Food Price interventions and the Distribution of Body Mass Index. Evidence from France.

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Abstract

Are individual differences in body mass index (BMI) related to differences in food prices? French food expenditures data are used to examine the relationship between the prices of 23 food product categories covering food-at-home consumption and the distribution of BMI in a sample of French adults. Using quantile regressions, we find significant negative correlations for the prices of fats, dairies, and sugar and sweets, and positive but less robust correlations for the prices of fruits and vegetables in brine. We simulate the impact of a taxation policy that would increase the price of the former, and decrease the price of the latter. In the estimation sample, a 10% price variation would reduce obesity by 5 percentage points, and overweight by 2 percentage points.

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1 Introduction

Trends in obesity have become a major public health concern in France. In 2002, 37.5% of French adults were overweight as against 29.7% in 1990 (OECD Health Data, 2005). Obesity is associated with a number of co morbidities, such as heart disease, diabete or mobility disability. This represents an increasing financial burden, taking the form of productivity losses, foregone earnings, and health care expenditures that are largely refunded by Social Security. It has been found that the medical cost of obesity was comprised between 0.64-1.33 billion euros in 1992 (Detournay *et al.*, 2000).[1] These externalities would seem to be an obvious arena for public policies. In this perspective, interventions on consumer prices through taxes and subsidies are the focus of the current paper. They may help to achieve two distinct objectives.

First, one may only be interested in internalising the social cost of obesity. In this case, an inelastic food demand is desirable in order to limit the consequences of the tax for producers and consumers. Note also that tax revenues may be used to finance information and food education programs. For instance, Kuchler *et al.* (2004) find that taxing snack foods and especially chips would have little effect on dietary quality, but could generate a non negligible revenue stream to finance public health interventions.

Second, price policies may help to make healthy food products (typically fruits and vegetables) more affordable, and unhealthy products (for instance alcohol or snacks) more expensive, in order to change diet quality. Here, the key question is whether taxes and subsidies have the expected impact on the prevalence of overweight and obesity.

Following Leicester and Windmeijer (2004), we argue that the implementation of a tax or a subsidy on targeted nutrient (for instance calories) gives rise to a number of normative and practical problems. Therefore, taxing or subsidising product categories may be more interesting. For instance, one may imagine a fat tax on dairy products as Chouinard *et al.* (2005), or a uniform tax on snack foods as Kuchler *et al.* (2004), or subsidising the prices of fruits and vegetables. The extent to which the distribution of body weight in the French adult population respond to price interventions targeted on specific product categories is the key concern of the current paper.

More precisely, we ask whether individual differences in Body Mass Index (BMI: weight in kg divided by height squared in meter) are related to variations in the prices of 23 food product categories, in order to identify interesting price

[1] Detournay *et al.* (2000) apply a top-down approach. Levy *et al.* (1995) find a similar result (0.88 billion euros on average) with a bottom-up treatment of the same data.

interventions.[2] Price variations have a direct effect on body weight through short term quality and quantity changes in the consumer basket. We show that changing the price of a product category has a negative impact as long as its own-price elasticity is high enough, and the base tax does not leave aside energy-dense substitutes. Food price changes may also affect weight indirectly, through changes in leisure-related energy expenditures. However this indirect effect is fairly negligible, as most energy expenditures are due to on-the-job exercise and basal metabolism.

To identify the price-BMI relationship, OLS and quantile regression techniques are applied to data from the household survey SECODIP (Société d'Etude de la Consommation, Distribution et Publicité), which provides a number of sociodemographic information at the household level, household scanner data of (daily) food-at-home expenditures throughout the year and, between 2002 and 2005, yearly measures of the BMI of all household members. The current research focuses on adults, and a companion paper on children is planned.

Food purchases (including beverages) are classified into seven functional groups (for instance dairies), which cover 23 product categories (e.g. yaourt, milk, cheese). Further, each category is broken into several food products whose construction takes into account, as far as the information exists, nutritional quality (e.g. low-fat cheese, mid-fat cheese, normal cheese). The prices of product categories are constructed as yearly local Paasche indices. The prices of functional groups are weighted average of product category indices (the weights equal the cluster average budget shares of each category within the group, following the construction of the food CPI by the French National Statistics office; see INSEE, 1998). To avoid simultaneity issues, correlations between prices at $t-1$, and BMIs at t are estimated and interpreted as price effects.

We find expected and significant price effects for a number of categories. The prices of dairies, fats, and sugar and sweets are negatively correlated with percentiles of the BMI distribution above the median. The correlations are positive for fruits and vegetables in brine. The most robust effects are found for fats. Around the 90^{th} percentile of the BMI distribution (obese individuals), a ten percent increase in the price of fats would reduce the weight of a 1.80 meter tall individual who weighs 99 kg by about 2.8 kg. We then simulate the impact of a reform that would increase the price of dairies, fats, and sugar and sweets by 10% and decrease the price of fruits and vegetables by 10%. Using cost-of-illness data from Detournay *et al.* (2000), we find that a lower bound for medical benefits would be comprised between 400 and 800 million euros, while

[2] The BMI is a widespread measure of anthropometric status. It is a very good predictor of weight-related morbidity and mortality.

an upper bound for the consumers welfare loss would be about 1.1 billion euros. The remaining medical cost of obesity would also be close 1.1 billion euro. As such, leaving aside the question of the elasticity of consumer prices to taxes and subsidies, this price policy may internalise the medical cost of overweight and obesity.

Section 2 hereafter proposes a survey of the recent literature on obesity, and eventually focuses on proposals of price interventions. Section 3 discusses the theoretical background and the econometric approach. Section 4 presents the data, and explains in details how price indices are constructed. Section 5 reports the results and simulates the impact of price interventions. Section 6 concludes and discusses the main limitations of the analysis presented here.

2 Taxes and subsidies as an instrument for obesity policies

2.1 The economic determinants of the obesity epidemic

From a physiological point of view, body weight is a variable of adjustment in the equilibrium relationship between caloric intakes and caloric expenditures. Caloric intakes K are produced exclusively by food consumption, while caloric expenditures are the sum of the basal metabolic rate (BMR), and the energy E necessary to process food and for physical activity. Caloric expenditures is often expressed as a multiple of the BMR. At the equilibrium of the energy balance:

$$K = BMR * (1 + E) \tag{1}$$

where E is an appropriate index.

A number of authors in biology have estimated the BMR as a linear or a Cobb-Douglas function of age, gender, height and weight (W in kg):[3]

$$\begin{aligned} BMR &= \alpha + W * \beta && (2) \\ or \quad BMR &= \alpha * W^{\beta} && (3) \end{aligned}$$

where the parameters α and β are estimated from appropriate biological data, and depend on age, gender and height.

The most popular estimation results are proposed by Schofield *et al.* (1985) with a linear specification, and Black *et al.* (1996) with a Cobb-Douglas specification (see Appendix A for a presentation). While Schofield *et al.* base their

[3] Climate may also affect BMR. In particular, it has been found that the BMR of circumpolar populations is higher (see for instance Galloway *et al.*, 2000).

empirical analysis on more than 7000 observations, Black *et al.* (1996) rely only on 574 observations, but they are more precise for predicting the BMR of obese and elderly people (AFSSA, 2001). Last, predictions are generally less precise for women than for men (Ramirez-Zea, 2005).

Using equations (1), and (2) or (3), W can be expressed as:

$$W = \frac{1}{\beta}\left(\frac{K}{1+E} - \alpha\right) \quad (4)$$

$$or \quad W = \left[\frac{1}{\alpha}\left(\frac{K}{1+E}\right)\right]^{1/\beta} \quad (5)$$

The studies cited above find that α and β are positive. Hence, W increases with the ratio $\frac{K}{1+E}$, *i.e.* when caloric intakes increase, or caloric expenditures decrease. Note that weight adjustment to a disequilibrium is fairly rapid (much less than a year). As such, upward *trends* in population average weight largely results from a divergence between *trends* in caloric intakes and *trends* in caloric expenditures. In turn, economic explanations of the obesity epidemic have focused on the role of two factors: the fall in the full price of caloric intakes and the rise in the full price of caloric expenditures.

The full price of caloric intakes has fallen for the past forty years, because the costs of primary food products and food preparation have declined (see *inter alia* Cutler *et al.*, 2003). These technological changes have favoured the growth of food consumption away from home: snacking is easier, and the density of low-price restaurants has increased. A number of papers uncover empirical evidence of the role of the food-away-from-home sector in the U.S. (Chou *et al.*, 2004; Rashad *et al.*, 2006; Rashad, 2006, Auld and Powell, 2006, Powell *et al.*, 2006).[4] We have less data regarding food-away-from-home consumption in France. While there has been an increase in the share of food expenditures devoted to food-away-from-home, it does not mean that the number of meals also increased.[5] Further, time spent on preparing meals and eating at home has not fallen in France (Warde *et al.*, 2006). More generally, the effect of food-away–from-home consumption on the overall diet quality is not easy to identify. On the one hand, the number of fast-food restaurants has dramatically increased, but on the other hand it is possible that the average nutritional

[4] These authors always find negative associations between the BMI distribution in adult or adolescent populations and the prices of fast-food and full-service restaurants. Evidence regarding the impact of the density of fast-food restaurants are mixed, at least for adolescents (see for instance Auld and Powell, 2006; Powell *et al.*, 2006).

[5] According to the National Account System, food-at-home expenditures represented 75.9 % of all food expenditures in 2005 as against 86.4% in 1959. But the aggregate price of food-away-from-home consumption increased two times faster than the price of food-at-home consumption.

quality of meals served in full-menu and company restaurants also increased. Nevertheless, regarding food-at-home consumption, it is certain that the cost of a healthy diet is now much higher than that of a fat- and sugar-rich diet, since time series over long period reveal a decrease in the price of energy-dense food relative to that of fruits and vegetables (Darmon *et al.,* 2002; Drewnowski and Darmon, 2004; Combris *et al.*, 2006). The unit cost of caloric intakes has decreased, which clearly contributes to the rise in obesity.[6]

As emphasised by Philipson and Posner (1999), while most individuals were paid to exercise in agricultural and industrial societies, this is no longer the case in post-industrial societies with public welfare. Hence, the price of caloric expenditures may have risen. While Lakdawalla and Philipson (2002) find evidence of a correlation between the fall in job-related exercise and rising obesity, Cutler *et al.* (2003) and Bleich *et al.* (2007) cast some doubt on this explanation. The former use aggregate data to show that the share of the U.S. population in energy-demanding jobs has been quite stable over the past twenty years. The latter recall that, in the developped world, the majority of the shift away from highly active jobs was observed in the 60s and 70s before the major rise in obesity. They also find in aggregate data that decreased caloric expenditures account for 18% of adult obesity in developed countries.[7] To our knowledge, accurate trend data in caloric expenditures are not available for France. However, it can be shown by using equation (1) that, at a micro-level, even an increase in caloric expenditures produced by 4 hours of sport per week could not offset more than 15% of the weight gain for a 30-years-old male weighting 70 kg whose caloric intakes increase (see Appendix A).[8] Hence, obesity policies have to focus first on trends in caloric intakes.

2.2 Obesity policies

Several policy instruments have been suggested for changing trends in caloric intakes. This subsection considers information provision and food price interventions, and eventually focuses on the latter. Interventions on the supply-side

[6]According to the FAO statistics, the per capita caloric intakes computed 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 an important increase in caloric intakes.

[7]Sturm (2004) examines very precisely U.S. trends in time-allocation. He finds significant declining trends in home production and increasing trends in travel time with a shift from walking or biking to driving. The former has an impact through increasing consumption on food-away, because the nutritional quality of food-away-from-home is lower (Lin *et al.*, 1999).

[8]Nevertheless, at a macro-level, it seems that rising obesity rates are explained by changes in lifestyle that affect *simultaneously* caloric intakes and caloric expenditures: rising female labor market participation (which increases the demand for ready-meals), urbanization process (associated with decreasing physical activity and increasing access to food) etc. (see Loureiro and Nayga, 2005; Bleich *et al.*, 2007).

that take the form of normalization of products' nutritional content or interdiction of vending machines in some places are discussed by Schmidhuber (2001), Finkelstein *et al.* (2004) or Combris *et al.* (2006). The conflict between public health objectives and current food supply policies is examined in details by Lobstein (2002) and Tillotson (2004).

2.2.1 Information policies.

Regarding information policies, advertising restrictions, mandatory labeling, public provision of information, and food and nutrition education programs have been suggested. There is a clear normative rationale for information disclosure: consumers have to be perfectly informed about the health consequences of their consumptions in order to make *ex-ante* utility maximising choices.[9] As generic information about the food-health relationship is a public good, firms have no incentives for disseminating it. This is a typical case for public intervention (Cawley, 2004). There are a number of economic studies on the correlations between generic information and health. For instance, yearly counts of MEDLINE articles on the cholesterol-heart disease connection are significantly correlated with the consumption of cholesterol-contributing food products such as eggs and dairies (see Kan and Yen, 2003; and for France, Nichèle, 2003). However, using these aggregate indices does not inform on the way individuals, especially those at risk for obesity, react to information. At a micro-level, empirical evidence in favour of a causal effect of individual knowledge on food choices is mixed and depends on the measure of knowledge that is used and the food choice that is under consideration (see *inter alia* Blaylock *et al.*, 1999).

Mandatory labeling is generally justified by the lack of benefits for firms to compete freely on the "unhealthy" characteristics of their products. This argument has somehow motivated the Nutrition and Eduction Labeling Act in the U.S. (Mojduszka and Caswell, 2000, Mathios, 2000).[10] Moreover, it is a cheap and relatively effective measure, with a benefit/cost ratio comprised between 10 and 70 US$ (in 1991 dollar, see Variyam and Cawley, 2006). The scientific debate now focuses on the labelling of food-away-from-home consumption.

Restricting advertising in television may be justified by the protection of children, as their preferences are often unstable (especially at young age and

[9] The normative starting point underlying the economic approach to public health problems is as follows. If consumers are perfectly rational (*i.e.* they know their preferences and are time-consistent utility maximisers), if information about health risks is perfect and freely available, if production and consumption do not generate externalities (under the form of medical costs for instance), if all markets are perfectly competitive with entry/exit freedom, then markets should maximise social welfare. If one of these conditions does not hold, then there is a market failure that may justify public intervention.

[10] Nevertheless, Coestier *et al.* (2005) show that, if competition is imperfect (for instance, when the number of firms is limited), then mandatory labeling is not optimal when the expected damage for the consumer is much lower than her immediate pleasure from consuming.

during adolescence), and they influence household's choices. This measure has been proved to be rather effective. For instance, a ban on fast-food restaurant advertisements in the U.S. would reduce the number of overweight children aged between 3 and 18 years by about 11 percent (Chou *et al.*, 2005).

It also appears that information has less impact on the less educated (Ippolito and Mathios, 1990; Putler and Frazao, 1994, Carlson and Gould, 1994, Yen *et al.*, 1996, Variyam *et al.*, 1996, 1998, 1999; Nayga, 2000, Kim et al., 2000, 2001a, 2001b).[11] A first reason is that the more educated have generally a better generic knowledge. Second, the costs of processing specific information (manipulating percentages in Guideline Daily Amounts for instance, or making comparisons between several varieties over a number of attributes), as well as financial constraints that do not able individuals to buy healthier products also explain these results.[12] Providing information is arguably necessary but not sufficient, because not all consumers are able to use it. Regarding more specifically the prevention of obesity, many people know that they have to control their weight at least for medical reasons if not for aesthetic ones. The problem is that loosing weight by applying simple recipes – eating less or healthier and exercising more – is not so simple. Diet quality is a key question, and many individuals do not know how to eat better given their budget constraint. Here, targeted programs of nutritional education may be helpful but are likely to be expensive. They are some evidence of significant but limited impacts (see, for a French example, Basdevant *et al.*, 1999).[13]

The current paper remains agnostic about informations held by consumers, and the potential consequences of this unobserved heterogeneity for the empirical analysis are discussed in Section 3 below. As suggested by Harris (1980), taxing unhealthy products may be a more efficient means of curbing the consumption of unhealthy products than disclosing generic information and setting up expensive education programs. Further, price interventions are also justified by external costs imposed by some consumers on other people in the society,

[11] As noted by Park and Davis (2001), information effects are quite difficult to identify since information is likely to be endogenous, and food demand and information search are affected by the same economic factors. Information or knowledge are often instrumented on weak instruments with *ad hoc* exclusion restrictions. Therefore, evidence about information effects have to be used cautiously.

[12] Using the programing linear technique proposed by Stigler (1945), Darmon *et al.* (2004) and Drewnowski and Darmon (2004) find in French data that, if one has to satisfy first one's caloric needs, the overall diet quality decreases dramatically as the budget constraint becomes more stringent.

[13] Basdevant *et al.* (1999) report results from the "Fleurbay-Laventie" experiment, which proposed food and nutritional education courses to primary school children in two French cities. The comparison of trends in children BMI between Fleurbay and Laventie on the one hand, and similar cities on the other hand, reveals that education program has had a significant effect. Yet, obesity also increased in Fleurbay and Laventie.

the existence of financial constraints that restrict possibilities to make healthy choices, and the presence of adjustment costs.[14]

2.2.2 Price policies

As emphasised in the introduction, the medical cost of obesity was about 1 billion Euros in 1991/1992. Given that the prevalence of obesity among adults has more than doubled since the beginning of the 90s, and that obesity rises rapidly among children, the future medical costs of obesity are likely to be much higher.[15] However, the social cost of obesity is not limited to its medical cost. It should include losses of productivity and foregone earnings, as well as intangible costs for the relatives. But premature deaths also yield some benefits in countries whith high public retirement pensions. Perhaps more important, the agroindustrial and restaurant sectors represent an important share of France's GDP and labour supply.[16] Actually, as pointed out by Strnad (2004), the internalization of medical costs and not social costs is perhaps the strongest case for price interventions. The latter would help to solve the ex-ante moral hazard problem that arise as a consequence of the inability of Social Security to charge individuals fairly: premiums (the social contribution on wage) do not depend on the level of efforts exerted to stay fit, but are broadly proportional to wages, and in France, as well as in most developped countries, sick individuals can not be denied medical treatment. Taxes could be thought of as an adjunct to health insurance systems. Their level would be fixed in such a way that Social Security be actuarially fair.[17]

A first option for internalising medical costs is a tax on "excess body weight" (Philipson, 2001; Schmidhuber, 2004). It has been found that, in the US, there is a wage penalty for individuals in excess weight, especially women (Averett and Korenman, 1996; Cawley, 2004). This labour market discrimination may be accounted for by the existence of employer-sponsored health insurance schemes, which adjust insurance premiums for individual risks (Bhattacharya and Bun-

[14]The presence of adjustment costs is revealed by hypo-caloric slimming diets. During moments of high awareness, dieters generally avoid satisfying their basic caloric needs (as shown by sensations of hunger and satiety). In this case, the body interprets calorie restriction as a threat and protects its fat reserves. Then, during moments of low awareness, it sends signals that induce loss of control. Maintaining awareness has a cost, as well as lack of self-control because it damages self-esteem (Heatherton *et al.*, 1993, Basdevant, 1998, Herman and Polivy, 2003).

[15]If the U.S. are France's future, then these costs should reach 5 to 7% of national health spending, *i.e.* at least 8 billions euros if one considers the 2003's budget. In 2003, public spending represented about 75% of all health expenditures.

[16]At least 960000 direct jobs and 6% of the GDP (73 billion euros) in 2002 according to the National Statistics data. Fast-foods represented about 110000 jobs in 2002.

[17]Of course, it is possible that obesity provides a net positive externality to Social Security since premature deaths and therefore lower health and pension costs at old ages may offset the medical costs at young ages.

dorf, 2005). Interpreting labour market discriminations in France as an implicit tax on “excess body weight” is probably incorrect, as Social Security largely covers health risks. Further, how could Social Security or even private insurers discriminate individuals on the basis of a health condition that could always have been caused by unknown genotypic predispositions? In the end, modifying the relative structure of food prices seems more interesting.

If one is only interesting in the internalisation of medical costs, then the point of the tax is to raise revenue, and a low elasticity of food demand (and therefore of body weight) may be desirable (Chouinard *et al.*, 2005).

Price interventions may also help to achieve other objectives, for instance correcting "internalities" that ensue from failures of rationality, or help consumers to adjust their food habits. In that case, the point of the policy is to constrain behaviours, which is feasible only if the elasticity of food demand is high enough, and taxes and subsidies are transmitted to consumer prices. Here, the parallel with the literature on addiction has to be made cautiously. The demand for cigarette taxation by smokers is interpreted by some authors as a demand for a self-control device (see *inter alia* Gruber and Mullainathan, 2005). However, Strnad (2004) emphasises that using taxes to address internalities is weaker in the case of food. First, there are no clear evidence that food products are as addictive as is tobacco, and that a majority of consumers suffer from time inconsistencies or other "weakness of the will". Second, eating is vital while this is not the case for smoking.

Tax and subsidies at the consumer level have however a number of drawbacks. First, they do not discriminate between those who follow the dietary guidelines and the over-eaters. Second, they are likely to be regressive. Poor consumers may not have healthier alternative choices to cover their basic caloric needs. Rich consumers purchase more fruits and vegetables, and their demand is more elastic.[18] Second, as noted by Schmidhuber (2001), waste may be much more elastic than actual food intakes. Third, the tax base will have to be rather large to avoid unintended substitutions between unhealthy food products. Section (3.1) comes back to this point.

2.3 Feasible price interventions

Tax and subsidies may target specific nutrients and/or specific food products. Producer price interventions targeting food products are commonly used in the framework of the EU Common Agricultural Policy. Regarding their impact on obesity, a key question is whether prices are transmitted along the food chain to consumers (Schmidhuber, 2001). It depends on the commodity, and for those

[18] See Caillavet and Darmont (2005).

products whose farm value share is low (typically soft drinks or ready-meals), one can not expect that price transmission be significant. Price interventions at the consumer level may be more interesting, and can take the form of extra-VAT (Value Added Tax) on unhealthy products and VAT exemptions on healthy food. Differentiated VAT taxes on food products (including food-away-from home items) exist for instance in UK, France, Canada and the U.S., and some of them explicitly target foods that are considered as unhealthy such as snacks, soft drinks, and sweets (Leicester and Windjmeijer, 2004). In France, there is for instance a higher VAT (20.6%) on sweets (but 5.5% on some chocolate products), margarine and vegetable fat (but 5.5% on butter). Obvisouly, current VAT modulations are not motivated by public health.

Leicester and Windmeijer (2004) examine the potential for nutrient-based taxes. They argue that their implementation may give rise to a number of practical problems. Besides technical difficulties for measuring the content of all food products or legal challenges with WTO rules, the main disadvantage of a nutrient-based tax for the consumer is that one would like to tax over-consumption of the targeted nutrient (fat, calorie, sodium etc.) in order not to penalize those individuals who follow the recommended dietary guidelines. A general tax on nutrients is therefore arguably difficult to implement. It seems more practical and cheaper to tax specific food products, such as snacks, ready-meals, dairy products, fats, or carbohydrate drinks, whose contribution to the epidemic of obesity could perhaps be pointed out. One could further target specific products within food groups, on the basis of their nutrient content.

Simulating the effect of price interventions requires that either the price-consumption or the price-BMI relationships be known.[19] Taking the first route, Chouinard *et al.* (2005) examines the potential of a 10% fat tax on dairy products. They find little effects on the quantity consumed, with a 1.4% reduction in average fat consumption only (see similar results by Kuchler *et al.*, 2005, for a tax on salty snack products). The tax would be very regressive, with more welfare losses for the poor and the elderly. They also show that the yearly revenue stream for the government would be lower than the immediate welfare loss for consumers.

Empirical works on the price-BMI relationship usually find larger effects. The long-term price-BMI relationship has been examined in papers by Cutler *et al.* (2003) and Lakdawalla and Philipson (2002). Lakdawalla and Philipson (2002) use regional variations in food taxes to estimate for the US the role of

[19] If one knows the caloric content of every food products and the price elasticities of food consumptions, then the equilibrium equation (5) can be used to simulate the effect of price interventions on the distribution of body weight without knowing the level of physical expenditures.

food supply prices in the rise of obesity. They find that, holding BMI and the socio-demographic composition of the population constant, the supply price decreased by more than 6% between 1981 and 1994. This fall resulted in a 0.72 unit increase in BMI, hence 41% of the growth in BMI over the period considered. These papers focus on the aggregate price of all food items, whereas a nutritional tax would apply to specific nutrients or food items. Moreover, in order to assess the benefits for public finance yielded by price interventions, one has to estimate the global effect of price changes on the BMI distribution (provided that the medical costs of being overweight or obese are known).

In this perspective, the current paper considers price interventions and try to identify interesting targets (*i.e.* tax bases). We abstract from the fact that tax and subsidy interventions may not be fully transmitted to consumer prices. As the data span four years, we only estimate *short term* price effects. The same approach is taken by Powell *et al.* (2006) and Auld and Powell (2006), who use seven waves of the Monitoring The Future survey (1997-2003) to show that there is a significant negative effect of the prices of fruits and vegetables on the BMI of american adolescents. The current paper improves on these researches by analyzing the correlations between BMI and the prices of 23 food groups classified into 7 functional categories. Before presenting the data in Section 4, the next section develops the economic framework.

3 Analytical framework and empirical specification

This section models the price-BMI relationship, and shows that price variations may produce substitution effects with potential unintended consequences on consumer's BMI. As a consequence, the tax base has to be carefully designed in order to include all substitutes. It then presents the econometric specification.

3.1 A model of the price-BMI relationship

The economic setting is a model in which individual utility $U(.)$ is produced by the consumptions c_js of J food products, body weight or BMI W, the intensity of off-the-job physical exercise e, and a numeraire good m.[20] Contrary to Lakdawalla and Philipson (2002) or Auld and Powell (2006), we abstract from dynamic considerations, because weight adapts quickly to disequilibria between

[20] One challenging point for consumption economists is that, in the diet-health problem, the structural derivation and estimation of a demand system, which usually assumes separability, is not straightforward. Indeed, food expenditures and other expenditures are connected through the weight production equation: they are not separable.

caloric intakes and expenditures.[21] The weight "production equation", which relates weight to intakes and expenditures as in equations (4) or (5) is static when the scale of observation is the calendar year. We also assume away that current weight may have an effect on future health outcomes. While this assumption is not innocuous, it is justified if one supposes that the current utility loss of being overweight (in terms of stigmatization, mobility problems etc.) is much more salient than all future losses. Hence, our framework is purely static and similar to the model proposed by Schroeter *et al.* (2005). Note K, the caloric intakes and E the index for energy expenditures (as in equations (4) or (5)), then the consumer's weight control problem is:

$$
\begin{array}{l}
Max_{c_1,c_2,...,c_J,m} U\left(c_1,c_2,...,c_J,e,m;W\right) \\
\left| \begin{array}{l}
W = w(K,E) \\
E = \theta + e \\
K = \sum_{j=1}^{J} a_j c_j \\
\sum_{j=1}^{J} p_j c_j + \pi e + m = I
\end{array} \right.
\end{array}
\tag{6}
$$

where I is income, π is price of physical exercise, θ is an index for on-the-job caloric expenditures, w is the weight production function, a_j is the per-unit caloric contents of food product j and p_j its price. The first-order conditions are:

$$
\begin{aligned}
\forall j,\ \frac{\partial U}{\partial c_j} &= \lambda p_j - a_j \frac{\partial U}{\partial W}\frac{\partial W}{\partial K} \\
\frac{\partial U}{\partial e} &= \lambda \pi - \frac{\partial U}{\partial W}\frac{\partial W}{\partial E} \\
\frac{\partial U}{\partial m} &= \lambda
\end{aligned}
\tag{7}
$$

Whatever the product, the full price of consumption is higher than the market price if body weight is a bad ($\partial U/\partial W < 0$), which is probably true for most obese individuals. Nevertheless the difference between the full price and the market price is attenuated if the consumer underestimates the caloric content of the product (a_j) or the impact of caloric intakes on the equilibrium weight ($\partial W/\partial K$).

[21] Lakdawalla and Philipson (2002) present a dynamic model, which is relevant for analysing consumer behaviour over a sequence of very short time periods (days or weeks). They eventually focus on a longer time period, for instance one year, and consider that the agent is at the equilibrium of the dynamic model. This assumption is tenable if there is a unique optimal consumption policy which converges to steady-state equilibrium. This is true only if the concavity of the utility function is higher than the concavity of the weight investment function i.e. the marginal utility of food consumption decreases faster than its marginal effect on weight. As a consequence, the case of individuals with specific preferences, such as the bulimics, can not be treated in this framework. A proof of this result is available upon request.

Consider now a change in the price p_1 of c_1, its effect on weight is given by differentiating the weight production equation:

$$\begin{aligned} \frac{dW}{dp_1} &= \frac{\partial W}{\partial K}\left[\sum_{j=1}^{P} a_j \frac{dc_j}{dp_1}\right] + \frac{\partial W}{\partial E}\frac{de}{dp_1} \\ \iff & \quad \varepsilon_{Wp_1} = \varepsilon_{WK}\left[\sum_{j=1}^{P} \frac{a_j c_j}{K}\varepsilon_{c_j p_1}\right] + \varepsilon_{WE}\varepsilon_{ep_1} \end{aligned} \tag{8}$$

where the εs are elasticities. The sign of the elasticity of weight to price, ε_{Wp_1}, can not be predicted without further assumptions, since it depends on the (marshallian) elasticities of substitution betwen food items, $\varepsilon_{c_j p_1}$, between food and exercise ε_{ep_1}, and on the relative share of each food item in total caloric intakes $\frac{a_j c_j}{K}$ (which captures somehow quality effects).

To illustrate this point, following Schroeter *et al.* (2005), we suppose that physical exercise is inelastic to changes in food price *i.e.* $\varepsilon_{ep_1} = 0$.[22] Then, all what matters is the sign of $\sum_{j=1}^{P} \frac{a_j c_j}{K}\varepsilon_{c_j p_1}$ (since weight is always an increasing function of intakes: $\varepsilon_{WK} > 0$).

Assume for instance that there are only two food products, with food product 1 being densier in energy than food product 2 *i.e.* $a_1 > a_2$. In general, the share of energy intakes coming from high-calorie foods is higher: $\frac{a_1 c_1}{K} >> \frac{a_2 c_2}{K}$.[23] If the goods are price complements, then $\varepsilon_{c_2 p_1} < 0$ and the effect of a price increase is unambiguously negative as $\frac{a_1 c_1}{K}\varepsilon_{c_1 p_1} + \frac{a_2 c_2}{K}\varepsilon_{c_2 p_1} < 0$. If the goods are weak substitutes ($\varepsilon_{c_2 p_1} > 0$ but small), then the effect is still negative because food product 2 does not contribute enough to total caloric intakes. In this example, substituabilities have to be very strong for the price effect to be positive.

Consider now that c_1 represents the consumption of snacks and ready-meals, and c_2 aggregates other food-at-home consumption. Then, we may arguably have for many consumers $\frac{a_1 c_1}{K} < \frac{a_2 c_2}{K}$ and a price substituability between these food groups. Taxing ready-meals may then have a positive effect on BMI. This is more likely to be the case when the own-price elasticity of ready-meals is low since then, condition $\frac{\frac{a_1 c_1}{K}}{\frac{a_2 c_2}{K}}\varepsilon_{c_1 p_1} > -\varepsilon_{c_2 p_1}$ probably holds.

In the end, taxing energy dense food products may be efficient only if it leaves no energy dense substitutes untaxed - the tax base has to be large -, and if the own-price elasticity of these products is high enough. Hence, there is no theoretical reason for believing that food prices and weight are negatively

[22] This assumption is rather credible as: (i) it is always possible to practice low-cost exercise (running, walking or even swimming as French swimming pools are highly subsidised); (ii) as shown in Appendix A, physical exercise is unlikely to have large effects on weight.

[23] As a consequence of the nutritional transition, the share of lipids in total caloric intakes is over 35% in developed countries, and the share of carbohydrates is about 50% (Combris *et al.*, 2006)..

related.[24] It is ultimately an empirical question, and we now turn our attention to the empirical specification.

3.2 Econometric modelling

The main objective of the paper is to estimate the elasticity of weight to food prices in order to evaluate the relevancy of price interventions. BMI rather than body weight will be the dependent variable, since it is a more relevant indicator of the effectiveness of price policies in the reduction of obesity-related diseases. We now derive an empirical specification from the model presented above.

Using the first-order conditions in (7), one may express the optimal levels of consumption as functions of prices, income, and the (fixed) parameters a_j and θ:

$$\begin{aligned} \forall j,\ c_j^* &= f_j(p_1, p_2, ..., \pi, I; a_1, ..., a_J, \theta) \\ e^* &= g(p_1, p_2, ..., \pi, I; a_1, ..., a_J, \theta) \end{aligned} \tag{9}$$

where the form of functions f_j and g depends on the preferences of the consumer (as captured by U).

Then, using the weight production equation, we have:

$$\begin{aligned} W &= w(K, E) \\ &= w\left(\sum_{j=1}^{J} a_j c_j^*, e^*\right) \end{aligned}$$

Replacing optimal levels of consumptions by their expression in (9) yields a reduced form specification that relates W to prices and income:

$$W = h(p_1, p_2, ..., \pi, I; a_1, ..., a_J, \theta)$$

This paper will estimate a first-order log-log linear approximation of $h(.)$:

$$\ln(W) = \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln(p_j) + \beta \ln(\pi) + \gamma \ln(I) + \delta\theta \tag{10}$$

where the α_js are the elasticities of interest (*i.e.* $\alpha_j = \varepsilon_{Wpj}$) in equation (8).

[24] Lakdawalla and Philipson's model predicts that the price elasticity of the steady-state food consumption is negative. When weight is produced only by food consumption then the price elasticity of the steady-state weight is also negative. This prediction relies heavily on the assumption that food is a homogeneous good. Relaxing this assumption modify substantially the theoretical prediction, as it has been shown here.

We do not observe the price π of physical exercise in our data, and it will therefore be omitted. This is unlikely to impact the results, since a recent general population survey on health behaviours of French shows that 69.1% of the population do not exercise at least once a week ("Enquête sur les Conditions de Vie des Ménages 2001"). Only 5.8% exercise explicitly for slimming down. The primary reason for not exercising is taste (36.9% of those who never exercise), lack of time (31.9%), impairing health condition (21.7%), and "other reasons" (9.4%). Hence, the market price of exercise plays a minor role here. This is all the more true that it is possible to exercise (walking or running moderately) without important financial investments [25].

Up to this point, we have assumed away that nutritional information is heterogeneous among consumers. Information is *a priori* uncorrelated with prices. However, if consumers do not know accurately the per-unit caloric values a_j or the marginal effect of intakes on body weight ($\partial W/\partial K$), then there may be some individual-specific slope and intercept heterogeneity in equation (10). One means for attenuating the resulting omission biases is to include dummies for education levels, as education and nutritional knowledge are closely related (see section 2.2). Nevertheless, the treatment of slope heterogeneity calls for the use of appropriate econometric tools. Here, there are two possibilities: latent class models and quantile regressions. Latent class models assume that the parameters (the αs, β, γ and possibly δ) are randomly and discretely distributed over a finite number of mass points. Their distributions can be parameterized as multinomial probability functions of variables that affect the information set, such as education (see for instance Clark *et al.*, 2005; Etilé, 2006).

This paper will rather use a quantile regression approach, which here presents two advantages over latent class models. First, following an argument by Kan and Tsai (2004), only the weight of individuals in the right tail of the distribution is actually a public health problem. Hence, we would rather like to know the effect of prices on the behaviour of those individuals who are in the highest percentiles. Second, the parameters of the equilibrium relationship between caloric intakes and expenditures may vary with weight (AFFSSA, 2001). This is an additional and perhaps predominant source of slope heterogeneity in equation (10). Using quantile regressions has however an important drawback. One has to assume that slope heterogeneity is function of the position the individual has in the distribution of the dependent variable only. In the context of the cur-

[25] Note however that food price interventions may alter the demand for physical exercise in a more general model that would include time constraints. For instance, raising the price of ready-meals renders cooking more attractive, but preparing meals implies less leisure time available for exercising.

rent paper, it implies that individual beliefs about the a_js and $\partial W/\partial K$ should be highly correlated with body weight. Although obese individuals are probably more informed than overweight individuals - they generally have medical follow-ups -, the amount of information held by non-obese individuals may be independent from their BMI.

Let X be the vector of socio-demographic variables that control for intercept heterogeneity in tastes, information, on-the-job physical expenditure (θ), and ϵ be a random i.i.d. error term with mean zero, we will estimate the following equation:

$$\ln(W) = \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln(p_j) + \beta \ln(\pi) + \gamma \ln(I) + \overline{\delta} X + \epsilon \tag{11}$$

Before estimating the model at various quantiles of the distribution of the logarithm of the BMI, we also apply simple OLS techniques to estimate the elasticities of the conditional mean BMI. Standard errors are computed by a bootstrap procedure for the conditional quantile regressions. Standard errors are adjusted for clustering at the household level in conditional mean regressions, but not in quantile regressions, as dependence between observations make the bootstrap method invalid (Buschinsky, 1998). However, there are a few number of observations per household (between 1 and 8), so that the downward bias in the estimates of the standard errors should not be too important.

4 Data

Our main interest in this paper is to explain the individual BMI as a function of the prices of a number of food groups, income, and a set of socio-demographic variables. In this effort, we use five years of household food-at-home expenditures and quantities that are drawn from the SECODIP (Société d'Etude de la Consommation, Distribution et Publicité) French household panel (2001-2005). Since we do not know the moment in the year when the BMI data are collected, we suppose that the right-hand side variables averaged over year t determine the BMI reported in year $t + 1$. Descriptive statistics for the full sample and the estimation sample are provided in Appendix B, table B4. The full sample (N=34736 individual-year) includes all individuals for which sociodemographic information was available in year t (2001, 2002, 2003, and/or 2004), and BMI was available in year $t + 1$ (2002, 2003, 2004 and/or 2005). The estimation sample (N=23304 individual-year) was obtained from the full sample by dropping observations with missing values, and keeping observations for which it was possible to impute food prices (see herebelow for the construction of these prices).

4.1 Body Mass Index

From 2002 to 2005, the BMI of all household members were self-reported. We are not able to correct for declaration biases, as data with both self-reported and measured weights are not yet available for France.[26] Figures B1 and B2 in Appendix B plots the distribution of the BMI and its logarithm for the estimation sample. Neither the former nor the latter are Gaussian according to standard statistical tests (see Table B1 in Appendix B). This is another rationale for applying quantile regressions (Koenker and Bassett, 1978).

Table B2 in Appendix B presents some correspondence between the weight and the BMI for selected heights. For instance an individual of 1.90 m height is overweight (BMI>25) if he weighs more than 90.2 kg, and obese if he weighs more than 108.3 kg (BMI>30), according to the standard international definition of these health statuses. Figure B1 shows that the BMI reported by adults in the estimation sample yields higher estimates of the prevalence of obesity than those provided by the OECD Health Data (2005). According to the latter, there were 9.4% of obese adults in France in 2002. In the estimation sample, the corresponding figure is 11.6%. 45.2.% of the estimation sample is overweight as against 37.5% in the OECD data.

4.2 Food purchases and their classification

Price indices are constructed from household daily purchase data averaged over the year (about 550,000 purchases per year). There are more than 8000 households. Each household is dropped from the panel after four years of activity. For each household, SECODIP records all purchases that have a barcode (Universal Product Code). For these products, additional information are provided about the characteristics that are advertised by producers. For instance, it is generally observed whether a yaourt is light, or what is the fat content of a cheese. But we do not know the caloric content of a bottle of red wine. For expenditures on products without barcode (e.g. fresh meat bought at the butcher), the panel was split up by SECODIP into two sub-panels. One sub-panel is dedicated to beverages, (fresh) meat and fish. Purchases of fresh fruits and fresh vegetables are recorded in the second sub-panel only.

To construct price indices at intermediate levels of aggregation, one has first to define an aggregation procedure, i.e. a nomenclature of all food products.

[26] See Cawley (2004) for a correction procedure in U.S. data.

To this aim, food purchases were shared out into seven functional groups, each group being made up of several product categories. These functional groups are: beverages (mineral water, alcohol, other drinks); fruits, vegetables and cereals (fresh fruits, processed fruits, fresh vegetables, processed vegetables, cereals); protein sources (raw/fresh meat and eggs, raw/fresh sea products, processed sea products, cooked meats, breaded/fried fish or meat), dairies (yaourt, cheese, milk), fats (animal fats and margarine, oil), sugar and sweets, snacks and ready-meals (pastries and deserts, sweet and fatty snacks, salty and fatty snacks, ready-meals).

Our objective for this grouping is twofold. First, food products in a functional group have to be somehow substitutes in the composition of a meal. This is arguably questionable since, for instance, nutritionists would consider that cereals and vegetables are not substitutes. Further, we choose to create a single category for all snacks (including pastries and deserts) and ready-meals (including take-aways), in an attempt to measure the price of a one-course meal that would not require preparation time. This may also be a means of accounting for food-away-from-home alternatives (fast-foods but not full-menu restaurants). Nevertheless, deserts may also be consumed at the end of a standard three-courses meal, and pastries during a breakfast. Second, any taxation policy will have to target specific food groups but will aso require the support of the opinion. Hence, we have to stick to the collective representations of what is an healthy or unhealthy category of food products. This concern has led us to make a distinction between breaded meat and raw meat for instance, but also to isolate dairies, and to make a single functional group for all snacks and ready-meals.

At a fully disaggregated level, each class is made up of between 1 and 77 food products. Adding all up, there are more than 350 food products. Appendix B, Table B3, gives more details on the construction of food categories with some examples. The classification of food products takes into account, as far as possible, the nutritional information that is, in some case, provided with the data. Once again, our concern is to obtain a classification that may fit collective representations. For instance, we are able to make a clear distinction between low-fat mid-fat and full-fat dairies. 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, we distinguish mid-fat cottage cheese (fat content between 15 and 29%) and full-fat cottage cheese (fat content higher than 30%). Last, some food products are not classified in their "natural" functional group, when their nutrional quality may have been profundly altered by the production process. As an 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. Since these classifications are the result of our own arbitration, we invite the reader to suggest us potential changes [27]

4.3 Food prices

By dividing for each household yearly expenditures by yearly purchase quantities for a given food product or product category, we can construct household specific unit values. Unfortunately, unit values are not supply prices, as they reflect also households' tastes for quality. We may well imagine that households with higher BMIs on average are more likely to buy energy-dense products, which have generally lower unit values within a given product category. Hence, we can not identify the price-BMI relationship by relying on variations in unit values, as the latter may be largely endogenous.

Several methods have been proposed to construct prices from unit values. Whatever the method, the law of one price is supposed to hold at the level of clusters that are defined by crossing calendar time and localization criteria. In the present paper, clusters are defined as follows: two households belong to the same cluster if their purchases are observed over the same calendar year, and if they live in the same or adjacent "departement" (roughly the size of an US county), and the same or a close type of residential area. There are 94 departements in Metropolitan France (Corse is excluded from the SECODIP 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 Great Paris)" and "Great Paris". These residential area are ordered according to their size so that it is easy to define closeness. For instance, for each year, 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 a urban unit of between 5000 and 9999 residents or in a rural area. They belong to the same cluster. We will therefore rely on geographic and time price variations in prices to identify price-BMI relationships.

Methods to construct cluster-specific prices generally boil down to one or another of the following approaches: computing cluster-averages of unit values ; regressing unit values on observable household characteristics and assuming that the residuals are cleaned out from taste (quality) effects ; or constructing cluster-specific price indices. A key problem in the existing empirical literature is that there is no consensus about the approach that should be preferred.

Lecocq and Robin (2006) and Chouinard *et al.* (2005) use respectively cluster

[27] Of course, as there are few experiments of nutritional taxes in the world (usually targeting soft-drinks or snacks), one limitation of the current paper is that we have to speculate on the categories of food products that could be the target of the administration.

average and cluster weighted average unit values. Index by k and l_k respectively a product category (for instance milk) and a purchase of a good in category k. The associated unit value $\nu_{l_k c}$ where c is an index for the cluster in which the purchase was made. The unit value is deflated by an appropriate CPI. Let L_{kc} be the total number of purchases in cluster c for category k. Then the price P_{kc} of product category k in cluster c is estimated as $\hat{P}_{kc} = (1/L_{kc}) \sum_{l_k=1}^{L_{kc}} \nu_{l_k c}$ in Lecocq and Robin (2005), and $\hat{P}_{kc} = \sum_{l_k=1}^{L_{kc}} \frac{\overline{q}_{l_k}^c}{\sum_{l_k=1}^{L_{kt}} \overline{q}_{l_k}^c} \nu_{l_k c}$ in Chouinard *et al.* (2005), where $\overline{q}_{l_k}^c$ is the average quantity of good l_k purchased in cluster c. To understand the intuition underlying this procedure, remember that Deaton (1989) proposed to specify the unit value of good k for a purchase l_k in cluster c as $\nu_{l_k c} = P_{kc}\nu(\rho_{l_k c})$ where $\nu(\rho_{l_k c})$ is a price index.for the quality $\rho_{l_k c}$ of the purchase [28] Then, the estimate $\hat{P}_{kc} = (1/L_{kc}) \sum_{l_k=1}^{L_{kc}} \nu_{l_k c}$ converges towards the true price P_{kc} if and only if $(1/L_{kc}) \sum_{l_k=1}^{L_{kc}} \nu(\rho_{l_k c})$ tends towards 1 when the number of purchases increase in the cluster. This assumption holds only if there are no systematic variations of quality between clusters. Suppose for instance that $\nu(\rho_{l_k c})$ is distributed log-normal with parameters μ_{kc} and σ_{kc} (i.e. $\ln\left(\nu(\rho_{l_k c})\right) \sim N\left(\mu_{kc}, \sigma_{kc}\right)$), then $(1/L_{kc}) \sum_{l_k=1}^{L_{kc}} \nu(\rho_{l_k c}) \uparrow \exp(\mu_{kc} + 0.5\sigma_{kc})$. Hence, the mean quality index do not vary across clusters if and only if the location parameter (the median quality index) and the dispersion of qualities are uniform in time and space. This is a rather strong assumption.

Following Cox and Wohlgenant (1986), Kuchler *et al.* (2005) opt for a regression approach, which is actually a variant of the cluster-average approach. Let ν_{kh}^t be the average unit value of household h's food purchases in category k throughout a calendar year t. $\overline{\nu}_k^c$ is the average unit value of purchases in cluster c (the index t is dropped as each cluster corresponds to one calendar year). Let X_{ht} be the vector of observable household characteristics for year t. Then, one can estimate the following equation:

$$\nu_{kh}^t - \sum_{c=1}^{C} \overline{\nu}_k^c 1\{h \in c\} = \alpha_k X_{ht} + \epsilon_{kh}^t \tag{12}$$

where $1\{h \in c\}$ is an indicator that takes value 1 if household h is in cluster c, α_k is the vector of coefficients to be estimated, $\nu_{kh}^t - \sum_{c=1}^{C} \overline{\nu}_{kh}^c 1\{h \in c\}$ is household h's deviation from the cluster-average unit value, and ϵ_{kh}^t is a residual. Then, the price of product category k in cluster c for household h is defined as $P_{kc}^h = \sum_{c=1}^{C} \overline{\nu}_k^c 1\{h \in c\} + \hat{\epsilon}_{kh}^t$. By adding the residuals $\hat{\epsilon}_{kh}^t$ estimated from equation (12) to the cluster average unit value, one obtains more variability in prices than by simply averaging unit values. However, this comes at the cost

[28] This specification of unit values has been widely used in theoretical applications since then.

of assuming that the residual heterogeneity stems only from unobserved supply factors. This strong assumption would not hold in the present study, as common unobserved factors may simultaneously determine quality of food purchase and BMI.[29]

We will therefore apply a third approach, which almost follows the methodology used by the French National Statistics to construct consumer price indices (INSEE, 1998). Section 4.2. has proposed a classification of food products with two levels of aggregation, and food expenditures were brought down into seven functional groups, made up of 23 product categories. In a first step, Paasche indices are computed at the level of categories. In a second step, the weighted average of these indices with weights equal to cluster average expenditure shares are computed to obtain price measures at the level of functional groups.

Household heterogeneity in the supply price of the latter is captured by Paasche indices. Let j, k, l index respectively functional groups, product classes and food products. The data set provides quantities q^h_{lkj}, and unit values ν^h_{lkj} associated to yearly expenditures of household h on food product l. Then, a Paasche price index for category k, and household h is defined as:

$$P^h_{jk} = \frac{\sum_{l=1}^{L_k} q_{lkj}\nu^h_{lkj}}{\sum_{l=1}^{L_k} q_{kkj}\nu^0_l}$$

where L_k is the number of food products in k and ν^0_l is a reference price for food product l. Here, the reference prices are average unit values of purchases that were made in 2004 in Paris and its bordering departements. A price is obtained by taking the mean or the median in the cluster:

$$P^c_{jk} = \overline{P^h_{jk}}^c \ or\ median\left(P^h_{jk}|h \in c\right)$$

In the current paper, following the advice of Deaton and Zaidi (2002), we employ medians rather than means, to avoid problems with outlying prices.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. This is the main reason for which the number of observations drops sharply between the starting sample and the estimation sample (more than 10000 observations are lost). We find that some results are sensitive to the minimum threshold for the number of households a cluster has to contain (see Section 5.2.).

[29] Obesity and overweight are generally associated with the consumption of energy-dense food products. Many of these products are conceived so as to be particularly palatable. Suppose that eating a large amount of these products alters the capacity of discriminating flavours. Then, this unobserved food habit may be positively correlated with body weight, and negatively correlated with the gustatory quality of purchases (and therefore their unit values).

The use of price indices, instead of average unit values, is a natural consequence of aggregation, which is allowed only under the assumption of constant within-category relative prices (CWRP): this is the Hicks composite commodity theorem (see Deaton and Mullbauer, 1980, p 121). Let $\overrightarrow{\nu}_{kj}^{h}$ be the vector of unit values, then under CWRP, we have $\overrightarrow{\nu}_{kj}^{h} = P_{jk}^{h}\overrightarrow{\nu}_{l}^{0}$. P_{jk}^{h} is the multiplicative factor that must applied to the reference prices $\overrightarrow{\nu}_{l}^{0}$ to obtain the prices $\overrightarrow{\nu}_{kj}^{h}$ that are actually faced by households. Under the CWRP assumption, it reflects the spatial and time heterogeneity in supply prices. Note that the variability of the latter may be low (especially for transformed food products), but prices can take a large number of values given the number of clusters. We prefer Paasche over Laspeyres indices, because computation of the latter requires that a reference basket of food products be chosen for each household, which is more arbitrary than defining reference prices. Further, the Paasche price index is also a good money metric measure of welfare, as it compares the cost of reaching the utility level provided by the actual diet to the costs that would have been paid at reference prices (Deaton and Zaidi, 2002).[30]

Let k_j index a food category in the functional group j, and K_j be the number of categories in j. $w_{k_j}^{c}$ is the cluster average of expenditures on k_j. The second step involves the computation of the following weighted average:

$$P_j^c = \sum_{k^j=1}^{K_j} \frac{w_{k_j}^c}{\sum_{k_j} w_{k_j}^c} P_{jk}^c$$

where P_j^c is the price of the functional group.

Figures B3 to B8 in Appendix B represent by box plots the distributions of prices in the estimation sample. The line in the middle of the box is the median, while the upper and lower hinges are respectively the 75^{th} and 25^{th} percentiles. The upper and lower adjacent lines represent the upper and lower adjacent values, while the dots are outside values.[31] One can observe that there are generally few outside values, that variations are not very important around the median price probably as the consequence of an uniformisation of food supply through the development of supermarket chains. Nevertheless, given the size of the estimation sample, these variations should be sufficient to identify price effects.

[30] Actually, Paasche indices are preferred when there are more spatial than time variations, and arise naturally in theoretical studies when one wants to model the joint choice of budget shares and unit values (*i.e.* qualities and quantities, see Crawford *et al.*, 2003 or Crawford, 2003). They generally overstate substitutions between goods, and understate differences in cost-of-living (Boskin *et al.*, 1998).

[31] The upper and lower adjacent values are defined as $Q(75) + 1.5 * (Q(75) - Q(25))$ and $Q(25) - 1.5 * (Q(75) - Q(25))$.

Our methodological choices call at least for five comments. First, expenditures on food away-from-home are not recorded by SECODIP. Hence, we will have to assume that the heterogeneity in the price of ready-meals represents well the price variations in food away-from-home.[32] Second, the CWRP assumption may be realistic as the supply market is rather centralized at the wholesale level.[33] Third, some indices can be computed only in one of the sub-panels. These prices are then imputed to households in the other sub-panel, by matching on variables that identify cluster. Fourth, we suppose that the prices faced by an individual are the prices faced by the household s/he belongs to. Fifth, we have to assume that at the most disaggregated level, goods are homogeneous in quality. Hence, a key point of this analysis is the definition of food products and, as emphasised in Section 4.2., we make use of all available information to define products that are as homogeneous as possible.

4.4 Other variables

Implicit costs of purchase include *inter alia* times to travel to usual places of purchase, which may vary according to the density of supply. We construct an indicator for the selling area (in square meters) per 100 inhabitants allotted to large-scale distribution stores in the (geographic) cluster in 2001 (SURFSALE).[34] We also control for the self-production of fruits and vegetables (FRUITS, VEGETABLES). A dummy (MEALPLANNER) indicates if the individual is responsible for household food expenditures, as the meal planner may be more able to control her/his weight.

Household income is measured by an 18-intervals indicator. We use the centre of each interval to construct a continuous proxie for income (the highest category, over 45000 Euros a year, being dropped), which is equivalenced (using an Oxford scale). Income and all unit values are deflated by the yearly Consumer Price Index provided by the National Statistics (INSEE) for households, according to their position in the income distribution (reference: 2004 Euros).

A number of socio-demographic effects are accounted for in the regressions. We control for gender, household structure, and education (six levels of qualification) since education renders health production through food choices more efficient (Grossman, 2001). In France, there is a strong association between education and the type of job one can apply to. Hence, education arguably controls for differences in on-the-job exercise. We include a polynomial trend in age, as

[32] However, we may imagine that unit values of food away-from-home expenditures are much more dispersed than those of ready-meals.

[33] For instance, 50% of fresh products are sold on the wholesale market of Rungis. (REFERENCE?) There may however be some particularities in rural areas of production. Our definition of clusters helps us to smooth these rural-urban differences.

[34] This indicator was constructed using the "Panorama Points de Vente"$^{(copyright)}$ data base of hyper and super markets.

well as a dummy which indicates recent pregnancy (BABYWOMEN), to capture specific weight variations produced by pregnancy. Last, regional and time variations in tastes are controlled by a set of dummies for the geographic region, the type of residential area, and the calendar year.[35] Descriptive statistics are presented in Table B4 in Appendix B.

5 Results

5.1 Baseline specification

Table C1 in Appendic C reports results from OLS and quantile regressions, wherein prices are measured at the most aggregated level (seven functional groups). The Table has six columns of estimates. Column 1 reports OLS results, and columns 2 to 6 quantile regressions results for the 50^{th}, 60^{th}, 70^{th}, 80^{th} and 90^{th} percentiles. The coefficients of price variables can be interpreted as elasticities.

There are two striking results. First, the negative correlation between BMI and the price of fats (animal and vegetal fats). Second, the positive correlation between BMI and the price of fruits, vegetables and cereals. These effects are found to be significant on conditional mean BMI, as well as on almost all percentiles. Table C4 translates the price effect of fats in weight changes for a 1.80 meter tall individual. A 10% increase in the price of fats would reduce weight by 2.8 kg, if initial weight was about 99kg (at the 90th percentile), and by -0.76 kg (not significant) if initial weight was 79.8 kg (at the median).

We find other interesting price effects, but they are generally less significant. Around the median of the BMI distribution (Column 2), there are negative price-BMI correlations for beverages and dairies. These results are not unexpected, as alcohol, syrups, juices and sodas are generally rich in sugar.[36] Dairies are rich in fat (especially saturated fat), and therefore contribute to cholesterol, which explains that they have been targeted by public health policies in the past. The link between dairy consumption and obesity has been recently challenged, as some studies suggest that calcium intakes from dairies attenuate obesity (Zemel and Miller, 2004). This might explain why the effect for dairies is not significant around the 90^{th} percentile.

There is also a negative price-BMI correlation for sugar and sweets at higher percentiles of the BMI distribution. Note that this correlation is close to zero around the median. Last, we find a positive association between the highest

[35] Hence, price effects are identified by the deviations from these cluster specific taste effect, as is usually done in estimations of food demand systems.

[36] In 2004, commercial information about the sugar content is available for 75% of the purchases. In this subsample, only 12.6% of quantities were advertised as light in sugar.

percentiles of the BMI distribution and the price of proteins. The protein-diet is often used by nutritionist in weight loss programs, as it is supposed to maintain muscles while enabling significant weight-loss and rapid decrease of fat-tissues without experiencing hunger or fatigue (they have a strong satietigenic power). This finding is therefore not surprising.

How may we explain that price elasticities sometimes vary along the BMI distribution? Suppose that the price elasticity of *consumption* do not vary with BMI. Then, increasing price elasticities of BMI along the BMI distribution is the consequence of higher consumption levels in the right of the distribution: the BMI of overweight/obese individuals is more elastic to price changes because they eat more. Under this assumption (constant elasticity of food demand) and according to the estimates in Table C1, it would mean that overweight/obese individuals consume more fats, sugar and sweets, but also more vegetables and proteins, and last but not least less sodas, juices and alcohol. Their consumption levels of snacks, ready-meals and dairies should be fairly similar to those of non overweight/obese individuals. Although, the data contains no information about individual consumptions, it is possible to compute quantities purchased per unit of consumption (UC), in order to make comparisons between households with at least one obese adult, and households without overweight or obese individuals. In 2004, in our estimation sample, quantities purchased per UC were on average between 10% and 30% higher in "obese households" for beverages (excluding mineral water : +30%), fruits, vegetables and cereals (+11%), proteins (+30%) and fats (+13%).[37] These quantities were almost similar for dairies, sugar and sweets, snacks and ready meals (between 0 and +2%). As a consequence, the interpretation in terms of difference in consumption levels between individuals at different percentiles of the BMI distribution does not hold for beverages and sugar and sweets. Overweight people's consumption of fizzy drinks or alcohol may be less elastic, and their consumption of sugar and sweets may be more elastic. Clearly, more studies are required regarding these two functional groups.

Table C2 in Appendix C presents estimates at the level of product categories, in the hope to identify more precisely the product category that may be responsible for Table C1's results. Table C2 should be read as Table C1. Regarding beverages, it appears that Table C1's results for the median were

[37] These figures should be understood as follows: the average quantity per UC of fruits, vegetables and cereals purchased by households with a least one obese adult is 11% higher than the average quantity per UC purchased by households without overweight adults (195.4 kg on average as against 175.3 kg). We systematically checked that these differences in average quantities were similar to differences in median quantities and the 90th percentiles of quantities. Regarding beverages, the differences are essentially due to alcohol consumption in the subsample of households without children.

driven by alcohol, and not "other drinks". The elasticity to the price of "other drinks" is negative but not significant. Results for fruits, vegetables and cereals were due to fruits and vegetables in brine, as correlations are not significant for the price of cereals. At the higher percentiles, elasticities to the price of fruits in brine and vegetables in brine are quite similar. Although both are insignificant, their sum may be significant, and may explain the estimate in Table C1. Table C4 simulates the effect of a 10% price decrease in the prices of fruits or vegetables in brine. The total weight loss for a 1.80 meter tall individual is comprised between 0.4 kg (around the median) to 1.45 kg (around the 90^{th} percentile).

It is interesting to note that negative price effects are associated to breaded/fried fishes or meats, while positive effects are found at the higher percentiles for meats in brine and eggs. This result illustrates the role of processed food vs. food made at home from distinct and raw components. In the same perspective, there is a negative and significant effect around the median for the price of processed vegetables. This product category includes soups and other canned or frozen vegetables, which are often cooked with fats and sometimes sweetenening additives. It was unpossible to adjust for this heterogeneity in quality in the construction of the price index (as it has been done for processed fruits). Regarding dairies, the responsability falls on milk, as cheese attracts rather unstable and never significant coefficients. Last, oils rather than animal fats (or margarine) explain the magnitude of the elasticity for fats in Table C1, while there are not large differences between Table C1's and Table C2's results for sugar and sweets.

Table C3 reports selected estimation results of a specification that includes price interactions between close substitutes (*i.e.* between products in a same functional group). The more interesting result is obtained for the group of fats.[38] The price elasticity of BMI to the price of oils (resp. animal fats) is higher when the price of animal fats (resp. oils) is higher, at every percentiles of the BMI distribution. Hence, the less affordable are animal fats (oils), the more important is the weight loss when the price of oils (resp. animal fats) increases. This result illustrates the interest of adopting a large taxation base.

Results for other variables are provided in Table C1. They are not reported in Tables C2 and C3 but correlations remain the same. Self-producing fruits or vegetables has a negative effect (although often not significant) on BMI, which is consistent with our findings about the price effects of these product categories. Note also that the development of large-scale distribution, which is measured by the density of hyper- and super-markets, is associated with a

[38] Introducing interaction terms creates multicollinearity problems for many products.

uniform, significant but small, increase in BMI. A one square meter increase in the selling area per 100 capita would imply a 40 to 60 gram weight gain for a 1.80m tall individual. Hence, differences in food availability matter. Being responsible for food expenditures is negatively related to BMI. Individuals who control their food purchases seem to be more able to control their weight.

Otherwise, we find the usual correlations for the socio-demographic variables. There are a positive gender effect and a concave age effect. Perhaps surprisingly, having a new-born has the same positive effect for males and females. Income elasticity is small, negative but significant (between -0.014 around the median up to -0.039 at the 90^{th} percentile). There is a negative education-BMI gradient. This may reflect either differences in the capability of using information (the efficiency argument proposed by Grossman, 2001), or differences in the opportunity costs of weight control. Indeed, the more educated have more incentives to control their weight, because their life expectancy is basically higher, as well as their life-cycle earnings. These effects prevail over the potential negative effect induced by the negative correlation between education and on-the-job exercise.

5.2 Sensitivity analysis

The results in Tables C1 to C4 provide interesting empirical evidence. As emphasised in the Data section, the construction of prices is a key research question, because prices must not reflect taste variations. In particular, we have assumed that, at the level of product categories, each local price has to be the average of at least 25 households' price indices in order to be a good estimate of the true price index. One may consider that this threshold of 25 households is not sufficiently high, or conversely that this criteria is too stringent. Tables C5 to C9 provide additional insights on the way the results are affected by variations of this threshold. Two alternative sample were constructed. The smallest sample drops all observations in clusters with less than 50 observations. There are about 12650 individual-years in this "restricted sample". The biggest sample keeps all observations. This "enlarged sample" represents 29573 individual-years. As shown by descriptive statistics displayed in Table C9, the restricted, estimation and enlarged samples do not differ by their socioeconomic composition, apart for the geographical distribution of observations. For instance, almost no one in the restricted sample comes from $REGION6$ (Aquitaine, Limousin, Poitou-Charente), while there are about 6.7% in the estimation sample. Hence, when the threshold for the size of the clusters increases, price measures are more robust, but the sample becomes less representative of actual price variations.[39]

The results do not change qualitatively between the enlarged and the esti-

[39] Ideally, one would like to construct sampling weight. This is left for future research.

mation samples, at least at the level of functional groups (see Table C5). Fats, and sugars and sweets attract negative coefficients in the higher percentiles of the distribution, while the signs are positive for proteins and the group of fruits, vegetables and cereals. There are still interesting results for beverages and dairies around the median. The results are qualitatively different for the restricted sample. Here, although the signs of the correlations are fairly similar, the weight of responsibility falls clearly more on sugar and sweets than on fats. There are less significant correlations, especially for fruits, vegetables and cereals.

At the level of product categories, the estimates are not affected by the use of the "enlarged sample" rather than the "restricted sample". However, the price of "other drinks" appears to be negatively correlated with the 70^{th} percentile while it was not the case in the estimation sample (see Table C7). Once again, the results change markedly in the "restricted sample" (see Table C8). For instance, the price of alcohol is no more significantly correlated with the BMI, while the price of "other drinks" attracts large and significant coefficients. The correlation is still positive for fruits in brine, but not significant, while it is strongly positive and very significant for processed fruits. The price of cereals is also positively correlated with the 60^{th} and the 70^{th} quantiles. Negative (and often not significant) effects are found for sea products in brine, while correlations tended to be positive in previous regressions. There are also unexpected positive effects for the prices of animal fats and ready meals, but they are significant at the level of 10% only. Last, we find a negative price effect for the functional group of snacks and ready-meals. This is entirely due to snacks, since at the level product categories, correlations are positive for ready-meals.

It appears eventually that the results are more sensitive to the geographical representativity of the sample, than to the threshold for the minimum size of clusters, as we would have found otherwise more differences between estimations in the enlarged and the estimation samples. Perhaps a lesson for future work is that we will have to find larger data sets, in order to have both robust price measures and representative samples.

In the Data section, we have described another means of constructing price measures: averaging unit values in each cluster. We have argued that this method hinges upon strong assumption regarding the variations of quality choices between clusters. The lack of theoretical background behind this assumption has led us to choose another method. Table C10 in Appendix C illustrates the consequence of this modelling choice. It reports estimation results of the baseline specification with prices measured at the level of product categories.

The prices are medians of unit values in each cluster.[40] A straight comparison with Table C2's results show that Table C9's results differ, but this is more a matter of magnitude and significance than of sign. In particular, the positive correlation with the price of alcohol was not significant in Table C2. It becomes significant at the highest percentiles in Table C9. The estimated elasticities for oils are lower in Table C9, while the converse holds for milk. Meats in brine and eggs attracts now a negative coefficient, which is the only major difference between Tables C2 and C9. Last, the price of breaded/fried meats and fishes is here clearly negatively correlated with the BMI distribution. Hence, the magnitude of the estimates is clearly affected by the methods used to measure the prices.

5.3 Simulation

To illustrate the results, we simulate the global effect of a 10% increase in the prices of dairies, fats and sugars associated with a 10% decrease in the prices of fruits and vegetables in brine on the medical cost of obesity. The price-BMI elasticities are picked up from the regressions at the 90^{th} quantile, since the corresponding BMI (30.48) is close to the threshold for obesity (30 kg/m^2). Elasticities for dairies, fats, and sugar and sweets may be taken from Tables C1, C5 or C6. Regarding fruits and vegetables in brine, we may base our computation on Table C2, C7 or C8's results. By adding elasticities for dairies, fats, and sugar and sweets and soustracting elasticities for fruits and vegetables in brine, one obtain the global elasticity of BMI to the price policy. Using values estimated in the estimation sample, this elasticity is -0.564, while it is -0.317 when one takes estimates from the enlarged sample and -0.738 in the restricted sample. Hence, using estimates from the estimation sample is a good compromise.

With an elasticty of -0.564, the price policy would decrease the BMI of those individuals around the 90^{th} percentile by 5.66%. This would almost cut by half the prevalence of obesity in the estimation sample (6.6% as against 11.6%), because many obese individuals in the estimation sample have a BMI close to the threshold of 30 kg/m^2.[41] Extrapolating this result to the entire adult population (about 48.5 billions people in 2004), it means that 2.418 million people would not be obese but only overweight. Detournay *et al.* (2000) estimate that the extra-cost associated to obesity varies between 166 and 344 Euros (in 2004 Euros). Hence, the price policy would yield a reduction of health care expenditures

[40] To avoid problems with outliers, we take the median rather than the mean. It amounts to assume that the quality of purchases is log-normally distributed in each cluster with identical location parameters.

[41] Of course, many individuals probably under-declare their true weight.

of between 401 and 832 million euros. This a likely to be the interval for a lower bound, as the cost of overweight-related diseases and the change in the proportion of overweight individuals was not taken into account. Actually, using elasticities at the 60^{th} percentile, the BMI of slightly overweight individuals should decrease by 1.9%. The prevalence of overweight should fall from 45.2% (in the estimation sample) to 43.3%. Last, assuming that overweight yields no medical costs, these figures imply that an upper bound on the remaining extra medical costs due to obesity would be about 1.1 billion euros.

To estimate upper bounds on the impact for the consumer food budget, we examine how household expenditures in 2004 are affected. Only the subpanel for which expenditures on fresh fruits and vegetables were recorded are used (1057 households). The policy would be regressive since, in the estimation sample, the average change in yearly food expenditures would be +61.6 euros for households in the lower equivalenced income decile, and +30.0 euros in the upper equivalenced income decile. On average, food expenditures would increase by +47.4 euros. Chouinard *et al.* (2005) find that a 10% fat tax on dairies would imply a welfare loss of about 20US$ for US households. Although our calculation does not account for substitutions in the consumer food baskets, our estimates are of similar magnitude.[42] Extrapolating to all French households (about 23.5 million), it means a stream of revenu of about 1.113 billion euros. This is an upper bound, since we simulated effects on expenditures without taking into account changes in the household's food basket (*i.e.* substitutions to offset the welfare impact of price variations), and we abstract from reactions to taxations/subventions on the supply-side.[43] This is also an upper bound for the compensating variation associated to this price policy. Hence, it appears that the policy may help to internalise signifcantly the medical costs of obesity.

6 Conclusion

This research has found significant correlations between individual BMI and the prices of a number of food product categories. In line with the previous literature (see Auld *et al.*, 2006), the prices of fruits and vegetables have a positive effect on BMI, while negative elasticties are found for fats and, to a lesser extent, for dairies, and sugar and sweets. We now suggest seven directions for future research.

First, specific studies of the functional groups whose prices have a significant

[42] Chouinard et al. (2005) also find little effect of a *fat* tax on dairies on caloric intakes. Indeed, we also find that the conditional mean elasticity to the price of dairies (a larger base tax) is low (-0.045 *cf.* Table C1), and not significant. Accordingly, a 10% increase in the price of dairies would translate in a 0.79 percentage points reduction in the prevalence of obesity.

[43] For instance, supermarkets could buy fats at a lower price etc...

effect are required. Chouinard *et al.* (2005) simulate the effect of a proportional fat tax on dairies in the US market, which could be usefully replicated for various functional groups (fats, dairies, beverages, fruits and vegetables) in France. By estimating demand systems, one can obtain more precise measures of households loss of welfare (*i.e.* compensating variations).

Second, our simulation use very rough assumptions regarding the medical cost of obesity. The actual cost is a continuous function of BMI, and better knowledge of this relationship is required for more precise estimates of the benefits yielded by price interventions. Further, the medical costs computed by Detournay *et al.* (2000) did not take into account the advantages of a weight loss for overweight individuals in terms of reduction of the cardio-vascular risk or the risk of certain cancers.

Third, to our knowledge, neither the willingness-to-pay of overweight people for a weight reduction, nor the social cost of obesity in terms of losses of productivity are known.

Fourth, we do not know how variations in VAT are transmitted to consumer prices. We are therefore able to compute the net benefit for public finance of the price interventions we have simulated only under the assumption of a perfect price transmission.

Fifth, the role of snacks and ready-meals has to be investigated much more in depth, but this task is clearly difficult given the variabilityof the nutrional content of these foods. Further, there are probably strong interactions between consumption of food-away-from-home and consumption of ready-meals.

Sixth, even if the welfare loss is important for consumers, a key question remains whether these tax revenues can be spent efficiently.

Last but not least, our model does not predict the long-term consequences of a price policy. There may be unintended feeback effects from the supply side.

As a conclusion, given our results and our knowledge regarding the cost of obesity, we have found that a vigourous price intervention may be interesting. However, its implementation would be difficult, and perhaps difficult to justify, as it is a regressive policy, and all consumers would have to pay for obese individuals.

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Appendix A. Basal Metabolic Rate equations.

Equations for the prediction of BMR have been estimated by a number of authors. This appendix presents first Schofield's linear equations, which are used for instance by Cutler *et al.* (2003) and Bleich *et al.* (2005).

- Males:
  - age < 3 years: $BMR=59.5*W-30.3$
  - age in [3,10[: $BMR=22.7*W+504.1$
  - age in [10,18[: $BMR=17.7*W+657.9$
  - age in [18,30[: $BMR=15.1*W+691.9$
  - age in [30,60[: $BMR=11.5*W+872.7$
  - age ≥ 60 years: $BMR=11.7*W+609.0$

- Females:
  - age < 3 years: $BMR=58.3*W-31.1$
  - age in [3,10[: $BMR=20.3*W+485.7$
  - age in [10,18[: $BMR=13.4*W+692.3$
  - age in [18,30[: $BMR=14.8*W+486.4$
  - age in [30,60[: $BMR=8.1*W+845.2$
  - age ≥ 60 years: $BMR=2.8*W+658.2$

Black *et al.* (1996)'s Cobb-Douglas equation use a continuous age-adjustment. Their use is recommended by the French authority for food security, on the ground that they are more precise for overweight and elderly people (AFFSA, 2001).

- Males:
  - $BMR=1.083*W^{0.48}*Height^{0.5}*age^{-0.13}$

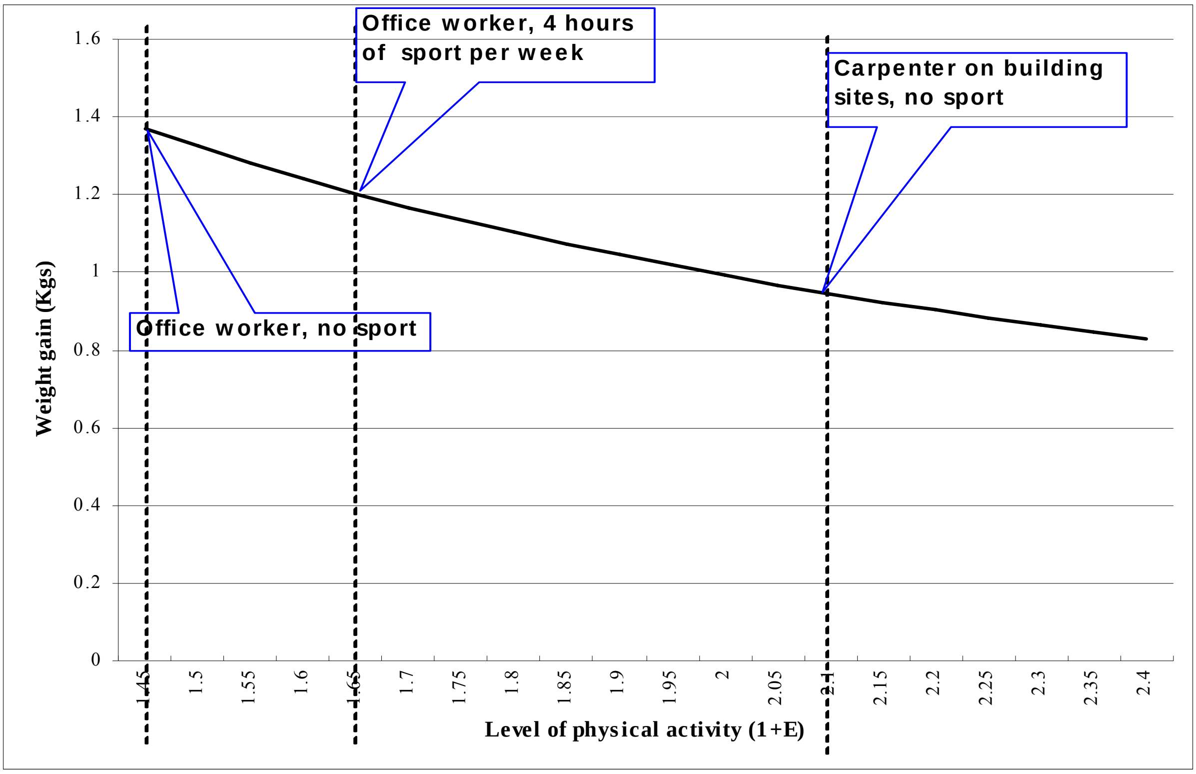
- Females:
  - $BMR=0.963*W^{0.48}*Height^{0.5}*age^{-0.13}$

Using these equations it is possible to simulate the weight gain of an individual whose caloric intakes increase. To illustrate this point, note that weight is an adjustment variable in the equilibrium equation between caloric intakes (*K*) and expenditures. More precisely, we have:

$$K=BMR*(1+E) \qquad \text{(A1)}$$

where *E* depends on physical activity and has been calibrated for various types of lifestyles (Black et al., 1996; AFFSA, 2001). For a carpenter working on building sites, we have for instance $E\approx1.08$, while for an office worker $E\approx0.45$. 4 hours of sport per week may increase these numbers by a maximum of 0.2 points. Consider now a 30-years old male who weighs 70kgs. If he is carpenter, his caloric intakes are about 3520 Kcal. If he is office worker (and does not exercise off the job), his intakes are about 2454 Kcal. Suppose now that intakes increase by 100Kcal. The resulting increase in body weight for various levels of physical activity is represented by the bold line in Figure A1. The weight gain is about 35% higher for the office worker as compared to the carpenter. Given that individuals can not easily switch from energy-demanding occupations to sedentary jobs (at least in France), one may only imagine that they exercise more in order to offset this change. Then, for 4 hours of sport the weight gain would be about 15% lower (about +1.2 Kg as against +1.4 Kg for the office worker). Hence, at a micro-level and, efforts to exercise frequently are not likely to have an important effect on weight. However, at a macro-level, trends in the occupational structure of the population, migrations from rural to urban areas, trends in job strenuousness may have a significant impact on trends in the population weight distribution.

Figure A1. Changes in weight when caloric intakes increase by 100 Kcal for a 30-years old male whose initial weight is 70 Kg.



Appendix B. Descriptive statistics.

Figure B1. BMI distribution.

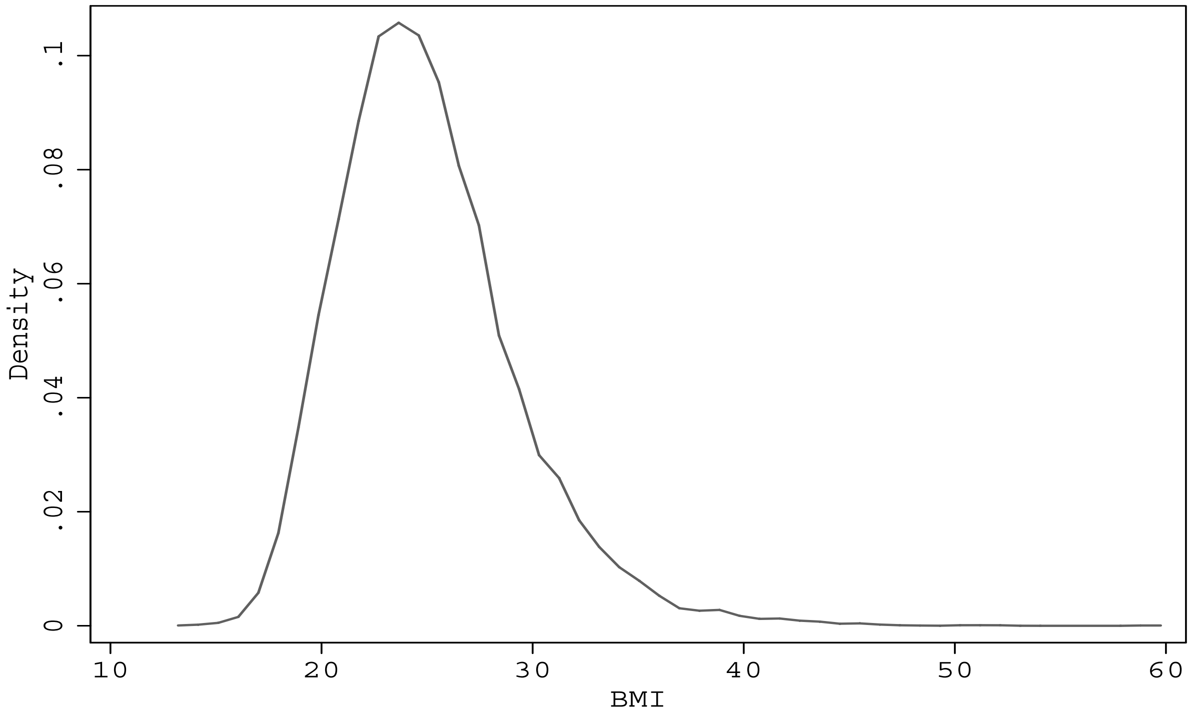


Figure B2. Log(BMI) distribution.

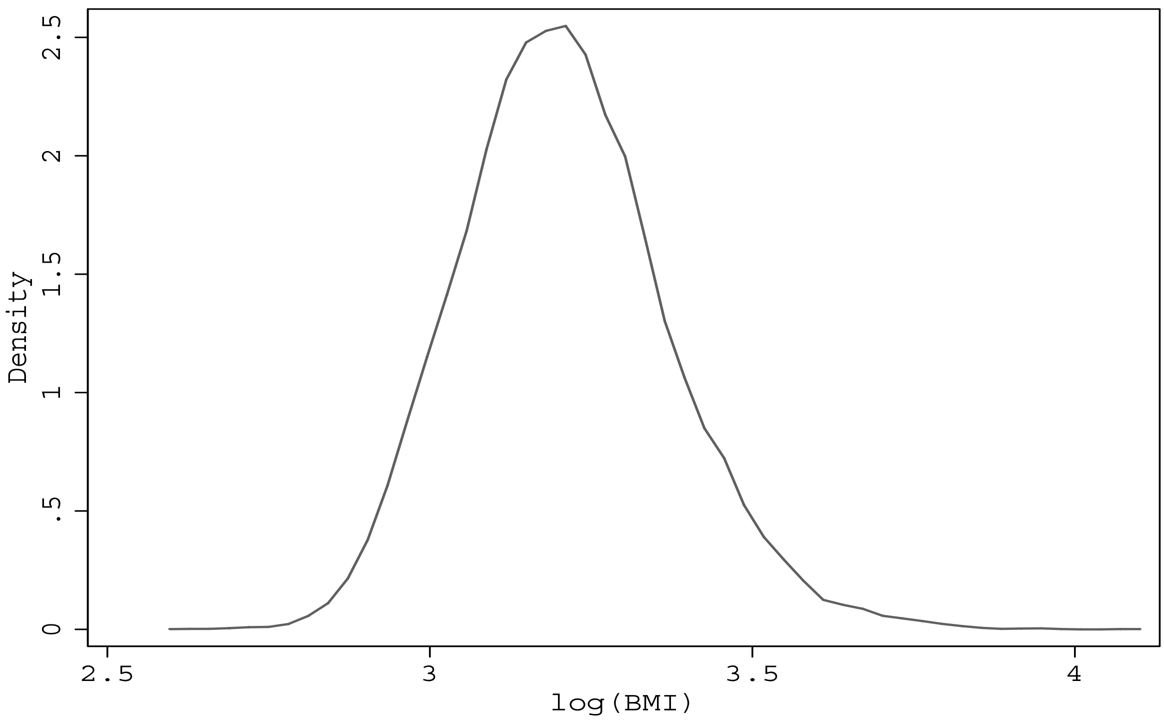


Table B1. Shapiro-Francia tests of normality (p-values)

Year	**2002**	**2003**	**2004**	**2005**
BMI	0.00101	0.00190	0.00057	0.00007
Log(BMI)	0.00642	0.00962	0.00469	0.00099

Note. The numbers are p-values for the test of the H0 hypothesis that the variable is Gaussian.

Table B2. Weight-BMI correspondence for selected heights.

Height (in m)	**BMI=18 (thin)**	**BMI=22.5 (standard)**	**BMI=25 (overweight)**	**BMI=30 (obese)**
1.90	64.98 kg	81.25 kg	90.25 kg	108.3 kg
1.80	58.32 kg	72.9 kg	81 kg	97.2 kg
1.70	52.02 kg	65.03 kg	72.25 kg	86.7 kg

Note. This table should be read as follows: a 1.80m tall individual with a BMI of 22.5 weighs 81kg.

Table B3. Classification of Food Products

Functional groups	Product categories	Food products (examples)	Comments
Beverages	Water	Plain or still, mineral or not.	
	Alcohol	All kind of wines, cocktails, beers, ciders, liquors etc.	Products are aggregated according to their average alcohol content.
	Other drinks	Fruit juices, sodas and other carbohydrate drinks (lemonade, syrups etc.). Flavoured waters were dropped.	Products are distinguished according to their sugar or fat content when available.
Fruits, vegetables and cereals	Fruits in brine	All fresh fruits and fruits canned/frozen in brine	
	Processed Fruits	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, flours, chestnuts, oat flakes, couscous etc.	
Proteins (except dairies)	Meats in brine and eggs	Fresh/raw meats: beef, veal, snails, variety meats, chicken, eggs etc.	
	Sea products in brine	All fishes, shellfishes, frogs etc. in brine	
	Processed sea products	Fish canned in oil, smoked salmon, marinated haddock, roll mops…	Canned
	Cooked meats	Sausages, ham, pâté, foie gras,	

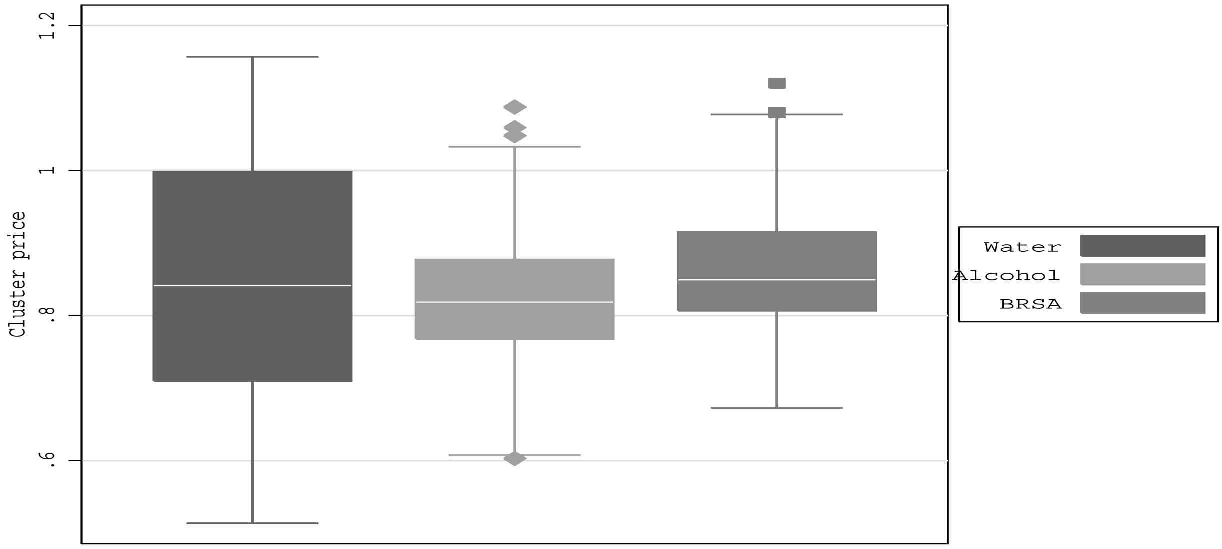
		bacon, salted smoked pork etc.	
	Breaded/fried fishes or meats		
Dairies	Yaourts and fresh uncured cheeses	Natural yoghurts, milk, fresh uncured cheese (fromage blanc ou frais)	Products are distinguished according to their fat content when available. Products without explicit fat content were dropped.
	Cheeses	All cheeses except fromage blanc and fromage frais.	Products are distinguished according to their fat content when available. Products without explicit fat content were dropped.
	Milks	All milks (soja milks where dropped).	Products are distinguished according to their fat content when available. Products without explicit fat content were dropped.
Fats	Animal fat and margarine	Butter, fresh cream,…	Products are distinguished according to their fat content when available. Products without explicit fat content were dropped.
	Oils	Oils. Sauces were dropped.	
Sugar and sweets	Sugar and confectionaries	Lump/caster sugar, honey, jam marmalades.	
Snacks and ready-meals	Pastries and deserts, , ,	Milky deserts, croissants, cakes, fresh or frozen pastries…	
	Sweet and fatty snacks	Breakfast cereals, cereal bars, chocolate bars, most chocolate products, biscuits, ice creams…	
	Salty and fatty snacks	Crackers, pop-corn, peanuts, most appetisers, olives, etc.	
	Ready-meals	All ready meals including sandwiches, and canned/frozen recipes of vegetables and cereals (ratatouille, etc.).	

Table B4. Variable definition and descriptive statistics

Variable Name	**Variable definition**	**Starting sample (N=34736)**	**Estimation sample (N=23304)**
BMI	Body Mass Index (Weight in kg divided by height squared in meter)	25.05 (4.21)	25.06 (4.21)
HHOLDOBESE	Households with obese adults	16.3%	19.2%
HHOLDOVERW	Households with overweight adults	34.7%	40.5%
LOGINC	Logarithm of real household income per unit of consumption (oxford scale, 2004 Euros)	9.53 (0.48)	9.56 (0.48)
DEG1	No qualification or primary school	15.3%	15.2%
DEG2	Short vocational or technical qualification	7.3%	7.2%
DEG3	First cycle of secondary school (BEPC)	34.1%	33.6%
DEG4	Baccalaureat (general, vocational or technical)	19.7%	19.8%
DEG5	Baccalaureat + 2 years	9.8%	9.9%
DEG6 (reference)	Baccalaureat + 3 years or more	13.9%	14.4%
SEXE	=1 for male, 0 otherwise	46.0%	45.9%
AGE	Age	50.8 (14.2)	50.7 (14.3)
BABYWOMAN	=1 for women with a bay aged less than one year.	1.3%	1.4%
BABYMAN	=1 for men with a bay aged less than one year.	1.3%	1.4%
COUPLE (reference)	Couples (reference)	68.2%	68.6%
SINGLE	Single without children	10.7%	10.7%
OTHHHOLD	Other household structure	21.1%	20.6%
NBIND	Number of person in the household	3.02 (1.35)	3.00 (1.35)
FRUITS	Household produces fruits	14.6%	14.0%
VEGETABLES	Household produces vegetables	6.8%	7.1%
SURFSALE	Selling area (in square meters) per 100 residents in the cluster allotted to large-scale distribution stores in 2001	2.84 (0.96)	2.84 (1.01)
MEALPLANNER	=1 if the individual is responsible for food-at-home expenditures	26.3%	25.9%
UNIT1	Lives in a rural residential area	26.2%	30.3%
UNIT2	Lives in an urban unit with between 2000 and 4999 residents	7.7%	8.9%
UNIT3	Lives in an urban unit with between 5000 and 9999 residents	5.8%	4.0%
UNIT4	Lives in an urban unit with between 10000 and 19999 residents	5.7%	3.7%
UNIT5	Lives in an urban unit with between 20000 and 49999 residents	5.9%	4.7%
UNIT6	Lives in an urban unit with between 50000 and 99999 residents	8.2%	6.6%
UNIT7	Lives in an urban unit with between 100000 and 199999 residents	6.3%	4.5%
UNIT8 (reference)	Lives in an urban unit with 200000 residents or more, or in Great Paris	34.2%	37.2%
REGION1 (reference)	Ile-de-France	14.3%	17.3%
REGION2	Picardie, Normandie	17.5%	16.3%
REGION3	Nord	7.0%	8.5%
REGION4	Champagne-ardennes, Alsace, Lorraine	10.3%	9.7%
REGION5	Bretagne, Pays de Loire, Centre	17.3%	18.7%
REGION6	Limousin, Aquitaine, Poitou-Charente	10.6%	6.7%
REGION7	Bourgogne, Franche-Comté, Rhône-Alpes, Auvergne, Midi-Pyrénées, Languedoc	12.5%	13.6%
REGION8	PACA	10.5%	9.3%
YR2002 (reference)	Calendar year = 2002 (for the dependent variable)	26.2%	25.9%
YR2003	Calendar year = 2003 (for the dependent variable)	26.2%	27.2%

YR2004	Calendar year = 2004 (for the dependent variable)	25.2%	24.9%
YR2005	Calendar year = 2005 (for the dependent variable)	22.5%	22.0%

Figure B3. Distribution of the Paasche indices for beverages.



Note: BRSA is the shortcut for the group of fizzy drinks (syrups, fruit juices, sodas, carbohydrated drinks).

Figure B4. Distribution of the Paasche indices for fruits, vegetables and cereals

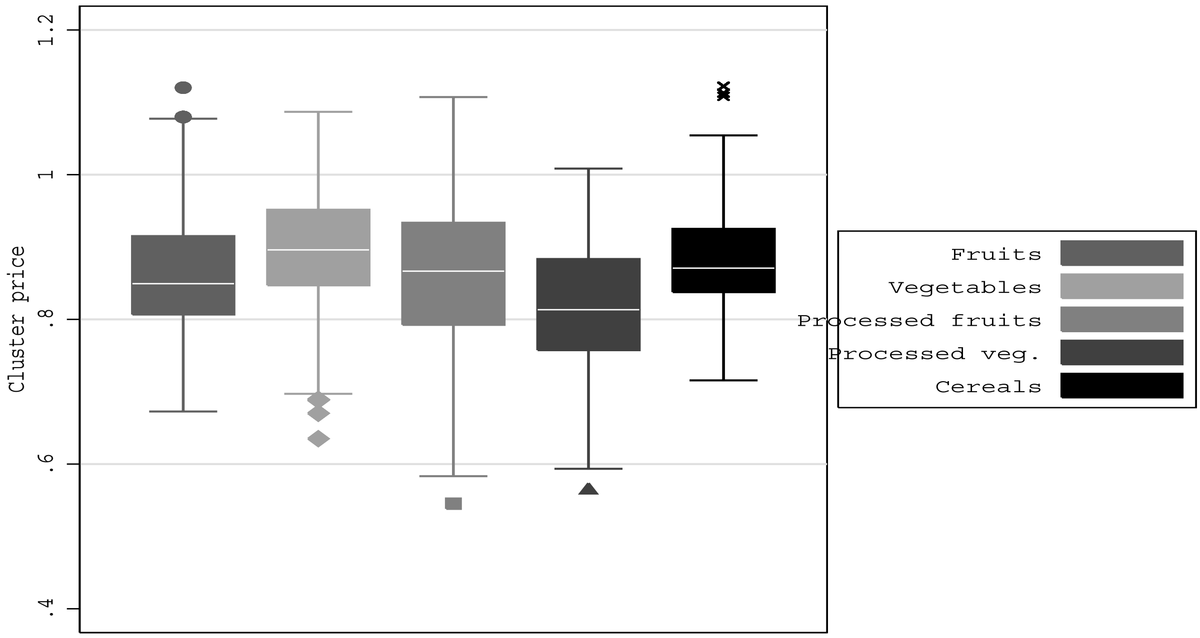


Figure B5. Distribution of the Paasche indices for dairies

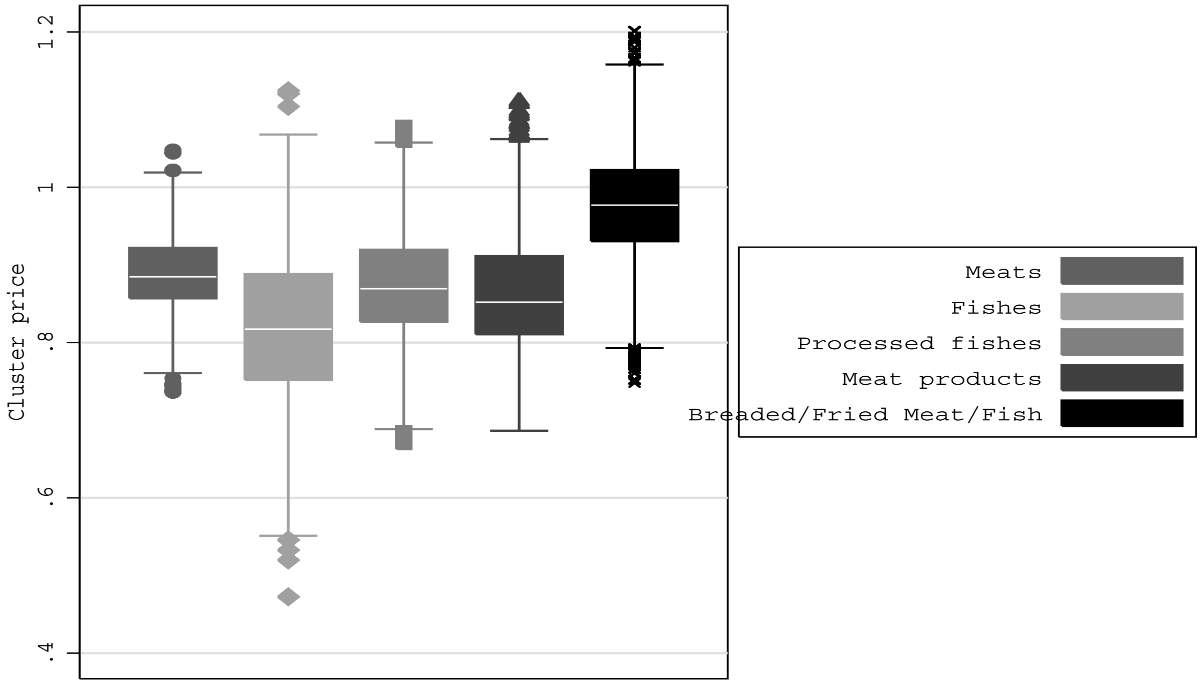


Figure B6. Distribution of the Paasche indices for dairies

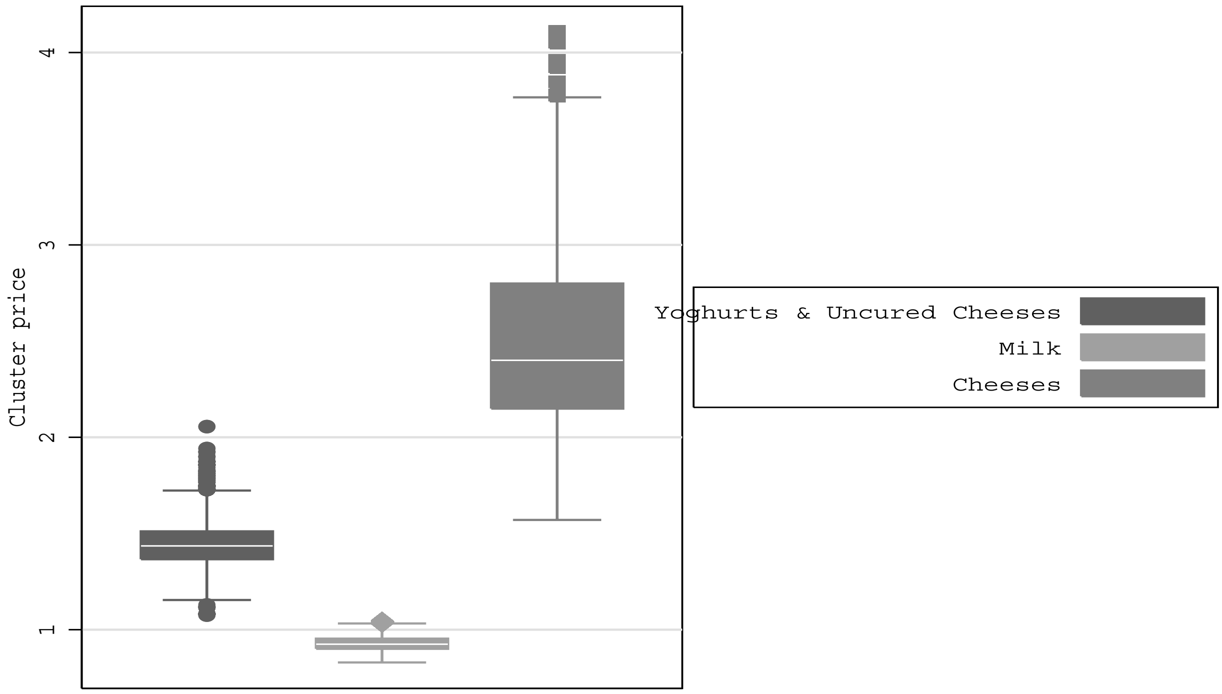


Figure B7. Distribution of the Paasche indices for sugars and fats

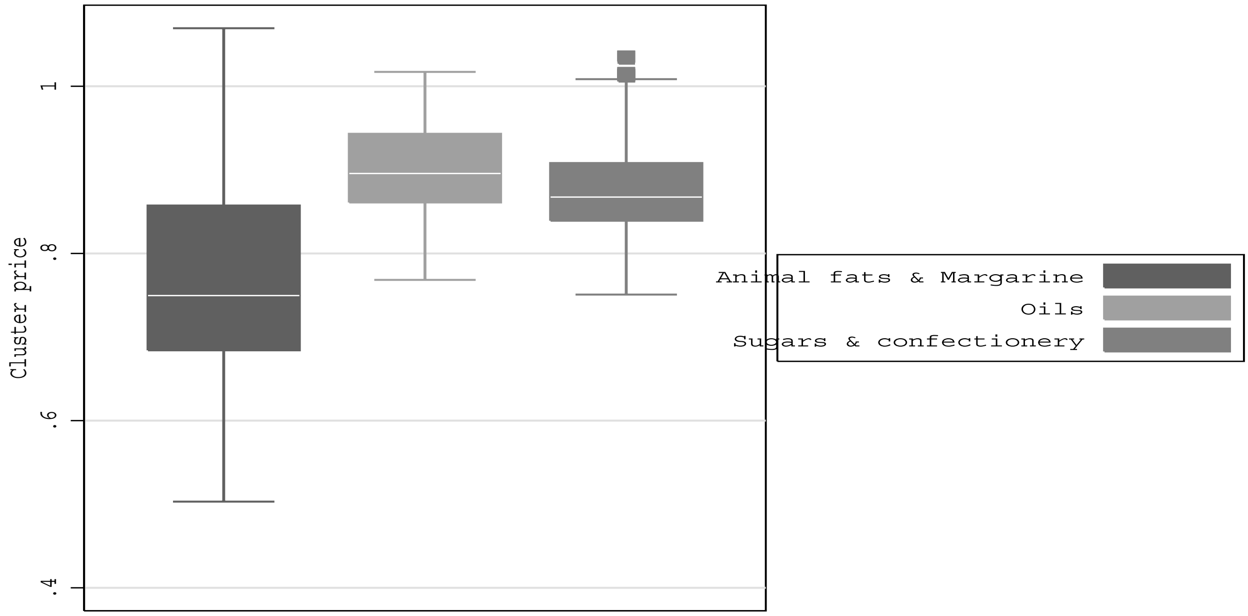
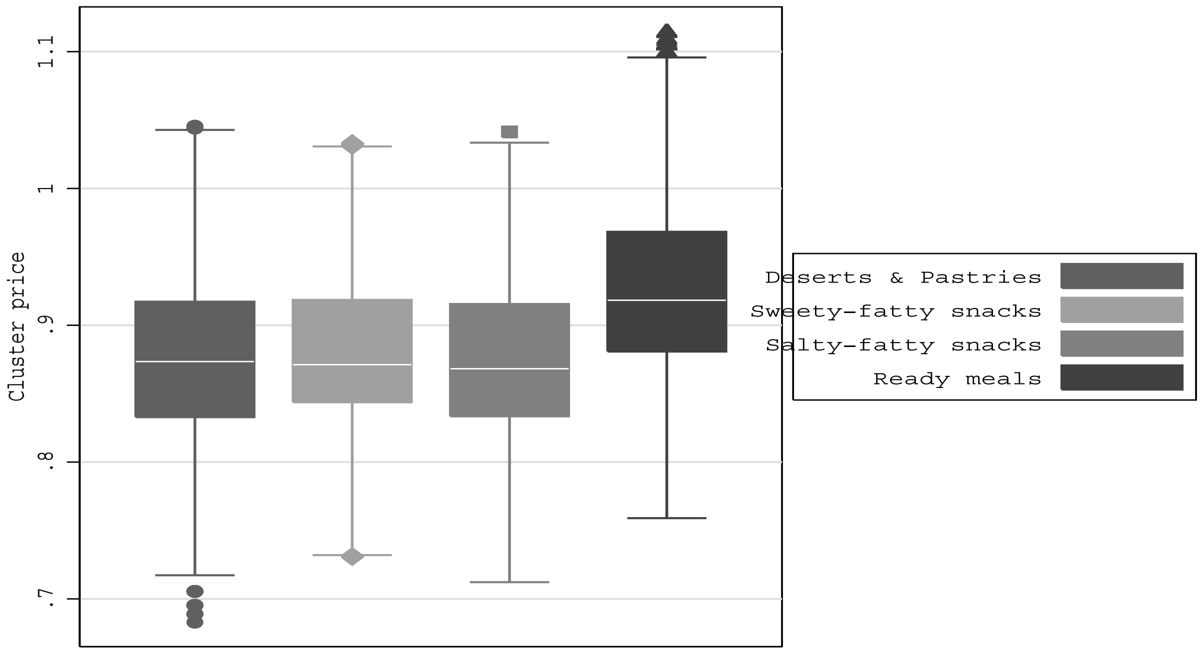


Figure B7. Distribution of the Paasche indices for snacks and ready-meals



Appendix C. Results

Table C1. Baseline results. Prices of functional groups. N=23304, estimation sample.

Moment	Mean	Q50	Q60	Q70	Q80	Q90
IMC value at the moment	25.06	24.53	25.51	26.67	28.05	30.48
Log prices (Log(P_j^c) where P_j^c is defined as in Section 4.2.)						
Beverages	-0.019 (0.037)	-0.045* (0.026)	-0.029 (0.028)	-0.007 (0.040)	0.014 (0.052)	0.001 (0.056)
Fruits, Vegetables and Cereals	0.084* (0.048)	0.062** (0.029)	0.075** (0.038)	0.075 (0.055)	0.176*** (0.051)	0.147** (0.070)
Proteins	0.021 (0.045)	-0.007 (0.045)	0.019 (0.040)	0.041 (0.046)	0.108* (0.062)	0.191** (0.089)
Dairies	-0.045 (0.027)	-0.064** (0.029)	-0.030 (0.028)	-0.038 (0.028)	-0.052 (0.033)	-0.064 (0.039)
Fats	-0.144*** (0.051)	-0.100 (0.065)	-0.135** (0.059)	-0.154** (0.060)	-0.217*** (0.069)	-0.284*** (0.092)
Sugar and sweets	-0.062 (0.039)	-0.002 (0.035)	-0.041 (0.030)	-0.056 (0.038)	-0.117** (0.046)	-0.090* (0.050)
Snacks and ready-meals	0.032 (0.062)	0.091 (0.059)	0.004 (0.071)	0.007 (0.075)	0.048 (0.093)	0.043 (0.107)
Sociodemographic characteristics						
LOGINC	-0.018*** (0.005)	-0.014*** (0.003)	-0.019*** (0.004)	-0.023*** (0.005)	-0.028*** (0.006)	-0.039*** (0.006)
DEG1	0.045*** (0.008)	0.042*** (0.004)	0.051*** (0.004)	0.055*** (0.007)	0.058*** (0.009)	0.053*** (0.007)
DEG2	0.043*** (0.009)	0.036*** (0.006)	0.043*** (0.007)	0.049*** (0.008)	0.052*** (0.010)	0.058*** (0.013)
DEG3	0.037*** (0.006)	0.039*** (0.003)	0.041*** (0.004)	0.043*** (0.006)	0.043*** (0.007)	0.043*** (0.009)
DEG4	0.019*** (0.006)	0.017*** (0.004)	0.022*** (0.005)	0.029*** (0.007)	0.035*** (0.007)	0.025*** (0.009)
DEG5	0.006 (0.007)	0.006 (0.004)	0.007* (0.004)	0.009 (0.006)	0.003 (0.007)	-0.002 (0.008)
SEXE	0.057*** (0.004)	0.068*** (0.003)	0.059*** (0.002)	0.050*** (0.003)	0.034*** (0.003)	0.011*** (0.004)
BABYWOMAN	0.019** (0.010)	0.022* (0.012)	0.018 (0.011)	0.022 (0.016)	0.022 (0.016)	0.021* (0.011)
BABYMAN	0.017** (0.008)	0.022** (0.009)	0.031*** (0.007)	0.031*** (0.009)	0.028*** (0.008)	0.026* (0.015)
MEALPLANNER	0.014*** (0.005)	0.015*** (0.004)	0.016*** (0.003)	0.018*** (0.005)	0.023*** (0.005)	0.011* (0.006)
AGE/10	0.071*** (0.009)	0.068*** (0.008)	0.075*** (0.007)	0.074*** (0.011)	0.078*** (0.011)	0.094*** (0.013)
$(AGE/10)^2$	-0.005*** (0.001)	-0.004*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.006*** (0.001)	-0.008*** (0.001)
SINGLE	-0.023** (0.011)	-0.018** (0.008)	-0.025*** (0.006)	-0.023** (0.011)	-0.028** (0.011)	-0.039*** (0.008)
OTHHOLD	0.009* (0.005)	0.006 (0.004)	0.008** (0.004)	0.014*** (0.005)	0.015*** (0.006)	0.024*** (0.007)
NBIND	-0.022** (0.012)	-0.024** (0.010)	-0.035*** (0.007)	-0.034*** (0.011)	-0.042*** (0.014)	-0.052*** (0.010)

$NBIND^2$	0.002 (0.002)	0.003** (0.001)	0.005*** (0.001)	0.004*** (0.001)	0.005*** (0.002)	0.006*** (0.001)
FRUITS	-0.008 (0.005)	-0.011*** (0.004)	-0.005 (0.004)	-0.005 (0.004)	-0.004 (0.005)	-0.005 (0.005)
VEGETABLES	-0.008 (0.007)	-0.005 (0.005)	-0.004 (0.005)	-0.012* (0.007)	-0.016*** (0.004)	-0.023*** (0.007)
SURFSALE	0.013*** (0.005)	0.020**** (0.002)	0.018*** (0.003)	0.017*** (0.004)	0.015*** (0.004)	0.012*** (0.004)
Other control variables : constant, UNIT1-UNIT7, REGION2-REGION7, YR2003-YR2005						

Asymptotic standard errors in parentheses. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level. Standard errors clustered on households for the conditional mean regressions, and computed by bootstrap for the quantile regressions.

Table C2. Baseline results. Prices of product categories. N=23304, estimation sample.

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.06	24.53	25.51	26.67	28.05	30.48
Log prices ($\text{Log}(P_{jk}^c)$ where P_{jk}^c is defined as in Section 4.2.)						
Mineral water	0.003 (0.017)	0.019 (0.013)	-0.011 (0.013)	-0.008 (0.013)	0.010 (0.017)	0.005 (0.026)
Alcohol	-0.030 (0.026)	**-0.068*** (0.024)**	**-0.042** (0.021)**	-0.029 (0.030)	0.007 (0.033)	0.009 (0.047)
Other drinks	0.003 (0.031)	0.025 (0.021)	0.033 (0.024)	0.015 (0.042)	-0.030 (0.053)	-0.051 (0.071)
Fruits in brine	0.036 (0.028)	**0.056** (0.025)**	**0.049*** (0.019)**	**0.069** (0.031)**	**0.056 (0.041)**	**0.060** (0.029)**
Processed Fruits	0.015 (0.023)	-0.023 (0.017)	0.016 (0.014)	0.037 (0.024)	0.025 (0.028)	0.035 (0.048)
Vegetables in brine	0.030 (0.028)	-0.005 (0.029)	0.013 (0.029)	0.014 (0.032)	**0.075** (0.035)**	**0.066 (0.050)**
Processed vegetables	-0.036 (0.024)	**-0.044** (0.022)**	**-0.042 (0.028)**	**-0.044* (0.024)**	-0.030 (0.034)	-0.026 (0.051)
Cereals	-0.017 (0.046)	-0.016 (0.038)	-0.032 (0.039)	-0.033 (0.050)	-0.016 (0.061)	-0.010 (0.097)
Meats in brine and eggs	-0.016 (0.041)	-0.024 (0.038)	-0.013 (0.041)	0.023 (0.043)	0.049 (0.061)	0.142 (0.090)
Sea products in brine	0.010 (0.019)	-0.001 (0.017)	0.010 (0.020)	0.007 (0.024)	0.019 (0.025)	0.053 (0.035)
Processed sea products	0.021 (0.029)	0.024 (0.021)	**0.030* (0.016)**	**0.053** (0.025)**	**0.062*** (0.024)**	0.024 (0.053)
Cooked meats	0.024 (0.029)	0.030 (0.021)	0.019 (0.032)	0.045 (0.040)	0.025 (0.039)	-0.013 (0.046)
Breaded/fried fishes or meats	-0.019 (0.028)	-0.016 (0.028)	-0.034 (0.030)	**-0.069* (0.037)**	-0.066 (0.045)	-0.044 (0.051)
Yogurts and fresh cheeses	0.027 (0.027)	0.026 (0.025)	0.013 (0.017)	0.028 (0.029)	0.015 (0.035)	-0.015 (0.046)
Cheese	0.001 (0.069)	-0.025 (0.070)	-0.073 (0.072)	-0.029 (0.101)	0.022 (0.104)	-0.041 (0.142)
Milk	**-0.026* (0.016)**	**-0.030*** (0.012)**	**-0.014 (0.012)**	**-0.025* (0.014)**	**-0.027 (0.018)**	**-0.047 (0.029)**
Animal fats and margarine	0.007 (0.020)	-0.008 (0.017)	-0.013 (0.015)	-0.008 (0.022)	0.005 (0.025)	-0.007 (0.031)
Oils	**-0.180*** (0.059)**	**-0.106** (0.051)**	**-0.116** (0.048)**	**-0.190*** (0.049)**	**-0.266*** (0.072)**	**-0.275*** (0.101)**

Sugar and sweets	-0.058 (0.040)	0.007 (0.042)	**-0.073*** **(0.040)**	**-0.051** **(0.054)**	**-0.106*** **(0.064)**	**-0.080** **(0.085)**
Pastries and deserts	0.032 (0.041)	0.051 (0.040)	0.009 (0.034)	0.016 (0.039)	0.066 (0.041)	0.071 (0.050)
Sweet and fatty snacks	0.003 (0.047)	0.046 (0.050)	0.050 (0.044)	0.043 (0.049)	0.026 (0.079)	0.014 (0.104)
Salty and fatty snacks	0.020 (0.041)	0.044 (0.036)	0.038 (0.043)	0.000 (0.046)	-0.008 (0.051)	-0.015 (0.069)
Ready-meals	-0.011 (0.037)	-0.031 (0.030)	-0.034 (0.030)	-0.035 (0.027)	-0.016 (0.055)	0.017 (0.056)
Other control variables as in Table C1						

Table C3. Additional results. Prices of product categories. N=23304, estimation sample.

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.06	24.53	25.51	26.67	28.05	30.48
Log prices (Log(P_{jk}^{c}) where P_{jk}^{c} is defined as in Section 4.2.)						
Animal fats and margarine: P1	-0.074** (0.036)	-0.068** (0.034)	-0.083*** (0.030)	-0.123*** (0.042)	-0.100** (0.048)	-0.176*** (0.060)
Oils P2	-0.393*** (0.104)	-0.252*** (0.084)	-0.310*** (0.086)	-0.493*** (0.131)	-0.555*** (0.120)	-0.711*** (0.184)
P1*P2	-0.705*** (0.260)	-0.495** (0.203)	-0.610*** (0.218)	-0.967*** (0.317)	-0.949*** (0.328)	-1.441*** (0.493)
Other control variables as in Table C1 + remaining price variables						

Table C4. Selected price effects on body weight (in grams) for a 1.80m tall individual.

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
Weight (in kg)	81.5	79.8	83.1	86.9	91.3	98.7
	Effect (in g) of a 10 % price change					
Dairies*	-365	**-509**	-248	-328	-473	-632
Oil &Animal fat*	**-1169**	-795	**-1116**	**-1331**	**-1972**	**-2805**
Sugar & Sweets*	**-503**	-16	**-339**	**-484**	**-1063**	**-889**
Fruits in brine**	-292	**-445**	**-405**	**-596**	-509	**-593**
Vegetables in brine**	-244	40	-107	-121	**-682**	-652

Note: * expected effect using Table C1's results, and simulating a 10% price increase. **=simulated effects using Table C2's results and simulating a 10% price decrease. Figures in bold are significant at the 10% level.

Table C5. Alternative results. Prices of functional groups. N=29573, enlarged sample.

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.04	24.52	25.51	26.67	28.07	30.47
Log prices (Log(P_j^c) where P_j^c is defined as in Section 4.2.)						
Beverages	-0.023 (0.027)	**-0.054**** **(0.024)**	**-0.051*** **(0.026)**	-0.021 (0.037)	-0.017 (0.042)	-0.036 (0.060)
Fruits, Vegetables and Cereals	0.038 (0.033)	0.003 (0.030)	0.047 (0.030)	0.044 (0.031)	**0.077*** **(0.041)**	0.018 (0.052)
Proteins	0.039 (0.035)	**0.056*** **(0.029)**	**0.047*** **(0.025)**	0.040 (0.035)	**0.096**** **(0.043)**	**0.124**** **(0.063)**
Dairies	-0.032 (0.022)	**-0.047**** **(0.021)**	-0.027 (0.024)	-0.031 (0.026)	-0.022 (0.030)	-0.044 (0.034)
Fats	**-0.091**** **(0.041)**	-0.023 (0.033)	**-0.094**** **(0.045)**	**-0.083*** **(0.045)**	**-0.133***** **(0.048)**	**-0.134**** **(0.056)**
Sugar and sweets	-0.018 (0.030)	***0.047**** ***(0.028)***	0.017 (0.031)	0.003 (0.032)	**-0.070**** **(0.034)**	**-0.094*** **(0.049)**
Snacks and ready-meals	0.009 (0.046)	-0.022 (0.034)	-0.042 (0.043)	-0.040 (0.043)	0.025 (0.050)	0.097 (0.086)
Other control variables as in Table C1						

For straightforward comparisons, results from table C1 are reproduced below:

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.06	24.53	25.51	26.67	28.05	30.48
Log prices (Log(P_j^c) where P_j^c is defined as in Section 4.2.)						
Beverages	-0.019 (0.037)	-0.045* (0.026)	-0.029 (0.028)	-0.007 (0.040)	0.014 (0.052)	0.001 (0.056)
Fruits, Vegetables and Cereals	0.084* (0.048)	0.062** (0.029)	0.075** (0.038)	0.075 (0.055)	0.176*** (0.051)	0.147** (0.070)
Proteins	0.021 (0.045)	-0.007 (0.045)	0.019 (0.040)	0.041 (0.046)	0.108* (0.062)	0.191** (0.089)
Dairies	-0.045 (0.027)	-0.064** (0.029)	-0.030 (0.028)	-0.038 (0.028)	-0.052 (0.033)	-0.064 (0.039)
Fats	-0.144*** (0.051)	-0.100 (0.065)	-0.135** (0.059)	-0.154** (0.060)	-0.217*** (0.069)	-0.284*** (0.092)
Sugar and sweets	-0.062 (0.039)	-0.002 (0.035)	-0.041 (0.030)	-0.056 (0.038)	-0.117** (0.046)	-0.090* (0.050)
Snacks and ready-meals	0.032 (0.062)	0.091 (0.059)	0.004 (0.071)	0.007 (0.075)	0.048 (0.093)	0.043 (0.107)
Other control variables as in Table C1						

Table C6. Alternative results. Prices of functional groups. N=12653, restricted sample.

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.04	24.54	25.51	26.70	28.06	30.48
Log prices (Log(P_j^c) where P_j^c is defined as in Section 4.2.)						
Beverages	-0.061 (0.067)	-0.068 (0.046)	-0.017 (0.052)	-0.058 (0.069)	-0.063 (0.084)	-0.107 (0.082)
Fruits, Vegetables and Cereals	0.082 (0.083)	0.099 (0.084)	0.146 (0.105)	0.116 (0.103)	**0.188*** **(0.096)**	0.147 (0.138)
Proteins	0.027 (0.080)	0.081 (0.103)	-0.001 (0.104)	0.088 (0.134)	0.027 (0.118)	-0.063 (0.112)
Dairies	-0.055 (0.048)	-0.059 (0.051)	-0.014 (0.066)	-0.097 (0.075)	-0.024 (0.082)	-0.118 (0.098)
Fats	-0.058 (0.083)	-0.110 (0.098)	-0.142 (0.102)	-0.054 (0.127)	**-0.227*** **(0.135)**	-0.146 (0.202)
Sugar and sweets	**-0.127*** **(0.067)**	-0.074 (0.082)	**-0.134*** **(0.079)**	**-0.211**** **(0.088)**	**-0.209*** **(0.112)**	-0.261 (0.177)
Snacks and ready-meals	-0.144 (0.106)	-0.088 (0.127)	-0.211 (0.132)	**-0.228**** **(0.115)**	-0.116 (0.116)	-0.118 (0.172)
Other control variables as in Table C1						

For straightforward comparisons, results from table C1 are reproduced below:

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.06	24.53	25.51	26.67	28.05	30.48
Log prices (Log(P_j^c) where P_j^c is defined as in Section 4.2.)						
Beverages	-0.019 (0.037)	-0.045* (0.026)	-0.029 (0.028)	-0.007 (0.040)	0.014 (0.052)	0.001 (0.056)
Fruits, Vegetables and Cereals	0.084* (0.048)	0.062** (0.029)	0.075** (0.038)	0.075 (0.055)	0.176*** (0.051)	0.147** (0.070)
Proteins	0.021 (0.045)	-0.007 (0.045)	0.019 (0.040)	0.041 (0.046)	0.108* (0.062)	0.191** (0.089)
Dairies	-0.045 (0.027)	-0.064** (0.029)	-0.030 (0.028)	-0.038 (0.028)	-0.052 (0.033)	-0.064 (0.039)
Fats	-0.144*** (0.051)	-0.100 (0.065)	-0.135** (0.059)	-0.154** (0.060)	-0.217*** (0.069)	-0.284*** (0.092)
Sugar and sweets	-0.062 (0.039)	-0.002 (0.035)	-0.041 (0.030)	-0.056 (0.038)	-0.117** (0.046)	-0.090* (0.050)
Snacks and ready-meals	0.032 (0.062)	0.091 (0.059)	0.004 (0.071)	0.007 (0.075)	0.048 (0.093)	0.043 (0.107)
Other control variables as in Table C1						

Table C7. Alternative results. Prices of functional groups. N=29573, enlarged sample.

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.04	24.52	25.51	26.67	28.07	30.47
Log prices (Log(P_j^c) where P_j^c is defined as in Section 4.2.)						
Mineral water	-0.007 (0.013)	-0.003 (0.014)	-0.014 (0.013)	-0.018 (0.011)	-0.002 (0.010)	0.006 (0.018)
Alcohol	-0.012 (0.017)	**-0.030*** **(0.017)**	**-0.029*** **(0.016)**	-0.008 (0.017)	-0.008 (0.024)	-0.009 (0.029)
Other drinks	-0.024 (0.024)	-0.035 (0.024)	-0.025 (0.023)	**-0.037*** **(0.020)**	-0.029 (0.030)	-0.012 (0.034)
Fruits in brine	0.013 (0.020)	-0.001 (0.016)	0.013 (0.016)	0.015 (0.018)	**0.041**** **(0.020)**	**0.059**** **(0.027)**
Processed Fruits	0.004 (0.016)	-0.019 (0.012)	0.003 (0.010)	0.011 (0.013)	0.001 (0.015)	0.009 (0.027)
Vegetables in brine	0.013 (0.020)	0.001 (0.022)	0.021 (0.021)	0.012 (0.023)	0.029 (0.023)	-0.014 (0.034)
Processed vegetables	-0.026 (0.018)	-0.017 (0.019)	-0.016 (0.021)	-0.018 (0.022)	-0.025 (0.032)	-0.023 (0.033)
Cereals	0.003 (0.034)	0.007 (0.030)	-0.014 (0.034)	0.012 (0.040)	-0.011 (0.049)	-0.055 (0.055)
Meats in brine and eggs	-0.004 (0.031)	0.002 (0.031)	0.012 (0.030)	0.010 (0.034)	0.037 (0.037)	0.062 (0.053)
Sea products in brine	0.008 (0.012)	0.013 (0.010)	0.013 (0.010)	0.010 (0.015)	0.007 (0.014)	**0.029*** **(0.017)**
Processed sea products	0.010 (0.022)	0.016 (0.017)	0.024 (0.019)	0.024 (0.027)	0.037 (0.032)	0.020 (0.038)
Cooked meats	0.026 (0.021)	0.027 (0.025)	0.015 (0.019)	0.023 (0.020)	0.030 (0.030)	0.022 (0.037)
Breaded/fried fishes or meats	-0.025 (0.021)	-0.016 (0.021)	**-0.046*** **(0.024)**	**-0.050***** **(0.017)**	-0.045 (0.028)	-0.036 (0.031)
Yogurts and fresh cheeses	0.026 (0.021)	0.013 (0.020)	0.013 (0.017)	***0.030**** ***(0.016)***	***0.036**** ***(0.020)***	0.027 (0.027)
Cheese	0.055 (0.053)	0.056 (0.053)	0.032 (0.053)	0.066 (0.062)	0.082 (0.065)	0.041 (0.106)
Milk	**-0.022*** **(0.013)**	**-0.020**** **(0.009)**	-0.014 (0.009)	**-0.022*** **(0.013)**	-0.013 (0.016)	**-0.031*** **(0.017)**
Animal fats and margarine	-0.003 (0.016)	-0.008 (0.015)	-0.015 (0.014)	-0.005 (0.017)	-0.005 (0.013)	0.010 (0.022)
Oils	-0.079* (0.045)	-0.039 (0.041)	**-0.062**** **(0.029)**	**-0.069*** **(0.039)**	**-0.132**** **(0.056)**	**-0.141**** **(0.061)**
Sugar and sweets	-0.004 (0.031)	***0.056****** ***(0.015)***	0.016 (0.018)	0.029 (0.019)	-0.045 (0.039)	**-0.100*** **(0.056)**
Pastries and deserts	-0.008 (0.029)	-0.012 (0.026)	-0.022 (0.034)	-0.051 (0.035)	-0.014 (0.032)	0.000 (0.046)
Sweet and fatty snacks	-0.005 (0.036)	-0.017 (0.039)	-0.003 (0.040)	-0.027 (0.050)	-0.031 (0.052)	0.046 (0.067)
Salty and fatty snacks	0.007 (0.028)	0.031 (0.025)	***0.036**** ***(0.020)***	0.037 (0.030)	0.005 (0.032)	-0.004 (0.034)
Ready-meals	0.004 (0.027)	-0.015 (0.028)	-0.023 (0.025)	-0.010 (0.027)	0.032 (0.027)	0.053 (0.037)
Other control variables as in Table C1						

Table C8. Alternative results. Prices of product categories. N=12653, restricted sample.

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.04	24.54	25.51	26.70	28.06	30.48
Log prices (Log(P_j^c) where P_j^c is defined as in Section 4.2.)						
Mineral water	-0.019 (0.029)	0.029 (0.021)	-0.006 (0.025)	-0.012 (0.029)	-0.033 (0.040)	0.002 (0.062)
Alcohol	-0.026 (0.051)	-0.039 (0.044)	0.036 (0.053)	0.034 (0.068)	0.021 (0.076)	-0.040 (0.105)
Other drinks	**-0.151**** **(0.062)**	-0.116 (0.084)	**-0.184***** **(0.067)**	**-0.241***** **(0.079)**	**-0.289***** **(0.103)**	**-0.239*** **(0.124)**
Fruits in brine	0.033 (0.061)	0.106 (0.068)	0.101 (0.063)	0.122 (0.073)	0.088 (0.107)	0.062 (0.156)
Processed Fruits	**0.105**** **(0.041)**	**0.091**** **(0.040)**	**0.108***** **(0.039)**	**0.155***** **(0.041)**	**0.199***** **(0.065)**	**0.196**** **(0.076)**
Vegetables in brine	0.065 (0.052)	0.030 (0.058)	0.036 (0.063)	0.086 (0.072)	**0.156*** **(0.089)**	0.151 (0.109)
Processed vegetables	-0.034 (0.037)	-0.031 (0.043)	-0.025 (0.045)	0.000 (0.046)	-0.040 (0.075)	-0.075 (0.092)
Cereals	-0.128 (0.092)	-0.123 (0.090)	**-0.173**** **(0.083)**	**-0.288***** **(0.100)**	-0.160 (0.167)	0.047 (0.214)
Meats in brine and eggs	0.044 (0.078)	0.154 (0.094)	0.136 (0.090)	**0.175*** **(0.090)**	0.024 (0.098)	0.168 (0.167)
Sea products in brine	-0.055 (0.041)	-0.093* (0.053)	-0.047 (0.051)	-0.082 (0.051)	***-0.094***** ***(0.047)***	-0.097 (0.064)
Processed sea products	**0.106**** **(0.051)**	0.072 (0.062)	**0.142**** **(0.067)**	**0.177**** **(0.077)**	0.110 (0.085)	0.012 (0.125)
Cooked meats	0.006 (0.056)	-0.022 (0.067)	-0.072 (0.072)	-0.001 (0.093)	0.015 (0.064)	-0.081 (0.114)
Breaded/fried fishes or meats	0.036 (0.049)	0.029 (0.049)	0.032 (0.048)	0.009 (0.052)	-0.036 (0.067)	-0.114 (0.101)
Yogurts and fresh cheeses	0.028 (0.052)	0.015 (0.053)	0.007 (0.053)	0.009 (0.044)	0.062 (0.075)	0.075 (0.077)
Cheese	0.146 (0.138)	0.046 (0.136)	0.001 (0.121)	0.208 (0.131)	0.166 (0.218)	-0.119 (0.332)
Milk	-0.021 (0.031)	-0.006 (0.036)	0.001 (0.030)	-0.005 (0.032)	0.001 (0.052)	-0.074 (0.075)
Animal fats and margarine	0.055 (0.037)	0.019 (0.052)	0.017 (0.042)	0.040 (0.044)	***0.093**** ***(0.057)***	0.072 (0.061)
Oils	-0.139 (0.096)	-0.151 (0.121)	-0.160 (0.136)	**-0.227*** **(0.129)**	**-0.346**** **(0.163)**	**-0.290*** **(0.161)**
Sugar and sweets	-0.116 (0.077)	-0.057 (0.086)	-0.123 (0.085)	-0.143 (0.110)	-0.198 (0.131)	-0.192 (0.142)
Pastries and deserts	-0.071 (0.084)	-0.026 (0.111)	-0.105 (0.104)	-0.174 (0.107)	-0.079 (0.163)	-0.078 (0.193)
Sweet and fatty snacks	-0.079 (0.095)	-0.043 (0.127)	-0.066 (0.132)	-0.112 (0.157)	-0.140 (0.179)	-0.177 (0.180)
Salty and fatty snacks	-0.025 (0.080)	0.012 (0.087)	0.006 (0.100)	-0.053 (0.100)	-0.087 (0.109)	0.040 (0.144)
Ready-meals	0.003 (0.075)	-0.028 (0.091)	0.006 (0.106)	0.106 (0.097)	***0.214**** ***(0.112)***	0.190 (0.141)
Other control variables as in Table C1						

Table C9. Sample descriptive statistics, comparisons.

	Restricted sample *(N=12653)*	**Estimation sample *(N=23304)***	**Enlarged sample (N=*29573)***
BMI	25.04 (4.2)	25.06 (4.21)	25.05 (4.21)
LOGINC	9.60 (0.49)	9.56 (0.48)	9.55 (0.47)
DEG1	14.9%	15.2%	14.8%
DEG2	7.0%	7.2%	7.2%
DEG3	31.8%	33.6%	33.5%
DEG4	19.5%	19.8%	20.1%
DEG5	10.1%	9.9%	10.2%
SEXE	45.6%	45.9%	45.8%
AGE	50.6 (14.4)	50.7 (14.3)	50.9 (14.4)
BABYWOMAN	1.5%	1.4%	1.3%
BABYMAN	1.5%	1.4%	1.3%
SINGLE	12.5%	10.7%	11.1%
OTHHHOLD	20.7%	20.6%	20.7%
NBIND	2.96 (1.34)	3.00 (1.35)	2.99 (1.33)
MEALPLANNER	26.5%	25.9%	26.6%
UNIT1	23.9%	30.3%	26.0%
UNIT2	9.5%	8.9%	7.6%
UNIT3	0.4%	4.0%	5.9%
UNIT4	0.0%	3.7%	5.8%
UNIT5	1.3%	4.7%	6.0%
UNIT6	1.3%	6.6%	8.1%
UNIT7	5.0%	4.5%	6.3%
REGION2	8.5%	16.3%	17.4%
REGION3	10.4%	8.5%	7.0%
REGION4	10.7%	9.7%	10.1%
REGION5	16.6%	18.7%	17.1%
REGION6	0.2%	6.7%	10.6%
REGION7	15.8%	13.6%	12.6%
REGION8	9.0%	9.3%	10.9%
YR2003	27.5%	27.2%	25.9%
YR2004	25.2%	24.9%	25.7%
YR2005	20.9%	22.0%	23.2%

Table C10. Alternative price definition. N=23304, estimation sample.

Moment	**Mean**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
IMC value at the moment	25.06	24.53	25.51	26.67	28.05	30.48
Log prices (Log(P_{jk}^{c}) where P_{jk}^{c} is defined as in Section 4.2.)						
Mineral water	-0.002 (0.017)	0.013 (0.012)	-0.011 (0.013)	-0.011 (0.016)	0.000 (0.018)	-0.002 (0.028)
Alcohol	0.009 (0.019)	-0.008 (0.023)	0.007 (0.022)	0.028 (0.025)	**0.052*** **(0.031)**	**0.051**** **(0.021)**
Other drinks	-0.013 (0.031)	-0.005 (0.029)	0.023 (0.032)	-0.008 (0.036)	-0.051 (0.042)	-0.023 (0.040)
Fruits in brine	0.027 (0.022)	0.006 (0.025)	0.001 (0.025)	0.024 (0.024)	0.015 (0.033)	0.039 (0.039)
Processed Fruits	0.025 (0.022)	-0.010 (0.023)	0.008 (0.022)	**0.043*** **(0.026)**	0.039 (0.030)	0.040 (0.037)
Vegetables in brine	-0.015 (0.025)	-0.014 (0.022)	-0.011 (0.022)	-0.029 (0.027)	-0.021 (0.038)	-0.035 (0.045)
Processed vegetables	**-0.040*** **(0.020)**	**-0.032*** **(0.019)**	-0.039 (0.025)	-0.031 (0.022)	**-0.042*** **(0.024)**	-0.039 (0.029)
Cereals	0.017 (0.035)	-0.017 (0.028)	-0.003 (0.026)	0.024 (0.025)	0.044 (0.039)	0.019 (0.059)
Meats in brine and eggs	-0.031 (0.019)	-0.049* (0.027)	**-0.041**** **(0.021)**	-0.016 (0.026)	0.001 (0.035)	-0.005 (0.037)
Sea products in brine	0.036* (0.018)	0.042* (0.021)	0.034 (0.021)	0.022 (0.028)	0.036 (0.030)	**0.102***** **(0.036)**
Processed sea products	0.002 (0.027)	0.025 (0.025)	0.023 (0.024)	0.023 (0.027)	0.005 (0.023)	-0.066 (0.044)
Cooked meats	-0.025 (0.028)	-0.018 (0.036)	-0.034 (0.035)	-0.062 (0.049)	-0.064 (0.067)	-0.041 (0.056)
Breaded/fried fishes or meats	-0.040 (0.027)	-0.028 (0.021)	**-0.057***** **(0.019)**	**-0.069**** **(0.031)**	**-0.095***** **(0.030)**	**-0.072*** **(0.043)**
Yogurts and fresh cheeses	**0.175**** **(0.085)**	0.063 (0.093)	0.131 (0.084)	**0.239*** **(0.144)**	0.204 (0.161)	0.222 (0.175)
Cheese	-0.042 (0.060)	0.001 (0.054)	-0.053 (0.050)	-0.069 (0.047)	-0.035 (0.070)	-0.042 (0.089)
Milk	**-0.225***** **(0.086)**	-0.128 (0.093)	**-0.166**** **(0.082)**	**-0.259*** **(0.137)**	-0.239 (0.153)	-0.280 (0.179)
Animal fats and margarine	0.018 (0.022)	-0.005 (0.025)	-0.003 (0.023)	0.007 (0.027)	0.016 (0.029)	0.018 (0.033)
Oils	-0.066 (0.046)	-0.041 (0.037)	**-0.063*** **(0.033)**	-0.065 (0.057)	-0.059 (0.057)	-0.117 (0.078)
Sugar and sweets	-0.005 (0.021)	0.017 (0.019)	0.016 (0.018)	0.016 (0.023)	0.033 (0.027)	-0.027 (0.023)
Pastries and deserts	-0.013 (0.038)	0.042 (0.037)	0.013 (0.040)	-0.034 (0.044)	0.019 (0.043)	0.059 (0.055)
Sweet and fatty snacks	0.010 (0.035)	0.016 (0.021)	0.026 (0.024)	**0.068**** **(0.028)**	0.030 (0.039)	0.027 (0.050)
Salty and fatty snacks	0.011 (0.034)	0.041 (0.044)	0.027 (0.037)	-0.005 (0.051)	0.029 (0.051)	-0.021 (0.046)
Ready-meals	0.012 (0.026)	-0.022 (0.026)	-0.018 (0.025)	-0.015 (0.025)	-0.017 (0.028)	0.041 (0.039)
Other control variables as in Table C1						