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Food Price Policies and the Distribution of Body Mass Index: Theory and Empirical Evidence from France.

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Abstract

This paper uses French food-expenditure data to examine the effect of the local prices of 23 food product categories on the distribution of Body Mass Index (BMI) in a sample of French adults. A dynamic choice model using standard assumptions in Physiology is developed. It is shown that the slope of the price-BMI relationship is affected by the individual's Physical Activity Level (PAL). When the latter is unobserved, identification of price effects at conditional quantiles of the BMI distribution requires quantile independence between PAL and the covariates, especially income. Using quantile regressions, unconditional BMI distributions can then be simulated for various price policies. In the preferred scenario, increasing the price of soft drinks, breaded proteins, deserts and pastries, snacks and ready-meals by 10%, and reducing the price of fruit and vegetables in brine by 10% would decrease the prevalence of overweight and obesity by 24% and 33% respectively. The fall in health care expenditures would represente up to 1.39% of total health care spendings in 2004.

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1 Introduction

In 2002, 37.5% of French adults were overweight and 9.4% were obese, compared to figures of 29.7% and 5.8% respectively in 1990 (OECD Health Data, 2005).[1] These trends have become a major public health concern, as reflected in the goal of the National Plan for Nutrition and Health (PNNS 2006-2010) to reduce the prevalence of adult obesity by 20%. In this perspective, this paper asks whether appropriate food price policies may help to attain this public health objective.[2]

The mechanism underlying the food price / body weight relationship is well known. When food prices are lower, ingesting food calories becomes cheaper, and calorie intake is likely to rise. Body weight then increases to restore the metabolic equilibrium between calorie intake and calorie expenditure. Cutler *et al.* (2003) note that the full price of calorie intake has fallen over the past forty years, as the cost of primary food products and food preparation have declined. Technical progress has been biased in favour of energy-dense food. As a result, the cost of a healthy and well-balanced diet is now much higher than that of an energy-dense diet (Drewnowski and Darmon, 2004). In France, for instance, long-run time series clearly reveal a fall in the price of vegetables processed with cheap additives (sugars and fats) relative to the price of vegetables in brine (Combris *et al.*, 2006). This suggests that taxing food calories to rise their price may change trends in overweight and obesity.

However, the main economic rationale for taxation would not be any public health goal, but rather the existence of externalities. For instance, the medical cost of obesity was about 2.6 billion Euros in 2002 and 3.6 billion Euros in 2006 (Emery *et al.*, 2007; IGF-IGAS, 2008). Taxing food would further help solve the *ex ante* moral hazard problem that arises from the inability of Social Security to charge individuals fairly (Strnad, 2005). In this perspective the consumer is held responsible for his/her health, and the primary goal of the tax is to raise revenue. A smaller elasticity of food demand (and therefore of body weight) may then be desirable (Chouinard *et al.*, 2007).

Public health concerns and economics can be reconciled when we consider less classic normative goals, for instance correcting the "internalities" that ensue from rationality failures, or from a Senian standpoint, making healthy food

[1] According to the World Health Organisation's international standards, a Body Mass Index (BMI: weight in kg divided by height squared in meters) over 25 signals overweight. Beyond 30, the individual is obese.

[2] Perhaps surprisingly, while public health authorities remain cautious about price policies, French consumer associations have taken a firm position in favour of a tax on snacks, carbohydrated drinks and confectionery (*Cf.* the lobbying campaign by the federation of consumer associations "UFC Que Choisir?" in favour of a nutritional VAT, www.quechoisir.org). In the U.S., consumer associations have traditionally been opposed to taxes (Sheu, 2006), while price interventions have long been advocated by the public health sector (see for instance Brownell K., 1994, "Get slim with higher taxes", New York Times, 15/12/1994, A29.).

products (typically fruit and vegetables) more affordable, in order to help consumers to adjust their food habits. Here, the environment is held responsible, to some extent, not the consumer. The point of the policy is to change behaviour, which is feasible only if the elasticity of calorie demand is high enough, and taxes and subsidies are transmitted to consumer prices.

A tax on calories may not be very efficient, as monitoring costs would be substantial - the recipes of food producers change constantly -, and human energy requirements are heterogenous (Leicester and Windmeijer, 2004). As such, considering taxes or subsidies for specific product categories is more interesting. Taxes on confectionery, carbohydrated drinks or snacks already exist in a number of U.S. states, although not for nutritional reasons (Jacobson and Brownell, 2000). Beyond these products, if the policy objective is to shift the BMI distribution to the left, then all energy-dense products might be covered *a priori* by a tax: soft drinks as well as foie gras, whatever their cultural legitimacy. As such, I here try to identify the effects of the prices of *23 food product categories,* which cover the entire diet, on the *BMI distribution* of French adults. Given any normative objective, the results may provide clues for the choice of a relevant tax base.[3]

Empirical work on the price-BMI relationship is relatively scarce. Lakdawalla and Philipson (2002) use regional variations in food taxes in the US to estimate the role of food prices in the rise of obesity. Holding BMI and the socio-demographic composition of the population constant, they find that the fall in supply price resulted in a 0.72 unit increase in BMI between 1981 and 1994, representing 41% of the growth in BMI over this period. Sturm et Datar (2005) present evidence that lower fruits and vegetables price predict smaller increase in body weight between the kindergarten and the third grade for American children. Asfaw (2006) relies on a single cross-section of a household survey to study the relationship between the prices of nine food groups and average BMI in Egyptian women. He finds, as expected, significant negative effects for energy-dense products, and positive effects for less dense products. Using seven repeated cross-sections of the Monitoring The Future survey (1997-2003), Powell *et al.* (2007) report positive, albeit not significant, effects of the price of fruits and vegetables on the BMI of American adolescents. The current paper also uses repeated cross-sections and spatial price variation to identify the price-BMI relationship, but improves on previous work in three ways. First, the prices of all food product categories are considered, therefore controlling the pattern of

[3]By working at a relatively disaggregated level, I want to identify a feasible price intervention, since opposition from numerous pressure groups would be encountered. Ideally, the tax base has to be not so wide as to produce sizeable coalitions of opponents and to override collective representations of food products' healthiness, but not so narrow as to be inefficient.

substitution between products. Second, food prices are carefully constructed so as to capture only supply-driven price variations. Third, the identification of price effects when individuals' Physical Activity Levels (PAL) are not observed is extensively discussed.

I employ data from the French TNS WorldPanel household survey. This data set provides socio-demographic information at the household level, and household scanner data of food-at-home expenditures throughout the year. The BMI of all household members was self-reported annually between 2002 and 2005; we focus here on adults. One challenge posed by the use of scanner data is that they do not provide truly exogenous prices, but rather unit values computed by dividing expenditures by quantities. Unit values are endogenous, as they reflect households' tastes for quality, which are unobserved and may be correlated with BMI. Empirical inference here relies on the spatial price variations that are generated by the peculiar spatial structure of the French retail market. Using assumptions widely-used in consumption economics, I construct exogenous local price indices that capture these variations.

A linear dynamic equation, which links body weight at time $t+1$ to body weight at time t, prices and income, is derived from a theoretical model that brings together standard assumptions from Physiology and Economics. The key prediction is that the coefficients on the right-hand side (RHS) variables depend structurally on the PAL. Since the latter is unobserved, there is slope heterogeneity in the price-BMI relationship. Identification then requires some form of independence between PAL and the RHS variables. Since independence between PAL and body weight at time $t-1$ is not credible, and given that individual body weight shows little time variance in the data, it is eventually assumed that body weight is at a stationary level. Price and income elasticities of the *whole* BMI distribution can then be estimated by quantile regressions, as long as PAL is quantile independent of the RHS variables. The price effects are estimated separately for men and women.

I then simulate the impact of several scenarii of price policy on the unconditional BMI distribution. In my preferred scenario, increasing the prices of non alcoholic beverages (other than water), pastries, ready-meals and snacks by 10%, and reducing the prices of fruit and vegetables in brine by 10% would reduce the prevalence of overweight and obesity by 24% and 33%, and the medical cost of obesity by 960 to 2133 million Euros. However, these results should be read cautiously, as the standard errors of the elasticities are large and there is some fragility in the quantile estimates.

Section 2 presents the data. Section 3 explains in detail how prices are constructed. Section 4 sets up the theoretical framework, and Section 5 discusses identification issues. Section 6 reports the main results and discusses the statistical limits of the analysis. Section 7 simulates the impact of several price scenarios, and Section 8 concludes.

2 Data

I use five waves of data drawn from the TNS French household panel survey (2001-2005). The data set has several specific features that to an extent limit the empirical analysis. Each year, up to 8000 households are observed. Each household leaves the panel after four years, during which all purchases with a barcode are recorded.[4] Additional information is provided on the products' labelled characteristics. For instance, the fat content of cheese is specified, but not the calorie content of a ready-meal. For purchases of products without barcodes (e.g. fresh meat bought at the butcher), the panel is split into two sub-panels. The first sub-panel is dedicated to fresh meat and fish, and the second to fresh fruit and vegetables. Hence, information on household purchases is not exhaustive. Individual food consumption and food-away-from-home intake are not observed.

The causal structural chain that connects prices to BMI is as follows. First, households and/or individuals buy products for food-at-home or food-away-from-home consumption. Food prices play a role at this stage. Second, purchases for food-at-home are shared between household members. A large part is consumed, and the remainder is wasted. It is not possible to recover individual consumption from household purchases for food-at-home without strong statistical assumptions and without ignoring food-away-from-home.[5] Third, individual consumption is converted into calories. Obviously, the structure of the TNS data set does not allow us to identify the structural chain which links prices to household purchases, individual consumption, calories and ultimately weight. As a consequence, this paper focusses directly on the relationship between food prices and BMI.

2.1 Sample selection

The starting sample (Sample 1: $N = 21407$ individual-year observations) consists of observations without missing values, and for which it was possible to assign food prices. I also drop observations in the first and 99^{th} percentiles of the BMI distribution for robustness. Descriptive statistics for all variables are

[4] The barcodes themselves (Universal Product Codes) are not provided with the data.
[5] One attempt to do so is Bonnet *et al.* (2007).

presented in Appendix B, Table B3. These statistics, as are all those in the paper, were adjusted for yearly sampling weights at the household level.[6]

2.2 Body Mass Index

From 2002 to 2005, the BMIs of all household members were self-reported. I am not able to correct for declaration biases, as correction equations that are valid for the whole population are not available.[7] While overweight and obesity are probably underestimated, this may be less of a concern here than in the OECD Health Data (2005). According to the latter, there were 9.4% of obese adults in France in 2002. In Sample 1, the corresponding figure is 10.4%. The sample prevalence of overweight is 44.6% as against 37.5% in the OECD data.

The left side of Figure B1 in Appendix B plots the distribution of the BMI in Sample 1. This distribution is not Gaussian according to standard statistical tests. Skewness is strongly positive, since the distribution has an elongated right tail. Applying a logarithmic transformation does not eliminate skewness. Empirical modelling takes this issue seriously by using quantile regressions.

Last, for 86.5% of those individuals who can be followed over two consecutive years (14576 transitions are observed), body weight remains stable (see Table B1). This stability will be exploited in the econometric analysis.

2.3 23 product categories

Purchases are first classified into food products, whose definition takes into account nutritional information that is labelled, and therefore available to the consumer. For instance, there is a distinction between mid-fat Brie cheese (fat content between 30 and 59%) and full-fat Brie cheese (fat content over 60%). Likewise, I distinguish diet/light sodas from standard ones. Overall, there are more than 350 food products.

Food products are then sorted into 23 product categories, for which I want to construct exogenous prices: mineral water, alcohol, soft drinks, vegetables in brine, fruit in brine, processed vegetables, processed fruit, cereals, meat in brine and eggs, seafood in brine, processed seafood, cooked meat, breaded proteins, yoghurt and fresh uncured cheese, cheese, milk, animal fats and margarine, oils, sugar and sweets, pastries and desserts, sweet and fatty snacks including

[6] These weights are rescaled to sum to the yearly number of observations, and therefore account for their relative representativity.

[7] Body weight is measured with errors that can be decomposed into two parts. First, there are deliberate declaration biases. It has been found in a company cohort of French middle-aged subjects that weight is systematically underestimated and height is systematically overestimated, leading to an underestimation of BMI that is larger for women (-0.44 kg/m^2) than for men (-0.29 kg/m^2). Overweight status, age, education and occupation are significantly correlated with this declaration bias (Niedhammer *et al.*, 2000). Second, there are errors due to rounding to the nearest integer value, heaping and digit preferences.

breakfast cereals, salty and fatty snacks, and ready-meals. Each category is made up of between 1 and 77 food products. Appendix B, Table B2, provides more details on the food categories with some examples.

This classification is intended to depict collective representations of food products' healthiness, as any taxation policy will require some support from public opinion. This concern, as well as advice from health professionals, leads me to distinguish between breaded meat and fishes, and cooked meat and meat in brine, but also fruit or vegetables in brine (even canned or frozen) from fruit and vegetables that are prepared with additives, such as fats or syrups. Some food products are not classified in their "natural" category, when their nutritional quality may have been profundly altered by the production process. For example, breakfast cereals are considered as sweet and fatty snacks, and not as cereals. Olives fall in the "salty and fatty snacks" category rather than in the "fresh fruits" category.

Section 3 hereafter explains how I construct local prices for these 23 categories.

2.4 Control variables

A number of economic, social and demographic potential confounders will be controlled for. Household income is measured over 18 intervals. I use the mean of each interval to construct a continuous proxy. Households in the highest category (over 7000 Euros a month) are dropped. Income is equivalenced and deflated by the yearly Consumer Price Index provided by the National Statistical Office (INSEE) for households, according to their position in the income distribution (reference: 2004 Euros). Unit values were also deflated by this CPI before being used for the construction of the price indices in the next section. The regressions will control for home-production of fruit and vegetables (FRUITSORVEG). A dummy (MEALPLANNER) indicates if the individual is responsible for household food expenditure, as the meal planner may be better able to control her/his weight through food choices if s/he is not prone to impulse buying.

Other control variables are: gender, household structure, education (six qualification levels, since education renders health production through food choices more efficient). A quadratic trend in age will be included, as well as a dummy crossed with gender which indicates recent pregnancy/birth in the household (BABYWOMEN and BABYMAN). Last, regional and time differences in tastes are controlled for with a set of dummies for region (which groups together several "departements"), the type of residential area, and the calendar year. Hence, price effects are identified by local deviations from the regional taste effects, as is usually the case in estimation of food demand systems.

3 The construction of local food prices

By dividing, for each household and for any given food product, yearly expenditure by the quantity purchased, a household-specific unit value can be constructed. Unfortunately, unit values are not exogenous, as they also reflect households' tastes for quality. We can imagine that households with higher average BMIs are more likely to buy, in a given food category, products that are more energy-dense, and the latter have generally lower unit values. To construct exogenous prices from unit values, I first suppose that the law of one price holds at the level of spatio-temporal clusters c (following Deaton, 1988). They are defined as follows: two households belong to the same cluster if their purchases are observed over the same calendar year t, and they live in the same or adjacent "departement" (roughly the size of a US county), and the same or similar type of residential area.[8] This paper therefore relies on spatial and time variations in prices to identify the price-BMI relationship.

A number of authors then construct cluster-specific prices by computing cluster-averages of unit values (see for instance Asfaw, 2006). However, this requires the undesirable assumption that the distribution of tastes be similar across clusters, so that between-cluster differences in average unit values reflect only differences in supply prices. I therefore implement a second approach, which involves two steps. First, household paasche price indices at the level of food categories are constructed from unit values computed for food products. Second, following Cox and Wohlgenant (1986), for each food category, I regress the price index on observable household characteristics that are likely to capture quality effects, and a set of cluster fixed effects. The latter represent my measure of local prices.

3.1 Procedure

3.1.1 Food categories as Hicks aggregates

The data set provides the quantities q_{lj}^{hc}, and unit values ν_{lj}^{hc} associated with the yearly expenditure of household h in cluster c on food product j in category l. Each food product aggregates items of different qualities, which are unobserved.

[8] There are 94 departements in Metropolitan France (Corsica is not covered by the survey), and each departement has between two and nine neighbours. There are eight types of residential area, from "rural" to "urban units with more than 20000 inhabitants (excluding Greater Paris)" and "Greater Paris". These residential area are ordered according to their size so that it is easy to define closeness. For instance, in a given year t, a household living in a urban unit of between 2000 and 4999 inhabitants is close to households in the same or adjacent departements who live in urban units of between 5000 and 9999 residents or in rural areas. These belong to the same cluster c.

Following Deaton (1988), I assume that the relative prices of items within each product category l are fixed everywhere. Hence, product categories are treated as Hicks aggregates. As such, if $\overrightarrow{p}_l$ is the vector of unobserved prices for items in product category l, there exists a scalar λ_l^c such that $\overrightarrow{p}_l = \lambda_l^c \overrightarrow{p}_l^0$, where $\overrightarrow{p}_l^0$ is the relative-price structure. λ_l^c a linear homogeneous price level for category l in cluster c, and differences in λ_l^c between clusters reflect spatial and time heterogeneity in supply prices. The goal here is to construct a measure of λ_l^c.[9]

Let $\overrightarrow{p}_{lj}$ and $\overrightarrow{p}_{lj}^0$ be vectors extracted from $\overrightarrow{p}_l$ and $\overrightarrow{p}_l^0$ that collect the prices of all different qualities of food product j, and $\overrightarrow{q}_j^{hc}$ the corresponding vector of unobserved quantities purchased by household h. The average unit value of food product j in category l for household h is:

$$\nu_{lj}^{hc} = \frac{\overrightarrow{p}_{lj} . \overrightarrow{q}_{lj}^{hc}}{\overrightarrow{1} . \overrightarrow{q}_{lj}^{hc}} = \lambda_l^c \frac{\overrightarrow{p}_{jl}^0 . \overrightarrow{q}_{lj}^{hc}}{\overrightarrow{1} . \overrightarrow{q}_{lj}^{hc}} \tag{1}$$

where $\nu_{lj}^{hc,0} = \frac{\overrightarrow{p}_{lj}^0 . \overrightarrow{q}_{lj}^{hc}}{\overrightarrow{1} . \overrightarrow{q}_{lj}^{hc}}$ can be considered as a quality index (Deaton, 1988), and $\overrightarrow{1} . \overrightarrow{q}_{lj}^{hc} = q_{lj}^{hc}$.

3.1.2 Local Paasche price indices

In order to weight the unit values by the household's structure of consumption, local Paasche indices are computed at the level of each category for each household:

$$P_l^{hc} = \frac{\sum_{j=1}^{J_l} q_{lj}^{hc} \nu_{lj}^{hc}}{\sum_{j=1}^{J_l} q_{lj}^{hc} \nu_{lj}^0} \tag{2}$$

where J_l is the number of food products in l and ν_{lj}^0 is a reference unit value for food product j. Here, the reference unit values are average unit values for purchases made in 2004 in Paris and surrounding departements and, accordingly, the price levels in this cluster are normalised, *i.e.* $\lambda_l^0 = 1$.

3.1.3 Adjusting prices for quality effects

Using (1) and (2):

$$\ln\left(P_l^{hc}\right) = \ln(\lambda_l^c) + \underbrace{\ln\left(\frac{\sum_{j=1}^{J_l} q_{lj}^{hc} \nu_{lj}^{hc,0}}{\sum_{j=1}^{J_l} q_{lj}^{hc} \mathbf{E}\left(\nu_{lj}^{h'c,0} \,|h' \in \{paris, 2004\}\right)}\right)}_{\rho_l^{hc}} \tag{3}$$

[9] The treatment of product categories as Hicks aggregates may seem approximate, but is quite standard in consumption economics.

where ρ_l^{hc} is a quality index for category l. If food products were perfectly homogenous in quality, then $\rho_l^{hc} = 1$, and P_l^{hc} would identify λ_l^c. However, although the classification of food purchases was constructed so as to define homogenous food products, a certain amount of heterogeneity may still remain. Following Cox and Wohlgenant (1986), a widely-used method is then to specify ρ_l^{hc} as a function of a vector of observable variables Z^{hc} and an error-term $\widetilde{\mu}_l^{hc}$:

$$\ln(\rho_l^{hc}) = \kappa_l Z^{hc} + \widetilde{\mu}_l^{hc} \tag{4}$$

implying:

$$\ln\left(P_l^{hc}\right) = \ln(\lambda_l^c) + \kappa_l Z^{hc} + \widetilde{\mu}_l^{hc} \tag{5}$$

κ_l is estimated by an OLS regression of $\ln\left(P_l^{hc}\right)$ on Z^{hc} after a within-cluster transformation of (5). Then, $\ln(\lambda_l^c)$ is identified by computing the cluster mean of the residuals:

$$\widehat{\ln(\lambda_l^c)} = \mathbf{E}\left\{\ln\left(P_l^{hc}\right) - \widehat{\kappa}_l Z^{hc} \,|h \in c\right\} \tag{6}$$

This will be my price index for product category l. It is (up to an additive constant) an unbiased measure of $\ln(\lambda_l^c)$ as long as $\mathbf{E}\left\{\widetilde{\mu}_l^{hc} \,|h \in c\right\} = 0$: the average value of unobservable factors that affect quality choices must not systematically differ between clusters. This is my second key assumption.[10]

The estimation of the quality effect in (5) basically control for the following variables: real equivalenced income; education, age and occupation of the meal planner; household structure; self-production of fruits and vegetables; region of residence; ownership of a micro-wave and a freezer, and the size of the latter. The quality index ρ_l^{hc} depends on quantities q_{lj}^{hc} purchased by the household, and the latter are functions of household income and supply prices.[11] My third important assumption is that variations in quality induced by variations in supply-prices can be proxied by variables that describe the local structure of the retail market. The latter are constructed from exhaustive yearly geocoded data on hypermarkets and supermarkets. After several tests, the most interesting

[10] It is possible, for instance, that ethnicity is correlated with quality choice (through cultural foodways), BMI (through gene expression), and that the racial mix in some clusters depart significantly from the national average (in the suburbs of big cities for instance). If we used U.S. data, this would produce a downward bias on the price effects. However, the literature has provided no evidence for France that, controlling for observable factors, ethnicity is correlated with the difference between "true prices" and unit values.

[11] The structural approach to quality, quantity and prices proposed by Crawford *et al.* (2003) produces an equation for unit values that is similar to (5), with $\ln\left(\sum q_{lj}^{hc}\right)$ as an explicit control variables. In prelimiary regressions, I tried to introduce this variable without success, because it has to be instrumented and the instruments they propose (see their section 3.1.) are weak.

results are obtained with a single indicator: the surface (in m^2) of supermarkets and hypermarkets in a radius of 20 km around the city of residence.[12] Since having a car potentially expand the choice set for a given market structure, I also introduce a dummy for car ownership.

The regression results show that unit values always depend positively on income (with elasticities between 0.065 for fresh fruits and 0.21 for sea products in brine). The characteristics of the meal planner, the local retail market and the region of residence also have some influences. In the end, the estimated price indices differ strongly from the average unit values.

3.2 Comments

3.2.1 Source of price variations

Descriptive statistics show that, in the estimation sample, between-individual standard deviations of prices are slightly higher than within-time standard deviations, so that the identification of price effects will rely more on spatial than time variation in prices (see Table B4 in Appendix B). There are also very few outlying values, in the sense that the maxima and minima are generally close to the means ± two standard deviations.

A key question is whether the variance is produced by actual variations in supply prices. There is an ongoing debate over the level of retail prices in France, as compared to other EU countries. A number of reports have emphasised that appropriate zoning regulations would benefit consumers, by introducing more competition in local markets and thus lowering prices (see *inter alia*, Canivet, 2004). Descriptive work has shown that the structure of retail distribution is largely characterised by a lack of spatial competition. In about 60% of the 630 consumption areas, a single national retail group has more than 25% of the market share, with the second firm lying at least 15 points behind (ASTEROP, 2008). Analysis of the price of a well-defined consumer basket confirms that there are significant spatial variations in price, even for supermarkets belonging to the same retail group.[13] As a result, I suppose that the variance in food prices is largely due to the structure of the food retail market

[12] I tried for instance to distinguish between the surface in hard-discount and the surface in standard stores, but both variables were highly collinear.

[13] See the study by the consumer association "UFC Que-Choisir?", published in the magazine *Que Choisir?*, 455, January 2008. As an illustration, compared to the national average, the price of a basket of national-brand products bought in a store owned by the retailing group Carrefour is more expensive in the 14th district of Marseilles (south-east of France, +2.5%) and Drancy (near Paris, +0.6%), and cheaper in the 8th district of Marseilles (-3.5%) and Lille (North of France, -0.1%).

3.2.2 Other remarks

A number of comments are in order. First, there are potentially 3008 clusters for the analysis (94 departements times 8 types of residential area times four years). Clusters with less than 25 households were dropped from the sample for greater precision, and household sampling weights were used everywhere. Second, some indices can be computed in one sub-panel only. These prices are then imputed to individuals in the other sub-panel, by matching on the variables that identify clusters. Third, expenditures on food away-from-home are not observed and, therefore, their prices can not be constructed. A number of papers have found empirical evidence of the role of the food-away-from-home sector in the U.S. (Chou *et al.*, 2004; Rashad *et al.*, 2006, Powell *et al.*, 2007). Since the prices of food-at-home are likely to be positively correlated with the prices of food away-from-home, the elasticities may be biased away from zero.

4 The food price - BMI relationship: Framework.

4.1 Physical activity and the food price-BMI relationship

For Physiology, body weight is an adjustment variable in the balance equation between calorie intake and expenditure. Therefore, relative trends in the full price of intake and expenditure may explain trends in the prevalence of overweight and obesity. As outlined in the introduction, trends in food prices are now well documented. However, evidence on calorie expenditure is scarce and mixed. Cutler *et al.* (2003) note that, in the developed world, the majority of the shift away from highly-active jobs occurred in the 1960s and 1970s, before the major rise in obesity. However, using US microdata, Lakdawalla and Philipson (2006) uncover empirical evidence of a relationship between the fall in job-related exercise and the increase in BMI over 1982-2000. There has also been an increase in leisure-time physical exercise, which concerns essentially the better-educated (Sturm, 2004).

To my knowledge, previous work has not investigated in depth how physical activity moderates the impact of changes in food prices. More precisely, it seems to be generally admitted that the effect of the latter and the former on body weight are separable. However, this assumption does not generally hold, if one is willing to fully consider the consequences of the energy-balance equation.

I now define more precisely this equation. Intakes K are produced exclusively by food consumption while, following the Physiology literature, expenditures are expressed as a multiple E (> 1) of the Basal Metabolic Rate (BMR), where

E is a normalised index for Physical Activity Level (PAL, see AFSSA, 2001). Instantaneous changes in body weight W at time τ are described by a differential equation:

$$\dot{W}_\tau = \gamma \left[K_\tau - E_\tau BMR_\tau \right] \tag{7}$$

where γ is a constant for the conversion of calories into Kgs per time unit τ. The World Health Organisation recommends specifying the BMR as a linear function of weight:

$$BMR_\tau = \alpha + \beta W_\tau \tag{8}$$

where the parameters α and β depend on age and gender (UNU/WHO/FAO, 2004). For any well-defined physical activity (e.g. walking one hour at a speed of 3km/h), calorie expenditures $E_\tau BMR_\tau$ increase with body weight

The rational consumer then chooses, under a budget constraint, the consumption basket that maximises the hedonic pleasure derived from food intake, while taking into account its potential impact on future well-being through changes in body weight, as shown in equation (7). In this context, Appendix A presents a model of the consumer's weight-control problem that combines standard assumptions from rational-choice theory and the above assumptions from Physiology. One important limit of the model is that PAL is supposed to be pre-determined.[14] However, letting the PAL appear explicitly in the model is sufficient to show that *physical expenditure affects the slope of the price-BMI relationship.*

To capture the intuition behind this result, consider two naive individuals with, initially, the same preferences, budget, environment and body weight. They differ only by their PALs because, for example, they are in different jobs. Then, if PALs do not enter the utility function, price changes affect their calorie intakes similarly. However, the body weight of the individual with the higher PAL will be less affected, because s/he burns a greater fraction of any calories ingested. The flow of kilograms, as described by equation (7), will be lower, and so will be the change in body weight. I now propose an expression for the

[14] While this assumption is likely to hold for work- and commuting-related energy expenditures, this may not be the case for leisure-time physical activity. A recent general population survey on the health behaviour of the French ("Enquête Conditions de Vie des Ménages", INSEE, 2001) shows that 69.1% of the population do not exercise at least once a week. Only 5.8% exercise explicitly to slim. The barriers to exercise are taste (36.9%), lack of time (31.9%), impairments to health (21.7%), and "other reasons" (9.4%), which may include prices. Regarding the latter, access to community facilities in France is heavily subsidised and the prevalence of local physical activity facilities does not notably differ between low- and high-income areas (Martin-Houssart and Tabard, 2002). Hence, endogenising the choice of leisure-time physical activity would essentially require us to take the consumer's time constraint into account.

price-BMI relationship that is derived from Appendix A's model, and which provides a starting point for the empirical work.

4.2 Specification of the price-BMI relationship

Proposition 1 *If, as an approximation, the consumer's indirect utility is quadratic, then body weights at time $t+1$ and t are linked by the following relationship:*

$$W_{t+1} = W_t \rho(E_t) + [1 - \rho(E_t)]\, \zeta(\mathbf{p}_t, I_t, E_t) \tag{9}$$

where $\rho(E_t)$ is a conservation factor, and $\zeta(\mathbf{p}_t, I_t, E_t)$ is a linear function of food prices $\mathbf{p}_t$ and income I_t, and can be written as:

$$\zeta(\mathbf{p}_t, I_t, E_t) = \frac{\sum_{l=1}^{L} \pi_l \ln(p_{lt}) + \pi_I \ln(I_t) - E_t \pi_0}{-\ln(\rho(E_t))} \tag{10}$$

Appendix A shows that depreciation is greater for more active individuals (ρ falls as E rises). It is smaller when the marginal effect of body weight on optimal calorie intake increases. $\zeta(\mathbf{p}_t, I_t, E_t)$ is the stationary weight that would pertain in the absence of shocks to prices, income and PAL. This stationary equilibrium is stable as long as the marginal effect of body weight on calorie intake is lower than its marginal effect on calorie expenditures.

The coefficients π_l and π_I depend on preference parameters, while π_0 also depends on the physiological parameter α in equation (8). The fact that the PAL affects the slope of the price-BMI relationship is not due to the parameterisation of utility. On the contrary, and logically, assuming that PALs and prices do not interact in the production of body weight would impose strong restrictions on the form of the optimal level of calorie intake and, ultimately, individual preferences.

Equations (9) and (10) specify how body weight is affected by prices and income, but not body mass index at time t, BMI_t. We must therefore divide each side of the equation by $H^2 = height^2$ (in meters squared) to obtain a specification for BMI_t:

$$BMI_{t+1} = \rho(E_t) BMI_t + [1 - \rho(E_t)] \left[\sum_{l=1}^{L} \frac{\pi_l}{-\ln(\rho(E_t))} P^*_{lt} + \frac{\pi_I}{-\ln(\rho(E_t))} I^*_t + \frac{E_t \pi_0}{\ln(\rho(E_t))} \frac{1}{H^2} \right]$$

where $P^*_{lt} = \frac{\ln(p_{lt})}{H^2}$ and $I^*_t = \frac{\ln(I_t)}{H^2}$ are log-prices and log-income adjusted for height-squared. Following Section 3, the prices $\ln(p_{lt})$ will be measured by $\widehat{\ln(\lambda^c_l)}$.

The effect of prices on BMI cannot be identified without further assumptions regarding the level of physical activity: there is slope heterogeneity in the relationship between the RHS variables and current body weight. As E_t is unobserved, it will be denoted $\widetilde{E}_t$ for the sake of clarity in the remainder of the paper. I further adopt the following more compact notations:

$$\begin{aligned} For\ X &= l, I,\ \theta_X^*\left(\widetilde{E}_t\right) = \tfrac{\pi_X}{-\ln\left(\rho(\widetilde{E})\right)}, \quad \theta_X\left(\widetilde{E}_t\right) = \left[1-\rho(\widetilde{E}_t)\right]\theta_X^*\left(\widetilde{E}_t\right) \\ \theta_0^*\left(\widetilde{E}_t\right) &= \tfrac{\widetilde{E}\pi_0}{\ln\left(\rho(\widetilde{E})\right)}, \quad \theta_0\left(\widetilde{E}_t\right) = \left[1-\rho(\widetilde{E}_t)\right]\theta_0^*\left(\widetilde{E}_t\right) \end{aligned}$$

4.3 Price effects

A priori, raising the price of all food items should decrease calorie intake, and therefore shifts the body weight distribution to the left. It is therefore unsurprising to find a negative relationship between BMI and aggregate food prices. But, when there are many food groups, as shown by Schroeter *et al.* (2008) or Auld and Powell (2008), the effect of a change in the price of one food group depends on the own- and cross-price elasticities of consumption, and on their relative energy densities (see Appendix A for a formal argument).

To illustrate this point, consider an increase in the price of some high-calorie products (e.g. snacks), but not all energy-dense products (e.g. pastries). Imagine that individuals substitute the former by the latter, and that the cross-price elasticity is strongly positive, while the own-price elasticity is fairly small. Then it could be the case that the fall in calories provided by snacks may be more than compensated by an increase in calories provided by pastries.

The estimation results will therefore depend on the choice of the nomenclature for classifying and aggregating food products. The more the energy-dense products are grouped together in a single category (including cereals, oil, sugar and sweets, most ready-meals and snacks, meat products, alcohol etc), the more likely it is that a significant negative effect of price on BMI will be obtained. However, this does not necessarily identify a feasible price intervention, since opposition from numerous pressure groups would be encountered. Ideally, we want to identify a tax base that is not so wide as to produce sizeable coalitions of opponents and to override collective representations of food products' healthiness, but not so narrow as to be inefficient.

5 Econometric modelling

This section first discusses model identification. This is not possible without assuming independence of PAL and BMI, which is obviously not credible. However, seeing that, for most people, body weight is stable over two consecutive years, I focus on the price-BMI relationship at the stationary equilibrium. The latter is identified only if we assume some form of independence between PAL, on the one hand, and the covariates on the other, and especially income. Quantile regression techniques can then be applied to estimate the stationary model (11) in the subsample of individuals at a stationary equilibrium.

5.1 Identification

5.1.1 Identification of the dynamic model

Since quantile regression techniques for dynamic models have not yet been developed, I here discuss only the identification of the econometric counterpart of (9) for the conditional mean. If we assume *conditional mean independence* between $\widetilde{E}_t$ and $\{BMI_t, P^*_{lt}, I^*_t, H\}$, then taking the conditional mean with respect to P^*_{lt} , I^*_t, H and BMI_t yields:

$$\begin{aligned}\mathbf{E}\left(BMI_{t+1}|P^*_{lt}, I^*_t, H\right) \quad &= \quad \mathbf{E}\left[\rho(\widetilde{E}_t)\right] BMI_t + \sum_{l=1}^{L} \mathbf{E}\left[\theta_l\left(\widetilde{E}_t\right)\right] \ln(P^*_{lt}) \\ &\quad + \mathbf{E}\left[\theta_I\left(\widetilde{E}_t\right)\right] \ln(I) + \mathbf{E}\left[\theta_0\left(\widetilde{E}_t\right)\right] \frac{1}{H^2}\end{aligned}$$

and average dynamic price effects $\mathbf{E}\left(\theta_l\left(\widetilde{E}_t\right)\right)$can be identified. How credible is this identifying restriction? Although PAL is probably not correlated with food prices[15], independence between PAL and income is less obvious, and related evidence is scarce due to a lack of data. Descriptive statistics for Europe show that leisure-time PALs are on average significantly lower in the first quartile of the income distribution, and do not differ over the remaining quartiles (Rütten and Abu-Omar, 2004). In developed countries, the gradient between PAL and SES is fairly flat, at least for men. In lower social classes, on-the-job physical activity is more important and often offsets the deficit in leisure-time physical activity. Even when individuals are unemployed, they tend to walk more because they use public transportation rather than cars. For women, on-the-job activity may not be more demanding in lower social classes, so that the SES gradient in PAL is rather positive. But the social gradient in PAL is weak or even insignificant when SES is measured by income rather than education or social

[15] A recent general population survey on the health behaviour of the French ("Enquête Conditions de Vie des Ménages", INSEE, 2001) shows that 69.1% of the population do not exercise at least once a week. Only 5.8% exercise explicitly to slim. The barriers to exercise are taste (36.9%), lack of time (31.9%), impairments to health (21.7%), and "other reasons" (9.4%), which may include prices. Regarding the latter, access to community facilities in France is heavily subsidised and the prevalence of local physical activity facilities does not notably differ between low- and high-income areas (Martin-Houssart and Tabard, 2002). Introduction of a time constraint may perhaps change this conclusion.

class, and when we consider both work and leisure-time PAL (Dowler, 2001; IARC, 2002; Gidlow *et al.*, 2006)..

Nevertheless, while independence may indeed be credible for PAL and income, the same is very unlikely for $\widetilde{E}_t$ and BMI_t. The dynamic model has random coefficients correlated with at least one right-hand side variable. In this case, the estimation of average elasticities is not trivial, as shown by Heckman and Vytlacil (1998) and Wooldridge (2005). Although this estimation is potentially feasible, it is left for future research.[16]

5.1.2 Identification of the stationary price-BMI relationship

Dynamic price effects are not trivially identified. However, for most individuals, self-reported body weight is stable between t and $t+1$ (see Section 2.1.). In the model, stability implies that body weight is at a stationary equilibrium. Hence, we consider the subsample of individuals for whom $W_{t+1} = W_t$. This is denoted Sample 2, and the descriptive statistics in Table B3 shows that the related socio-demographic characteristics do not differ from those of Sample 1. Equation (9) then implies:

$$BMI_{t+1} = \sum_{l=1}^{L} \theta_l^* \left(\widetilde{E}_t\right) P_{lt}^* + \theta_I^* \left(\widetilde{E}_t\right) I_t^* + \theta_0^* \left(\widetilde{E}_t\right) \frac{1}{H^2} \tag{11}$$

Conditional mean effects Taking the conditional mean with respect to P_{lt}^*, I_t^* and H, we have:

$$\mathbf{E}\left(BMI_{t+1}|P_{lt}^*, I_t^*, H\right) = \sum_{l=1}^{L} \mathbf{E}\left[\theta_l^*\left(\widetilde{E}_t\right)\right] \ln\left(p_l\right) + \mathbf{E}\left[\theta_I^*\left(\widetilde{E}_t\right)\right] \ln\left(I\right) + \mathbf{E}\left[\theta_0^*\left(\widetilde{E}_t\right)\right] \frac{1}{H^2}$$

as long as *conditional mean independence between* $\widetilde{E}_t$ *and* $\{P_{lt}^*, I_t^*, H\}$ holds. A simple OLS estimator will then produce unbiased estimates of the average price effects.

Conditional mean regressions have at least two drawbacks. First, they are not robust to outliers, e.g. individuals with very high or low BMI (although the distribution was trimmed). Second, the BMI distribution is not Gaussian. Hence, price elasticities of the conditional mean may not accurately characterise changes in the conditional BMI distribution in response to price interventions,

[16] More specifically, following Wooldridge, we need to instrument BMI_t by a set of variables Q such that : (i) Q is strongly correlated with BMI_t ; (ii) Q only affects BMI_{t+1} through BMI_t ; (iii) $\widetilde{E}_t$ is mean-independent of Q, conditional on income, prices, and the set of control variables Z ; (iv) the covariance between BMI_t and $\widetilde{E}_t$ does not depend on $\{Q, Z\}$. Were slopes to be homogenous, after differentiation of the equation , we would typically instrument ΔBMI_t by lags of BMI_t, which satisfy conditions (i) and (ii). However, it is not clear that conditions (iii) and (iv) would hold

especially for those who are in the right-hand tail, which is the most interesting for public health. I here follow a number of papers in the field, by using quantile regressions to obtain a more complete picture (see, *inter alia*, Kan et Tsaï, 2004, Lakdawalla and Philipson, 2006, and Auld and Powell, 2008).

Quantile effects Assuming *quantile independence* between $\widetilde{E}_t$ and $\{P_{lt}^*, I_t^*, H\}$, *i.e.* that the conditional quantile τ of $\widetilde{E}_t$, $Q_\tau\left(\widetilde{E}_t | P_{lt}^*, I_t^*, H\right)$, is independent of $\{P_{lt}^*, I_t^*, H\}$, the conditional quantile τ of BMI_{t+1} is:

$$Q_\tau\left(BMI_{t+1} | P_{lt}^*, I_t^*, H\right) = \sum_{l=1}^{L} \theta_l^*(\tau) P_{lt}^* + \theta_I^*(\tau) I_t^* + \theta_0^*(\tau) \frac{1}{H^2} \tag{12}$$

Not only do quantile regressions offer a number of statistical advantages over OLS, but expression (12) for the conditional quantile is also a natural by-product of the theoretical model, since it fully takes slope heterogeneity into account. However, identification of quantile treatment effects requires quantile independence between unobserved physical expenditures and income, which is stronger than conditional mean independence.

Comment: stationarity and measurement errors The apparent stability of BMI over time may partly result from measurement error. Rounding to the nearest integer implies that changes in body weight must at least exceed 1 kg to be systematically measured. Beyond "conscious" reporting bias, most individual yearly changes in W are likely to remain undetected, because the disequilibrium between intake and expenditure has to be permanent and greater than $30 - 40$ kCal/day in order to produce a weight gain of 1 kg over a year.[17] Measurement errors are usually thought to be benign when they only concern the dependent variable, but here the structural model is dynamic in essence. As such, observed body weight may be stable while actual body weight is not, and measurement errors are likely to produce the standard attenuation bias, *i.e.* the true price elasticities are actually larger than those that will be estimated below. In addition, rounding errors are not Gaussian, which is a problem for OLS but not for quantile regressions.

To counterbalance this point, it is worth noting that empirical longitudinal observations by physiologists have shown that individual body weight variance

[17] More precisely, using calibrated data for energy balance, it can be shown that a disequilibrium of 50 kCal/day for a 30-year old male carpenter, and 39 kCal/day for an office worker of the same sex and age, is required to produce a weight gain of 1 kg over a year. Albeit seemingly modest, this represents more than three times the average yearly increase in calorie intake observed between 1961 and 2002 according to FAO statistics: the per capita calorie intake computed by the FAO using food-supply data was 3654 kCal/day in 2002, as against 3194 in 1961. Although food spoilage has probably increased over the same period, these figures suggest that the average yearly increase in daily calorie intakes was about 11 kCal.

is generally very small over periods of several weeks to several years. There are strong biological and cognitive control mechanisms that prevent body weight from moving away from its habitual (and *de facto* stationary) level (see Harris, 1990, Cabanac, 2001, and Herman and Polivy, 2003). In economic terms, it is as if consumers face substantial marginal adjustment costs when they want to change their eating habits. Hence, stability of body weight over several years may simply mean that consumers are at an equilibrium that remains stable in the absence of major shocks. In this context, self-reported body weight should be interpreted as a habitual or reference body weight rather than an imperfect measure of "true" body weight.

5.2 Estimation techniques

5.2.1 Conditional mean regressions

The general econometric specification associated with (11) is:

$$BMI_{t+1} = \sum_{l=1}^{L} \theta_l^* P_{lt}^* + \theta_I I_t^* + \theta_0^* \frac{1}{H^2} + \theta_Z^{*\prime} Z + \widetilde{\epsilon}_{it}^* \tag{13}$$

This includes the set of control variables Z described in Section 2 above, and an i.i.d. error term $\widetilde{\epsilon}_{it}^*$.

This stationary equation will be estimated assuming away persistent idiosyncratic heterogeneity.[18] The elasticities will be computed at the sample median of the explanatory variables. Let $\theta^* = \{\theta_l^*, \theta_I^*, \theta_0^*, \theta_Z^*\}$ and $X = \{P_{lt}^*, I_t^*, 1/H^2, Z\}$, then the "stationary" elasticity can be computed as:

$$\hat{\varepsilon}_{BMIp_l}^* = \frac{\widehat{\theta}_l^*}{\overline{H^2}^{50} \times \widehat{\theta}^{*\prime} \overline{X}^{50}}$$

where $\overline{X}^{50}$ is the sample median of vector X_i.

5.2.2 Conditional quantile regressions

The conditional quantile that will be estimated is:

$$Q_\tau \left(BMI_{t+1} | P_{lt}^*, I_t^*, H, Z\right) = \sum_{l=1}^{L} \theta_l^*(\tau) P_{lt}^* + \theta_I^*(\tau) I_t^* + \theta_0^*(\tau) \frac{1}{H^2} + \theta_Z^* Z \tag{14}$$

[18] Adding individual fixed effects in the regressions would be a way to control for systematic differences in unobservables between clusters, which may bias the price measures (see Section 3.1.3). Attempts to estimate conditional mean models with fixed-effects in Sample 2 failed because inference relies essentially on the few individuals whose BMI moves between $t-2$ and t, but not between $t-3$ and $t-2$, and between $t-1$ and t. To circumvent this information problem, one could assume that residuals in levels are orthogonal to price changes, as proposed by Blundell and Bond (1998) in their system-GMM approach. Specification tests rejected this identifiying assumption.

where the parameters θ^*_Z of Z are free to vary across quantiles. The parameters $\theta^*(\tau)$ can be estimated for any $\tau \in [0,1]$ by minimizing the following loss function in the sample:

$$\frac{1}{N}\sum_{i=1}^{N}\rho_\tau\left(BMI_{it+1} - \theta^*(\tau)'X_i\right)$$

where

$$\rho_\tau(u) = \begin{cases} \tau u & if\ u \geq 0 \\ (\tau-1)u & if\ u < 0 \end{cases}$$

The asymptotic inference procedure is described by Koenker and Basset (1978) and has been implemented in standard statistical packages (see also the expository survey in Buschinsky, 1998).

The following quantile elasticity (QE) will be computed at the sample medians of the control variables as:

$$\hat{\varepsilon}_{BMIp_l}(\tau) = \frac{1}{\hat{Q}_\tau\left(BMI|\overline{X}^{50}\right)}\frac{\partial\hat{Q}_\tau\left(BMI|\overline{X}^{50}\right)}{\partial\ln(p_l)} = \frac{\widehat{\theta}_l(\tau)}{\overline{H^2}^{50}\times\widehat{\theta}(\tau)'\overline{X}^{50}}$$

Regressions were run separately for women and men for three reasons. First, as shown in Figure B2, men have on average an higher BMI, although the prevalence of obesity in men and women is about the same. Second, the parameters α and β in the weight production function (**??**) depend on sex. The assumption of independence between PALs and the right hand side variables is also more likely to hold in same-sex samples. Third, food habits differ. For instance, men consume more alcohol and meat, and less fruits and vegetables.

Individuals are observed over a certain length of time. Confidence intervals are thus constructed by bootstraping the quantile estimates so that, at each replication, individuals rather than individual-year observations are drawn with replacement [19]

6 Empirical results

6.1 Main results

Table C1 and C2 in Appendix C shows the results, for women and men respectively. Each table has 8 columns. They display respectively the results from OLS regressions, and quantile regressions for the median and deciles above it, and the sample quantiles corresponding to overweight and obesity for the *unconditional* BMI distributions (see the second bold line). Each cell presents a

[19] I use 1500 replications.

point estimates of the elasticity with clustered standard errors. Food categories for which elasticities are significant at the 5% level in at least one of the regressions are in bold; italics indicate that significance is reached only at the 10% level in at least one of the regressions. I focus here, for illustrative purpose, on what happens at the overweight and obesity quantiles only.

Regarding the methodological issues, there are three important results. First, a number of elasticities are not significant, and significant effects for men are not always the same as for women. Second, price elasticities for the conditional mean and at the overweight and obesity quantiles distribution are often of same sign, but not of same significance. They also vary between means and quantiles, and between quantiles, for a number of product categories, although the statistical differences are generally not significant. For instance, for women, elasticities of the conditional mean are significant for oils (around -0.25), while quantile elasticities are of the same magnitude but not significant. The price elasticity is negative and significant for cheese at the overweight quantile (-0.625), but becomes insignificant at the obesity quantile albeit still large (-0.454). Elasticities to the price of sugar and confectionery are positive at the overweight quantile, and turn out to be negative at the obesity quantile. Nevertheless, they are insignificant. Third, distinguishing between processed food and food made at home from raw ingredients matters, as shown by the results for fruits and vegetables.

For men, negative elasticities are found for soft drinks (-0.161 at the overweight quantile, -0.108 at the obesity quantile), breaded proteins (resp. -0.066 and -0.121), milk (resp. -0.220 and -0.156) and ready-meals (but only at the overweight quantile: -0.113). For women, elasticities are negative for cheese, oils, pastries and deserts (-0.209 at the overweight quantile and -0.309 at the obesity quantile), and ready meals (but, once again, only at the overweight quantile: -0.192).

To discuss these estimates, it is worth noting that there are no clear-cut predictions about the sign of the price effects. When there are many food groups, as shown by Schroeter *et al.* (2008), the effect of a change in the price of one food group depends on the own- and cross-price elasticities of consumption, and on their relative share in total energy intakes. The results can then be interpreted in the light of this analysis and current knowledge about energy intake by product category and elasticities of quantities for food-at-home purchases. Here, information is drawn from Allais *et al.* (2008).[20]

[20] I am indebted to Olivier Allais, who provided me with estimates of Marshallian elasticities of household purchases for food-at-home and proportion of calorie intakes. The estimates in Allais *et al.* (2008) were computed using the same data set and a pseudo-panel approach that

The results for soft drinks (respectively dairy products and fats) may be explained by strong own-price elasticities, and negative cross-price elasticity of alcohol purchases.(resp. cereals and meat) to the price of soft drinks (resp. dairy products and fats).

Allais *et al.* find that increasing the price of mixed dishes is associated with lower expenditure on meat, and usually leaves expenditures on dairy products, cereals and fats unaffected. Hence, the BMI elasticity to the price of ready-meals and snacks should rather be negative. This is the case only for ready-meals, and elasticities are positive for snacks. However, Bellisle (2004) recalls that, in France, snacking is associated to an increase in total energy intakes only for obese individuals. Non obese individuals tend to consume snacks that have better nutritional properties than standard meals. If snacking and going to a full-meal restaurant are substitutes, then raising the price of the former may increase total energy intakes in non obese individuals. The lack of information about substitution between food-at-home and food-away weakens any prediction that could have been made on the sole basis of expenditure on food-at-home exploited in Allais *et al.*

For both men and women, positive elasticities are found for (bottled) water. While water brings no calories, increasing its price increases strongly the consumptions of energy-dense food such as starches and dairy products, which explain the result. Positive elasticities are also found for fruits in brine, but for women only, although they should rather be negative according to Allais et al.'s estimates.

Income elasticities are shown at the bottom of Tables C1 and C2. These are small, negative and significant only for obese women (-0.055 at the obesity quantile). Results for the control variables Z are available upon request. These show that self-producing fruit and vegetables is negatively correlated with women's BMI, whilst the correlation is positive for men. Being responsible for food expenditure is positively related to BMI for women, and the converse for men. Otherwise, there is a positive and concave age effect (with a peak around 60/70 years old), and a negative education-BMI gradient, which may reflect information and efficiency effects. Some dummies for regional effects are significant.

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helps overcome the problem of unobservability outlined in the Data section. In comparison to the work here, Allais *et al.* work with a slightly different nomenclature, and predictions about the price effects have to be made in terms of individual consumption elasticities, not household purchase elasticities.

6.2 Statistical robustness

The conditional quantile function (12) is well-identified if it is monotonic in τ (Koenker, 2005, section 2.6.). In the theoretical model, the sign of $\partial\theta_X^*(\widetilde{E}_t)/\partial\widetilde{E}_t$ and $\partial\theta_0^*(\widetilde{E}_t)/\partial\widetilde{E}_t$ does not change with $\widetilde{E}_t$.[21] However, the statistical inference may not be robust, especially when there are a lot of RHS variables. Following Machado and Mata (2005), problems with monotonicity can be evaluated by estimating conditional quantiles at a number of equally-spaced points $\tau \in [0.05, 0.95]$, and by seeing whether, for particular values of the covariates X^0, there are frequent monotonicity violations. There is crossing when $\hat{Q}_\tau\left(BMI_{t+1}|X^0\right) < \max\left\{\hat{Q}_t\left(BMI_{t+1}|X^0\right); t < \tau\right\}$, e.g. the predicted median is smaller than the predicted first quartile. When the design point X^0 sets all log prices to their mean+one standard deviation, and other variables to their median (as in Machado and Mata), there are violations for 36.5% and 34.5% of the quantiles for women and men respectively. The results are illustrated in Figures C1 and C2 in Appendix C, which represents the value of $\Delta(\tau) = \max\left\{\hat{Q}_t\left(BMI_{t+1}|X^0\right); t < \tau\right\} - \hat{Q}_\tau\left(BMI_{t+1}|X^0\right)$ for women and men respectively, as a function of $\tau \in [0, 1]$: when $\Delta(\tau)$ is negative, there is a violation. These violations are frequent but generally small: less than 0.131 and 0.080 points of BMI for women and men respectively, in 90% of the cases. Their magnitude is more important in the extreme quantiles (above 0.95)

6.3 Aggregating product categories for greater robustness

Although the above robustness checks rarely appear in empirical papers, they are useful because they indicate the reliability of the empirical inference. Here, they somewhat weaken the main findings. However, this may reflect the large number of covariates in the model. To illustrate, I now present complementary results obtained by aggregating food categories into nine broad food groups: water, beverages other than water, fruit and vegetables, meat and seafood, dairy products, fats, sugar and confectionery, snacks and ready-meals. For each group k, a price index is constructed as follows:

$$P_k^c = \sum_{l_k=1}^{L_k} \frac{w_{l_k}^c}{\sum_{l_k} w_{l_k}^c} p_{l_k}^c$$

where l_k is an index for the L_k food categories making up the functional group k (e.g. for dairy products: cheese, yoghurt and milk); $p_{l_k}^c = \widehat{\ln(\lambda_{l_k}^c)}$ is the cluster-specific index computed in Section (2); and $w_{l_k}^c$ is the cluster-average

[21] As $\alpha > 0$ and $\beta > 0$, it can be shown that $sign\left[\partial\theta_X^*(\widetilde{E}_t)/\partial\widetilde{E}_t\right] = sign\left[\pi_X\right]$ (with $X = l, I$) and $sign\left[\partial\theta_0^*(\widetilde{E}_t)/\partial\widetilde{E}_t\right] = -sign\left[\frac{\gamma(\kappa_{KW}+\lambda_{WW}\gamma)}{\kappa_{KK}}\right]$ where $\frac{(\kappa_{KW}+\lambda_{WW}\gamma)}{\kappa_{KK}}$ is a taste factor defined in Appendix A which equals $\partial K_\tau/\partial W_\tau$ at the optimum.

share of household expenditures on l_k. The stationary price-BMI equation was re-estimated *via* quantile regressions Tables C3 and C4 in Appendix C shows the results for women and men respectively.

Prices are less significant than in Tables C1 and C2. One reason is that some groups (e.g. alcohol and soft drinks) aggregate food categories for which price elasticities had opposite signs in the previous regressions.For women, dairies and fats attract negative coefficients, and the price elasticity of water is positive. For the last category - pastries, deserts , sancks and ready-meals - the positive effect that was found for snacks is clearly dominated by the negative price effects for pastries, deserts and ready-meals. This is not surprising as expenditures on ready-meals, pastries and deserts are higher than expenditures on snacks and, as a consequence, the price of the food group gives less importance to the latter. For man, the elasticities for water and fruits and vegetables are positive and sometimes significant. It is interesting to note that fats and sugar products attract negative coefficients, which are significant only for the highest quantiles. last, negative elasticities are associated to dairies and cereals around the median. These results thus confirm and strengthen the findings in Section 6.

Since there are fewer variables, statistical inference is also more robust, . The rate of violations (at the design point X^0) falls to 23% and 18.5%, for men and women respectively. Figures C3 and C4 shows that violations are rather small. However, they occur more frequently in the quantiles of the conditional distribution above the median. This calls for caution in the use of the results.

7 Food price policies and the distribution of BMI

A number of elasticities were found to be significant in the regression. These seem to be of small size, which is in line with previous empirical findings. Chou *et al.* (2004) find that the elasticity of BMI to food-at-home price is -0.039. In Powell *et al.* (2008), the OLS price elasticity of fruit and vegetables is small and insignificant (0.012). In quantile regressions, values are between 0.001 at the median and 0.015 at the 90^{th} quantile. A larger and significant elasticity is found at the 95th quantile (+0.049), with a potential "extremal quantile" bias (see Chernozhukov, 2005). To our knowledge, only Asfaw (2006) has found strong empirical evidence of price effects, but for a developing country - Egypt - with perhaps greater spatial price variation: the BMI elasticities of energy-dense products (bread, sugar, oil and rice) range between -0.1 .and -0.2, while the BMI elasticity of fruits was significantly positive (+0.09), as was that on milk and eggs (+0.141).

I will now show that small price elasticities may produce large price effects on the BMI distribution, when the prices of several product categories vary simultaneously.

7.1 Simulation method

Table C5 translates naively the estimated elasticities in weight changes for a 1.70 meter tall woman, and 1.80 meter tall man. For instance, a 10% *decrease* in the price of fruit and vegetables in brine would reduce a man's weight by 1.2 kg, if his initial weight was about 81 kg (at the overweight quantile), and by 1.5 kg if his initial weight was 97.2 kg (at the obesity quantile). A policy that would increase the prices of soft drinks, pastries and deserts, snacks and ready-meals by 10%, and would reduce the price of fruit and vegetables in brine by 10% produces weight losses of 2.6 kg at the overweight quantile and 3.6 kg at the obesity quantile for men. These numbers are respectively -3.2 kg and -2.9 kg for women.

However, these simulations are naive, because price elasticities at conditional quantiles are not price effects on unconditional quantiles. Moreover, they do not fully profit from the advantage of quantile regression over OLS, as the former also provide information on how the *unconditional* distribution of BMI is affected by price changes, which is more interesting for the simulation of price policies. The method proposed by Machado and Mata (2005) is applied to simulate the marginal densities *implied by the conditional quantile model* under a given price regime. The procedure consists of five steps:

1. Draw a random sample of B numbers from a uniform distribution on $[0, 1]$: $\tau_1, \tau_2, .., \tau_B$. Each number represents a quantile of the distribution. Here, $B = 1500$.

2. For each quantile τ_b, estimate using the actual data the quantile regression model (14). This generates B quantile regression parameters $\widehat{\theta}(\tau_b)$, that can be used to simulate the predicted conditional distribution

3. Generate a random sample of size B by drawing with replacement observations in the actual data set (i.e. from the rows of X): this generates a sample of size B with typical observation X_i.

4. Then $\{BMI_i^* = \widehat{\theta}(\tau_b)'X_i\}$ is a random sample of the BMI distribution integrated over the covariates X, i.e. the unconditional distribution of BMI that is consistent with the conditional quantile regressions results.

5. Construct a hypothetical data set from the actual data set, by replacing actual prices by their desired levels (for instance increase by 1% the price of vegetables). And repeat step 3 to obtain a new sample of size B, and step

4 to obtain the marginal distribution that would prevail under the new price regime. Comparing the latter to the actual (predicted) distribution draws a precise picture of the effect of price policies on the prevalence of overweight and obesity.[22]

Confidence intervals can in theory be constructed by repeating these five steps. However, given that the procedure is time-consuming, we here focus on point estimates of the effect of hypothetical policy reforms.

7.2 Results

I now compare the simulated distribution of BMI in the current price regime, and the distribution that would prevail under five different price scenarios. In scenario 1, the price of soft drinks and snacks increases by 10%,while the price of fruits and vegetables in brine decrease by 10%, as suggested by a recent official report (IGF-IGAS, 2008). Scenario 2 adds a 10% increase in the price of soft drinks, breaded proteins, pastries and deserts, and ready-meals, but do not decrease the price of fruits and vegetables. In scenario 3, the latter fall again by 10%. Scenario 4 imagines that the prices of fats and sugar and confectionery also increase by 10%. In scenario 5, dairies, especially cheese, which is at the heart of the French gastronomy, also enter in the tax base.

Table C6 reports for each scenario the prevalence of overweight and obesity in the *simulated* sample before and after the implementation of the policy. Emery *et al.* (2000) estimate that the extra medical costs associated with obesity vary between 506 Euros and 648 Euros. The lower bound considers only a limited set of medical conditions and individuals with BMI over 30, while the upper bound extends the set of medical conditions and takes into account all individuals with BMI over 27. Hence, by extrapolating the percentages to the entire adult population (about 48.5 million adults in 2004), we have a point estimate of the expected reduction in health-care expenditure. This evaluation does not take into consideration the statistical uncertainty in the estimated conditional quantiles.

The minimum reduction in health care expenditure varies between 534 million Euros (Scenario 1 - lower bound) and 2498 million Euros (Scenario 5 - upper bound). Given the regression results, it is not surprising that the larger the tax base, the higher the expected effects. Scenario 3 seems to have a good design, since the tax base does not include symbolic products such as cheese or olive oil, and has sizeable effects. The prevalence of adult obesity would fall by 33%. Figures C5 and C6 in Appendix C present the results for men and

[22] The results are robust to the choice of different seeds.

women separately. Figure C5 shows the non-parametric estimates of the BMI distribution before and after the price changes. The distribution of BMI in the population is clearly more favourable in a public-health sense. Figure C6 plots the expected change in BMI against pre-policy BMI. It is negative for most individuals, whatever their initial BMI. As a result, the prevalence of "risky overweight" (BMI>27) in the simulated sample drops respectively from 28.6% to 21.8%. The maximum fall in health care expenditure would represent 1.39% of total health-care spendings in 2004.

8 Conclusion

Would appropriate taxes and subsidies help to reduce the prevalence of obesity? To answer this question, we have estimated whether and how the distribution of BMI in the French adult population is affected by the prices of 23 food products.

A model combining standard assumptions from rational-choice theory and Physiology was proposed. Its main empirical implication is that unobserved heterogeneity in physical expenditure creates slope heterogeneity in the food price-BMI relationship. Data drawn from an exhaustive household survey on food-at-home purchases, the French TNS-World Panel Survey, were used to investigate this relationship. Two technical points were emphasised. First, identification relies on the presence of spatial price variation. It is shown that measuring local prices by Paasche indices limits the necessary assumptions required to construct exogenous prices from the endogenous unit values that can be computed for each household. Second, slope heterogeneity requires quantile independence between unobserved physical expenditure and observed covariates of BMI in order to identify the price elasticities of BMI at various quantiles of its distribution.

There are modest correlations between individual BMI and the prices of a number of food products. The elasticities are negative for oils and, probably, for dairy products, animal fats, cereals, meat in brine, breaded/fried meat and fish, processed fruit and vegetables, and sugar and sweets. They are positive for fruit and vegetables in brine, and, perhaps surprisingly, for ready-meals, snacks and desserts.

Based on the regression results, and using a Monte-Carlo simulation technique, several policy scenarios were analysed. A 10% fall in the price of fruit and vegetables in brine, together with a similar increase in the prices of alcohols, soft drinks, breaded proteins, pastries and deserts, snacks and ready-meals may reduce the prevalence of obesity by about 33%, with a corresponding reduction in health-care costs of 960 to 2133 million Euros. However, given the width of estimated confidence intervals and the lack of monotonicity in the estimated quantile functions, the results should be taken with caution. This is all the more true that micro- and macro-nutrient needs differ according to job requirements, age, gender and health status. Hence, optimal obesity taxes may not be so if we consider other health/nutritional outcomes, or specific socio-demographic groups.

There are a number of useful avenues for future research. First, we have made rough assumptions about the nutritional quality of food products, by grouping them together in categories that are supposed to be homogenous. More precise studies of price effects within food categories are required, following the example of Chouinard *et al.* (2005) on dairy products or Kuchler *et al.* (2004) on snacks.

Second, the simulation uses very imprecise data on the medical overcost of obesity. The actual cost is a continuous function of BMI, and better knowledge of this relationship in overweight individuals is required for more precise forecasts.

Third, how can price policies be implemented efficiently? Producer price interventions targeting food products are commonly used in the framework of the EU Common Agricultural Policy. A key question for their impact on obesity, is whether prices are transmitted along the food chain to consumers, since reactions on the supply-side are to be expected. For instance, producers may seek to lower production costs, by changing their recipes and using cheaper but unhealthy additives. Price interventions at the consumer level, via extra VAT (Value Added Tax) on unhealthy products and VAT exemptions on healthy food seem more interesting.[23] However, it may also impact the average quality of food supply.

Fourth, fiscal policies are likely to be regressive. Poor consumers may not have healthier alternative choices to cover their basic caloric needs. Richer consumers purchase more fruit and vegetables, and their demand for healthy foodstuffs is more elastic (Caillavet and Darmon, 2005). Hence, political support for nutritional taxation is not guaranteed.

To conclude, our results suggest that a well-designed price policy may have sizeable effects on the distribution of body weight. However, its implementation may be problematic, for a number of practical reasons, and may encounter a coalition of opponents, bringing together part of the agro-industrial sector as well as some segments of the population.

[23] Differentiated VAT taxes on food products (including food-away-from home items) are found in the UK, France, Canada and the U.S., and some of them explicitly target foods that are considered unhealthy, such as snacks, soft drinks, and sweets. In France, there is for instance a higher VAT rate (20.6%) on sweets (but 5.5% on some chocolate products), margarine and vegetable fat (but 5.5% on butter). Obviously, current variations in VAT are not motivated by public health concerns.

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A Model

Using the modelling framework proposed by Arnade and Gopinath (2006), I here propose a dynamic model that simultaneously captures the health and hedonic aspects of the consumer's weight-control problem.

A.1 Set-up

Time The consumer is time-consistent and forward-looking. Time is continuous and divided up into periods (e.g. years). Each period is indexed by $t \in \{0, 1, 2, ...\}$ and, for the empirical analysis, we are mainly interested in any changes that may occur between t and $t + 1$.

Budget constraint and choice set At each moment $\tau \in [t, t+1[$, the consumer has to allocate her consumption budget between a numeraire good, y_τ, and a diet made up of L food items, which is represented by a vector of consumptions $\mathbf{c}_\tau$. Let I_t be the consumption budget at τ. This is considered to be exogenously predetermined. The vector of food prices $\mathbf{p}_t$ is also constant over period t. Further, expectations are static, *i.e.* prices and income are expected to remain constant over all future periods. The budget constraint is:

$$\forall \tau \in [t, t+1[, \ \mathbf{p}_t' \mathbf{c}_\tau + y_\tau = I_t \tag{15}$$

Physiology of weight production Food consumption at τ is converted into calorie intake K_τ by a simple linear operation:

$$K_\tau = \mathbf{A}\mathbf{c}_\tau \tag{16}$$

where $\mathbf{A}$ is a vector of energy densities. Information about the latter is assumed perfect. Using equation (8) for the basal metabolic rate, equation (7) becomes:

$$\forall \tau \in [t, t+1[,\ \dot{W}_\tau = \gamma K_\tau - E_t \beta \gamma W_\tau - E_t \alpha \gamma \tag{17}$$

Physical activity level Only calorie intake is endogeneised, and the index E_τ for PAL is treated as pre-determined (constant over t):

$$\forall \tau \in [t, t+1[, E_\tau = E_t. \tag{18}$$

Preferences Instantaneous preferences are represented by the following utility function:

$$U_\tau = u(\mathbf{c}_\tau, y_\tau; W_\tau, E_t)$$

The utility function has the usual properties.

A.2 The consumer-decision problem

In order to derive the Bellman equation associated with the decision problem of a rational consumer, it is worth expressing the latter in a discrete time framework, with arbitrary small time periods of length $\Delta\tau$. Let $V(W_\tau; \mathbf{p}_t, I_t, E_t)$ be the value function of the consumer at time $\tau \in [t, t+1[$. Between any date $\tau \in [t, t+1[$ and $\tau + \Delta\tau$, the consumer's utility flow is $U(\mathbf{c}_\tau, y_\tau; W_\tau, E_t)\Delta\tau$. The expected value function for the consumer at $\tau + \Delta\tau$ is $V(W_{\tau+\Delta\tau}; p_t, I_t, E_t)$. Consequently, if σ is the subjective discount rate, the following Bellman equation holds:

$$V(W_\tau; \mathbf{p}_t, I_t, E_t) = Max_{\mathbf{c}_\tau, y_\tau} u(\mathbf{c}_\tau, y_\tau; W_\tau, E_t)\Delta\tau + \frac{1}{1+\sigma\Delta\tau} V(W_{\tau+\Delta\tau}; \mathbf{p}_t, I_t, E_t)$$

under the budget constraint (15).

Let $F(\tau) = V(W_\tau; \mathbf{p}_t, I_t, E_t)$, then, assuming that $V(.)$ is C^1, we have by a Taylor expansion:

$$\begin{aligned} V(W_{\tau+\Delta\tau}; \mathbf{p}_t, I_t, E_t) &= F(\tau + \Delta\tau) \\ &= F(\tau) + \frac{dF(\tau)}{d\tau}\Delta\tau + o(\Delta\tau) \\ &= V(W_\tau; \mathbf{p}_t, I_t, E_t) + V_W(W_\tau; \mathbf{p}_t, I_t, E_t)\dot{W}_\tau \Delta\tau + o(\Delta\tau) \end{aligned} \tag{19}$$

Since $V(W_\tau; \mathbf{p}_t, I_t, E_t)$ does not depend on the control variables $\{\mathbf{c}_\tau, y_\tau\}$, the above approximations can be used to rewrite the Bellman equation as:

$$\sigma V(W_\tau;\mathbf{p}_t,I_t,E_t)\Delta\tau = Max_{\mathbf{c}_\tau,y_\tau} \begin{array}{l}\{u(\mathbf{c}_\tau,y_\tau;W_\tau,E_t)\Delta\tau \\ +V_W(W_\tau;\mathbf{p}_t,I_t,E_t)\dot{W}_\tau\Delta\tau + o\left(\Delta\tau\right)\Big\}\end{array} \tag{20}$$

Divide each side by $\Delta\tau$ and let $\Delta\tau \to 0$. Since $\lim_{\Delta\tau\to 0}\left(\frac{o(\Delta\tau)}{\Delta\tau}\right) = 0$, this yields the following Bellman equation:

$$\sigma V(W_\tau;\mathbf{p}_t,I_t,E_t) = Max_{\mathbf{c}_\tau,y_\tau}\Big\{u(\mathbf{c}_\tau,y_\tau;W_\tau,E_t) + V_W(W_\tau;\mathbf{p}_t,I_t,E_t)\dot{W}_\tau\Big\} \tag{21}$$

$$\left| \begin{array}{c} \mathbf{p}_t'\mathbf{c}_\tau + y_\tau = I_t \\ \dot{W}_\tau = \gamma K_\tau - E_t\beta\gamma W_\tau - E_t\alpha\gamma \end{array} \right. \tag{22}$$

where σ is the discount rate. The left-hand term represents the "annuity" from optimal investment decisions, and can be decomposed into the instantaneous stream of utility plus the marginal change in well-being produced by a small change in W.

A.3 Propositions

To solve the decision problem, a two-step approach is used (see Epstein, 1981). Note that, at time τ, given an optimal path for W, or equivalently K, the consumer would like to choose $\{\mathbf{c}_\tau, y_\tau\}$ in order to maximise $u(\mathbf{c}_\tau, y_\tau; W_\tau, E_t)$. Hence, the first-step of the maximisation procedure consists in finding $\Psi(K_\tau; W_\tau, \mathbf{p}_t, I_t, E_t)$ such that:

$$\begin{aligned} \Psi(K_\tau;W_\tau,\mathbf{p}_t,I_t,E_t) &= Max_{\mathbf{c}_\tau}\left\{u(\mathbf{c}_\tau, I_\tau - \mathbf{p}_t'\mathbf{c}_\tau; W_\tau, E_t)\right\} \\ \text{such that } K_\tau &= \mathbf{A}\mathbf{c}_\tau \end{aligned} \tag{23}$$

This decision program yields demand functions $\mathbf{c}_\tau$ that are conditional on a fixed level of calory intake K_τ.

Then, in a second step, the consumer maximises a Bellman equation, in which the control variable is calorie intake K_τ. Replacing $\dot{W}_\tau$ from equation (17) of Section 2.2. yields:

$$\sigma V(W_\tau;\mathbf{p}_t,I_t,E_t) = Max_{K_\tau} \begin{array}{l}\{\Psi(K_\tau;W_\tau,\mathbf{p}_t,I_t,E_t) \\ +V_W(W_\tau;\mathbf{p}_t,I_t,E_t)\left(\gamma K_\tau - E_t\beta\gamma W_\tau - E_t\alpha\gamma\right)\}\end{array} \tag{24}$$

The first-order condition for the above maximisation problem is:

$$\Psi_K + \gamma V_W = 0 \tag{25}$$

Consider the following quadratic local approximations for the indirect utility functions,

$$
\begin{aligned}
V(W_t;\mathbf{p}_t,I_t,E_t) = & \quad \tfrac{1}{2}\lambda_{WW}W_t^2 + \textstyle\sum_{l=1}^{L}\lambda_{p_lW}\ln(p_{lt})W_t \\
& +\lambda_{IW}\ln(I_t)W_t + \lambda_{EW}E_tW_t + h^V(p_t,I_t,E_t) \\
\Psi(K_t;W_t,\mathbf{p}_t,I_t,E_t) = & \quad \tfrac{1}{2}\kappa_{KK}K_t^2 + \kappa_{KW}K_tW_t + \textstyle\sum_{l=1}^{L}\kappa_{p_lW}\ln(p_{lt})K_t \\
& +\kappa_{IK}\ln(I_t)K_t + \kappa_{EK}E_tK_t + h^{\Psi}(W_t,p_t,I_t,E_t)
\end{aligned}
$$

then equation (25) implies:

$$
\begin{aligned}
K_\tau \;\; = \;\; & -\frac{1}{\kappa_{KK}}\Big[\left(\kappa_{KW}+\lambda_{WW}\gamma\right)W_\tau + \\
& \sum_{l=1}^{L}\left(\kappa_{p_lK}+\lambda_{p_lW}\gamma\right)\ln(p_{lt}) + \left(\kappa_{IW}+\gamma\lambda_{IW}\right)\ln(I_t) + \left(\kappa_{EK}+\gamma\lambda_{EW}\right)E_t\Big]
\end{aligned}
$$

and replacing K_τ in equation (17) of Section 2.2. yields:

$$
\dot{W}_\tau = -\left[E_t\beta\gamma + \frac{\gamma\left(\kappa_{KW}+\lambda_{WW}\gamma\right)}{\kappa_{KK}}\right]W_\tau + \left[E_t\beta\gamma + \frac{\gamma\left(\kappa_{KW}+\lambda_{WW}\gamma\right)}{\kappa_{KK}}\right]\zeta(\mathbf{p}_t,I_t,E_t)
$$

where:

$$
\zeta(\mathbf{p}_t,I_t,E_t) = \frac{-\frac{\gamma}{\kappa_{KK}}\left[\sum_{l=1}^{L}\left(\kappa_{p_lK}+\lambda_{p_lW}\gamma\right)\ln(p_{lt}) + \left(\kappa_{IW}+\overline{\gamma}\lambda_{IW}\right)\ln(I_t)\right] - \gamma E_t\left(\alpha + \frac{(\kappa_{EK}+\gamma\lambda_{EW})}{\kappa_{KK}}\right)}{\left[E_t\beta\gamma + \frac{\gamma(\kappa_{KW}+\lambda_{WW}\gamma)}{\kappa_{KK}}\right]}
$$

The dynamics of W_τ is given by a first-order linear differential equation, whose solution is:

$$
W_\tau = \left[W_t - \zeta(\mathbf{p}_t,I_t,E_t)\right]\exp\left(-\left[E_t\beta\gamma + \frac{\gamma\left(\kappa_{KW}+\lambda_{WW}\gamma\right)}{\kappa_{KK}}\right](\tau-t)\right) + \zeta(\mathbf{p}_t,I_t,E_t)
$$

From which we have an explicit specification for W_{t+1}:

$$
W_{t+1} = \left[W_t - \zeta(\mathbf{p}_t,I_t,E_t)\right]\exp\left(-\left[E_t\beta\gamma + \frac{\gamma\left(\kappa_{KW}+\lambda_{WW}\gamma\right)}{\kappa_{KK}}\right]\right) + \zeta(\mathbf{p}_t,I_t,E_t)
$$

A stable stationary equilibrium exists iff:

$$
-\left[E_t\beta\gamma + \frac{\gamma\left(\kappa_{KW}+\lambda_{WW}\gamma\right)}{\kappa_{KK}}\right] < 0
$$

To interpret this condition, consider the effect of a small change in W_t on the optimal choice of K_τ, when the environmental variables and E_t are held constant. Implicitly differentiating equation (25) yields:

$$
\frac{dK_\tau}{dW_t} = -\frac{\left(\kappa_{KW}+\lambda_{WW}\gamma\right)}{\kappa_{KK}}
$$

Hence, stability requires that:

$$\frac{dK_\tau}{dW_t} < \frac{d\left(BMR_\tau E_\tau\right)}{dW_t}$$

which leads to the following proposition:

Proposition 2 *A unique stable equilibirum exists if and only if the marginal effect of body weight on calorie intake is lower than the marginal effect on calorie expenditures*

Clearly, were this condition not to hold, individuals would continue to eat more without an adequate counterbalance in terms of energy expenditure, and body weight would grow indefinitely. Stationary weight is:

$$W_t^* = \zeta(\mathbf{p}_t, I_t, E_t)$$

The weight-production equation then becomes:

$$W_{t+1} = W_t\rho(E_t) + \left[1 - \rho(E_t)\right]\zeta(\mathbf{p}_t, I_t, E_t)$$

where $\rho(E_t) = \underbrace{\exp\left(-\gamma\beta E_t\right)}_{\rho^0(E_t)}\left(-\gamma\left[\frac{(\kappa_{KW}+\lambda_{WW}\gamma)}{\kappa_{KK}}\right]\right) = \rho^0(E_t) \times \exp\left(\gamma\frac{dK_\tau}{dW_t}\right)$ is a conservation factor.

Regarding the latter, I have a third proposition:

Proposition 3 *Depreciation of body weight increases when the individual is more physically active, and when the marginal effect of body weight on calorie intake decreases*

Depreciation of body weight is greater when the individual is more active (since then $\rho^0(E_t)$ decreases), and when the marginal impact of body weight on optimal intake decreases. α and β were estimated by Schofield *et al.* (1985) using biological data collected in a sample of more than 7000 individuals (although questions have been raised about the generality of these equations: climate and lifestyle behaviours such as smoking have some effect on the BMR). We can set γ to 365 $days \times 1/c$, where c is close to 9000 $kcal/kg$. This comes from the fact that (i) excess calories are stocked into fat cells, (ii) a kg of dietary fat contains about 9000 $kcal$. It then appears that $\rho^0(E_t)$ varies between 0.65 for sedentary old women and 0.25 for highly-active young men. Estimation of the dynamic model, the results of which are available upon request, shows that, if the identifying restriction of Section 5 is credible, $\mathbf{E}\left\{\rho^0(\widetilde{E}_t)\right\} = 0.86$. The marginal effect of body weight on optimal intake - dK_τ/dW_t -, is a constant of the model. Then, assuming that tastes are homogenous, we have $\mathbf{E}\left\{\rho^0(\widetilde{E}_t)\right\} < \mathbf{E}\left\{\rho(\widetilde{E}_t)\right\} = \hat{\rho}$, and dK_τ/dW_t is positive. For average values of $\rho^0(\widetilde{E}_t)$, between 0.4 and 0.5, the marginal effect of body weight on intake lies in the interval [13.4 $kCal/kg$, 18.9 $kCal/kg$].

A.4 Price effects

As daily calorie expenditures are constant over the period $[t, t+1[$, a general solution to (7) is:

$$W_{t+1} = \exp\left(-\beta\gamma E_t\right) W_t + \int_t^{t+1} \left[\gamma K_\tau \exp\left(-E_t\beta\gamma((t+1)-\tau)\right)\right] d\tau - \frac{\alpha}{\beta}\left[1 - \exp\left(-\beta\gamma E_t\right)\right] \tag{26}$$

This equation expresses body weight at the beginning of period $t+1$ as a function of body weight at the beginning of period t and the stream of calorie intake (represented by the integral). Prices act implicitly in this equation by determining eating behaviour, and therefore the path followed by K_u. The conservation factor $\exp\left(-E_t\beta\gamma((t+1)-\tau)\right)$ moderates the way in which calorie intake is transformed into body weight.

Equation (16) implies that $K_u = \sum_l a_l c_{\tau l}$, where c_{ul} is the consumption of food product l at time τ and a_l is its per-unit caloric content. Denote its price by p_{lt}, and consider the effect of a change in the price p_{1t} of c_{1t} by differentiating (26). Under the usual regularity conditions regarding the function K_u, we have:

$$\begin{aligned} \frac{\partial W_{t+1}}{\partial p_{1t}} &= \int_t^{t+1} \gamma \frac{\partial K_\tau}{\partial p_{1t}} \rho^0(E_t, \tau) d\tau \\ &= \int_t^{t+1} \gamma \left\{ \sum_{l=1}^{L} a_l \frac{\partial c_{\tau l}}{\partial p_{1t}} \right\} \rho^0(E_t, \tau) d\tau \end{aligned} \tag{27}$$

The sign of the price effect cannot be predicted without further assumptions regarding the own- and cross-price elasticities of consumption and the relative densities of each food item. This is positive if $\forall\tau \in [t, t+1[,\ \sum_{l=1}^{L} a_l \frac{\partial c_{\tau l}}{\partial p_{1t}} > 0$. When there are only two product categories, this condition may hold when category 1 and category 2 have the same densities ($a_1/a_2 \approx 1$), and when the own-price elasticity of category 1 is small while the cross-price elasticity is positive and fairly high (categories 1 and 2 are strong substitutes).

Appendix B. Descriptive statistics.

Figure B1. BMI distributions – Sample 1 and Sample 2.

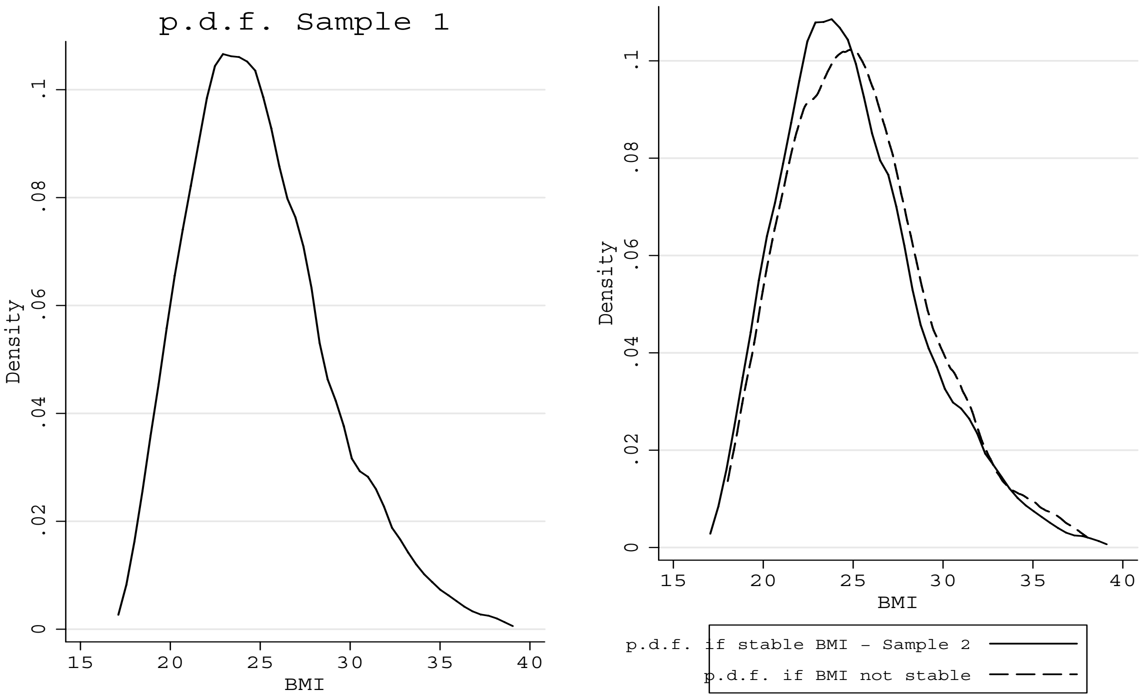

Figure B 2. BMI distributions by gender – Sample 2

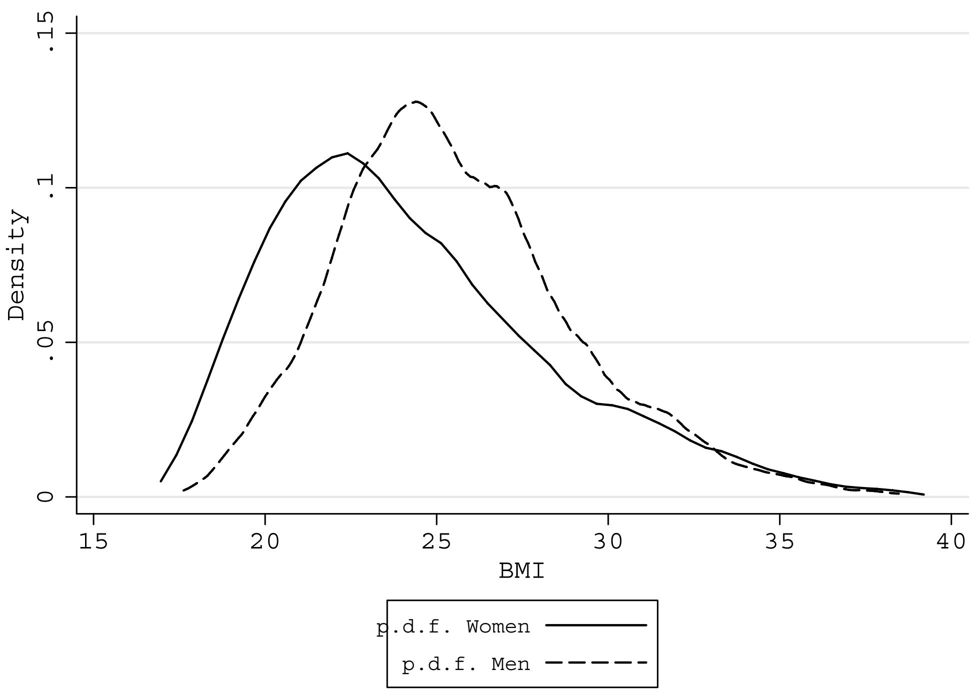

Table B1. Changes in BMI

Transition	**2002-2003**	**2003-2004**	**2004-2005**	**Total**
Number of observed transitions	5527	4605	4444	14576
% with stable body weight	86.65	83.41	89.51	86.65% (N=12608)

Note. This table should be read as follows: 4999 individuals were observed in 2001 and 2002, of whom 86.58% declared the same body weight in 2001 and in 2002.

Table B2. Classification of Food Products

Product category	**Food products (examples)**	**Comments**
Water	Fizzy or still, mineral or not.	
Alcohol	All kind of wines, cocktails, beers, ciders, liquors etc.	Products are aggregated according to their average alcohol content.
Soft drinks	Fruit juice, soda and other carbohydrated drinks (lemonade, syrups etc.). Flavoured waters were dropped.	Products are distinguished according to their sugar or fat content when available.
Fruit in brine	All fresh fruit and fruit canned/frozen in brine	
Processed Fruit	Fruits canned in syrup etc.	Products light in sugar are distinguished.
Vegetables in brine	All fresh vegetables plus vegetables canned/frozen in brine	
Processed vegetables	Cooked frozen vegetables, vegetables and soups canned/frozen with additives.	
Cereals	Dried vegetables, potatoes, beans except fresh green or yellow beans, pasta, rice, bread, flour, chestnuts, oat flakes, couscous.	
Meat in brine and eggs	Fresh/raw meat: beef, veal, snails, chicken, eggs…	
Seafood in brine	All fish, shellfish, frogs etc. in brine	
Processed sea products	Fish canned in oil, smoked salmon, marinated haddock, rollmops	Canned
Cooked meat	Sausages, ham, pâté, foie gras, bacon, smoked pork	
Breaded proteins	Breaded/fried fish or meat	
Yoghurt and fresh uncured cheese	Natural yoghurt, milk, fresh uncured cheese (fromage blanc ou frais)	Products are distinguished according to their fat content when available. Products without explicit fat content were dropped.
Cheese	All cheese except fromage blanc and fromage frais.	
Milk	All milk (soja milk was dropped).	
Animal fat and margarine	Butter, fresh cream.	
Oils	Oils. Sauces were dropped.	
Sugar and confectionery	Lump/caster sugar, honey, jam marmalades.	
Pastries and desserts	Milk desserts, croissants, cakes, fresh or frozen pastries	
Sweet and fatty snacks	Breakfast cereals, cereal bars, chocolate bars, most chocolate products, biscuits, ice creams	“sweet” here means either simple or complex carbohydrates.
Salty and fatty snacks	Crackers, pop-corn, peanuts, most appetisers, olives	
Ready-meals	All ready meals including sandwiches, and canned/frozen recipes of vegetables and cereals (ratatouille, etc.).	

Table B3. Variable definition and descriptive statistics

Variable Name	Variable definition	Sample 1 (N=21407)	Sample 2 (N=12608)
BMI	Body Mass Index (Weight in Kg divided by height in squared meters)	24.91 (3.86)	24.92 (3.86)
CONTHEIGHT*	[Height (in meters)]$^{-2}$	0.359 (0.039)	0.359 (0.038)
INCOME	Logarithm of real household income per unit of consumption (Oxford scale, 2004 Euros)	1137.1 (613.3)	1142.2 (617.1)
DEG1	No qualification or primary school	15.5%	16.2%
DEG2	Short vocational or technical qualification	6.8%	6.8%
DEG3	First cycle of secondary school (BEPC)	30.5%	30.7%
DEG4	Baccalaureat (general, vocational or technical)	19.0%	18.7%
DEG5	Baccalaureat + 2 years	10.6%	10.4%
DEG6 (reference)	Baccalaureat + 3 years or more	17.6%	17.2%
SEX*	=1 for male, 0 otherwise	47.1%	47.2%
AGE	Age	50.40 (15.73)	51.65 (15.67)
BABYWOMAN	=1 for women with a baby aged under one year.	1.3%	1.2%
BABYMAN	=1 for men with a baby aged under one year.	1.4%	1.3%
COUPLE (reference)	Couples (reference)	66.6%	65.9%
SINGLE	Single without children	17.9%	18.0%
OTHHHOLD	Other household structure	15.6%	16.1%
NBIND	Number of person in the household	2.63 (1.27)	2.61 (1.27)
FRUITSORVEG	Household produces fruit or vegetables	19.0%	18.8%
MEALPLANNER	=1 if the individual is responsible for food-at-home expenditures	30.6%	30.5%
UNIT1	Lives in a rural residential area	30.3%	30.3%
UNIT2	Lives in an urban unit of between 2000 and 4999 residents	6.4%	6.7%
UNIT3	Lives in an urban unit of between 5000 and 9999 residents	2.7%	2.9%
UNIT4	Lives in an urban unit of between 10000 and 19999 residents	2.6%	2.4%
UNIT5	Lives in an urban unit of between 20000 and 49999 residents	3.7%	3.3%
UNIT6	Lives in an urban unit of between 50000 and 99999 residents	5.6%	5.6%
UNIT7	Lives in an urban unit of between 100000 and 199999 residents	4.2%	3.6%
UNIT8	Lives in an urban unit of 200000 residents or more, or in Ile-de-France outside Paris	22.8%	23.6%
REGION1 (reference)	Ile-de-France	23.5%	23.2%
REGION2	Picardie, Normandie	15.0%	14.9%
REGION3	Nord	8.6%	8.7%
REGION4	Champagne-Ardennes, Alsace, Lorraine	8.9%	9.1%
REGION5	Bretagne, Pays de Loire, Centre	15.8%	16.4%
REGION6	Limousin, Aquitaine, Poitou-Charente	6.1%	5.4%
REGION7	Bourgogne, Franche-Comté, Rhône-Alpes, Auvergne, Midi-Pyrénées, Languedoc	12.6%	12.9%
REGION8	Provence – Alpes - Côte d'Azur	9.4%	9.5%
YR2002	Calendar year = 2002 (for the dependent variable)	26.9%	_
YR2003	Calendar year = 2003 (for the dependent variable)	27.8%	38.0%
YR2004 (reference)	Calendar year = 2004 (for the dependent variable)	23.5%	30.5%
YR2005	Calendar year = 2005 (for the dependent variable)	21.8%	31.6%

Table B4. Descriptive statistics for prices (Sample 2)

Product category	Mean price	Overall standard deviation	Between standard deviation	Within standard deviation	Min	Max
Water	-1.410	0.230	0.195	0.144	-1.834	-0.785
Alcohol	-0.801	0.110	0.093	0.067	-1.081	-0.387
Soft drinks	-1.156	0.091	0.077	0.055	-1.471	-0.963
Fruit in brine	-0.603	0.193	0.153	0.147	-0.932	-0.126
Processed Fruit	-1.194	0.130	0.116	0.069	-1.566	-0.722
Vegetables in brine	-0.471	0.086	0.078	0.048	-0.686	-0.120
Processed vegetables	-0.972	0.147	0.120	0.098	-1.372	-0.544
Cereals	-0.743	0.126	0.106	0.082	-1.036	-0.459
Meat in brine and eggs	-0.876	0.128	0.101	0.095	-1.170	-0.525
Seafood in brine	-1.507	0.170	0.129	0.128	-2.097	-0.906
Processed sea products	-1.006	0.206	0.159	0.158	-1.456	-0.490
Cooked meat	-1.314	0.125	0.086	0.102	-1.650	-1.046
Breaded proteins	-1.226	0.144	0.117	0.104	-1.704	-0.763
Yoghurt and fresh uncured cheese	-0.639	0.081	0.059	0.064	-0.842	-0.432
Cheese	-0.696	0.056	0.047	0.038	-0.846	-0.555
Milk	-0.573	0.053	0.046	0.033	-0.743	-0.457
Animal fat and margarine	-1.591	0.098	0.085	0.060	-1.901	-1.337
Oils	-0.715	0.065	0.058	0.032	-0.880	-0.544
Sugar and confectionery	-0.531	0.118	0.099	0.076	-0.786	-0.263
Pastries and desserts	-0.880	0.063	0.049	0.046	-1.045	-0.718
Sweet and fatty snacks	-0.888	0.092	0.068	0.069	-1.205	-0.673
Salty and fatty snacks	-0.959	0.117	0.091	0.088	-1.197	-0.619
Ready-meals	-0.914	0.186	0.145	0.137	-1.291	-0.483

Appendix C. Results

Table C1. Conditional mean and quantile regression results - 23 food categories – Elasticities - Sample 2 - Women – N=6633

Estimator	**OLS**	**Quantile Regressions**						
Conditional moment	**Mean**	**τ=0.5 median**	**τ=0.6 6th decile**	**τ=0. 7 7th decile**	**τ=0.8 8th decile**	**τ=0.9 9th decile**	**τ=0.637 "overweight quantile"**	**τ=0.898 "obesity quantile"**
Price Elasticities								
Water	0.065* (0.038)	0.075 (0.052)	0.075 (0.053)	0.093 (0.060)	0.152*** (0.059)	0.099 (0.065)	0.062 (0.056)	0.098 (0.061)
Alcohol	0.058 (0.047)	0.058 (0.060)	0.058 (0.063)	0.069 (0.074)	0.040 (0.079)	0.036 (0.081)	0.059 (0.066)	0.035 (0.078)
Soft drinks	-0.055 (0.068)	-0.055 (0.088)	-0.080 (0.097)	-0.023 (0.113)	-0.104 (0.123)	-0.137 (0.133)	-0.030 (0.100)	-0.141 (0.129)
Fruit in brine	0.134* (0.060)	0.155** (0.077)	0.184** (0.081)	0.140 (0.097)	0.209* (0.110)	0.091 (0.113)	0.166* (0.087)	0.093 (0.111)
Processed Fruit	0.018 (0.053)	0.098 (0.067)	0.081 (0.070)	0.016 (0.087)	-0.050 (0.089)	-0.006 (0.108)	0.040 (0.077)	-0.008 (0.109)
Vegetables in brine	-0.025 (0.080)	-0.050 (0.107)	0.013 (0.117)	0.100 (0.132)	-0.030 (0.130)	-0.010 (0.152)	0.049 (0.121)	-0.002 (0.150)
Processed vegetables	-0.002 (0.060)	0.045 (0.071)	0.027 (0.080)	-0.041 (0.097)	-0.079 (0.106)	-0.001 (0.123)	0.017 (0.086)	0.009 (0.120)
Cereals	0.045 (0.073)	-0.009 (0.097)	-0.061 (0.096)	-0.084 (0.107)	-0.020 (0.124)	0.065 (0.131)	-0.064 (0.102)	0.061 (0.133)
Meat in brine and eggs	-0.006 (0.088)	-0.016 (0.108)	0.013 (0.128)	0.023 (0.135)	0.109 (0.145)	0.082 (0.172)	0.009 (0.131)	0.085 (0.166)
Seafood in brine	-0.007 (0.035)	-0.027 (0.044)	-0.021 (0.047)	-0.024 (0.058)	-0.016 (0.061)	0.055 (0.065)	-0.050 (0.049)	0.049 (0.065)
Processed sea products	-0.019 (0.050)	-0.031 (0.067)	-0.033 (0.071)	-0.065 (0.080)	-0.098 (0.087)	-0.087 (0.096)	-0.067 (0.072)	-0.081 (0.092)
Cooked meat	0.135* (0.079)	0.098 (0.099)	0.110 (0.109)	0.102 (0.121)	0.172 (0.137)	0.185 (0.147)	0.182 (0.114)	0.185 (0.145)
Breaded proteins	0.005 (0.032)	0.030 (0.045)	0.007 (0.045)	0.016 (0.051)	0.027 (0.048)	-0.021 (0.053)	0.011 (0.048)	-0.018 (0.053)
Yoghurt and fresh uncured cheese	0.134 (0.112)	0.050 (0.151)	0.089 (0.163)	0.139 (0.177)	0.298 (0.189)	0.190 (0.193)	0.150 (0.164)	0.194 (0.193)
Cheese	-0.386**	-0.585**	-0.784***	-0.464	-0.591*	-0.455	-0.625**	-0.454

	(0.193)	(0.251)	(0.270)	(0.321)	(0.356)	(0.330)	(0.276)	(0.329)
Milk	-0.020 (0.100)	-0.049 (0.132)	0.032 (0.136)	0.043 (0.157)	-0.001 (0.165)	0.013 (0.179)	-0.043 (0.141)	0.001 (0.180)
Animal fat and margarine	-0.021 (0.055)	-0.009 (0.073)	-0.031 (0.076)	-0.120 (0.085)	-0.062 (0.092)	-0.040 (0.104)	-0.102 (0.075)	-0.041 (0.101)
Oils	-0.304** (0.154)	-0.206 (0.203)	-0.338 (0.221)	-0.287 (0.255)	-0.226 (0.266)	-0.258 (0.276)	-0.284 (0.227)	-0.258 (0.276)
Sugar and confectionery	0.046 (0.093)	0.220* (0.123)	0.204 (0.133)	0.101 (0.149)	0.107 (0.148)	-0.213 (0.171)	0.183 (0.143)	-0.207 (0.167)
Pastries and desserts	-0.182** (0.078)	-0.220** (0.103)	-0.251** (0.105)	-0.128 (0.132)	-0.223* (0.135)	-0.317** (0.142)	-0.219** (0.106)	-0.309** (0.140)
Sweet and fatty snacks	0.136 (0.100)	0.119 (0.126)	0.178 (0.125)	0.226 (0.146)	0.122 (0.166)	0.201 (0.205)	0.176 (0.133)	0.190 (0.208)
Salty and fatty snacks	-0.042 (0.088)	-0.034 (0.115)	0.023 (0.113)	-0.074 (0.132)	0.002 (0.135)	0.054 (0.154)	0.034 (0.117)	0.051 (0.150)
Ready-meals	-0.058 (0.068)	-0.114 (0.093)	-0.162* (0.092)	-0.160* (0.094)	-0.089 (0.117)	-0.031 (0.139)	-0.192** (0.092)	-0.038 (0.137)
Income Elasticities								
Income	-0.030*** (0.009)	-0.018 (0.011)	-0.013 (0.013)	-0.031** (0.015)	-0.040*** (0.015)	-0.055*** (0.016)	-0.019 (0.014)	-0.055*** (0.015)
Other control variables	*CONTHEIGHT, DEG1-DEG6, SEX, (AGE/10), $(AGE/10)^2$, BABYWOMAN or BABYMAN, COUPLE, SINGLE, OTHHHOLD, NBIND, FRUITSORVEG, MEALPLANNER, UNIT1-UNIT8, REGION1-REGION8, YR2003-YR2005*							

Note: For each regression and each variable, the point estimates of elasticities at median values of the control variables are shown, with their standard deviations in parenthesis; * = significant at the 10% level. ** = at the 5% level. *** = at the 1% level.

Table C2. Conditional mean and quantile regression results - 23 food categories – Elasticities - Sample 2 - Men – N=5975

Estimator	**OLS**	**Quantile Regressions**						
Conditional moment	**Mean**	**τ=0.5 median**	**τ=0.6 6th decile**	**τ=0. 7 7th decile**	**τ=0.8 8th decile**	**τ=0.9 9th decile**	**τ=0.484 "overweight quantile"**	**τ=0.888 "obesity quantile"**
				Price Elasticities				
Water	0.092*** (0.031)	0.095*** (0.037)	0.094** (0.037)	0.112*** (0.042)	0.118** (0.055)	0.125** (0.062)	0.092*** (0.036)	0.127** (0.064)
Alcohol	-0.013 (0.044)	-0.027 (0.047)	-0.034 (0.051)	0.021 (0.067)	0.071 (0.083)	0.115 (0.084)	-0.026 (0.046)	0.132 (0.089)
Soft drinks	-0.113* (0.059)	-0.162** (0.077)	-0.161** (0.076)	-0.100 (0.086)	-0.093 (0.109)	-0.115 (0.123)	-0.160** (0.076)	-0.108 (0.122)
Fruit in brine	0.045 (0.050)	0.055 (0.064)	0.042 (0.066)	0.099 (0.078)	0.138* (0.083)	0.121 (0.096)	0.044 (0.064)	0.142 (0.096)
Processed Fruit	0.022 (0.047)	0.000 (0.056)	0.034 (0.059)	0.044 (0.070)	0.094 (0.078)	0.164* (0.093)	-0.007 (0.057)	0.175* (0.090)
Vegetables in brine	0.027 (0.073)	0.102 (0.085)	0.000 (0.085)	0.086 (0.107)	0.043 (0.135)	-0.038 (0.150)	0.105 (0.091)	0.011 (0.154)
Processed vegetables	0.016 (0.054)	0.041 (0.064)	0.059 (0.065)	0.029 (0.080)	-0.065 (0.095)	-0.125 (0.096)	0.036 (0.061)	-0.111 (0.097)
Cereals	0.009 (0.059)	-0.042 (0.076)	-0.064 (0.074)	-0.141 (0.094)	-0.031 (0.116)	0.151 (0.114)	-0.036 (0.076)	0.111 (0.121)
Meat in brine and eggs	0.078 (0.079)	0.035 (0.092)	0.000 (0.097)	0.018 (0.122)	0.066 (0.151)	0.033 (0.155)	0.049 (0.087)	0.036 (0.156)
Seafood in brine	-0.022 (0.030)	-0.053 (0.040)	-0.032 (0.040)	-0.062 (0.047)	-0.039 (0.055)	0.013 (0.057)	-0.043 (0.038)	0.021 (0.057)
Processed sea products	0.068 (0.044)	0.059 (0.052)	0.074 (0.055)	0.031 (0.066)	0.053 (0.077)	0.045 (0.078)	0.049 (0.051)	0.029 (0.081)
Cooked meat	-0.042 (0.067)	0.013 (0.083)	-0.010 (0.090)	0.011 (0.102)	0.021 (0.114)	-0.039 (0.122)	0.006 (0.078)	-0.043 (0.121)
Breaded proteins	-0.047 (0.029)	-0.073** (0.033)	-0.041 (0.034)	-0.055 (0.044)	-0.090 (0.057)	-0.120* (0.062)	-0.066** (0.033)	-0.121* (0.063)
Yoghurt and fresh uncured cheese	0.057 (0.094)	0.033 (0.115)	0.068 (0.117)	0.086 (0.139)	0.263 (0.170)	0.177 (0.167)	0.053 (0.109)	0.231 (0.164)
Cheese	-0.135 (0.166)	-0.268 (0.206)	-0.130 (0.187)	-0.234 (0.226)	-0.303 (0.301)	-0.135 (0.321)	-0.283 (0.198)	-0.140 (0.314)

Milk	-0.185** (0.085)	-0.229** (0.102)	-0.252** (0.107)	-0.185 (0.133)	-0.333** (0.161)	-0.185 (0.160)	-0.220** (0.101)	-0.156 (0.167)
Animal fat and margarine	0.032 (0.047)	0.057 (0.061)	0.060 (0.059)	0.025 (0.068)	0.034 (0.081)	-0.051 (0.086)	0.051 (0.058)	-0.063 (0.084)
Oils	-0.060 (0.127)	0.008 (0.152)	-0.018 (0.171)	-0.085 (0.206)	-0.133 (0.221)	-0.183 (0.225)	-0.017 (0.153)	-0.195 (0.224)
Sugar and confectionery	0.018 (0.078)	0.044 (0.096)	0.035 (0.101)	-0.034 (0.121)	-0.001 (0.136)	-0.068 (0.140)	0.035 (0.091)	-0.110 (0.146)
Pastries and desserts	-0.041 (0.071)	-0.030 (0.084)	-0.049 (0.086)	0.045 (0.102)	-0.064 (0.124)	-0.155 (0.133)	-0.035 (0.084)	-0.211 (0.138)
Sweet and fatty snacks	-0.018 (0.083)	0.036 (0.094)	-0.031 (0.103)	-0.025 (0.122)	-0.025 (0.165)	0.273 (0.182)	0.031 (0.091)	0.234 (0.187)
Salty and fatty snacks	0.033 (0.074)	0.116 (0.086)	0.158* (0.090)	0.122 (0.104)	0.073 (0.135)	-0.210 (0.142)	0.104 (0.088)	-0.148 (0.145)
Ready-meals	-0.033 (0.063)	-0.121* (0.072)	-0.130* (0.077)	-0.075 (0.097)	-0.091 (0.117)	0.037 (0.126)	-0.113* (0.068)	0.015 (0.127)
Income Elasticities								
Income	-0.008 (0.008)	-0.009 (0.010)	-0.014 (0.010)	-0.013 (0.012)	-0.007 (0.014)	-0.013 (0.014)	-0.005 (0.010)	-0.019 (0.014)
Other control variables	*CONTHEIGHT, DEG1-DEG6, SEX, (AGE/10), $(AGE/10)^2$, BABYWOMAN or BABYMAN, COUPLE, SINGLE, OTHHHOLD, NBIND, FRUITSORVEG, MEALPLANNER, UNIT1-UNIT8, REGION1-REGION8, YR2003-YR2005*							

Note: For each regression and each variable, the point estimates of elasticities at median values of the control variables are shown, with their standard deviations in parenthesis; * = significant at the 10% level. ** = at the 5% level. *** = at the 1% level.

Figure C1. Δ(τ)- Women – 23 food categories.

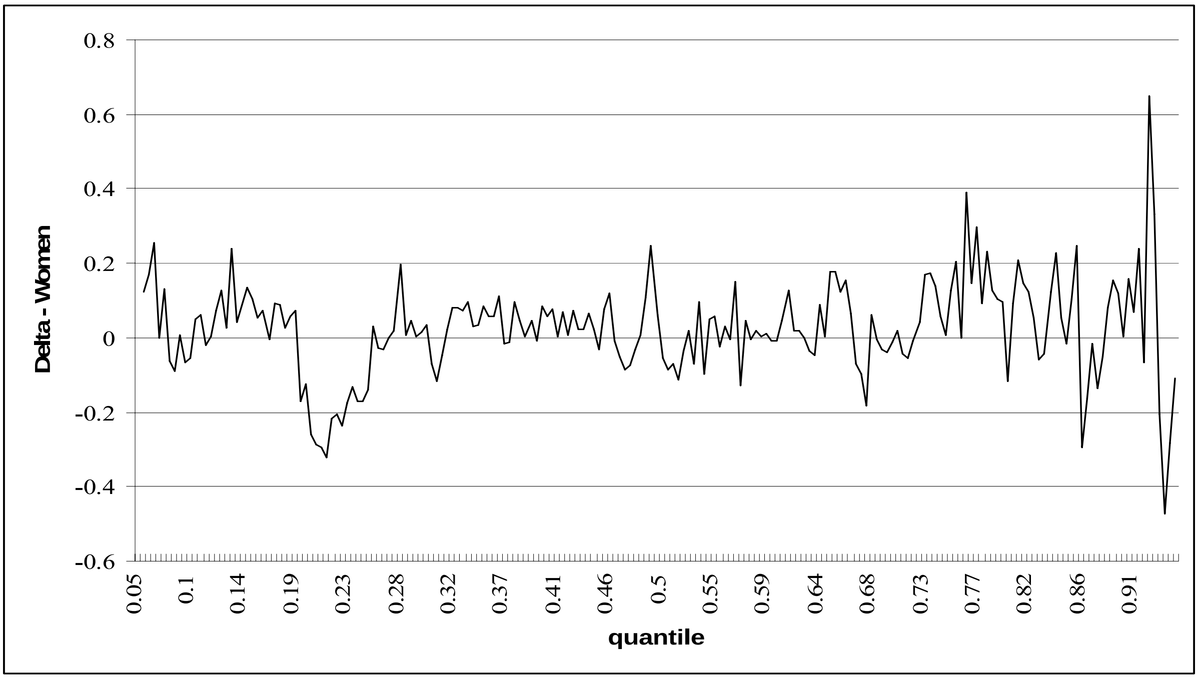

Figure C2. Δ(τ) – Men – 23 food categories.

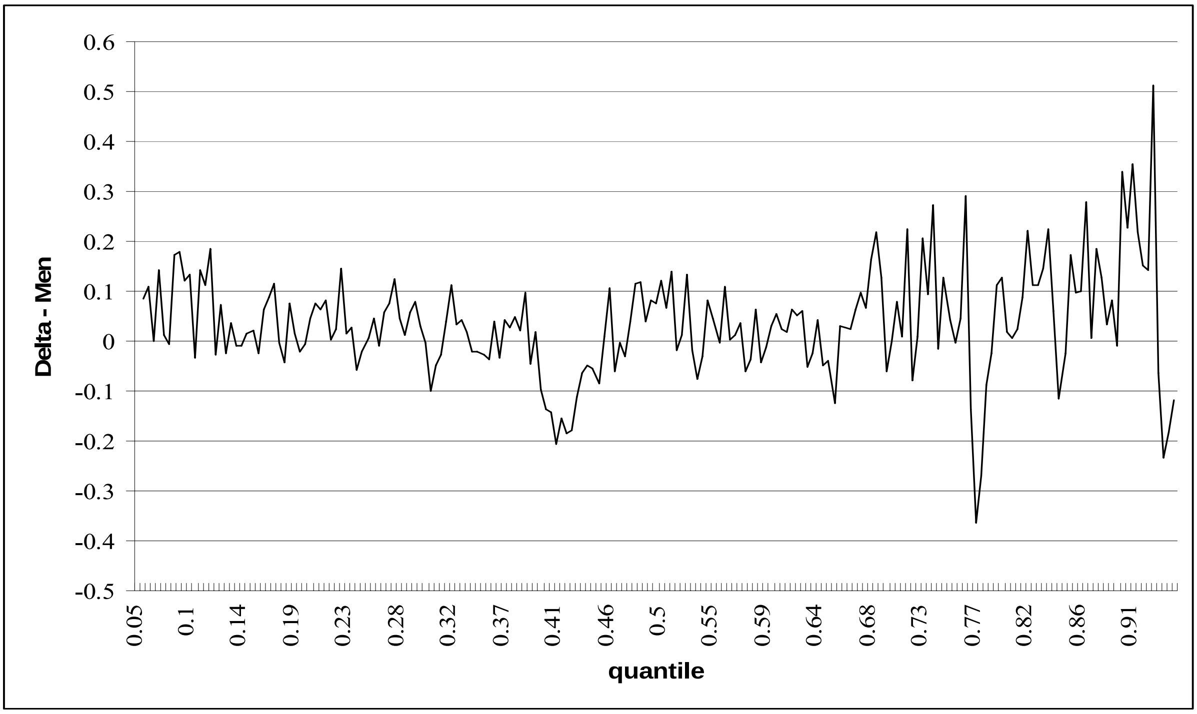

Table C3. Conditional mean and quantile regression results - 9 food groups – Elasticities - Sample 2 - Women – N=6633

Estimator	**OLS**	**Quantile Regressions**						
Conditional moment	**Mean**	**τ=0.5 median**	**τ=0.6 6th decile**	**τ=0. 7 7th decile**	**τ=0.8 8th decile**	**τ=0.9 9th decile**	**τ=0.637 "overweight quantile"**	**τ=0.898 "obesity quantile"**
				Price Elasticities				
Water	0.050* (0.029)	0.049 (0.035)	0.066* (0.039)	0.092** (0.045)	0.124*** (0.045)	0.074 (0.049)	0.073* (0.041)	0.077 (0.049)
Alcohol & Soft drinks	0.042 (0.050)	0.025 (0.066)	0.023 (0.066)	-0.001 (0.078)	0.004 (0.079)	-0.016 (0.076)	-0.029 (0.069)	-0.029 (0.075)
Fruits & Vegetables	0.037 (0.082)	-0.019 (0.100)	0.062 (0.110)	0.012 (0.126)	-0.001 (0.142)	0.066 (0.147)	0.113 (0.118)	0.071 (0.142)
Cereals	-0.004 (0.058)	0.016 (0.074)	-0.065 (0.081)	-0.037 (0.088)	-0.097 (0.091)	0.031 (0.101)	-0.078 (0.086)	0.027 (0.102)
Meats & Seafood products	0.004 (0.064)	-0.036 (0.080)	-0.042 (0.090)	0.030 (0.102)	0.058 (0.108)	0.137 (0.103)	-0.031 (0.094)	0.149 (0.105)
Dairies	-0.065 (0.173)	-0.315 (0.228)	-0.207 (0.217)	-0.050 (0.256)	-0.142 (0.313)	-0.258 (0.346)	-0.194 (0.234)	-0.176 (0.343)
Fats	-0.135 (0.084)	-0.040 (0.116)	-0.155 (0.117)	-0.152 (0.118)	-0.032 (0.138)	-0.079 (0.164)	-0.117 (0.115)	-0.091 (0.164)
Sugar products	-0.017 (0.069)	0.103 (0.079)	0.092 (0.092)	0.024 (0.107)	0.050 (0.113)	-0.107 (0.116)	0.105 (0.095)	-0.125 (0.118)
Pastries, Deserts, Snacks, Ready-meals	-0.073 (0.091)	-0.064 (0.113)	-0.150 (0.124)	-0.255** (0.126)	-0.161 (0.148)	-0.113 (0.178)	-0.213* (0.124)	-0.117 (0.185)
				Income Elasticities				
Income	-0.027*** (0.008)	-0.014 (0.011)	-0.016 (0.012)	-0.029** (0.014)	-0.034** (0.014)	-0.044*** (0.015)	-0.015 (0.013)	-0.044*** (0.015)
Other control variables	*CONTHEIGHT, DEG1-DEG6, SEX, (AGE/10), $(AGE/10)^2$, BABYWOMAN or BABYMAN, COUPLE, SINGLE, OTHHHOLD, NBIND, FRUITSORVEG, MEALPLANNER, UNIT1-UNIT8, REGION1-REGION8, YR2003-YR2005*							

Note: For each regression and each variable, the point estimates of elasticities at median values of the control variables are shown, with their standard deviations in parenthesis; * = significant at the 10% level. ** = at the 5% level. *** = at the 1% level.

Table C4. Conditional mean and quantile regression results - 9 food groups – Elasticities - Sample 2 - N=5975

Estimator	**OLS**	**Quantile Regressions**						
Conditional moment	**Mean**	**τ=0.5 median**	**τ=0.6 6th decile**	**τ=0. 7 7th decile**	**τ=0.8 8th decile**	**τ=0.9 9th decile**	**τ=0.484 "overweight quantile"**	**τ=0.888 "obesity quantile"**
				Price Elasticities				
Water	0.053** (0.025)	0.048 (0.029)	0.049 (0.032)	0.064* (0.034)	0.072* (0.043)	0.050 (0.045)	0.057** (0.028)	0.074 (0.046)
Alcohol & Soft drinks	-0.022 (0.046)	-0.018 (0.048)	-0.037 (0.057)	0.030 (0.065)	0.022 (0.080)	0.066 (0.087)	-0.027 (0.050)	0.072 (0.084)
Fruits & Vegetables	0.097 (0.071)	0.170 (0.088)	0.140 (0.097)	0.219** (0.111)	0.189 (0.127)	0.033 (0.133)	0.198 (0.085)	0.057 (0.126)
Cereals	-0.020 (0.050)	-0.056 (0.062)	-0.109 (0.067)	-0.187** (0.076)	-0.086 (0.096)	0.074 (0.094)	-0.062 (0.060)	0.110 (0.093)
Meats & Seafood products	-0.004 (0.058)	-0.021 (0.062)	-0.010 (0.071)	-0.055 (0.083)	-0.038 (0.102)	-0.113 (0.107)	-0.009 (0.062)	-0.123 (0.104)
Dairies	-0.185 (0.161)	-0.321* (0.189)	-0.219 (0.205)	-0.184 (0.236)	0.010 (0.265)	0.181 (0.275)	-0.357* (0.195)	0.092 (0.280)
Fats	-0.095 (0.073)	-0.019 (0.093)	-0.055 (0.103)	-0.149 (0.118)	-0.197 (0.134)	-0.234* (0.130)	-0.026 (0.089)	-0.197 (0.129)
Sugar products	-0.031 (0.061)	-0.040 (0.070)	-0.021 (0.083)	-0.025 (0.090)	-0.073 (0.103)	-0.184 (0.114)	-0.039 (0.069)	-0.238** (0.109)
Pastries, Deserts, Snacks, Ready-meals	-0.014 (0.080)	0.025 (0.084)	-0.001 (0.098)	0.058 (0.108)	0.035 (0.132)	0.067 (0.147)	-0.031 (0.083)	0.116 (0.145)
				Income Elasticities				
Income	-0.008 (0.008)	-0.009 (0.010)	-0.017* (0.010)	-0.014 (0.012)	-0.005 (0.014)	-0.017 (0.014)	-0.009 (0.010)	-0.014 (0.014)
Other control variables	*CONTHEIGHT, DEG1-DEG6, SEX, (AGE/10), $(AGE/10)^2$, BABYWOMAN or BABYMAN, COUPLE, SINGLE, OTHHHOLD, NBIND, FRUITSORVEG, MEALPLANNER, UNIT1-UNIT8, REGION1-REGION8, YR2003-YR2005*							

Note: For each regression and each variable, the point estimates of elasticities at median values of the control variables are shown, with their standard deviations in parenthesis; * = significant at the 10% level. ** = at the 5% level. *** = at the 1% level.

Figure C3. Δ(τ)- Women – 9 food groups.

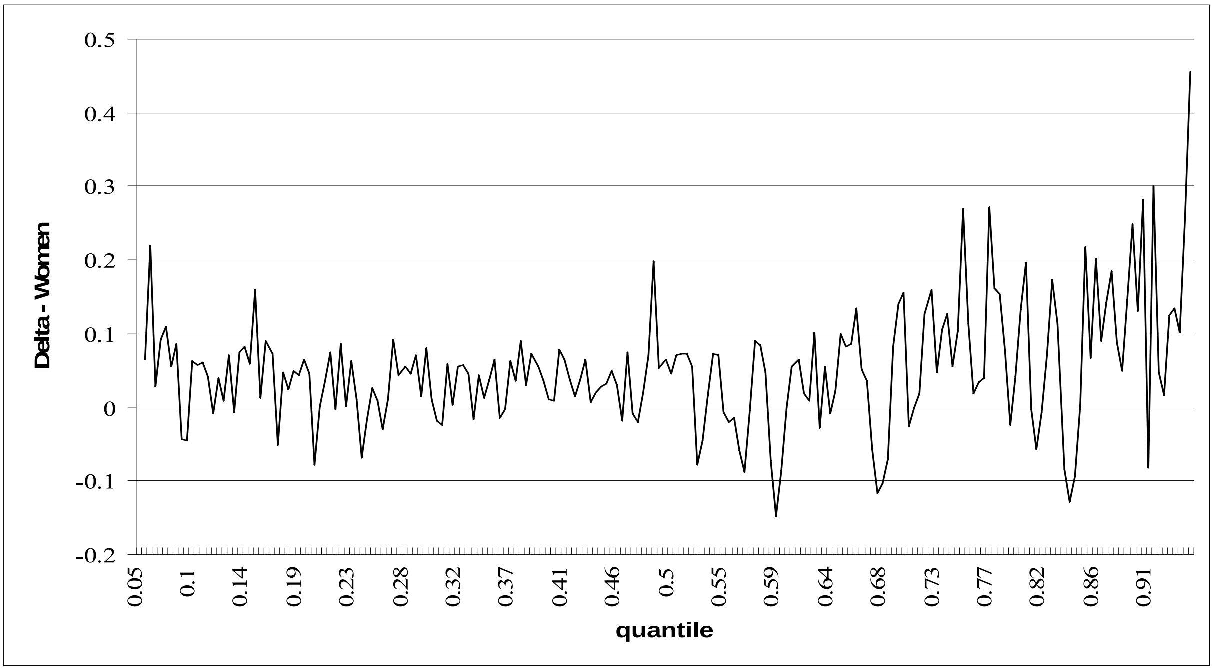

Figure C4. Δ(τ)- Men – 9 food groups.

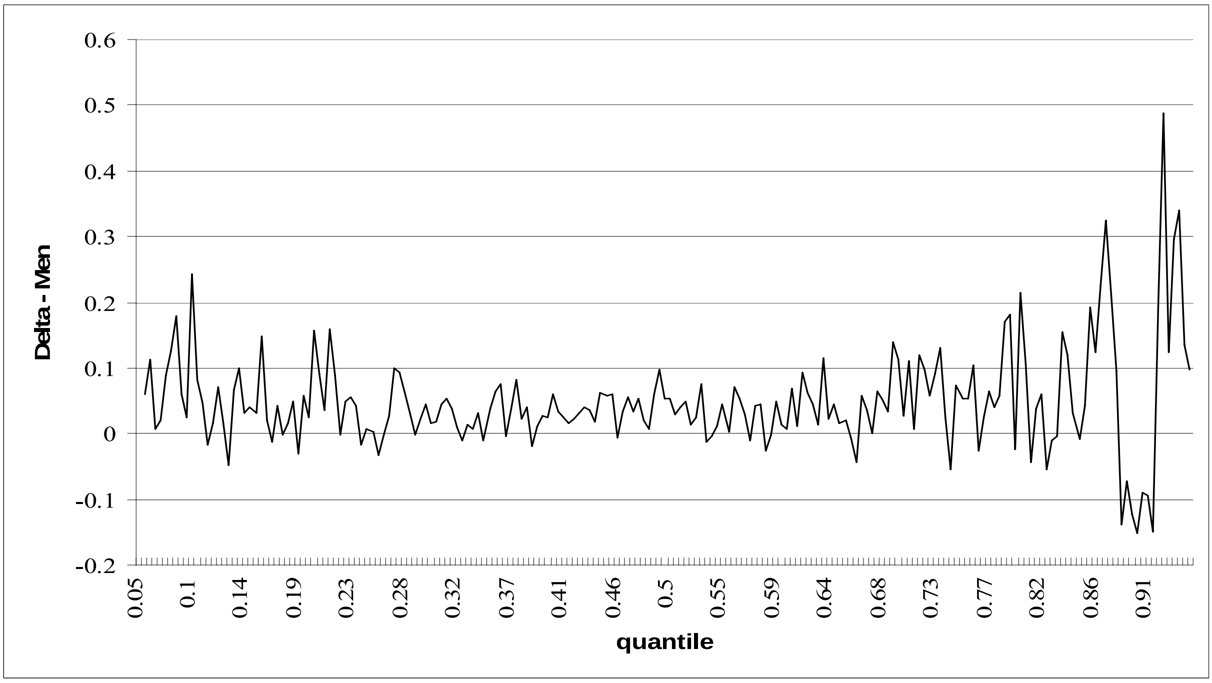

Table C5. Illustrations of the price effects for typical individuals.

	Women		Men	
BMI	25	30	25	30
Height	1.70	1.70	1.80	1.80
Weight	72.25	86.70	81.00	97.20
Effect (in kg) of a 10 % price decrease				
Fruits and vegetables in brine	-1.55	-0.79	-1.21	-1.49
Effect (in kg) of a 10 % price increase				
Soft drinks	-0.22	-1.22	-1.31	-1.05
Pastries, deserts, snacks and ready-meals	-1.45	-0.92	-0.11	-1.07
Total Effect	-3.22	-2.93	-2.62	-3.61

Note: approximate effects using Tables C2 and C3' results.

Table C6. Five simulated policy scenarios

Scenario		**1**	**2**	**3**	**4**	**5**
Price increase: 10%		Softs, Snacks	Softs, Snacks, **Alc**, **Br. P., Past. & D., R-Meals**	Alc., Softs, Br. P., Past. & D., Snacks, R-Meals	Alc., Softs, Br. P., Past. & D., Snacks, R-Meals, **Fats, S&C**	Alc., Softs, Br. P., Past. & D., Snacks, R-Meals, Fats, S&C, **Dairies**
Price decrease: 10%		F & V in B	_	**F & V in B**	F & V in B	F & V in B.
Prevalence of obesity	Pre-policy			11.7%		
(simulated)	Post-policy	9.5%	9.3%	7.8%	7.1%	7.6%
% BMI>27	Pre-policy			28.6%		
(simulated)	Post-policy	24.6%	24.5%	21.8%	23.0%	20.7%
Prevalence of overweight	Pre-policy			34.3%		
(simulated)	Post-policy	32.7%	31.4%	30.4%	34.3%	27.3%
Reduction in health care	Min	534	603	960	1131	1004
expenditure (million Euros)	Max	1257	1302	2133	1781	2498

Note: Alc = alcohol; Softs = soft drinks; Br. P. = breaded proteins; Past. & D. = pastries and deserts; Snacks = either sweet and fatty or salty & fatty R-meals = ready-meals; F& V in B = Fruit and Vegetables in brine; Fats = animal fats + oils; S & C = sugar and confectionery; Proc F & V = processed fruit and vegetables; Dairies = yogurt, cheese & milk.

Figure C5. Scenario 3 – pre/post BMI distributions – Sample 2

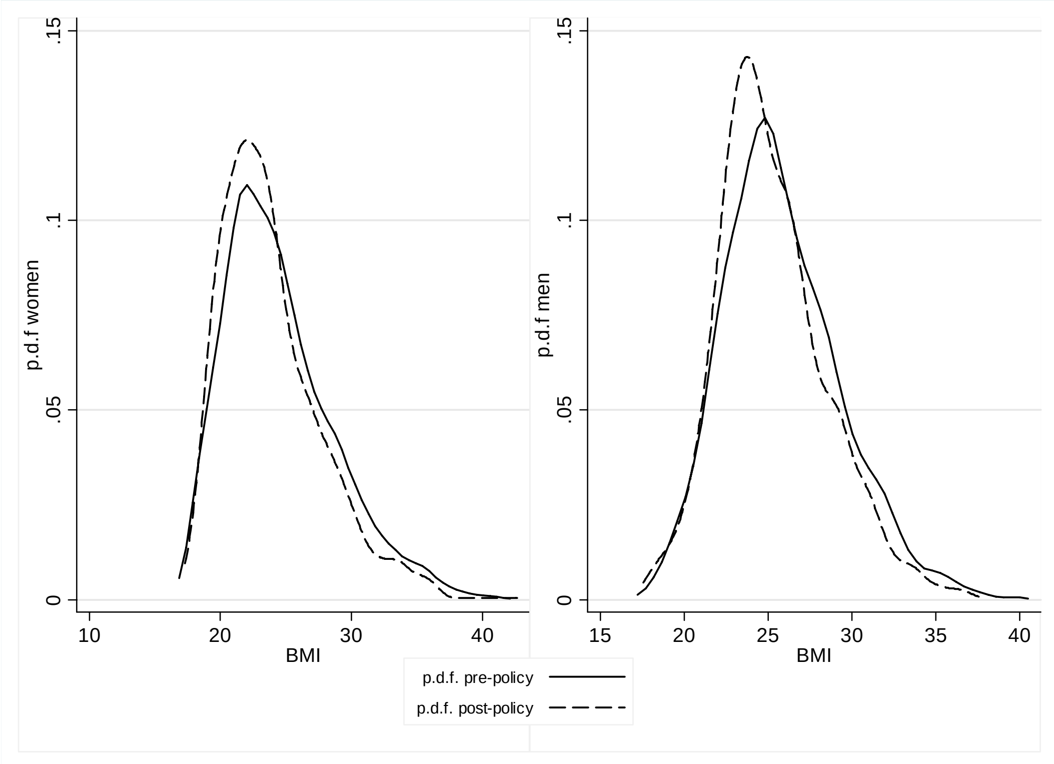

Figure C6. Scenario 3 – Change in BMI vs pre-policy BMI – Sample 2