with a presentation of the data used and an explanation of why the construction of cohorts is needed to estimate a complete food demand system in France. Then, we detail the construction of the cohort.

The Data

The TNS Worldpanel is the principal source of information on food purchases in France. Each annual survey contains weekly food acquisition data of approximately 5,000 households, with an annual rotation of 1/3 of the participants. The households are selected by stratification according to several socioeconomic variables and remain in the survey for a mean period of 4 years. All participating households register grocery purchases through the use of EAN bar codes (Universal Product Code), allowing their purchases to be categorized under such heading as cereals, dairy products, cheese, eggs, sugar, and pastries. To register grocery purchases without a bar code, households are assigned to two groups to alleviate the workload. Each group (half of the survey) is requested to register its "at home" purchases for a restricted set of products: meat, fish, and wine for the first group and fresh fruits and vegetables for the second group. Hence, each group covers a different set of products. Although the two lists together include nearly all possible food products at a very disaggregated level, this method means that purchasing information is never complete for a given household. In other words, expenditures, quantities, and supply prices are missing for some food categories for any given household. This has strong implications for micro-econometric studies of food consumption in France: it means that complete demand systems cannot be estimated for the country. It is then impossible to estimate the global impact of price reforms on household behavior, particularly the product substitutions that these reforms seek to encourage. To solve the problem of data availability resulting from data structuring, we follow the methodology of Deaton (1985) by using cohorts to estimate the demand system on TNS Worldpanel data for the period 1996 to 2001. How cohorts are constructed is presented just below.

To facilitate the estimation procedure and to reduce the number of parameters to be estimated, food items are grouped into 22 categories. We considered carefully how to categorize different food products regarding consumer preferences, willingness to substitute products and similarities in the nutritional content of the products. The following categories of goods are defined: red meat (beef and veal); other meats; cooked meats (ham, pâté, sausages, bacon, etc.); fish and sea foods; eggs; grain products (bread, pasta, rice, wheat flour, and cereals); potatoes; fresh fruits; processed fruits; fruit juices; fresh vegetables; processed vegetables; dried fruits; milk products (milk, yoghurt, dairy desserts, etc.); cheese, butter and cream; ready meals (pizza, sauerkraut, cassoulet, etc.); oils; salt-fat products (finger food, chips, salt biscuits, appetizers); sugar-fat products (candy, chocolate, sugar biscuit, pastry, ice-cream, jam, etc.); mineral and spring waters; other soft drinks; alcoholic beverages (including wine). The online appendix provides a detailed discussion of why we choose this classification.

All the quantities and prices of these categories of goods are expressed in the same unit (kilogram, and French franc per kilogram) to ensure that the demand model used to estimate elasticity is "Closed Under Unit Scaling" (CUUS), meaning that the estimated economic effects are invariant to a simultaneous change in unit, as stressed by Alston, Chalfant, and Piggott (2001).

We then determined the quantities of the 32 nutrients in the 22 food categories, based on consultations with nutritionists and the composition tables of food products developed by Favier et al. (1995). The nutrients of interest are energy (measured in food calories); fat, subdivided into saturated (red meat, egg, whole milk, etc.), monounsaturated (olive oil, canola oil, peanut oil, etc.), and polyunsaturated (oils from corn, soybean, safflower, cottonseed, fish, etc.); cholesterol and alcohol; proteins, subdivided into vegetable and animal protein; carbohydrates; dietary fibres; micronutrients such as vitamin A (retinol and beta-carotene), B vitamins (1, 2, 3, 5, 6, 9, 12), vitamin C, vitamin D, and vitamin E; and minerals (calcium, iron, magnesium, sodium, phosphorus, potassium).

Cohort Construction

The population is split into homogeneous cohorts based on the following two variables:

(1) a geographical variable that indicates the region of residence of the household. Adjacent regions where traditions and food purchasing patterns show significant similarities are grouped together. In particular, French regions are aggregated by comparing the main food categories that are over- or under-consumed relative to the national average consumption. For example, the North regions (North-Pas de Calais, and Picardy), and North-East regions (Lorraine, Alsace, Champagne-Ardenne) are aggregated into one region since both regions show over-consumptions of meat, cooked meat, potato, Cheese-butter, and under-consumptions of fresh fruit and vegetable and Fish. This approach leads

to six regional modalities: Paris and its suburbs; North regions, and North-East regions; South-East regions (Provence-Alps-Côte d'Azur and South Rhône Alps departments i.e. Ardèche, and Drôme); South-West regions (Poitou-Charente, Aquitaine, Midi-Pyrenees, Languedoc-Roussillon) with Limousine and Auvergne; West regions (Brittany, Western Loire, and Normandy); and the Center-East regions (Centre, Burgundy, Free County of Burgundy, East Rhône-Alps departments i.e.Savoy, Upper Savoy and Isère). More details on how region selection was implemented is given in the online appendix.

(2) A socioeconomic classification of the households constructed by TNS Worldpanel. This variable is based on household's monthly income with respect to the number of members in the household and to consumption units defined by OECD. This classification scheme comprises four modalities. The first modality contains the households with the highest levels of income, well-off; the second includes households whose income is above the national average, average upper; the third comprises the households whose income is below the national average, average lower; and the fourth contains the households with low income levels, modest. Below these types of agent are respectively called well-off, average upper, average lower, and modest households. The intervals of household's monthly income chosen by TNS Worldpanel data to characterize the four income classes are provided in the online appendix.

This set of variables enables us to detect the likely differences in dietary intake patterns across regions of residence, and income. We get 24 cells, which represent typical households for a given region, and income level, and each cell contains sufficient number of households, as table 1 illustrates.

Estimation of the Unobserved Data

The problem of unobserved data is addressed using cohorts. Unobserved consumption and expenditures in the 22 food categories defined above are estimated for 13 four-week periods over six years. The estimates are based on the mean consumption and price values over all households in a given cohort,as it is detailed below.

Estimation of Unobserved Quantities and Expenditures

In the following discussion, $\mathscr{S}_k$, $k = 1,2,3$ designates, respectively, the sub-panel corresponding to group 1 (meat, fish, and wine), the sub-panel corresponding to group 2 (fresh fruits and vegetables), and, finally, the sub-panel of products that are registered by all households. Notice that a household appears either in both sub-panels S_1 and S_3 or in sub-panels S_2 and S_3. Moreover, we denote $\mathscr{P}(i) = \mathscr{S}_l$ if $i \in \mathscr{S}_l$. So writing $h \in \mathscr{P}(i)$ (resp. $h \in \mathscr{P}(i)^c$) means that the household h has (resp. has not) registered the product i.

In the TNS Worldpanel dataset, we never observe the full consumption of any given household basket. Thus, items are aggregated at the cohort level using the following procedures. For a given cohort $c \in \{1,...,C = 24\}$, at time $t \in \{1,...,T = 78\}$, we observe $N_{c,t}$ households in the corresponding cohort denoted $H_{c,t}$. Let Y_{iht} be some variable of interest in a food category i of a household h at period t which is observed only in the subpanel $\mathscr{S}_l$, $l = 1,2,3$. The unobserved value for a household h at period t who belongs to the cell $H_{c,t}$ but who does not register the product i is predicted by the mean $\overline{Y}_{ict}$, over the households in a cell c at period t to whom product i is registered.

Estimation of Unobserved Prices

Similar to the situation with food quantities consumed, not all supply prices are captured in the TNS Worldpanel database. Generally, food prices are approximated by unit values obtained by dividing expenditures by quantities purchased for a given good. In the present study, however, unit values cannot be calculated for each household since we do not observe all the expenditures and quantities purchased for any given household. Second, the unit value is not the supply price of a good, as it reflects both its average market price and consumer choices of food quality: two different households subject to the same pricing scheme may well exhibit different unit values because food items purchased by households have different qualities.

The first problem is addressed by approximating the unobserved quantities and expenditures for any given household using the cohort method described above. Yet contrary to unobserved quantities and expenditures, the unit values are constructed across regions to capture variations in market prices induced by transportation costs. This means that unit values within regions are constant. This aggregation process also attenuates the second problem. The unit values that it provides are used below as prices for households.

The second problem is further addressed using a procedure similar to that of Park and Capps (1997). Prices are quality-adjusted by regressing the log of unit values on total household food expenditure and household characteristics that may affect the choice of food quality, such as income level, household composition and size, and the education level of the principal household earner. We find significant food quality effects for all food group at the 5% level, with the exception of red meat, fish, potato, processed fruits and vegetables, fruit juices, milk products and salt-fat product. However, these effects are much smaller than those obtained by Huang and Lin (2000) since our study aggregated data over a longer period of time (four weeks vs. seven days) and for a larger group of consumers (aggregated across cohort vs. no aggregation). Estimation results can be found in the online appendix.

Aggregating AIDS Model: A Cohort Model

The total household food expenditure cannot be directly calculated for a given household in the TNS Worldpanel database. As a consequence, this variable must be extrapolated for each cell. In the following discussion, we describe the AIDS model and propose a simple model for estimating the total household food expenditure of each household as well as the shares that will be compatible with the aggregation of the AIDS system. The consequences of the aggregation for the estimation, in terms of bias and heteroscedasticity, are carefully examined in the last subsection.

The AIDS Model

We focus, here, on a standard AIDS model developed by Deaton and Muellbauer (1980). Quadratic AIDS models (Banks, Blundell, and Lewbel 1997) are more flexible, but the non-linear quadratic term in these models makes them difficult to aggregate and estimate when considering cohorts. However, Banks, Blundell, and Lewbel (1997) show that the AIDS is unlikely to be rejected for most food items. Other models, particularly in the framework of an incomplete demand system, have been proposed by LaFrance (1990), LaFrance et al. (2002), and Beatty and LaFrance (2005) based on the work of LaFrance and Hanemann (1989). The purpose of these models is essentially to propose incomplete demand models consistent with standard microeconomic theory. To avoid some complications induced by the non-linearities in their models (see, for instance, the box-cox transformation model proposed in LaFrance et al., 2000), we do not apply any non-linear transformation to our data prior to analyzing it. Another reason for not using this kind of model is that our database contains gaps in the unit values for all the households in our database. We now recall a few facts about the AIDS model.

In the framework of the household production model, the consumption behavior at the household level during period t can be described with an AIDS by replacing unit values for prices. As such, in this framework, the budget share w_{iht}, for product i, household h, and time t is given by

$$(1) \qquad w_{iht} = \mu_{ih} + \sum_{j=1}^{N} \gamma_{ij} \ln v_{jht} + \beta_i \left[\ln x_{ht} - \ln a(v_{ht})\right] + u_{iht},$$

for $i = 1,..,N$ food categories and $h = 1,..,H$ households, where $a(v_{ht})$ stands for the price index given by $\ln(a(v_{ht})) = \mu_0 + \sum_{i=1}^{N} \mu_{ih} \ln v_{iht} + \frac{1}{2}\sum_{i,j=1}^{N} \gamma_{ij} \ln v_{iht} \ln v_{jht}$. The variable v_{iht} stands for the unit value of a category of goods i for household h at period t. The variable x_{ht} stands for the total expenditure of household h at period t; and α_i, γ_i, and β_i are the parameters to be estimated. To take into account the heterogeneity of behavior, the parameter μ_{ih} is modeled as a linear form $\mu_{ih} = \alpha_{i0} + Z_h \alpha_i$, where $Z_h = (Z_{kh},\ k = 1,...K)$ is a vector $(1, K)$ of household characteristics. We denote as $\mathscr{I}_{iht} = \{(v_{jht})_{j=1,...,N},\ \ln(x_{ht}),\ Z_h\}$ the set of all explanatory variables for the share w_{iht}. It may be proved that this system is derived from some cost minimization if it satisfies the restrictions imposed by the properties of demands i.e., additivity, homogeneity of degree zero in prices and total household food expenditure together, and the symmetry of Slutsky's matrix. This implies the well-known additivity constraints $\sum_{i=1}^{N}\alpha_{i0}=1$, $\sum_{i=1}^{N}\alpha_i=0$, $\sum_{i=1}^{N}\gamma_{ij}=0$, for all j and $\sum_{i=1}^{N}\beta_i=0$ and the homogeneity and symmetry constraints $\sum_{j=1}^{N}\gamma_{ij}=0$, and $\gamma_{ij}=\gamma_{ji}$ for all i and j. All the shares add up to one, giving us $\sum_{i=1}^{N}w_{iht}=1+\sum_{i=1}^{N}u_{iht}=1$. It follows that the u_{iht} perturbations are not independent. However, it is assumed, that if we drop one share then the u_{iht} perturbations are independent conditionally to the whole information $\mathscr{I}_{iht}$. Of course, this is a strong assumption that can be tested in future works. Even if these residuals are independent, they may not be identically distributed because of product or temporal effects.

The Underlying Cell Models

The AIDS model is based on budget share, which we cannot calculate at the household level in the present study because our database does not capture total household food expenditure. Nevertheless, we have sufficient information in our dataset to predict budget share by aggregating over cells.

We assume that the expenditure of a household h to purchase a product i at time t essentially depends on the characteristics of the cell to which the household belongs

(2) $\quad x_{iht}=x_{ict}+\varepsilon_{iht}^{(1)}$, for $i=1,...,N,\ h\in H_{ct},\ c=1,...,C,\ t=1,...,T.$

Here, the x_{ict} should be seen as the parameters of the model, i.e., the quantities to be predicted. To simplify, we assume that the expenditures of households are not correlated to each product. We also assume that the expenditures of any household in a given cell are not correlated over time. This is partially true insofar as the households which that belong to H_{ct} are generally not the same and are independent from the ones in $H_{ct'}$, for t' and t far-distant enough. We take into account that the partial correlation in a short period would make the estimation procedure more difficult. For a given household, $\varepsilon_{ht}^{(1)}=[\varepsilon_{iht}^{(1)}]_{1\leq i\leq N}$ has variance $V(\varepsilon_{ht}^{(1)})=\Omega_t$, where $\Omega_t=[\omega_{ijt}]_{1\leq i,j\leq N}$ is a $N\times N$ full-rank matrix. For a given product i and a time t, an estimator of x_{ict} is given by $\bar{x}_{ict}=\frac{1}{N_{ict}}\sum_{h\in H_{ct}\cap\mathscr{P}(i)}x_{iht}$, where N_{ict} is the number of households in a cell c at time

t for which product i is registered. So, the best predictor of x_{iht} of a household that belongs to H_{ct} and for which we do not observe the expenditure, $h \in \mathscr{P}(i)^c$ [equivalently $h \notin \mathscr{P}(i)$], is $\widehat{x}_{iht} = \overline{x}_{ict}$. It follows that total expenditure for a given household is predicted in an unbiased manner by

$$(3) \quad \widehat{x}_{ht} = \sum_{i=1}^{N} x_{iht} I_{h \in H_{ct} \cap \mathscr{P}(i)} + \sum_{j=1}^{N} \overline{x}_{jct} I_{h \in H_{ct} \cap \mathscr{P}(i)^c},$$

where I_A stands for the indicator function of event A. Similarly, we define the total predicted expenditure over a cell as $\widehat{x}_{ct} = \sum_{i=1}^{N} N_{ct}\overline{x}_{ict}$, where N_{ct} is the number of households in the cell c at period t.

Finally, the predicted household shares are given by $\widehat{w}_{iht} = \frac{x_{iht}}{\widehat{x}_{ht}}$ if $h \in \mathscr{P}(i) \cap H_{ct}$, and $\widehat{w}_{iht} = \frac{\overline{x}_{ict}}{\widehat{x}_{ht}}$ if $h \in \mathscr{P}(i)^c \cap H_{ct}$; the predicted shares over cells are given by $\widehat{w}_{ict} = \frac{N_{ct}\overline{x}_{ict}}{\widehat{x}_{ct}}$ which clearly satisfy the share equation $\sum_{i=1}^{N} \widehat{w}_{ict} = 1$.

Aggregation of AIDS Model over Cells

For aggregating the model, it is better to write the shares over cells $\widehat{w}_{ict}$ as the weighted sums of household estimated shares. A simple calculation shows that $\widehat{w}_{ict} = \sum_{h \in H_{ct}} \widehat{\theta}_{hct}\widehat{w}_{iht}$, where $\widehat{\theta}_{hct} = \frac{\widehat{x}_{ht}}{\widehat{x}_{ct}}$ and satisfies $\sum_{h \in H_{ct}} \widehat{\theta}_{hct} = 1$. Gardes et al. (2005) propose the same aggregation process, but the main difference in their approach is that, in our study, the total household food expenditure is not known and $\widehat{\theta}_{hct}$ estimates the true share θ_{hct}. By aggregating model (1) over cells, i.e., by reweighing the shares with the estimated values $\widehat{\theta}_{hct}$, for $h \in H_{ct}$, we get

$$(4) \quad \widetilde{w}_{ict} = \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} w_{iht} = \alpha_{i0} + \overline{Z}_{c,t}\alpha_i + \sum_{j=1}^{N} \gamma_{ij} \ln \overline{v}_{irt} + \beta_i \left(\overline{\ln x_{ct}} - \overline{\ln(a(v_{rt}))} \right) + \overline{u}_{ict},$$

where $\overline{Z}_{ct} = \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} Z_h$ is the weighted mean characteristic of a cell. By recalling the constancy of unit values within regions, the log unit value of product j over a cell c in region r, we have $\ln \overline{v}_{jct} = \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} \ln \overline{v}_{irt} = \ln \overline{v}_{irt}$. The weighted mean total log-expenditure of a cell is equal to $\overline{\ln x_{ct}} = \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} \ln x_{ht}$, and, similarly, the weighted mean price index over a cell c in region r is equal to

$$(5) \quad \overline{\ln(a(v_{rt}))} = \mu_0 + \sum_{i=1}^{N} \left(\alpha_{i0} + \overline{Z}_{ct}\alpha_i\right) \ln \overline{v}_{irt} + \frac{1}{2} \sum_{i,j=1}^{N} \gamma_{ijt} \ln \overline{v}_{irt} \ln \overline{v}_{jrt},$$

In the end, we note that, since $\overline{u}_{ict} = \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} u_{iht}$, we have $E\overline{u}_{ict} = 0$ and $V(\overline{u}_{ict}) = \sum_{h=1}^{N_{ct}} E\widehat{\theta}_{hct}^2 V(u_{iht})$.

Estimation of the Aggregated Model

The aggregated AIDS model is estimated using the iterated least squares estimator developed by Blundell and Robin (1999). It amounts to iterating a series of ordinary least squares regressions until convergence on the parameters is reached. Within each iteration, the estimation is performed equation by equation while imposing the constraints of additivity, homogeneity, and symmetry. Thus, in contrast to the approach of Blundell and Robin (1999), the symmetry constraint is directly imposed in the present study.[5]

The main problems in the estimation step are bias and heteroscedasticity, both of which result from the use of estimated variables instead of the true ones, as well as the potential endogeneity of total household food expenditure, as stressed by Blundell and Robin (1999), and Lecocq and Robin (2006). These problems are solved as follows:

(1) Induced bias: Estimating budget shares and expenditure cause a bias problem, but its is negligible as we highlight just below. Recall that $\widetilde{w}_{ict} = \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} w_{iht}$ is unknown and is replaced by the predictor $\widehat{w}_{ict}$. More precisely, if we define $\varepsilon_{iht}^{(2)} = \widehat{w}_{iht} - w_{iht}$, we get over each cell $\widetilde{w}_{ict} = \widehat{w}_{ict} - \overline{\varepsilon_{ict}^{(2)}}$, where $\overline{\varepsilon_{ict}^{(2)}} = \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} \varepsilon_{iht}^{(2)}$. This creates a bias term -as well as an additional source of heteroscedasticity (see below)-that can be approximated to the first order (see the online Appendix) by

$$(6) \quad E\varepsilon_{iht}^{(2)} \approx \begin{cases} \theta_{hct}\, N_{ict}^{-1} \left[\sum\limits_{j:h \in \mathscr{P}(j)^c \cap H} \omega_{i,j,t} \right], \text{ if } h \in \mathscr{P}(i) \cap H_{ct} \\ x_{ct}^{-2} \sum\limits_{h \in \mathscr{P}(i)^c} \theta_{hct}\, N_{ict}^{-1} \left[\sum\limits_{j:h' \in \mathscr{P}(j)^c \cap H_{ct}} \frac{1}{N_{jct}} \omega_{i,j,t} + \sum\limits_{j} \omega_{i,j,t} \right] \text{ else} \end{cases}$$

This bias is eventually negligible regarding the magnitude of x_{ct}^2, and we do not need to take into account in the estimation.

(2) Heteroscedasticity: Due to the aggregation process, the new model becomes heteroscedastic. Notice that, if the u_{iht} is i.i.d., then the variance of the aggregated residual is $V(\overline{u}_{ict}) = V(u_{iht})\sum_{h=1}^{N_{ct}} E\widehat{\theta}_{hct}^{2}$. Since $\sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} = 1$, we have from the preceding computations $E\widehat{\theta}_{hct} = O(1/N_{ct})$ and $E\widehat{\theta}_{hct}^{2} = O(1/N_{ct}^{2})$, so that $V(\overline{u}_{ict}) = O(1/N_{ct})$. In this case, it is possible to correct for most of the heteroscedasticity simply by multiplying each variable defined at the cell level by the square root of the size of the cell. However, if the residual can be decomposed into some fixed effects and a mixed effect, say $u_{iht} = u_i^* + u_t^* + u_{it}^* + u_{iht}^*$, where the components are centered and independent, then, by aggregation, we get $\overline{u}_{ict} = u_i^* + u_t^* + u_{it}^* + \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} u_{iht}^*$ with $V(\sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} u_{iht}^*) = O(1/N_{ct})$ and fixed variances for the other components. In addition, it is also worth noting that $\overline{\varepsilon_{ict}^{(2)}}$, the error introduced by using predictors instead of the true values may be interpreted precisely as a cross effect of the form u_{it}^*. It follows that, if the products and temporal effects are large, then the heteroscedasticity should not be corrected by multiplying the equations by $\sqrt{N_{ct}}$ because this would lead to even greater heteroscedasticity. In these circumstances, for reasons that are unclear, the aggregation process tends to reduce the variance inside the cell (the intra-variance), but the imputation process tends to increase the variance of the predictor of the total household food expenditure and, therefore, of the shares. Since we want to obtain robust estimates, we will essentially use standard two-step methods and generalized least square estimators to correct for the heteroscedasticity.

(3) Endogeneity of total household food expenditure: The log total household food expenditure variable $\overline{\ln x}_{ct}$ and regression residuals $\overline{u}_{ct}$ may be correlated for at least one of the following two reasons: first, either because of simultaneity of the determination of total household food expenditure and budget shares since common shocks may both determine taste and total household food expenditure changes, and/or second, because of unobserved heterogeneity. Following Blundell and Robin (1999), the first likely source of correlation is usually controlled for by means of instrumental variable techniques, using income as an instrument for total household food expenditure. In particular, we augment the AIDS specification with the residuals υ_{ct} of the regression of the total household food

expenditure $\overline{\ln x_{ct}}$ on socio-demographic variables $\overline{Z}_{ct}$, prices $\ln \overline{v}_{irt}$, and the logged income of cohort c at period t, denoted by $\overline{\ln y_{ct}} = \sum_{h=1}^{N_{ct}} \widehat{\theta}_{hct} \ln y_{ht}$.

The likely second source of correlation is corrected as in Lecocq and Robin (2006). Following Mundlak (1978), they show that unobserved heterogeneity can be fully taken into account by integrating the means of the log of income and the log total household food expenditure for each cell c in the set of socio-demographic variables $\overline{Z}_{ct}$, i.e., $\overline{\ln y_{c\bullet}} = \frac{1}{T} \sum_{t=1}^{T} \overline{\ln y_{ct}}$, and $\overline{\ln x_{c\bullet}} = \frac{1}{T} \sum_{t=1}^{T} \overline{\ln x_{ct}}$ respectively. Testing for the absence of $\overline{\ln y_{c\bullet}}$, and $\overline{\ln x_{c\bullet}}$ in the regressions allows direct testing to detect biases due to unobserved heterogeneity.

Finally, we estimate the following aggregated AIDS model over cells, in region r

$$(7) \qquad \widehat{w}_{ict} = \alpha_{i0} + \overline{Z}^{*}_{c,t} \alpha_i + \sum_{j=1}^{N} \gamma_{ij} \ln \overline{v}_{jrt} + \beta_i \left(\overline{\ln x_{ct}} - \overline{\ln(a(v_{rt}))} \right) + \overline{u}_{ict}.$$

$\overline{Z}^{*}_{ct}$ is composed of two sets of variables: i) a set of variables containing the variables υ_{ct}, $\overline{\ln y_{c\bullet}}$, and $\overline{\ln x_{c\bullet}}$ to correct the likely endogeneity of total household food expenditure; ii) a set of socio-demographic factors that may influence consumer food choices. Socio-demographic variables include the education level of the principal household earner (no diploma, low degree of diploma, level of bac, *bac, and higher degree*); urbanization (rural, small city less than 10,000 inhabitants, city less than 50,000 inhabitants, *city less than 200,000 inhabitants*, big city, and Paris and its suburbs); the proportion of households in the cell that have a garden, a cellar, and home ownership; and the composition of children in the household.[6] The child household composition is characterized by 4 groups: children for age groups 0-5, 6-10, 11-15, and 16-18. We also include the proportion of households in the cell that have at least one child younger than 18. Finally, four-week and annual dummies are introduced in the model. Table 2 displays some descriptive statistics for these variables. These variables are then aggregated over cohorts.

Estimation and Elasticities

Estimation of the AIDS

Table 3 presents some descriptive statistics for expenditure shares and unit values in French francs per kilogram (1 euro was taken to equal 6.55957 French francs). Table 3 also displays the standard errors of the regressions, denoted by RMSE. The close correspondence between simulated values and sample observations indicates that our estimated AIDS is reliable for use in estimating demand elasticities. The goodness-of-fit appears to be satisfactory in the standard of analyzing household survey data, with R^2 value in a range of 0.82 to 0.24. In addition, biases due to unobserved heterogeneity are detected. Table 3 shows that $\overline{\ln x_{c\bullet}}$ is significant for all food items except beef, cooked meat, eggs, potato, fruit juice, processed vegetable, dried fruit, cheese-butter, soft drink and water; and $\overline{\ln y_{c\bullet}}$ is significant for all groups except fish, eggs, potato, processed fruit and vegetable, fruit juice, dried fruit, cheese-butter, soft drink and water. As Lecocq and Robin (2006) also suggests, these results show that the usual instrumentation by income, proposed by Blundell and Robin (1999), is not sufficient on its own to control fully for the endogeneity of total food expenditure in the AIDS.

Given the number of food categories, and the large number of sociodemographic variables, the coefficient estimates are not reported here, but they are available in the online appendix. We find that the higher the education level of the head of the household, the more they allocate their food budgets to fresh vegetables and fruits, milk products, cheese and butter, and the less they allocate it to beef, cooked meat, grain products, fruit juices, and alcohol. Having a child younger than 18 contributes significantly to the purchase of more meat, dairy products, ready meals, cheese-butter, sugar-fat products, and soft drinks, but to fewer purchases of fish, fresh fruits and vegetables, ready meals, and alcoholic beverages.However, if we focus our attention on households with children aged 0-5, our estimates show that they allocate significantly more of their food expenditure to fresh fruits, and soft drink, and less to meat, and cheese-butter.

Demand Elasticities

Following the approach of Banks, Blundell, and Lewbel (1997), we calculate uncompensated price elasticity matrix $D_c = [e_{ij,c,t}]_{1 \leq i,j \leq N}$, such that the price elasticity of demand for food category i with respect to price j $e_{ij,c,t} = -\iota_{ij} + \widehat{w}_{ict}^{-1} \left[\gamma_{ij} - \beta_i \left(\mu_{ic} + \sum_{j=1}^{n} \gamma_{ij} \ln \overline{v}_{jrt}\right)\right]$, where ι_{ij} equals one when $i = j$ and zero otherwise for $i, j = 1,...,N$, $\mu_{ic} = \alpha_{i0} + \overline{Z}_{c,t}^{*} \alpha_i$ and for a cell $c = 1,...,C$ in region $r = 1,...,R$. The elasticities are calculated using the average estimated shares and the mean point of the other variables for each income class. Total expenditure elasticities are reported in the online appendix. To save space, table 4 reports the estimated own- and cross-price elasticities for selected food categories across income class that will be useful later: it gives the percent of change in the 22 food category quantities involved by modifying the prices of fresh fruits and vegetables, fruit juices, milk products, cheese-butter, ready meals, sugar fat products, and other soft drinks by 1%. All price elasticity values, and their corresponding standard deviations,[7] across income class are reported in the online appendix. In the latter, we show that all of the own-price elasticities are negative, except for alcohol for modest households, and almost all are significant, and they are below one, except for beef, fish, dried fruits, ready meals, salt-fat products and water. Furthermore, own-price elasticities for grain, fruits, fruit juices, vegetables, and milk products are comparable to those reported by Huang (1996). We also find that modest households are significantly more sensitive to own-price change for fish, dried fruits, milk products, cheese-butter, oils, sugar fat products, mineral and spring waters than well-off households but less sensitive for fresh vegetables and fruits, and alcohol. Table 4 shows substantial disparities across income class for fresh vegetable and fruit own-price effects, as it is also found by Bertail and Caillavet (2008), while we get no disparity across income class for own-price effect of fruit juices. An other insightful result is that decreasing fresh vegetable price strongly decreases potato purchases (salt fat product purchases fall also but at a much less extent). Note also that increasing soft drink price brings about a fall in potato, ready meal and salt fat product purchases. This result is interesting since sodas are generally drunk while eating the latter products. We find that the increase of soft drink price benefits for fruit juice purchases. These results may give some arguments in favor of a tax in other soft drinks, although the level of the corresponding price elasticities are quite weak, as Jacobson and Brownell (2000) proposed. More comments are given in the online appendix.

Nutrient Elasticities

The nutrient elasticities are calculated following the approach of Huang (1996) and using the demand elasticities calculated above. He shows that combining demand elasticities with the values of the nutrient shares of each composite good category, the L nutrient elasticities with respect to good prices and total food expenditure can simply be calculated as

$$Nut_c = S_c * D_c$$

where Nut_c stands for the $(l \times N + 1)$ matrix of nutrient elasticities, and $S_c = [S_{li,c}]_{\substack{1 \le l \le L \\ 1 \le i \le N}}$ is the $(L \times N)$ matrix of the food's share of the L nutrients, where $S_{li,c}$ represents the ith food's contribution to the lth nutrient, so that $\sum_{i=1}^{N} S_{li,c} = 1$, for a cell $c = 1, ..., C$. It shows the effects on L nutrients in response to changes in N food prices for a particular cell c. It results that a change in a particular food price will affect all food quantities demanded through the interdependent demand relationships and thus cause the levels of consumer nutrient availability to change simultaneously. The online appendix gives details on the construction of S_c.

The crucial finding is that nutrient price elasticities are inelastic, as Huang and Lin (2000) and Beatty and LaFrance (2005) also found. Here, to the save space, we only display energy, saturated and polyunsaturated fat, sodium, calcium, beta carotene, vitamin C, and magnesium elasticities for the 22 food categories, across income class in table 5. All the nutrient elasticity values can be found in the online appendix. Table 5 reports that decreasing total energy intakes involves reducing all the food prices, except fish price. An other interesting point is that we estimate disparities in energy elasticities across income class for majority of food categories. In particular, for sugar fat products, we find that energy elasticity is 34% higher for modest households than for well-off households. We found also that energy intakes for well-off households is particularly sensitive to ready meals, and cheese-butter category, while it is ready meals, and sugar fat products for modest households. Table 5 displays disparities across income class for saturated fat elasticities. This is particularly true again for sugar fat products. We also estimate that saturated fat intakes falls by decreasing other meat category price, characterized by a lower saturated fat content than red meats. Increasing cheese-butter, and sugar fat product prices also reduces households' intakes in saturated fat, and at the same time increases their intakes in polyunsaturated fat. A detailed discussion of the trade-offs between the nutrients is provided in the next section.

Simulation of a Fat Tax

In this section, we examine whether a fat tax policy can alter French household intake of calory as well as its consequences on the intakes of other nutrients. As Chouinard et al. (2007) pointed out, the assessment of the impact of a fat tax policy is relevant only if we assume that the percentage change in targeted food prices is exactly equal to the tax rate. As it was recently proposed by French State policy makers, IGF-IGAS (2008), the fat tax in this paper concretely consists in increasing the value added tax (VAT) of the targeted food categories by τ. Nichèle and Robin (1995) also simulate VAT reform in France for food products. The new price of food item i after the implementation of the fat tax is now equal to $\overline{v}_{ir,1} = (1 + \frac{\tau}{1+VAT})\overline{v}_{ir,0}$, where $\overline{v}_{ir,0}$ stands for the pre-tax price.[8] The VAT rate is assumed, for simplicity sake, to be equal to 5.5% for all food items, except for alcohol which is equal to 19.6%.[9] The fat tax impact is appraised by calculating (1) the percentage change in nutrient quantities caused by a price variation in a specified food category, (2) the level of revenue raised per household and at the national level, (3) the welfare cost of a fat tax in terms of equivalent variation in total household food expenditure. Below, all the quantitative effects are calculated at the average point over time for an increase of targeted food category prices by $\frac{\tau}{1+VAT} = 10\%$.

Which food categories should be taxed to reduce households' energy?

Taxing all food products high in energy is of course politically unrealistic. So, we should determine which food category(ies) should be taxed to have the highest impact on calory intake. We have two ways for answering to this question. First, we can analyze the food's contribution of the 22 food categories to energy and second, the corresponding nutrient elasticities. The first analysis reveals interesting differences in the sources of energy across income and may, therefore, provides insightful information to food policymakers. The food's shares of the 32 nutrients can be found in the online appendix. Interesting disparities in the main sources of energy intakes across income groups are found. In particular, the highest food's share of energy for well-off households is cheese-butter category, which provides 14.94% of total energy intake, compared to 14.02% for modest households. While the highest one for modest households is sugar fat products, accounting for 16.86% of total energy intake, compared to 13.56% for well-off households.

The analysis of energy elasticities given in the previous section provides further support to the previous analysis, and additional information. Indeed, table 5 shows that if we want to reduce households' total energy intakes, the most efficient way (less than -0.10%) to do is to increase ready meal, cheese-butter category and sugar fat product prices. Modifying cooked meat price could be relevant also.

Ultimately, given the two previous analysis, cheese-butter, sugar fat products, and ready meals (especially for energy) should be taxed to have the most effective impact on households' total energy intake. An additional effect of taxing the latter food categories is that they are also the main sources of saturated fat intake for households.

The Effects of a Fat Tax

The effects of imposing a fat tax on cheese-butter category, and sugar fat products on nutritional intake were also assessed by Marshall (2000), and Mytton et al. (2007) for

Great Britain. Chouinard et al. (2007), for the U.S., estimated the effects of a fat tax on dairy products. But they all focused their attention only on several nutrients (saturated fats for Marshall (2000), poly-, mono- and un-saturated fats, cholesterol, and sodium for Mytton et al. (2007), and fats for Chouinard et al. (2007)). For France, Bonnet, Dubois, and Orozco (2008) simulate the impact of a fat tax on calory, protein, lipid, and carbohydrate intakes. To the best of our knowledge, the present study is the first time that such an complete assessment has been carried out in France.

(1) Impact on nutrient intakes. Given how nutrient elasticities are constructed, the percentage quantity change in nutrient n, caused by a price variation in food category i, is equal to $\frac{\tau}{1+VAT} Nut_{ni,c}$. If the tax affects a subset I of food categories, or in other words, if the reader would like to assess the percentage change brings about by a tax on several food categories, then the latter value is equal $\frac{\tau}{1+VAT} \sum_{i \in I} Nut_{ni,c}$. Note also that change is proportional to the price increase. Table 6 reports the percentage quantity change in total nutrient intakes for modest and well-off households if cheese-butter category, sugar fat product and/or ready meal prices increase by 10%, over a 4-week period. Two major results can be underlined. First, taxing the latter food categories decreases total energy, as it was targeted. This is mainly due to a fall of fat intake, and especially saturated fat intake. At first glance this result could appear as a mechanical effect or quite intuitive. However, the effects of a fat tax on nutrient intake is difficult to predict given that food purchases are highly interdependent: taxing food to reduce total calory intakes could lead to the opposite effect as a result of cross-price elasticities, as it was illustrated by Mytton et al. (2007) in the case of a tax based on foods high in saturated fat in U.K. or by Schroeter, Lusk, and Tyner (2008) in the case of a tax based on food away from home in U.S. Furthermore, the magnitude of the effects of a tax based on the three food categories are comparable to those reported by Mytton et al. (2007) for their best outcome: they found that extending VAT to food items high in saturated fat (their "best outcome") leads to a percentage in change of energy equal to -6.1% (we found 6.0 and 6.4% for well-off and modest households, if we set $\frac{\tau}{1+VAT} = 17.5\%$). Second, we found, as expected regarding the nutrient elasticity

disparities displayed above for sugar fat products, that tax on sugar fat products has quite different impact on total nutrient intake among income class. In particular, we assess that a 10% increase in the price of sugar fat products decreases household total energy intake by 0.79% for well-off versus 1.20% for modest households.

If we turn to results in details, table 6 shows that taxing ready meals has the highest effect on total energy intakes. This tax leads to additional nutritionally beneficial effects for sodium (a decrease of 2.35% and 2.17% for well-off and modest households respectively), retinol or vitamin A (mainly found in fruits and vegetables), beta carotene intakes (which it is consistent with the result that ready meals and fresh vegetable are substitutes, see table 4), and vitamin D (mainly found in fish, and so coherent with table 4). However, these positive effects are at the expense of vegetal protein, polyunsaturated and monounsaturated fat, vitamins B1, B6 and E. Table 6 shows that taxing cheese-butter category has the second highest impact on calory intake for well-off households, while it is when sugar fat products are taxed for modest households. A very appealing resulting effect of taxing the latter food categories is that the percentage drops in saturated fat and cholesterol are among the highest. An other outstanding result is that contrary to the case in which ready meals are taxed, taxing the two latter food categories increases the polyunsaturated fat intakes especially for well-off households–consistent with the result reported in table 4 which shows that cheese-butter category (sugar fat products) and oils are substitutes. As for ready meals, taxing these two food categories reduces the quantity of sodium, but to a less extent. Interestingly, the decrease in sodium is strongest when sugar fat products are taxed for modest households, while it is cheese-butter category for well-off households. We also get a positive effect on beta carotene (only when cheese-butter category is taxed), and vitamin E (mainly found in oils) intakes. However, these positive effects are offseted by the negative impact on all vitamin (except vitamin E), calcium, magnesium, potassium and phosphorus intakes.

Although it is hard to assess the effects of these taxes on health, we can *approximate* their effects on weight in the short and long term based on a biological model proposed by Kozusko (2001) which defines the body weight dynamic. The details of calculation and results for different types of consumers (gender, age and life style differences) are given in the online appendix. We estimate that increasing cheese-butter category (ready meal; sugar fat product) price by 10%, reduces total calory intakes of an individual, on average, to 16.65 and 17.58 (19.30 and 19.25; 10.69 and 18.02) kcal per day, given that the average family size in France is 2.3, if he belongs to a well-off or modest household, respectively. The estimated effects are quite small, but if this decrease is *persistent*, we find that this weak caloric variation could have impact on weight in long term. Indeed, if we assume a male between 30 and 60 years old, with a weight of 70 kg, a light activity lifestyle, belonging to a well-off households and for whom the total energy expenditure equals calory intake before the implementation of a 10% tax on ready meals, his weight would reduce by 56 grams after one month, and 559 grams after one years, and he would finally weight 71.1 kilograms. Yet, it takes 7 years and 6 months to reach the long term effect. Taxing the three food categories decreases the body mass of the same consumer by 136 grams after one month, 1.351 kilograms after one year, and he would weight 72.7 kilograms after almost 9 years after implementing the fat tax. We could wonder whether consumers will be enough patient to benefit from long term health effects, given that they feel in the short run worse off, since they consume less without immediate substantial effects on their weight. Chouinard et al. (2007) found much weaker effect if dairy items are taxed: fat decreases by 6 calories if a 10% tax is implemented. However, their fat tax is based on the percentage of fat in each dairy item, rather than the item itself, and the caloric variation is calculated only using fat variations. Etilé (2008), who estimates price-BMI relationship in France, finds comparable long term effects of a fat tax on body weight.

(2) Revenue raised. Simple calculations shows that if the VAT of the food category i is increased by τ, the average tax revenues raised are equal to $R_c = \sum_{k=1}^{N} R_{kc}$, for cohort c, where $R_{ic} = \left(\frac{VAT+\tau}{1+VAT+\tau}\right)\overline{Q}_{ic,1}\overline{v}_{ir,1}$, and $R_{jc} = \left(\frac{VAT}{1+VAT}\right)\overline{Q}_{jc,1}\overline{v}_{jr}$ for $i \neq j$, and $\overline{Q}_{ic,1} = \left(1+\frac{\tau e_{ii,c}}{1+VAT}\right)\overline{Q}_{ic,0}$, and $\overline{Q}_{jc,1} = \left(1+\frac{\tau e_{ji,c}}{1+VAT}\right)\overline{Q}_{jc,0}$ stand for the average post-tax quantity

purchased of the food category i and j, of an household of cohort c. Despite the small impact on nutrient intake, we find quite substantial tax revenue: a 10% raise (or equivalently $\tau = 0.1055$) in cheese-butter category (ready meal and sugar-fat product) price, brings about an increase of tax revenues equal on average to 1.80 (1.07 and 1.60) and 1.86 (1.09 and 2.15) euros per household and 4-week period for well-off and modest households, respectively. The corresponding national additional tax revenues, calculated for the average household, are €45.64 million, €25.96 million and €45.55 million, given that the 1999 census counted 23.8 million households in France. In other words, to give the importance of these fat taxes on revenue, we find that the government revenue increases by 16.3%, 9.26% and 16.59% respectively. These substantial effects are due to highly *inelastic* price elasticities. If the tax is implemented over the three food categories, the government gets additional tax revenues equal to 4.31 and 4.96 euros per household and 4-weeks period from well-off and modest households, respectively.

(3) The impact on short-run welfare. The short-run welfare cost is defined as the fall in total household food expenditure that a household living in an environment with no tax is willing to accept while remaining indifferent to living in an environment with a tax. This definition means that the welfare assessment does not include the long-term effects of the tax on household physical health. Its measurement for the aggregated AIDS is presented in the online appendix. We estimate that a modest and well-off households would be willing to accept on average a total household food expenditure reduction of 2.27 (1.38, 1.28) euros and 2.30 (1.41, 4.33) euros per four-week period, respectively, instead of facing a 10% tax on cheese-butter category (ready meals, sugar fat products). So, first, welfare costs vary greatly across income level when ready meals, sugar fat products are taxed. Second, they are higher than the tax revenue for cheese-butter category and ready meals, and especially for modest households when the fat tax is based on sugar-fat products. At the national level, we find that the welfare cost if cheese-butter category (ready meal and sugar fat product) is taxed, calculated for the average household, is equal to €57.36 million (€33.45 million and €39.51 million).

How regressive are these fat taxes? We assess that the tax's regulatory burdens, defined as the 4-week equivalent variation to household's 4-week income ratio, are equal, on average, to 0.068% (0.041%, 0.038%) for well-off households, 0.11% (0.058%, 0.068%) for average upper households, 0.15% (0.083%, 0.11%) for average lower households, and 0.22% (0.14%, 0.42%) for modest households if the fat tax is based on cheese-butter category (ready meals, sugar-fat products). As Chouinard et al. (2007), we found that this kind of political instrument used to modify households' nutrient intakes can be *extremely* regressive, as it is illustrated for sugar fat products.

Discussion

This paper questioned the relevance of a fat tax policy in influencing households' nutrient intakes by estimating a complete demand model.

We developed a cohort model by aggregating AIDS over cohorts, and we precisely analyzed how the aggregation process affected estimations in terms of bias and heteroscedasticity. Especially as the number of data sources available to researchers increases, the cohort method developed here may be useful for combining information obtained from two or more samples drawn from the population. It should be particularly relevant when there is no single sample that contains all relevant variables, as in our case and in many other cases when economists want to combine administrative data sets.

Our general approach was applied to the French sub-panels of the TNS Worldpanel for the period 1996-2001. We show that price elasticities and the resulting nutrient elasticities are inelastic, and so we conclude that a fat tax policy is unsuitable for *substantially* affecting the nutrient intake of French households, and leads to ambiguous effects. Furthermore, although it generates large tax revenue, fat tax is extremely regressive.

All assessments of fat tax policy so far have assumed a fixed set of food products, thereby excluding the possibility of changes in the food industry in response to a fat tax policy. If a tax is implemented, how would the food industry hedge the tax? Would the food industry change the nutritional quality of the taxed products to smooth retail prices and avoid a decrease in sales? Would the food industry modify the composition of the taxed products by substituting them for more expensive components and/or implementing new industrial production processes, thereby making the innovative product less affordable for modest households? These likely strategies would aggravate socio-economic disparities in the nutritional quality of food selection and may have major implications for health since nutrition is related to the development of certain chronic diseases. Thus, food policymakers need to keep in mind that a fat tax policy may have perverse effects insofar as it could exacerbate nutritional disparities among consumers.

Finally, given its small and ambiguous impact on nutrient intake, its regressive property, and its likely perverse effects, we wonder whether a fat tax could be used rather as a credible threat to urge on *voluntary* approaches by food industries to reduce calory, via saturated fat content in food products. We calculate that if saturated fat in cheese-butter category is voluntary reduced by 1%, the saturated fat intake would fall on average by 0.39% per household per four-week period, all else equal (particularly prices[10] and average quantities consumed) vs 0.17% if the prices of cheese-butter category is raised by 1%.

Notes

[1]Taxing food to reduce total calory intakes could lead to the opposite effect as a result of cross price elasticities, as it was illustrated by Mytton et al. (2007) and Schroeter, Lusk, and Tyner (2008).

[2]The first program was implemented in 2001.

[3]However, in some cases, incomplete system provides a relevant approximation for assessing the global effects of a tax on specific group of products on particular nutrient intakes, as it was shown by Chouinard et al. (2007) in the case of the impact of a tax based on dairy products on U.S. households' fat intakes.

[4]Another advantage of considering cohorts of households is that we never observe null mean consumption for the categories of products considered.

[5]In Blundell and Robin (1999), the symmetric restricted parameters are obtained in the second step of the estimation using a minimum distance estimator.

[6]The reference modality for each socioeconomic variable is in italics.

[7]Standard errors are assessed using the delta method and the estimated covariance matrix of the estimated parameters.

[8]VAT is imposed on all food items in France and is fixed proportional addition to the producer price $\widetilde{v}_{ir}$, such that $\overline{v}_{ir,0} = (1+VAT)\widetilde{v}_{ir}$.

[9]A VAT of 19.6% is actually charged on sweets, margarine, vegetable fats, caviar and certain kind of chocolate (milk, hazelnut, white chocolate) in France.

[10]Constant prices are not so unrealistic regarding the assumed weak reduction in saturated fat.

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Tables

Table 1. Descriptive statistics of the number of households in cells

	Observations	Mean	Standard deviation	Min	Max
N_{ct}	1872	208.12	132.97	59	634

Table 2. Proportion of households for each sociodemographic variables

Sociodemographic variables	Mean	Standard error
Level of education of the principal household earner		
No diploma	0.159	0.180
Low degree of diploma	0.351	0.169
Level of Bac	0.176	0.093
Bac and Higher degree	0.314	0.253
Urbanization		
Rural city	0.242	0.143
Small city less than 10,000 inhabitants	0.120	0.070
City less than 50,000 inhabitants	0.128	0.080
City less than 200,000 inhabitants	0.144	0.088
Big city	0.226	0.166
Paris and its suburb	0.140	0.316
Child household composition		
Children for age group 0-5	0.181	0.252
Children for age group 6-10	0.210	0.268
Children for age group 11-15	0.248	0.252
Children for age group 16-18	0.160	0.171
Proportion of households that have at least a child (less 18)	0.418	0.337
Proportion of households with a garden	0.680	0.174
Proportion of households with a cellar	0.749	0.115
Proportion of home owners	0.653	0.173

Table 3. Sample mean shares and unit values (in Francs by kilo, 1 euro was taken to equal 6.55957 French francs), estimation summary statistics and tests for existing biases due to unobserved heterogeneity

Food categories	Shares	Unit values	RMSE	R^2	$\overline{\ln x_{c\bullet}}$	$\overline{\ln y_{c\bullet}}$
Beef	0.068	62.713	0.011	0.433	0.021	0.010*
Other meats	0.085	39.767	0.010	0.426	0.044*	0.017*
Cooked meats	0.088	58.771	0.008	0.603	0.012	-0.015*
Fish	0.064	53.535	0.011	0.683	0.022*	0.005
Egg	0.011	17.226	0.001	0.511	-0.003	-0.001
Grain	0.023	13.839	0.002	0.729	-0.011*	-0.004*
Potatoes	0.009	5.743	0.003	0.241	0.001	-0.001
Fresh fruit	0.062	10.766	0.010	0.708	-0.035*	0.012*
Processed fruits	0.005	16.083	0.001	0.334	-0.008*	0.000
Fruit juices	0.018	6.900	0.002	0.612	0.002	-0.001
Fresh vegetables	0.050	11.300	0.008	0.696	0.032*	0.026*
Processed vegetable	0.019	16.978	0.002	0.685	-0.000	0.001
Dried fruits	0.004	43.171	0.001	0.577	0.001	-0.003*
Milk products	0.085	9.404	0.006	0.774	-0.060*	-0.020*
Cheese-butter	0.093	40.823	0.005	0.693	-0.012	-0.010*
Ready meals	0.060	34.263	0.009	0.442	-0.054*	0.014*
Oil	0.016	17.273	0.002	0.646	0.007*	-0.006*
Salt-fat products	0.010	43.748	0.001	0.534	0.006*	-0.006*
Sugar-fat products	0.096	37.653	0.007	0.822	-0.040*	-0.023*
Soft drinks	0.014	6.971	0.002	0.804	-0.001	-0.010*
Water	0.021	1.869	0.003	0.656	-0.004	-0.004*
Alcohol	0.103	24.478	0.002	0.569	0.081*	0.019

Note: An asterisk shows that we can reject the null hypothesis that the elasticity is zero at the 5 percent level.

Table 4. Price elasticities across income class

Households	Beef	Other meats	Cooked meats	Fish	Egg	Grain	Potato	Fresh fruits	Pro[a] fruits	Fruit juice	Fres[b] veget	Pro[c] veget	Dried fruit	Milk products	Cheese butter	Ready meal	Oil	Salt[d] fat	Sug[e] fat	Soft drinks	Water	Alcohol
Fresh fruits																						
Well-off	.239*	-.158*	-.048	-.250*	-.084	-.089	-.052	-.355*	-.231	.142	-.025	.041	-.053	-.048	-.121*	.037	-.093	-.016	-.156*	.323*	.198*	-.067
Ave upper[f]	.231*	-.143*	-.044	-.288*	-.073	-.078	-.044	-.234*	-.208	.140	-.030	.041	-.075	-.040	-.123*	.053	-.089	-.024	-.134*	.247*	.203*	-.089
Ave lower[g]	.232*	-.138*	-.041	-.328*	-.069	-.069	-.042	-.118	-.189	.134	-.038	.040	-.099	-.035	-.122*	.061	-.086	-.028	-.118*	.202*	.217*	-.107*
Modest	.255*	-.146*	-.041	-.360*	-.067	-.059	-.042	-.057	-.184	.134	-.044	.036	-.104	-.031	-.119*	.058	-.078	-.027	-.104*	.165*	.245*	-.126*
Fruit Juices																						
Well-off	.037	-.008	-.087*	-.040	-.053	.169*	-.356*	.023	-.034	-.867*	.012	-.024	.131	.035	-.018	-.046	.039	.048	.054*	.255*	.024	-.027*
Ave upper	.036	-.007	-.079*	-.045	-.049	.156*	-.319*	.027	-.033	-.865*	.013	-.020	.160	.032	-.018	-.049	.035	.047	.048*	.198*	.025	-.031*
Ave lower	.036	-.007	-.074*	-.051	-.049	.143*	-.316*	.031	-.032	-.868*	.015	-.019	.197	.029	-.017	-.048	.032	.045	.043*	.164*	.026	-.035*
Modest	.039	-.007	-.074*	-.056	-.047	.124*	-.321*	.033	-.031	-.868*	.018	-.016	.202	.027	-.017	-.044	.029	.041	.038*	.134*	.030	-.041*
Fresh vegetables																						
Well-off	-.170*	-.103*	.023	-.031	.106	-.046	.896*	-.050	-.130	.045	-.443*	-.026	.250	-.116*	.110*	.101	-.161*	.446*	-.122*	.058	-.026	-.134*
Ave upper	-.163*	-.094*	.021	-.037	.100	-.041	.805*	-.057	-.122	.044	-.398*	-.021	.303	-.105*	.108*	.110	-.146*	.427*	-.107*	.044	-.027	-.159*
Ave lower	-.162*	-.090*	.019	-.045	.102	-.035	.798*	-.063	-.107	.041	-.305*	-.016	.365	-.094*	.104*	.116	-.139*	.407*	-.094*	.035	-.030	-.187*
Modest	-.177*	-.095	.019	-.053	.103	-.028	.810*	-.065	-.098	.039	-.204*	-.012	.370	-.084*	.098*	.115	-.128*	.368*	-.082*	.027	-.034	-.224*
Milk products																						
Well-off	.122	-.131*	.075	-.067	-.027	.260*	.085	-.042	.651*	.197	-.103*	.137	-.623*	-.780*	-.103	.008	-.249	.382*	-.110*	.683*	-.055	-.042
Ave upper	.116	-.121*	.068	-.074	-.027	.239*	.076	-.051	.620*	.200	-.110*	.115	-.757*	-.800*	-.101	.003	-.221	.371*	-.098*	.532*	-.056	-.046
Ave lower	.115	-.118*	.065	-.080	-.030	.216*	.074	-.062	.579*	.198	-.125*	.102	-.923*	-.818*	-.096	-.005	-.203	.363*	-.090*	.441*	-.060	-.044
Modest	.125	-.126*	.065	-.083	-.034	.184*	.073	-.070	.558*	.203	-.140*	.089	-.942*	-.837*	-.090	-.016	-.179	.339*	-.082*	.363*	-.067	-.040
Cheese and butter category																						
Well-off	-.080	.209*	-.060	-.068	-.601*	-.298	.267	-.193*	-.590	-.089	.167*	.079	-.080	-.180*	-.254*	-.118	.378*	-1.548*	-.285*	-.317	.034	.040
Ave upper	-.077	.191*	-.054	-.076	-.561*	-.277	.240	-.229*	-.569	-.089	.181*	.066	-.095	-.166*	-.262*	-.127	.340*	-1.486*	-.253*	-.246	.036	.049
Ave lower	-.077	.185*	-.051	-.085	-.555*	-.254*	.237	-.263*	-.542	-.086	.211*	.060	-.115	-.153*	-.280*	-.127	.318*	-1.435*	-.227*	-.202	.038	.057
Modest	-.085	.196*	-.051	-.093	-.543*	-.220*	.240	-.282*	-.532	-.087	.242*	.054	-.118	-.139*	-.303*	-.118	.286*	-1.312*	-.202*	-.165	.043	.067
Ready meals																						
Well-off	-.166*	.064	-.113	.698*	.054	-.244*	-.643*	.076	-.378	-.077	.182*	-.106	.677*	.049	-.000	-1.389*	-.103	-.364*	-.115*	-.699*	-.047	-.009
Ave upper	-.159*	.059	-.103	.787*	.053	-.223*	-.576*	.093	-.355	-.081	.195*	-.087	.821*	.047	-.002	-1.399*	-.096	-.355*	-.100*	-.545*	-.048	-.017
Ave lower	-.159*	.057	-.097	.889*	.052	-.205*	-.570*	.106	-.338	-.078	.227*	-.080	1.010*	.043	-.002	-1.396*	-.089	-.341*	-.090*	-.449*	-.052	-.017
Modest	-.176*	.059	-.096	.978*	.046	-.181*	-.580*	.109	-.343	-.075	.264*	-.076	1.053*	.036	.001	-1.377*	-.076	-.305*	-.082*	-.365*	-.058	-.008
Sugar fat products																						
Well-off	-.053	-.003	-.250*	.035	-.336*	-.231*	.242	-.160*	-.207	.296*	-.120*	-.114	.023	-.118	-.205*	-.208*	.277*	.434*	-.244*	.341	-.019	.100*
Ave upper	-.052	-.003	-.226*	.043	-.316*	-.216*	.215	-.191*	-.208	.302*	-.128*	-.101	.035	-.111*	-.200*	-.227*	.252*	.423*	-.335*	.267	-.019	.124*
Ave lower	-.053	-.004	-.213*	.053	-.317*	-.201*	.211	-.223*	-.208	.299*	-.145*	-.096	.052	-.105*	-.192*	-.236*	.240*	.416*	-.407*	.223	-.020	.150*
Modest	-.061	-.006	-.211*	.065	-.315*	-.179*	.212	-.245*	-.219	.305*	-.161*	-.091	.068	-.100*	-.182*	-.233*	.221*	.389*	-.476*	.185	-.021	.189*
Other soft drinks																						
Well-off	.039	.062*	-.036	-.000	.074	-.072	-.345*	.036	.184	.141*	.009	.093	-.217	.082*	-.035	-.126*	.079	-.295*	.035	-.984*	-.042	-.030*
Ave upper	.037	.057*	-.032	.001	.068	-.068	-.311*	.041	.173	.143*	.010	.078	-.263	.075*	-.034	-.135*	.073	-.281*	.030	-.986*	-.043	-.033*
Ave lower	.036	.054*	-.030	.002	.066	-.063	-.308*	.046	.161	.141*	.012	.070	-.320	.068*	-.032	-.136*	.069	-.270*	.026	-.988*	-.046	-.035*
Modest	.040	.057*	-.030	.004	.064	-.056	-.313*	.048	.155	.143*	.015	.062	-.328	.061*	-.031	-.129*	.063	-.245*	.023	-.990*	-.052	-.037*

[a] Processed Fruits [b] Fresh vegetables [c] Processed vegetables [d] Salt fat products [e] Sugar fat products [f] Average upper [g] Average lower

Note: The table shows the effect on the food category shown in column given that the price of the selected food category changes. An asterisk shows that we can reject the null hypothesis that the elasticity is zero at the 5 percent level.

Table 5. Nutrient elasticities across income class

Households	Beef	Other meats	Cooked meats	Fish	Egg	Grain	Potato	Fresh fruits	Pro [a] fruits	Fruit juice	Fres[b] veget	Pro [c] veget	Dried fruit	Milk products	Cheese butter	Ready meal	Oil	Salt[d] fat	Sug[e] fat	Soft drinks	Water	Alcohol
Energy																						
Well-off	-.069	-.039	-.109	.022	-.001	-.080	-.022	-.084	-.022	-.002	-.020	-.007	-.005	-.088	-.123	-.142	-.031	-.012	-.079	-.019	.000	-.098
Ave upper[f]	-.066	-.042	-.111	.022	-.001	-.082	-.024	-.073	-.022	-.003	-.017	-.007	-.004	-.092	-.119	-.133	-.042	-.012	-.092	-.022	-.000	-.085
Ave lower[g]	-.065	-.041	-.110	.024	-.002	-.088	-.023	-.065	-.021	-.002	-.015	-.008	-.003	-.097	-.120	-.128	-.047	-.013	-.107	-.025	.001	-.075
Modest	-.059	-.037	-.105	.025	-.002	-.095	-.022	-.060	-.020	-.002	-.012	-.008	-.003	-.100	-.117	-.128	-.057	-.013	-.120	-.028	-.000	-.065
Saturated fat																						
Well-off	-.058	.050	-.129	-.002	-.027	-.032	.001	-.092	-.028	-.001	.008	.003	-.003	-.139	-.172	-.114	-.010	-.045	-.146	-.006	-.002	-.052
Ave upper	-.054	.045	-.131	-.003	-.026	-.031	.001	-.087	-.026	-.001	.008	.003	-.003	-.141	-.168	-.104	-.018	-.043	-.157	-.005	-.002	-.049
Ave lower	-.053	.041	-.130	-.001	-.026	-.030	.001	-.082	-.025	-.001	.008	.003	-.002	-.142	-.170	-.100	-.022	-.042	-.168	-.005	-.002	-.047
Modest	-.048	.041	-.124	-.000	-.025	-.030	.001	-.077	-.024	-.001	.008	.003	-.002	-.143	-.172	-.100	-.031	-.040	-.179	-.005	-.002	-.045
Polyunsaturated fat																						
Well-off	-.027	-.047	-.191	-.019	.103	.028	-.045	-.086	-.132	.020	-.079	-.027	.001	-.151	.113	-.172	-.222	.146	.106	.026	-.059	-.073
Ave upper	-.024	-.044	-.180	-.018	.095	.026	-.042	-.082	-.123	.019	-.073	-.025	.001	-.141	.106	-.156	-.269	.136	.095	.025	-.055	-.070
Ave lower	-.023	-.042	-.173	-.014	.089	.022	-.040	-.078	-.115	.018	-.069	-.023	.002	-.132	.096	-.149	-.292	.125	.082	.023	-.052	-.068
Modest	-.022	-.038	-.160	-.012	.082	.018	-.037	-.071	-.106	.016	-.064	-.021	.002	-.121	.089	-.142	-.333	.114	.071	.022	-.048	-.067
Beta carotene																						
Well-off	-.100	-.127	.012	-.068	.016	-.003	.084	-.068	-.012	-.002	-.318	-.042	.007	-.085	.080	.113	-.038	.047	-.119	.016	.013	-.290
Ave upper	-.108	-.133	.015	-.073	.017	-.003	.091	-.053	-.013	-.002	-.286	-.050	.008	-.092	.088	.123	-.042	.051	-.127	.017	.013	-.313
Ave lower	-.116	-.149	.015	-.082	.018	-.003	.098	-.043	-.015	-.003	-.207	-.068	.009	-.101	.091	.132	-.048	.055	-.142	.020	.015	-.344
Modest	-.130	-.161	.018	-.089	.020	-.003	.109	-.039	-.016	-.003	-.134	-.079	.011	-.110	.101	.146	-.054	.061	-.154	.021	.015	-.380
Vitamin C																						
Well-off	.059	-.121	-.122	-.132	-.001	.040	-.032	-.103	-.005	-.204	-.082	-.025	.008	-.001	-.049	-.012	-.024	.011	-.023	.029	.020	-.246
Ave upper	.061	-.129	-.130	-.140	-.000	.042	-.039	-.052	-.006	-.214	-.068	-.031	.009	-.005	-.050	-.009	-.026	.012	-.026	.028	.020	-.262
Ave lower	.068	-.137	-.142	-.149	-.001	.045	-.043	-.010	-.007	-.235	-.035	-.039	.009	-.007	-.058	-.013	-.027	.012	-.028	.029	.023	-.276
Modest	.068	-.141	-.147	-.152	-.000	.046	-.044	.010	-.007	-.243	-.006	-.044	.010	-.011	-.056	-.015	-.028	.013	-.029	.027	.022	-.286
Calcium																						
Well-off	.040	.019	-.024	-.079	-.017	.004	.001	-.062	.019	.000	-.022	.020	-.016	-.300	-.172	-.014	-.005	-.054	-.132	.007	-.151	-.110
Ave upper	.039	.018	-.024	-.075	-.017	.003	.000	-.055	.018	.000	-.018	.018	-.015	-.319	-.170	-.011	-.006	-.052	-.133	.006	-.147	-.105
Ave lower	.037	.016	-.024	-.070	-.017	.001	.000	-.050	.017	.000	-.012	.016	-.014	-.343	-.174	-.011	-.006	-.051	-.136	.006	-.132	-.099
Modest	.036	.017	-.023	-.065	-.016	-.001	.000	-.046	.017	.000	-.007	.014	-.013	-.362	-.176	-.014	-.006	-.050	-.137	.004	-.122	-.093
Sodium																						
Well-off	-.025	.011	-.196	.034	-.021	-.049	-.026	-.064	-.005	-.031	.044	-.028	.005	-.037	-.156	-.235	.000	-.066	-.150	-.042	-.017	-.091
Ave upper	-.024	.008	-.210	.038	-.021	-.050	-.030	-.059	-.004	-.030	.045	-.033	.005	-.042	-.151	-.216	-.001	-.065	-.153	-.041	-.017	-.084
Ave lower	-.023	.007	-.219	.044	-.021	-.053	-.027	-.056	-.004	-.028	.046	-.037	.005	-.048	-.152	-.209	-.001	-.064	-.159	-.039	-.014	-.079
Modest	-.021	.008	-.212	.050	-.020	-.058	-.027	-.053	-.004	-.028	.049	-.040	.005	-.053	-.150	-.217	-.002	-.064	-.165	-.040	-.014	-.073
Magnesium																						
Well-off	-.030	-.066	-.053	-.026	.007	-.060	-.027	-.064	.015	-.022	-.023	-.010	-.010	-.092	-.129	-.096	-.003	-.047	-.070	-.023	-.109	-.127
Ave upper	-.029	-.070	-.056	-.022	.007	-.064	-.033	-.050	.015	-.023	-.015	-.013	-.009	-.102	-.126	-.091	-.004	-.048	-.079	-.025	-.109	-.115
Ave lower	-.031	-.071	-.058	-.015	.006	-.073	-.031	-.041	.015	-.021	-.005	-.017	-.008	-.115	-.132	-.092	-.003	-.050	-.092	-.025	-.100	-.104
Modest	-.027	-.067	-.057	-.010	.006	-.083	-.031	-.035	.015	-.022	.004	-.019	-.007	-.127	-.129	-.098	-.004	-.051	-.102	-.028	-.095	-.095

[a] Processed Fruits [b] Fresh vegetables [c] Processed vegetables [d] Salt fat products [e] Sugar fat products [f] Average upper [g] Average lower

Note: The table shows the effects on the selected nutrients given that the price of the food category shown in the column changes.

Table 6. Percentage quantity change of a 10 percent cheese-butter, ready meal and/or sugar fat product tax in nutrient intakes for well-off and modest households, over a 4-week period

Tax base	Cheese-butter		Ready meals		Sugar fat products		Targeted products [a]	
	Well-off	Modest	Well-off	Modest	Well-off	Modest	Well-off	Modest
Energy	-1.229	-1.167	-1.424	-1.278	-0.789	-1.196	-3.443	-3.641
Protein	-1.139	-1.150	-0.603	-0.604	-1.163	-1.294	-2.904	-3.049
Vegetal protein	-1.981	-1.739	-2.295	-2.062	-1.078	-1.569	-5.353	-5.370
Animal protein	-0.924	-0.991	-0.049	-0.088	-1.163	-1.191	-2.135	-2.270
Carbohydrate	-2.001	-1.679	-2.060	-1.766	-0.974	-1.639	-5.035	-5.084
Sugar	-1.831	-1.622	-0.623	-0.564	-0.741	-1.561	-3.195	-3.747
Starch	-2.229	-1.747	-4.082	-3.271	-1.277	-1.684	-7.588	-6.701
Fat	-0.913	-0.932	-1.416	-1.224	-0.730	-1.051	-3.058	-3.207
Saturated fat	-1.719	-1.723	-1.137	-0.996	-1.461	-1.791	-4.317	-4.510
Monounsaturated fat	-0.901	-0.896	-1.642	-1.420	-0.691	-1.029	-3.234	-3.345
Polyunsaturated fat	1.127	0.892	-1.723	-1.419	1.064	0.710	0.467	0.183
Cholesterol	-2.179	-2.113	-0.488	-0.482	-1.837	-2.100	-4.503	-4.694
Alcohol	0.393	0.653	-0.103	-0.098	0.992	1.859	1.281	2.414
Fiber	-1.031	-1.040	-1.085	-1.144	-1.045	-1.502	-3.161	-3.686
Retinol	-0.955	-1.037	0.057	0.031	-1.520	-1.602	-2.419	-2.608
Beta carotene	0.800	1.015	1.130	1.460	-1.189	-1.537	0.742	0.937
Vit B1	-0.991	-0.919	-2.013	-1.899	-1.271	-1.494	-4.275	-4.312
Vit B2	-1.352	-1.292	-0.362	-0.350	-1.269	-1.426	-2.983	-3.068
Vit B3	-0.454	-0.453	-0.771	-0.804	-0.838	-0.937	-2.064	-2.194
Vit B5	-1.132	-1.105	-0.452	-0.457	-1.114	-1.289	-2.698	-2.851
Vit B6	-0.752	-0.755	-1.116	-1.141	-0.956	-1.103	-2.824	-2.999
Vit B9	-0.850	-0.931	-0.250	-0.286	-1.205	-1.513	-2.305	-2.730
Vit B12	-0.643	-0.735	0.970	0.906	-0.871	-0.960	-0.543	-0.789
Vit C	-0.492	-0.562	-0.115	-0.154	-0.233	-0.290	-0.840	-1.007
Vit D	-2.057	-2.213	2.303	2.272	-1.225	-1.675	-0.979	-1.616
Vit E	1.524	1.247	-1.134	-0.940	1.271	0.914	1.661	1.221
Iron	-1.723	-1.760	-0.135	-0.138	-1.318	-1.373	-3.176	-3.271
Calcium	-1.142	-1.124	-0.822	-0.831	-0.905	-1.233	-2.869	-3.188
Magnesium	-1.286	-1.286	-0.960	-0.977	-0.700	-1.021	-2.945	-3.285
Sodium	-1.562	-1.499	-2.351	-2.167	-1.502	-1.651	-5.415	-5.317
Phosphorus	-1.533	-1.522	-0.502	-0.493	-1.184	-1.340	-3.219	-3.355
Potassium	-0.634	-0.652	-0.613	-0.659	-0.647	-0.879	-1.894	-2.190

[a] By targeted products, we mean cheese-butter, ready meals, and sugar fat products

Note: The table shows the effects on nutrient intakes given that the price of the food category shown in the column changes.