Tommi Härkänen, Kaisa Kotakorpi, Pirjo Pietinen, Jukka Pirttilä, Heli Reinivuo, and Ilpo Suoniemi

The Welfare Effects of Health-Based Food Tax Policy

Aboa Centre for Economics
Discussion Paper No. 81
Turku 2012

The Aboa Centre for Economics is a joint initiative of the economics departments of the University of Turku and Åbo Akademi University.

Copyright © Author(s)

ISSN 1796-3133

Printed in Uniprint
Turku 2012

Tommi Härkänen, Kaisa Kotakorpi, Pirjo Pietinen, Jukka Pirttilä, Heli Reinivuo, and Ilpo Suoniemi

The Welfare Effects of Health-Based Food Tax Policy

Aboa Centre for Economics
Discussion Paper No. 81
December 2012

ABSTRACT

This paper examines the effects of health-oriented food tax reforms on the distribution of tax payments, food demand and health outcomes. Unlike earlier work, we also take into account the uncertainty related to both demand estimation and health estimates and report the confidence intervals for the overall health effects instead of only point estimates. Taxation of sugar leads to a statistically significant reduction in both the incidence of type 2 diabetes and coronary heart disease. The health effects appear to be most pronounced for low-income individuals, and the reforms may therefore reduce health inequality. This effect undermines the traditional regressivity argument against the heavy taxation of unhealthy food.

JEL Classification: H200, I140, I180

Keywords: Sin taxes, food taxation, tax incidence, commodity demand, obesity, diabetes, coronary heart disease, bootstrapping

Contact information

Tommi Härkänen, Pirjo Pietinen, and Heli Reinivuo

National Institute for Health and Welfare

Kaisa Kotakorpi (corresponding author)

Department of Economics

Turku School of Economics

20014 University of Turku

Tel: +358-2-3339339.

E-mail: kaisa.kotakorpi@utu.fi

Jukka Pirttilä

University of Tampere and CESifo

Ilpo Suoniemi

Labour Institute for Economic Research

Acknowledgements

We are grateful to participants at the CESifo Area Conference on Public Sector Economics 2011, 8th European Conference on Health Economics, 67th Congress of the International Institute of Public Finance and 5th Nordic Conference on Behavioral and Experimental Economics, as well as numerous seminar participants for useful comments. Jari Hännikäinen and Jose Lahtinen provided outstanding research assistance. Funding from the Yrjö Jahnsson Foundation is gratefully acknowledged. Kotakorpi acknowledges financial support from the Academy of Finland.

1. Introduction

Obesity is one of the most severe threats to public health in developed countries.[1] Since obesity is a major determinant of a number of illnesses, including coronary heart disease (CHD) and, especially, type 2 diabetes (T2D), governments have become increasingly interested in the possibility of using tax policy to guide consumers' dietary choices.[2]

The traditional view in economics has been that taxation can have a corrective role only if consumption causes negative externalities. However, recent literature on behavioural economics has shown that consumers sometimes make sub-optimal decisions even from the point of view of their own welfare. In particular, consumers often behave myopically, and therefore consume too much of goods with delayed negative effects - excess consumption of unhealthy food and the resulting rise in obesity rates is an important example of this type of behaviour (see e.g. O'Donoghue and Rabin 2006). Taxation can potentially be used to counteract this tendency for over-consumption, and can, therefore, have corrective effects even in the absence of externalities.[3]

The use of tax policy tools in influencing diet choices has attracted a large amount of recent research. One part of the earlier empirical literature on health-based differentiation in food taxation has concentrated on estimating the impact of price changes on the demand for certain food categories such as soft drinks (Fletcher et al 2010, Dharmasena and Capps 2011, Gustavsen and Rickerstsen 2011), different types of butter and margarine (Griffith et al. 2010), dairy products (Chouinard et al. 2007) or grain products (Nordström and Thunström 2009, 2011), often without a full-scale assessment of the potential health impacts. Another strand of earlier work has examined broader models of commodity demand (see e.g. Irz 2010, Allais et al. 2010, Smed et al. 2007), again without a full analysis of the health issue. Finally, some papers concentrate on detailed analysis of the health effects, but this literature typically uses existing estimates on commodity demand or just assumed cross-price elasticities (Mytton et al 2007; Nnoaham et al 2009).[4] One exception is the paper by Tiffin and Arnoult (2011) that offers both a full commodity demand analysis and also examines the health effects of a fat

[1] See Brunello et al (2009) for a recent survey on this issue.
[2] Various types of health-motivated food taxes have been discussed and/or implemented, to name a few countries, in the US, the UK, France, Denmark and Finland.
[3] Relatedly, Lusk and Schroeter (2012) argue that policies such as the soda tax are hard to justify unless traditional rationality assumptions are relaxed. On the other hand, even if one dislikes paternalism in general, heavy taxation of unhealthy food may be justified by externalities arising through higher public health care expenditures, as well as by the need to protect children from the long-term consequences of their parents' unhealthy lifestyles (Brunello et al. 2009).
[4] Powell and Chaloupka (2009) provide a review of articles studying the link between food prices and obesity. Two of the studies reviewed, Miljkovic and Nganje (2008) and Miljkovic et al.(2008) consider the effects of sugar prices.

tax. To the best of our knowledge, all earlier work has concentrated on estimating the mean health impacts of potential food policy reforms without examining the statistical significance of the response. Given that both the commodity demand estimates and the association between diet changes and health outcomes involve some uncertainty, taking into account both sources of uncertainty is potentially important.

A general worry raised in previous literature is that food tax reforms that involve price increases on unhealthy types of food and subsidies for healthier food items would be heavily regressive (see e.g. Allais et al 2010). However, if low-income individuals have more elastic demand and/or higher levels of consumption of unhealthy food and/or poorer health to start with, the beneficial health effects of the high taxation of unhealthy food would also be greatest for them. The regressivity argument against the heavy taxation of (unhealthy) food may therefore be overturned when not only the monetary cost but also the beneficial health effects of taxation are taken into account (Kotakorpi 2008). While Tiffin and Arnoult (2011) do not examine the issue in detail, they also point out that a possible widening of inequality in the income dimension may thus be counteracted by narrower inequality in the health dimension.[5] Nnoaham et al. (2009) study income group differences in the health and economic impacts of targeted food taxes and subsidies, but find no clear pattern for the health effects across income groups. However, they assume that price elasticities do not differ between income groups, thus assuming away a key channel through which different income groups may be differently affected by tax changes.

This paper provides an example of how to conduct a comprehensive analysis of health-based tax policy, including both an estimation of a complete food demand system and a simulation of the health consequences of changes in the consumption of different kinds of food, accounting for the uncertainty inherent in each step of the analysis. The paper is based on cross-disciplinary research by economists and nutrition specialists. We use household-level budget share data from the Finnish Household Budget surveys (1995, 1998, 2001 and 2006) to estimate demand elasticities for different categories of food, using a quadratic extension of the Almost Ideal Demand System (QAIDS) drawing on Banks et al. (1997).[6] Second, we use these elasticity estimates to assess the effects of health-oriented tax reforms on the demand of different food categories. We consider two types of tax reforms: an excise tax on sugar that leads to a price increase for all foods containing (added) sugar; and (ii) a reduction in

[5] See Gruber and Köszegi (2004) for an analysis of the incidence of sin taxes in the context of cigarette taxation.
[6] Irz (2010) also examines food demand using Finnish data. His main point is methodological: he uses macro-level data and explicitly models the link between composite demand and physical quantities, which leads to a novel way to estimate nutrient elasticities. He also simulates the effects of tax changes, and we discuss below some of the differences in our results to his findings.

the VAT rates for fresh fish, fruit and vegetables. Third, we combine detailed data on the nutrient content of different foods and the Health 2000 Survey (Aromaa and Koskinen, 2004, Männistö et al. 2008), which represents the food intake in the Finnish population, to calculate the corresponding changes in the intake of nutrients and energy. Fourth, the implied changes in the incidence of obesity and overweight and the most important overweight-related diseases (CHD and T2D) are then calculated using the results of meta-analyses reported in the literature. We also briefly discuss the possible cost savings for the public health system from tax policy changes.

This study contributes to the literature in three main ways. First, a key element that distinguishes our paper from the earlier literature is that we fully account for the sources of uncertainty in the four steps of the analysis described in the previous paragraph, so that we are able to obtain standard errors and confidence intervals for the overall health effects of the tax reforms that we consider. What is typically done in earlier literature is that point estimates of demand changes (derived from demand elasticities) are combined with point estimates of health impacts of those demand changes, to obtain an estimate of the health effects of tax changes. (Mytton et al. 2007, Nnoaham et al. 2009, Tiffin and Arnoult 2011). In previous studies, confidence intervals of these final health effects have not been reported.[7] It is important to note that signifigance in each independent stage of the analysis is a necessary, but not a sufficient condition for joint significance.[8] That is, even if the demand response caused by price changes, as well as the change in disease incidence caused by a change in demand are both statistically significant, the overall health effect is not necessarily so. In just about any other strand of econometric work, reporting standard errors of estimates is standard practice, and there is no need for this particular area of research to deviate from this standard. Our study provides an example where the uncertainty involved in each step of the analysis is taken into account to obtain standard errors for the final health effects.

Our second contribution is that our main interest is in a general sugar tax, the impacts of which have received less attention in the earlier work than for example fat taxes or more narrowly targeted taxes on sugar-sweetened beverages have. To our knowledge, ours is the first paper providing a

[7] Nnoaham et al. (2009) provide estimates for a ”worst case” and ”best case” scenario of outcomes associated with each tax reform that they consider.

[8] To see this consider a simplified case where joint effect is estimated as a product of statistically independent and unbiased estimators, $\hat{f}\hat{a}$, with estimators for their variance. Using $\mathrm{Var}(\hat{f}\hat{a}) = \mathrm{Var}(\hat{f})\mathrm{Var}(\hat{a}) + \left(E\hat{f}\right)^2\mathrm{Var}(\hat{a}) + \left(E\hat{a}\right)^2\mathrm{Var}(\hat{f})$ gives ”t-values” $\frac{1}{t^2_{\hat{f}\hat{a}}} = \frac{\mathrm{Var}(\hat{f}\hat{a})}{\left(E\hat{f}\right)^2\left(E\hat{a}\right)^2} = \frac{1}{t^2_{\hat{f}}}\frac{1}{t^2_{\hat{a}}} + \frac{1}{t^2_{\hat{f}}} + \frac{1}{t^2_{\hat{a}}}$. Therefore, $t^2_{\hat{f}\hat{a}} > \alpha \Rightarrow \min\left\{t^2_{\hat{f}}, t^2_{\hat{a}}\right\} > \alpha$.

comprehensive analysis of the health effects of an excise tax on sugar, combining demand estimation with a simulation of the health effects of tax reform.

Third, we pay particular attention to the way in which the effects of food taxation are distributed between population groups by examining both the monetary incidence of taxation as well as potential heterogeneity in health outcomes. In analysing differences in health outcomes across income groups, we take into account both heterogeneous responses to tax policy, as well as differences in prior eating habits and health status (body weight) across income groups.[9]

We find statistically significant effects of both the sugar tax as well as the VAT cut on fresh fish, fruit and vegetables on health outcomes. The sugar tax leads to a reduction in the demand of sugary products, which reduces calorie intake and weight. The associated weight increase lead to considerable lowering of the incidence of T2D, since this disease is strongly associated with overweight. The sugar tax also reduces the incidence of CHD, but these impacts are smaller as the magnitude of the link between weight and heart disease is smaller. Lower VAT rates on fruit, vegetables and fish lead to reduction in cardiovascular disease incidence via increased intake of beneficial micronutrients. This type of reform might also have indirect effects through changes in energy intake, but we find these effects to be insignificant.

The elasticity of demand of sugary products is estimated to be high (from 2 to 2.5); a result which seems to hold in our data irrespective of the actual estimation methods (system estimation, single equation IV or OLS). Nevertheless, it should be noted that our results are not solely driven by this one point estimate, as a major part of the effects that we find is e.g. due to the strong association between over-weight and the incidence of T2D. Therefore even a much lower elasticity estimate would yield sizeable health benefits. And the general main lesson of our paper – that is essential to also calculate and report standard errors of health effects – remains valid even if this estimate was smaller.

Turning to the results concerning the question of how the effects of health-based food tax differentiation vary between population groups, the direct monetary incidence of the reforms that we have considered appears to be mildly regressive. However, even though our income-group specific estimation results are rather imprecise, they suggest that the price elasticities for sugary products as well as for fish are higher among individuals with a low socioeconomic status. We also find some tentative evidence that the overall health effects, which take into account differences in elasticities as

[9] Gustavsen and Rickertsen (2011) use quantile regression analysis and allow changes in demand and body weight in response to a tax on sugar-sweetened carbonated soft-drinks to differ among light drinkers and heavy users. However, there is no discussion of how these differences in behaviour relate to differences in income.

well as original consumption patterns, are also highest for them. Since it is well-known that overweight and the associated diseases are more prevalent among these groups, health-based food taxation can be an effective instrument for reducing health inequality. Interestingly, we also find that benefits from the sugar tax are more pronounced for women than for men. This finding has some significance, since earlier studies have shown that the adverse impact of both T2D and CHD may be greater for women (Forssas et al 2010).

The paper proceeds by first discussing, in Section 2, commodity demand estimation methods and the corresponding results. Section 3 introduces the tax reforms that we consider. Section 4 describes the methods for assessing the health impacts and their confidence intervals. Section 5 concludes.

2. Demand system estimation

2.1 Data and descriptive analysis

To estimate the food demand system, we use repeated cross sections of the Household Budget Survey of Statistics Finland from four years (1995-6, 1998, 2001, 2006). The sample size varies somewhat from year to year, with approximately 4000-5000 households in each wave. The number of households in our final estimations is around 17 000. The households keep a diary of all their expenditure over a two-week period. Consumption expenditure is classified according to the national COICO-HBS classification (around 900 headings) that has 12 main categories of consumption; we concentrate on food expenditure (category 1).

The consumption data are combined with independent price information from consumer price index data, collected by Statistics Finland. The list of available prices closely matches the food categories in the Household Budget Survey data set. The prices are measured monthly, and as we have information on the date of the budget survey for the households in the data, we can match households with month-specific price data. The price variation used to estimate commodity demand stems therefore from cross-sectional and yearly changes in the relative prices of various types of foodstuff.

We first present some descriptive statistics of food demand. Table 2.1 below shows how consumption of some food categories depends on the educational background of the household. As expected, there are large differences in the eating habits so that the expenditure share of fish and fruit and vegetables are greatest in highly-educated households, whereas households with a basic educational level have a higher share of fat purchases.

There are also similar demographic differences in food consumption with respect to the income level of the households. This can be seen from the Engel curve figures below, which depict the share of the overall food expenditure for fish, fruit and vegetables, sugar and sweets and fat. These Engel curves (Figures 2.1, 2.2, 2.3 and 2.4) are drawn for a particular type of family (two-parent households with children) – to obtain a reliable comparison – using non-parametric techniques (quadratic Kernel estimation). The expenditure share of fish as well as fruit and vegetables appears to increase moderately with income, and the expenditure share of fat decreases. For the expenditure share of sugar and sweets there is no monotonic pattern.

2.2 Regression analysis

We follow Deaton (1985), Blundell et al. (1993) and Banks et al. (1997) and estimate a quadratic version of the almost ideal demand system (QAIDS) for different categories of food and drinks consumption. The food categories used in the estimation are bread and cereals, meat products, fish, milk products, fats, fruit and vegetables, and sugar, sweets and sweet drinks. Together with the rest of consumption (which covers all other consumption goods and to which we have also allocated small food items such as coffee and tea that do not contain energy), this forms a demand system of eight categories. Since we aim to estimate a complete demand system, the food categories to be analysed need to be kept at a broad level.

The system is estimated using three-stage least squares. The estimated equations are of the following type:

$$w_i^h = \alpha_i + X^h \beta_i + \sum_j \gamma_{ij} \ln p_j^h + \delta_i m^h + \phi_i (m^h)^2 + e_i^h ,$$

where w_i^h refers to the budget share of food category i for household h, which is explained by household-specific prices ($\ln p_i^h$), household real expenditure (m^h) and its square. The model also includes a set of control variables, X^h. The control variables include the following indicator variables: the socioeconomic background of the household (10 categories), the size of the household, the number of children of different ages, the area code (4 categories), the sex of persons in single-person households, the mean age of the adults in the household (5 categories) and the season of the year.

Expenditure is measured in real terms: the expenditure variable used in the estimations is $m^h = \ln M^h / n^h - \ln a(p)^h$, where M denotes the nominal outlays of the household, n refers to the number of OECD equivalent consumption units, and $\ln a(p)^h$ is a household-specific price index approximated with the Stone index, $\sum_i w_i^h \ln p_i^h$.

Using the standard procedure in demand analysis, we instrument for the endogenous overall expenditure and its square by using household income and a quadratic household income term as instruments. One of the benefits of structural consumption analysis is that one can impose the restrictions set by consumer optimisation on the estimates, and therefore we also set the following restrictions: adding-up (the sum of different types of expenditure must equal the overall expenditure), zero-degree homogeneity (multiplying all prices and total expenditure with a constant does not affect the choice set and demand) and symmetry (the cross-price elasticities of compensated demand are symmetric).

The compensated price elasticities, $\varepsilon_{i,j}$, in this model are given by $\varepsilon_{i,j} = -1 + \overline{w}_j + \gamma_{i,j} / \overline{w}_i$ if i=j and $\varepsilon_{i,j} = \overline{w}_j + \gamma_{i,j} / \overline{w}_i$ otherwise. Here, $\overline{w}_i$ refers to the budget share of market demand, which is a weighted average of individual budget shares, with survey weights and share of the individual demand from overall consumption of good i used as weights. The expenditure elasticity is given by $\eta_i = 1 + (\delta_i + 2\phi_i \overline{m}) / \overline{w}_i$, where $\overline{m}$ refers to weighted mean expenditure (with similar weights as above). The uncompensated price elasticities can be calculated using the Slutsky equation $\tilde{\varepsilon}_{i,j} = \varepsilon_{i,j} - \eta_i \overline{w}_j$. Since the elasticities are functions of many estimated parameters, we use both bootstrapping and the delta method to calculate the standard errors of the elasticities.[10]

[10] We mainly report below bootstrapped standard errors (with 200 repetitions). The standard errors derived by the delta method are very similar but somewhat smaller.

2.3 Regression results

Table 2.2 presents the compensated price elasticities for the 8X8 demand system. Most of the own-price elasticities seem fairly reasonable and we will discuss them in more detail below when presenting our final specification. However, the elasticity of demand for fat is very imprecisely estimated. It is rather common for price data to include common trends and suffer from near multicollinearity. Therefore the price parameters tend to be estimated quite imprecisely in complete systems of demand equations. However, in our case the most likely reason for the imprecise estimation of the fat demand elasticity is associated with the standard practice of using expenditure data on food categories (e.g. fat) aggregated over individual food items (e.g. butter, different types of margarine) for demand estimation. That is, the consumption survey data only measures expenditure on fat, but it cannot account for the quality change within fat consumption: many consumers have moved, for example, from cheap margarine to more expensive varieties with a greater share of unsaturated fats. This can give rise to biased price estimates. A similar phenomenon can have taken place in the consumption of dairy products, where, at this aggregate level, quality improvements that are not observable for the econometrician may drive the price estimates upwards.

For these reasons, we proceed to a smaller, 6X6 demand system, where fat and dairy products are allocated to the final, 'other' category. The estimates of this system are presented in Table 2.3. Moving the two food categories to the omitted, 'other', category does not greatly affect the elasticity estimates of the remaining categories. Hence, we decided to base the simulations analysis on this reduced modelling of food demand.

The expenditure elasticities, expressed in Table 2.4, are very reasonable.[11] All the food items appear to be necessities, with fish products having the greatest expenditure elasticity. The squared terms of expenditure in the regression results is statistically significant for meat, sugar and sweets and other consumption, confirming the need to use the QAIDS rather than AIDS framework. Finally, the uncompensated price elasticities, which will be the basis for our simulation analysis, are presented in Table 2.5. These are very close to the compensated elasticities, since the expenditure elasticities that are added to the compensated elasticities to obtain the uncompensated elasticities are multiplied with the expenditure shares (see section 2.2); and as they are measured out of overall outlays, they are small for single food categories. With the exception of meat products, all the estimated own-price elasticities

[11] The expenditure elasticity of other consumption is 1.052. Because of its large expenditure share, the adding-up constraint that a weighted mean of expenditure elasticities sum to unity is satisfied.

are negative and statistically significant. Fish products and sugar and sweets, especially, appear to be quite price-elastic. This suggests that tax reforms targeted to affect the consumption of these items have potentially large effects on consumption patterns. Many of the cross-price elasticities are, as we expected, statistically insignificant.

We have also examined the robustness of this price elasticity by estimating single-equation models for sugar demand (both with and without instrumenting for total expenditure), where the cross-equations restrictions are not present and cannot drive the results, and by estimating the system as a seemingly unrelated model. All these different modelling techniques yield quantitatively large and statistically significant own-price elasticities for sugary products in our model.

Finally, it is of interest to examine whether the elasticities differ with respect to the households' socioeconomic backgrounds. To study this possibility, we estimated the system separately for three different income classes, where the division has been made on the basis of household disposable income (where household income is adjusted to take into account household size using the so-called modified OECD equivalence scales). The estimated own-price elasticities from these models are presented in Table 2.6. They convey the plausible message that demand for many food categories appears to be more price-elastic among low-income households. This holds Yes, for example, for fish, but most notably for sugary products. Some of the health effects simulations below will be based on these, income-dependent, elasticities.

One final note on the estimation results is in order: Our method of calculating elasticities, which is standard in the literature, is based on observing the value of food purchases, not actual physical quantities consumed. Quality changes may therefore affect the estimation results, as discussed above. The direction of the possible bias is, however, not clear a priori: quality increases that lead to both increased demand and a higher price would cause an upward bias (toward zero) on the estimates. On the other hand, if consumers respond to a price increase by substituting towards cheaper, lower quality varieties within the same food category, this would cause a downward bias (away from zero) on the estimates. [12] In our case, this latter type of bias is however countered by the fact that we consider a unit

[12] Concentrating on this latter type of bias, Irz (2010) obtains smaller elasticities (around -0.5) for different types of sugary products, using a very different approach including multi-stage budgeting. While our actual point estimates need to be interpreted cautiously, it should be noted that the approach taken in Irz (2010) has its own problems. He uses macro-level data and it is well-known (see e.g. Blundell et al 1993) that macro data can lead to biased estimates, especially regarding income effects. In particular, the possibility of a commodity changing its status from a relative luxury to a necessity as the income level increases is lost when aggregate data is used, a case pertaining to our sub-group Sugar & Sweets (Figure 2.4).

tax on sugar: the tax burden is relatively heavier on cheap foods, and if any substitution occurs within food categories, this should therefore be away from cheap varieties.

3. The tax reforms

As mentioned in the introduction, we analyse the following tax reforms:

- Sugar tax: a tax of one euro per kilogram of added sugar applied to each food category based on its sugar content.
- Cut in VAT: Abolition of the current VAT on fresh fruit, vegetables and fish
- Combined reform: both of the reforms above.

A one € tax per added kilogram of sugar would raise the consumer price of the foods in the sugar and sweets category by 9.2 per cent and the price of the foods in the bread category by 1.7 per cent (since this category includes sweet pastry). This can be calculated, as we have information about both the purchases in euros and the purchased quantities for the latest consumption survey, 2006, as well as about the average nutrition content of the food categories listed in the consumption survey. The current VAT on all foodstuffs is 13%, and its abolition would lead to an 11.5% reduction in the consumer price of fruit, vegetables and fish. In the above calculations, we have assumed for convenience that the tax changes are fully passed on to prices.[13]

The impact of these tax reforms on the food expenditure of households of different socioeconomic backgrounds is illustrated in Tables 3.1 and 3.2. In line with traditional analysis of the distributional extent of taxation, these impacts are shown here without behavioural responses. These tables confirm the intuition that those households with a lower educational background and/or a lower income level benefit relatively less financially from tax cuts on healthy food. Thus, health-motivated food tax reforms appear to be mildly regressive if one only considers the monetary incidence (not the health benefits) of the taxes.

In addition, correction of aggregation bias due to the functional form used in Irz (2010) would require inclusion of some distributional measures (see e.g. Blundell et al 1993).

[13] In the vast majority of this literature full pass-through is assumed. An exception is Griffith et al. (2010), who account for producer reactions to tax changes. In their empirical application, there is either less than or more than full pass-through of tax changes onto prices, depending on the product.

The impact of the tax changes on consumption demand can be calculated by multiplying the uncompensated demand matrix with a vector containing the percentage changes in consumer prices. The demand changes are reported in Table 3.3.

4. Calculating the health effects of the tax reforms

4.1 Methods

The health benefit calculations are based on nutrition-epidemiological meta-analyses on the linkages between the nutrition content of different foods, energy intake, weight gain, and the incidence of two overweight-related illnesses, T2D and CHD. We consider both changes in illness incidence that stem from weight changes, as well as effects that stem from changes in nutritional intake (holding weight constant).

We utilise detailed data on the nutrient intake of Finnish individuals, derived from the Health 2000 Survey of the National Institute of Health and Welfare.[14] The survey was a representative survey of 10,000 individuals with information on different aspects of health (including their body mass index (BMI)) and detailed information on their eating habits. The data on eating habits are then combined with information on the average nutrition content of different foods, also based on data at the National Institute for Health and Welfare (Food Composition Database Fineli[R], www.fineli.fi).

In more detail, the procedure that we use to calculate the health effects is the following. First, the individual level data from the Health 2000 survey is used to evaluate the corresponding change in energy intake due to changes in food consumption. The food frequency questionnaires and the corresponding average portion sizes yield information on food intake as grams per day. We then calculate the changes in food intake at the individual level, using the relative demand changes reported in Table 3.3, and on energy intake, using the average energy contents of different types of food.

Second, the new weight and the corresponding new BMI are then calculated based on the old weight and the estimated change in weight. The effect of changes in energy intake on body weight was

[14] For more information on this survey, see http://www.terveys2000.fi/indexe.html.

estimated in Dall et al. (2009). During a long follow-up, a daily reduction of 20 kcal for men and 12 kcal for women was associated with a one kilogram reduction in body weight.

Third, higher body weight is associated with increased incidence of type 2 diabetes and coronary heart disease: for diabetes, the risk ratio (RR) of an obese person (BMI >30) compared with a person with normal weight is 7.2 (Abdullah et al. 2010). For coronary heart disease, the RR is 1.8 (Bogers et al 2007). As the risk ratios in the studies that we have used were reported for a categorical BMI classification with $S = 4$ categories based on the threshold values 25, 30 and 35, we calculate the old (O) and new (N) prevalence figures, p_s^O and p_s^N, of each BMI category $s = 1,...,S$ before and after a particular tax reform.

The effects of the change in the distribution of BMI are assessed using the population attributable risk (PAR) statistic. The PAR combines the individual-level hazardousness of the risk factor, given by the risk ratio, and the population-level prevalence of the risk factor. We apply a version of the PAR developed for a comparison of two different populations (Spiegelman et al. 2007, Laaksonen 2005); in our case the populations before and after the reform:

$$(1) \qquad PAR_{2C} = \frac{\sum_{s=1}^{S} p_s^O RR_s - \sum_{s=1}^{S} p_s^N RR_s}{\sum_{s=1}^{S} p_s^O RR_s}$$

The PAR_{2C} demonstrates the potential change in disease incidence, if the distribution of the risk factor was transformed from p_s^O and p_s^N, $s = 1,...,S$ and individuals moving from a high risk (high BMI) category to a low risk (low BMI) category would become similar to individuals who are already in the low risk category.

A key benefit of carrying out both demand estimation and a simulation of the health effects of tax reform in one paper is that we are able to account for the uncertainty involved in all stages of the analysis, and combine these to obtain confidence intervals for the overall health effects that we report below. There are several sources of uncertainty in the estimates, which generally have not been combined in previous studies.[15] We account for the three sources of uncertainty present in our

[15] In addition to the previous literature on health-based food taxation that we cite in the introduction, papers in the epidemiological literature, e.g. He et al. (2001) and Schnohr et al. (2002), appear to have incorporated only the variances of the RR estimates and to have ignored the uncertainty in the prevalence estimates in estimating the PAR.

estimates of the health effects of food tax reform. First, the uncertainty involved in the demand system estimation is embodied in the standard errors of the demand changes reported in Table 3.3. Second, the estimated covariance matrices of the RR estimates, which we obtained from the literature, reflect the uncertainty in the association between overweight, and the health outcomes T2D and CHD. Third, the estimated BMI distributions are based on the Health 2000 survey, which involved a complex sampling design (Laiho et al. 2008), and are subject to sampling uncertainty. The effects of missing data and the oversampling of people aged 80 or over were accounted for using post-stratification weights (Djerf et al. 2008). We account for these sources of uncertainty using the one-stage bootstrap method described by Ogden and Tarpey (2006), which can handle externally estimated parameters. The complex sampling design is also accounted for in the bootstrap algorithm (Korn and Graubard 1999). The procedure for obtaining the standard errors for the health effect estimates is described in more detail in an appendix.

When calculating the standard errors for the health effect estimates, we also demonstrate the implications of not taking into account all the three sources of uncertainty mentioned above: we leave one or two of them out at a time by using the corresponding point estimates instead of the bootstrapped value, and then calculating the confidence intervals using a similar procedure as above; the alterations to the procedure in each case are also described in the appendix.

In addition to considering the effects of changes in BMI on disease incidence, we also take into account the direct impact of the nutritional content of food consumption on the incidence of CHD. These effects materialize even if body weight remains unchanged. On the basis of the meta analysis of Mozaffarian and Rimm (2006), the intake of fish fat is associated with a reduced risk of death due to CHD: Eating on average 29 grams of salmon or other fatty fish or 48 g of less fatty fish per day, from which one obtains 250 mg of EPA and DHA fatty acids per day, reduces the risk of coronary death by 36% compared with individuals whose intake of these fatty acids is zero mg per day. On the other hand, a daily intake of fish fats exceeding this level is not associated with any additional reduction in risk. Similar positive effects can also arise from a larger intake of fruit and vegetables. According to the meta-analysis of Dauchet et al. (2006), one additional portion (106 grams) of vegetables and fruit reduces the risk of cardiovascular mortality by 26%, and the risk of CHD by 4% (fruit and vegetable intake) and 7% (fruit intake). Again, we use these coefficients of CHD incidence together with the estimated demand changes to obtain estimates of the health effects of the tax reforms that we consider.

4.2 Results regarding a tax on sugar

We first consider the impacts of the sugar tax on body weight, the incidence of T2D and CHD. There are large movements towards lower BMI classes as a response to the sugar tax (Table 4.1).

The average reduction in body weight is 3.2 kilograms (Table 4.2). The effects appear larger for females than males. Further, if income-dependent elasticities are used, the weight loss is higher for individuals in low-income households than for those living in households with a higher disposable income. As individuals with lower incomes respond more to changes in prices, the health benefits of a sugar tax are greatest for them. It should be noted, however, that the income-dependent elasticities are rather imprecisely estimated and the results based on these should therefore be regarded with some caution. Indeed, when income-specific elasticities are used, the reduction in body weight appears to be significant only for low-income individuals.

Since T2D is strongly associated with weight changes, these weight reductions can lead to sizable reductions in diabetes incidence (Table 4.3). The point estimate of the reduction on incidence is 13.4%, and again, in line with the pattern on weight changes, the effects are larger for females and those with a low-income background.[16] Since the CHD risk ratios increase less rapidly with body weight, the associated reduction in CHD incidence is smaller (3.0% on average, see Table 4.4).

4.3 Results regarding other tax changes

Consider next the impacts of VAT cuts on CHD. There are potentially two conflicting effects: on the one hand, increased consumption of fish, fruit and vegetables tends to increase body weight. Since most of the cross-price elasticities in our analysis were not significant and some are close to zero in any case, according to our results people would not reduce the consumption of other types of food when they increase the consumption of fish, fruit and vegetables.[17] Using the same kind of procedure

[16] Notice that the calculations are based on average elasticities for different sexes and educational groups. Differences across these groups, therefore, only arise from differences in eating habits. However, income-dependent elasticities are used for the breakdown of health effects according to household income. These changes reflect both different price elasticities and differences in eating habits.

[17] It may be the case that the aggregate reactions hide simultaneous quality changes (e.g. if fish becomes cheaper, people may respond by buying more expensive and perhaps more healthy types of meat, thereby not reducing the overall amount of money allocated to meat).

as in the case of the sugar tax, VAT cuts could lead to a 0.9% increase in the incidence of CHD via weight gain, but this increase is not significant (95% CI -0.8, 2.8).

On the other hand, the beneficial nutrition content of fish, fruit and vegetables helps prevent deaths resulting from CHD. In the Health 2000 survey, the average daily intake of fish was 36.7 grams. If one only takes into account those individuals whose initial intake of EPA+DHA fatty acids is less than 250 mgs per day, one finds that their intake of these nutrients would increase by 10 mgs a day. Such an increase would help to avoid 1.8% (95% CI 0.6-3.1) of coronary deaths, based on the results of Mozaffarian and Rimm (2006). The health benefits of VAT cuts also apply to fruit and vegetables: as a response to the VAT cut that we have considered, people would start to consume 0.2 additional portions of these food items, thereby reducing the risk of cardiovascular mortality by 4.4% (95% CI 2.2-6.7) and the risk of CHD by approximately 0.9% (95% CI 0.2-1.7) on the basis of the results of Dauchet et al. (2006).

To conclude, the changes in food consumption caused by the VAT cuts that we have considered appear to have direct beneficial effects for health, measured in terms of CHD incidence, early deaths and cardiovascular mortality. The indirect health effects of the reform through weight changes, on the other hand, were found to be insignificant.

Consider finally the combined reform of a sugar tax plus VAT reductions. Such a tax reform leads to decreased body weight (average change -2.34 kg with 95% confidence interval from -4.78 to -0.26) and to an associated reduction in diabetes 2 incidence of 9.7 per cent (CI 0.8, 18.7). In comparison to merely imposing a sugar tax, a combined tax reform including VAT cuts on fruit, vegetables and fish leads, therefore, to smaller reductions in the incidence of diabetes. But it also brings about the beneficial direct impacts via an increased intake of healthy nutrients in fish, fruit and vegetables, leading to reductions in mortality due to CHD.

4.4 Different sources of uncertainty

Finally, we demonstrate the implications of not taking into account all the three sources of uncertainty mentioned above, by leaving out one or two of them at a time. We only report the results for the effects of the sugar tax on the incidence of T2D for the whole sample (Table 4.5). The results were qualitatively similar when considering the subgroups defined by gender, education and income, as well as for other health outcomes (body weight, CHD incidence).

Table 4.5 indicates that accounting for the uncertainty in the estimated change in demand had the largest effect on the confidence intervals of the estimated health effects, compared to the other sources of uncertainty: the final confidence intervals were considerably wider when the uncertainty in the estimated changes in demand (DC) was accounted for, than when it was ignored. . The width of the T2D full sample confidence interval without accounting for the uncertainty in the demand estimation was between 1.5 and 2.6, whereas accounting for the uncertainty in the demand changes increased the width of the confidence interval to between 12.9 and 13.2.

While in our case leaving out one or more sources of uncertainty turns out not to affect our conclusions on the significance of the final health effects – this happens since the effects that we obtain are statistically significant even when we take into account all three sources of uncertainty – it is of course clear that in general, ignoring some key sources of uncertainty can lead to false inference.

5. Conclusion

This paper examined the potential health impacts of health-based food taxation in Finland by, first, estimating a complete demand system for different types of food, then using the demand system to simulate the impacts of a tax increase on sugary products and a tax reduction on fresh fish, fruit and vegetables on food demand, and finally by assessing the effect of these demand changes on energy and nutrient intake. A key contribution of the paper is to demonstrate how confidence intervals can be calculated for multi-stage estimation with different data sources based on bootstrapping. This distinguishes the present paper from all earlier literature on the health effects of food taxation that has only reported point estimates of the health effects.

The results indicate that the demand for sugar and sweets appears to be very price elastic, and a sugar tax of 1 € / kg has a sizable effect on the incidence of obesity and overweight: the sugar tax causes on average, an approximately 13% reduction in the incidence of T2D and a smaller reduction in the incidence of CHD. Reduced VAT rates for fresh fish, fruit and vegetables have a small positive effect on the incidence of CHD and cardiovascular mortality. All these effects are also statistically significant. Further, we find some evidence that the health effects are most pronounced for low-income individuals, and the reforms may therefore reduce health inequality.

We would like to stress that the exact magnitude of the health effects needs to be taken cautiously, because of the substantial uncertainty the estimates involve, and because of a common caveat associated with the standard type of commodity demand analysis that we use: this type of analysis utilises data where outlays are observed but unit prices are not. The analysis thus cannot account for potential changes in the quality of food consumption, which can affect the estimates.[18] Nevertheless, it is important to note that the health effects of smaller sugar consumption are so substantial that even a much smaller elasticity for consumption of sugary products would still be very likely to generate sizable health benefits.

These findings suggest that society could achieve significant savings in health care costs if the sugar tax was introduced. The current excess costs of treating diabetes in Finland amount to 800 million euros annually or 2,800 euros per patient with diabetes (Jarvala et al 2010); and a 13 per cent reduction in diabetes incidence could lead to cost savings of the order of 100 million euros annually. Needless to say, this figure does not involve any valuation for the changes in the loss of or quality of life if diabetes cases are prevented. Further, a tax on sugar is a prevention mechanism that affects the overall population at the same time, which makes it potentially a very powerful mechanism in comparison to individual health-counselling policies.

A major part of the motivation behind our paper lies in the behavioral justification for heavy taxation of “sin goods” such as unhealthy food. From the point of view of this behavioral justification, the result that the health benefits of the tax reforms that we have considered are likely to be concentrated on low-income individuals is of importance for two reasons. Firstly, the theoretical literature on behavioral economics has raised the concern that while sin taxes are beneficial for individuals who suffer from problems such as obesity, they cause distortions for individuals who do not suffer from such problems. The overall desirability of sin taxes hinges on the balance of these benefits and distortions. Our results suggest that the demand responses and the resulting health effects of the reforms that we have studied are strongest for the group which has the most severe health problems to start with. Secondly, this finding is significant from the point of view of the behavioral modification of traditional incidence analysis: even though the burden of high taxation of unhealthy food is in

[18] See the discussion on p.10.

percentage terms heaviest for low income individuals, the health effects are likely to be most positive for them, which counteracts the traditional regressivity argument against sin taxes – overall, taking into account not only the monetary but also the health effects of taxation, sin taxes may lead to a more equal distribution of welfare.

Appendix: The method for calculating the confidence intervals of the health effects

1. Set the number of bootstrap samples to 400.
2. For each bootstrap sample, log (RR) is generated from the multinormal distribution defined by the point estimates and standard errors obtained from the literature.[19]
3. Relative demand changes corresponding to each particular tax reform are generated from the multinormal distribution using the point estimates (Table 3.3) and estimated covariance matrix.[20]
4. A bootstrap sample is generated from the Health 2000 Survey data by sampling primary sampling units (PSUs), which were individuals in the 15 largest Finnish towns and health centre districts in the remaining part of continental Finland.[21]
5. The BMI prevalence estimates for p_s^O are calculated based on the bootstrapped data and the post-stratification weights.
6. The individual weight and BMI changes are then calculated as described in the text, using the relative demand changes (step 3). The new BMI prevalence estimates p_s^N are calculated based on the new BMI values.
7. The PAR estimate is then calculated according to equation (1), using the RR, p_s^O and p_s^N, values obtained in steps 2, 5 and 6.
8. Steps 2 to 7 are then repeated 400 times, and the procedure yields 400 point estimates of PAR and average weight changes.
9. The point estimates, which we report, are the point estimates obtained using the original Health 2000 Survey data, and point estimates of RR and relative changes without bootstrapping. The 95% confidence intervals (CI) are based on the 2.5% and 97.5% quantile points of the 400 point estimates obtained using the bootstrap.

[19] If the uncertainty corresponding to the RR estimate is ignored, then the point estimates log(RR) are used instead.
[20] If the uncertainty corresponding to the RC estimate is ignored, then the point estimates log(RC) are used instead.
[21] If the uncertainty corresponding to the Health 2000 Survey data is ignored, then the original Health 2000 data are used instead.

References

Abdullah A., Peeters A., Courten de M, and Stoelwinder (2010). The magnitude of association between overweight and obesity and risk of diabetes: a meta-analysis of prospective cohort studies, Diabetes Research and Clinical Practice, 89:309-319.

Allais, O., Bertail, P. and Nichèle (2010) The effects of a fat tax on French households' purchases: A nutrional approach, American Journal of Agricultural Economics, 92: 228-245.

Andreyeva, T., Long, M., and Brownell, K. (2010). The impact of food prices on consumption: a systematic review of research on price elasticity of demand for food, American Journal of Public Health, 100: 216–222.

Aromaa, A., and Koskinen, S. (2004) Health and functional capacity in Finland. Baseline Results of the Health 2000 Health Examination Survey. Publications of the National Public Health Institute. Helsinki, Finland.

Banks, J., Blundell, R. and Lewbel A. (1997) Quadratic Engel curves and consumer demand, Review of Economics and Statistics, 79: 527-539.

Blundell, R., Pashardes, P. and Weber, G. (1993). What do we learn about consumer demand patterns from micro-data? American Economic Review, 83: 570-597.

Bogers R.B., Bemeals W.J.E., Hoogenveen R.T., Boshuizen H.C., Woodward M., Knekt P. et al. (2007). Association of overweight with increased risk of coronary heart disease partly independent of blood pressure and cholesterol levels, Archives of Internal Medicine, 167: 1720-1728.

Brunello, G., Michaud, P-C and Sanz-de-Galdeano, A. (2009). The rise of obesity, Economic Policy, 59: 551-596.

Chouinard, H. H., Davis, D. E., LaFrance, J. T. and Perloff, J. M. (2007). Fat taxes: Big money for small change. Forum for Health Economics & Policy, 10(2), article 2.

Dall T.M., Fulconi V.L., Zhang Y., Reimers K.J., Packard P.T., and Astwood J.D. (2009). Potential health benefits and medical cost savings from calorie, sodium, and saturated fat reductions in the American diet, American Journal of Health Promotion, 23: 412-422.

Dauchet L., Amouyel P., Hercberg S., and Dallongeville J. (2006). Fruit and vegetable consumption and risk of coronary heart disease: a meta-analysis of cohort studies, Journal of Nutrition, 136: 2588-2593.

Deaton, A. (1985). Demand Analysis, in Z. Griliches and M.D. Intriligator (eds), Handbook of Econometrics, Vol. III, Amsterdam, North-Holland, 1986, pp. 1767-1839.

Dharmasena S. and Capps, O. Jr. (2012). Intended and unintended consequences of a proposed national tax on sugar sweetened beverages to combat the US obesity problem, Health Economics. 21: 669-694.

Djerf, K., Laiho, J., Lehtonen, R., Härkänen, T., and Knekt, P. (2008). Weighting and Statistical Analysis. Pp. 182-200. In: Heistaro, S. (ed.) Methodology Report. Health 2000 Survey. Publications of the National Public Health Institute. Helsinki, Finland.

Fletcher, J.M., Frisvold, D.E. and Tefft, N. (2010). The effects of soft drink taxes on child and adolescent consumption and weight outcomes, Journal of Public Economics, 94:967-74.

Forssas, E., Sund, R., Manderbacka, K., Arffman, M., Ilanne-Parikka, P. and Keskimäki, I. (2010). Diabetics have still larger excess mortality than comparison groups (in Finnish). Finnish Medical Journal 26-31/2010, 2359-2367.

Griffith, R., Nesheim, L. and O'Connell, M. (2010). Empirical estimates of the effects of a fat tax. CEMMAP Working Paper CWP37/10.

Gruber, J. and Köszegi, B. (2004). Tax Incidence when Individuals are Time-Inconsistent: the Case of Cigarette Excise Taxes, Journal of Public Economics, 88: 1959-1987.

Gustavsen, G. W and Rickertsen, K. (2011). The effects of taxes on purhcases of sugar-sweetened carbonated soft drinks: a quantile regression approach, Applied Economics, 43: 707-716.Irz, X. (2010)

Modelling physical quantities of food and nutrients consumed from aggregate data – with an application to Finland, Agricultural Economics, 41: 293-304.

He, J., Ogden, L. G., Bazzano, L. A., Vupputuri, S., Loria, C., Whelton P. K. (2001). Risk Factors for Congestive Heart Failure in US Men and Women: NHANES I Epidemiologic Follow-up Study. Archives of Internal Medicine, 161: 996-1002.

Jarvala, T., Raitanen, J. and Rissanen, P. (2010). The cost of diabetes in Finland 1998-2007 (in Finnish). University of Tampere, mimeo. Korn, E.L. and Graubard, B.I. (1999). Analysis of Health Surveys. Wiley, New York.

Kotakorpi, K. (2008). The Incidence of Sin Taxes, Economics Letters, 98: 95-99.

Laaksonen M. (2005). Model-based estimation of Population Attributed Risk (PAR). Master's thesis, Jyväskylä University.

Laiho, J., Djerf, K., and Lehtonen, R. (2008). Sampling Design. Pp. 13-15. In: Heistaro, S. (ed.) Methodology Report. Health 2000 Survey. Publications of the National Public Health Institute. Helsinki, Finland.

Lusk, J. L. and Schroeter, C. (2012). When Do Fat Taxes Increase Consumer Welfare?, Health Economics, forthcoming.Männistö, S., Montonen, J., Pietinen, P., and Knekt, P (2008) Dietary questionnaire. Pp. 121-123. In: Heistaro, S. (ed.) Methodology Report. Health 2000 Survey. Publications of the National Public Health Institute. Helsinki, Finland.

Miljkovic, D., and Nganje, W. (2008). Regional Obesity Determinants in the United States: A Model of Myopic Addictive Behavior in Food Consumption, Agricultural Economics, 38: 375–84.

Miljkovic, D., Nganje, W. and de Chastenet, H. (2008). Economic Factors Affecting the Increase in Obesity in the United States: Differential Response to Price, Food Policy, 33: 48–60.

Mozaffarian D. and Rimm E.B. (2006). Fish intake, contaminants, and human health. Evaluating the risk and benefits, Journal of the American Medical Association, 296: 1885-1899.

Mytton, O., Gray, A., Rayner, M. and Rutter, H. (2007). Could Targeted Food Taxes Improve Health? Journal of Epidemiology and Community Health, 61: 689-694.

Nnoaham, K.E., Sacks, G., Rayner, M., Mytton, O. and Gray, A. (2009) Modelling income group differences in the health and economic impacts of targeted food taxes and subsidies, International Journal of Epidemiology, 38: 1324-1333.

Nordström, J. and Thunström, L. (2009) The impact of tax reforms designed to encourage healthier grain consumption, Journal of Health Economics, 28: 622-634.

Nordström, J. and Thunström, L. (2011) Can targeted food taxes and subsidies improve the diet? Distributional effects among income groups, Food Policy, 36: 259-271.

O'Donoghue, T. and Rabin, M. (2006). Optimal Sin Taxes. Journal of Public Economics, 90: 1825-1849.

Ogden, R. T. and Tarpey, T. (2006). Estimation in regression models with externally estimated parameters, Biostatistics, 7: 115–129.

Powell L.M., Chaloupka F.J. (2009). Food prices and obesity: evidence and policy implications for taxes and subsidies, Milbank Quarterly, 87: 229-257.

Schnohr, P., Jensen, J. S., Scharling, H., Nordestgaard, B. G. (2002). Coronary heart disease risk factors ranked by importance for the individual and community - A 21 year follow-up of 12 000 men and women from The Copenhagen City Heart Study. European Heart Journal 23: 620–626.

Smed S. , Jensen J. D. and Denver S. (2007),. Socio-economic characteristics and the effect of taxation as a health policy instrument. Food Policy 32: 624-639.

Spiegelman, D., Hertzmark, E. and Wand, H. C. (2007). Point and interval estimates of partial population attributable risks in cohort studies: examples and software, Cancer Causes & Control, 18: 571–579.

Tiffin, R. and Arnoult, M. (2011) The public health impacts of a fat tax, European Journal of Clinical Nutrition, 65: 427-433.

Table 2.1: Share of certain foods from food expenditures by level of education.

Education[1]	Fish	Fruit & veg	Sugar & sweets	Butter & margarine
1 = lowest	3.7%	15.9%	8.0%	2.6%
2	4.4%	17.0%	8.0%	2.2%
3	4.8%	17.4%	7.3%	1.8%
4 = highest	5.2%	19.4%	7.5%	1.7%

[1] 1 = both spouses have basic or secondary education; 2 = at least one spouse has tertiary education; 3 = one spouse has higher education; 4 = both spouses have higher education. (Households with only one adult have been excluded.)

Source: Authors' own calculations based on the Finnish household budget survey, 2006.

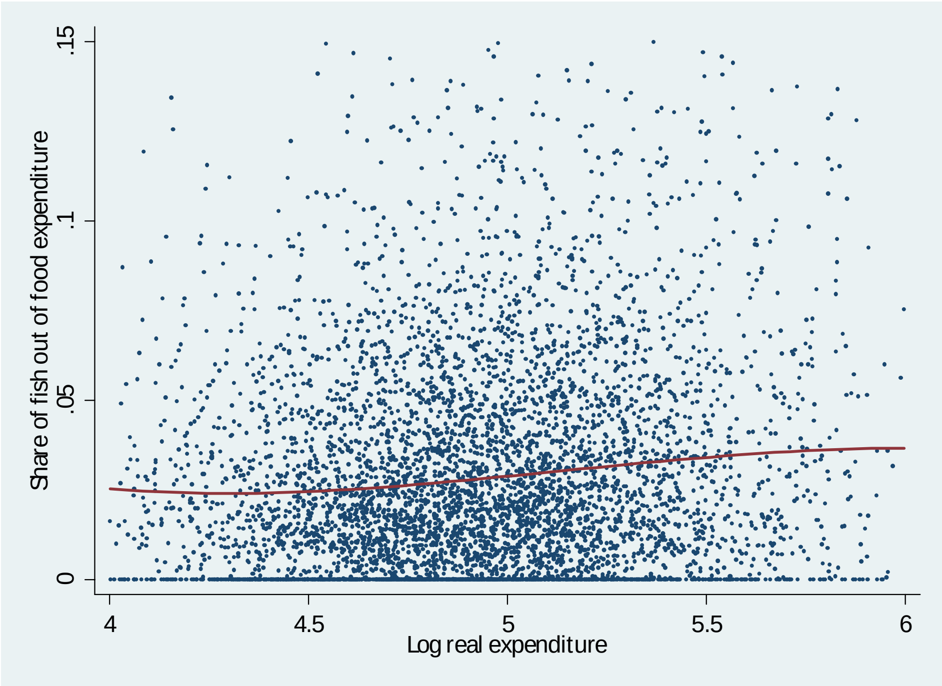

Figure 2.1 Non-parametric Engel curve for fish, two parent households with children in 2006.

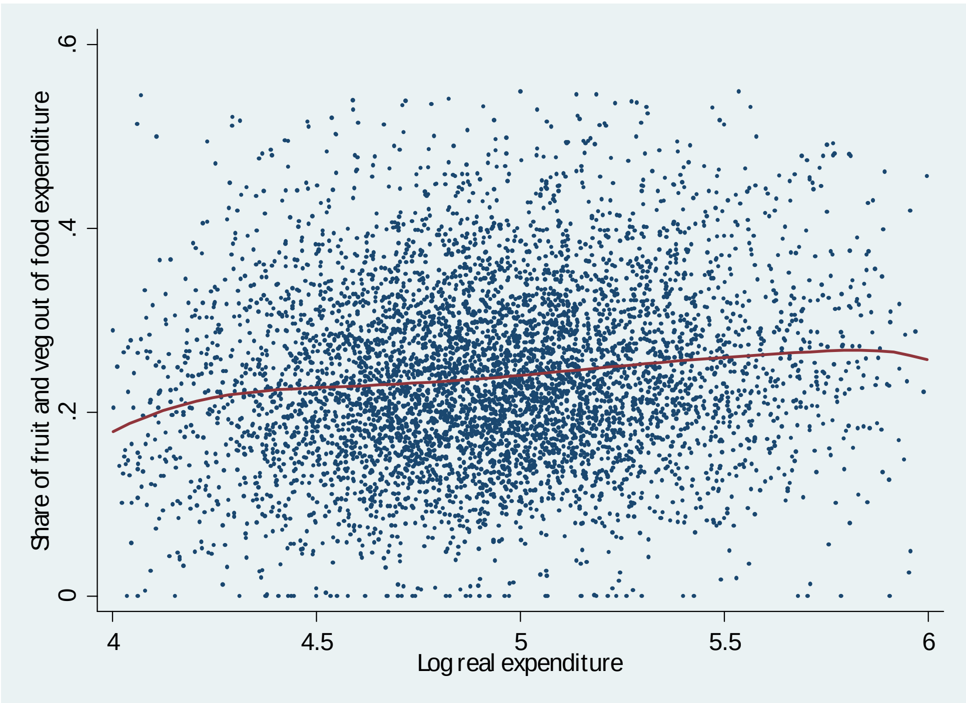

Figure 2.2: Non-parametric Engel curve for fruit and vegetables, two parent households with children in 2006.

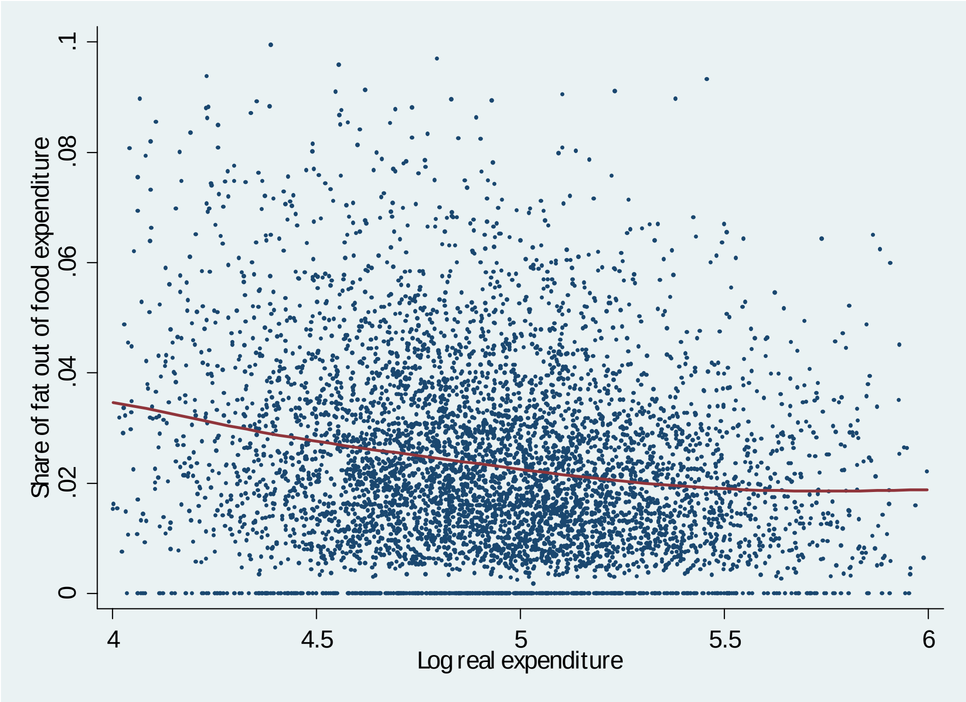

Figure 2.3 Non-parametric Engel curve for fat, two parent households with children in 2006.

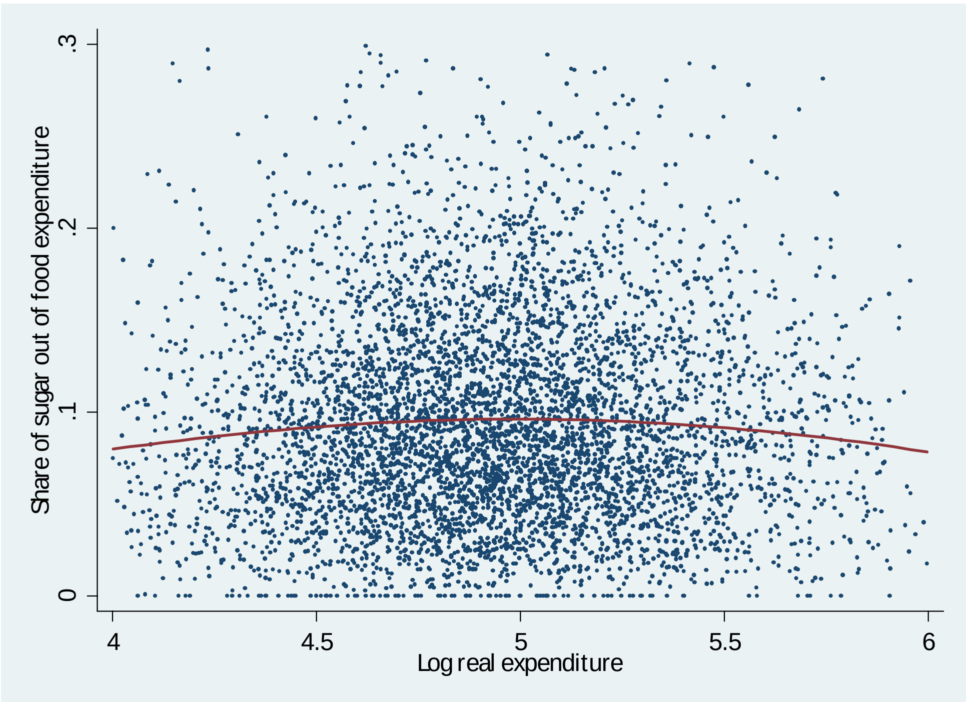

Figure 2.4: Non-parametric Engel curve for sugar and sweets, two parent households with children in 2006.

Table 2.2: Estimated compensated price elasticities for 8 consumption categories.

	Bread	Meat	Fish	Milk	Fats	Fruit & veg	Sugar & sweets	Other
Bread	-0.713 (0.298)	0.253 (0.131)	-0.079 (0.082)	-0.216 (0.165)	0.138 (0.138)	0.237 (0.066)	-0.160 (0.205)	0.539 (0.393)
Meat	0.245 (0.127)	-0.034 (0.125)	-0.033 (0.491)	0.348 (0.091)	0.025 (0.036)	-0.275 (0.067)	0.223 (0.097)	-0.498 (0.288)
Fish	-0.409 (0.428)	-0.177 (0.264)	-0.725 (0.261)	0.032 (0.338)	-0.850 (0.2099	0.009 (0.160)	1.042 (0.423)	1.079 (0.727)
Milk	-0.248 (0.189)	0.414 (0.108)	0.007 (0.075)	0.297 (0.221)	0.051 (0.079)	0.001 (0.068)	-0.037 (0.175)	-0.485 (0.374)
Fats	1.079 (1.083)	0.200 (0.294)	-1.280 (0.314)	0.345 (0.542)	2.502 (1.433)	-0.053 (0.164)	-3.081 (0.928)	0.286 (0.991)
Fruit & veg	0.332 (0.092)	-0.398 (0.097)	0.002 (0.043)	0.001 (0.083)	-0.009 (0.293)	-0.415 (0.084)	-0.128 (0.084)	0.615 (0.273)
Sugar & sweets	-0.307 (0.391)	0.442 (0.173)	0.385 (0.156)	-0.061 (0.292)	-0.736 (0.227)	-0.175 (0.114)	-2.169 (0.596)	2.641 (0.703)
Other	0.016 (0.118)	-0.015 (0.009)	0.006 (0.004)	-0.013 (0.010)	0.001 (0.004)	0.013 (0.006)	0.042 0.011	-0.050 (0.029)

Notes: Bootstrapped standard errors in parentheses.

Table 2.3: Estimated compensated price elasticities for 6 consumption categories.

	Bread	Meat	Fish	Fruit & veg	Sugar & sweets	Others
Bread	-0.726 (0.277)	0.319 (0.119)	-0.133 (0.083)	0.237 (0.074)	-0.283 (0.198)	0.575 (0.319)
Meat	0.309 (0.116)	-0.025 (0.117)	-0.049 (0.302)	-0.302 (0.060)	0.203 (0.087)	-0.135 (0.216)
Fish	-0.695 (0.430)	-0.264 (0.230)	-0.932 (0.233)	0.003 (0.166)	0.591 (0.378)	1.297 (0.596)
Fruit & veg	0.346 (0.104)	-0.439 (0.087)	0.001 (0.045)	-0.426 (0.099)	-0.119 (0.083)	0.637 (0.237)
Sugar & sweets	-0.542 (0.381)	0.404 (0.174)	0.219 (0.140)	-0.163 (0.113)	-2.538 (0.557)	2.621 (0.576)
Others	0.017 (0.009)	-0.004 (0.007)	0.006 (0.000)	0.013 (0.005)	0.040 (0.009)	-0.074 (0.019)
Notes: Bootstrapped standard errors in parentheses.						

Table 2.4. Estimated expenditure elasticities.

Bread	0.33765 (0.0356)
Meat	0.3884 (0.04208)
Fish	0.6879 (0.09056)
Fruit and veg	0.5831 (0.03756)
Sugar & sweets	0.32843 (0.04896)
Notes: Bootstrapped standard errors in parentheses.	

Table 2.5: Estimated uncompensated elasticities.

	Bread	Meat	Fish	Fruit & veg	Sugar & sweets	Others
Bread	-0.736 (0.277)	0.309 (0.119)	-0.136 (0.083)	0.240 (0.074)	-0.287 (0.199)	0.270 (0.328)
Meat	0.297 (0.116)	-0.037 (0.117)	-0.051 (0.043)	-0.311 (0.060)	0.197 (0.088)	-0.484 (0.227)
Fish	-0.713 (0.430)	-0.283 (0.229)	-0.935 (0.233)	-0.010 (0.166)	0.581 (0.378)	0.672 (0.628)
Fruit and veg	0.330 (0.104)	-0.456 (0.087)	-0.002 (0.045)	-0.437 (0.010)	-0.128 (0.083)	0.111 (0.242)
Sweets & sugar	-0.552 (0.382)	0.394 (0.174)	0.217 (0.140)	-0.170 (0.113)	-2.543 (0.557)	2.236 (0.576)
Others	-0.0112 (0.009)	-0.033 (0.006)	0.002 (0.003)	-0.007 (0.005)	0.025 (0.008)	-1.035 (0.019)
Notes: Bootstrapped standard errors in parentheses.						

Table 2.6: Estimated uncompensated own-price elasticities for different income levels.

	Bread	Meat	Fish	Fruit & veg	Sugar & sweets	Others
Low income (N=5139)	-0.54 (0.63)	-0.26 (0.33)	-1.00 (0.53)	-0.57 (0.23)	-3.05 (1.25)	-1.06 (0.06)
Middle income (N=6142)	-0.52 (0.67)	-0.06 (0.28)	-0.91 (0.43)	-0.35 (0.28)	-2.59 (1.04)	-0.95 (0.08)
High income (N=5912)	-0.60 (0.63)	-0.72 (0.34)	-0.72 (0.46)	-0.53 (0.18)	-1.90 (1.27)	-1.04 (0.03)
Notes: Bootstrapped standard errors in parentheses.						

Table 3.1: The impacts of tax reforms on food expenditure at different income levels without behavioural changes.

Change in food expenditure, €				
Decile	Sugar tax	Fish VAT down	Fruit & veg VAT down	Altogether
1	25.80	-9.84	-30.48	-14.52
5	47.63	-15.78	-61.38	-29.53
10	86.64	-31.20	-117.15	-61.71
Percentage change in food expenditure				
Decile	Sugar tax	Fish VAT down	Fruit & veg VAT down	Altogether
1	1.67 %	-0.57 %	-1.74 %	-0.64 %
5	1.59 %	-0.51 %	-2.01 %	-0.93 %
10	1.44 %	-0.54 %	-2.01 %	-1.11 %

Table 3.2: The impacts of tax reforms on food expenditure at different educational levels without behavioural changes.

Change in food expenditure, €				
Education	Sugar tax	Fish VAT down	Fruit & veg VAT down	Altogether
Low	49.73	-15.33	-60.27	-25.87
Medium	60.21	-21.48	-81.48	-42.75
High	66.40	-28.05	-90.87	-52.52
Percentage change in food expenditure				
Education	Sugar tax	Fish VAT down	Fruit & veg VAT down	Altogether
Low	1.58 %	-0.48 %	-2.01 %	-0.91 %
Medium	1.56 %	-0.57 %	-2.13 %	-1.14 %
High	1.54 %	-0.63 %	-2.10 %	-1.19 %

Table 3.3. The impact of the tax reforms on demand: relative changes.

Sugar tax		
	Change	Std error
Bread	-0.0377*	0.0177
Meat	0.0224*	0.0086
Fish	0.0392	0.0344
Fruit and veg	-0.0057	0.0077
Sugar and sweets	-0.2331*	0.0469
VAT cut		
Bread	-0.0128	0.0130
Meat	0.0442*	0.0100
Fish	0.1155*	0.0344
Fruit and veg	0.0537*	0.0131
Sugar and sweets	-0.0057	0.0202
Both reforms		
Bread	-0.0505*	0.0229
Meat	0.0666*	0.0131
Fish	0.1547*	0.0502
Fruit and veg	0.0480*	0.0144
Sugar and sweets	-0.2389*	0.0537
Notes: * refers to significance at 5 % level. Standard errors calculated using the delta method.		

Table 4.1: Change in the BMI distribution (%) as a result of the sugar tax.

	BMI<25	25<BMI <30	30<BMI <35	BMI>35	Distribution in 2000
BMI<25	40.7	0	0	0	40.7
25<BMI<30	10.1	28.4	0	0	38.5
30<BMI<35	0	4.8	11.0	0	15.8
BMI>35	0	0	1.2	3.7	4.9
Distribution after intervention	50.8	33.2	12.2	3.7	100.0
Notes: The column on the right-hand side gives the observed distribution of BMI cases in the absence of the intervention, the bottom row the simulated distribution after the intervention. The other off-diagonal entries show the changes in the BMI distribution after the intervention.					

Table 4.2: Change in body weight (kgs) as a result of the sugar tax.

All	-3.19 (-4.89, -1.44)		
By sex:	-2.54 (-3.89, -1.13) (males)	-3.79 (-5.81, -1.73) (females)	
By education:	-3.02 (-4.73, -1.30) (basic education)	-3.17 (-4.87, -1.40) (secondary)	-3.44 (-5.20, -1.63) (tertiary)
By household income:	-5.41 (-8.59, -2.53) (low income)	-0.78 (-3.7, 2.11) (middle income)	-2.63 (-5.4, 0.28) (high income)
Notes: The calculations are based on average elasticities for different sexes and educational groups and on income-dependent elasticities for households at different income levels.			

Table 4.3: Change (negative PAR_{2c} , %) in the incidence of T2D as a result of the sugar tax.

All	-13.4 (-6.3, -19.9)		
By sex:	-10.8 (-5.2, -15.7) (males)	-15.9 (-7.1, -23.6) (females)	
By education:	-12.5 (-5.5, -19.0) (basic education)	-13.8 (-6.7, -20.0) (secondary)	-14.4 (-7.2, -21.3) (tertiary)
By household income:	-20.8 (-10.3, -30.5) (low income)	-3.2 (9.6, -16.0) (middle income)	-11.8 (2.3, -22.6) (high income)
Notes: The calculations are based on average elasticities for different sexes and educational groups and on income-dependent elasticities for households at different income levels.			

Table 4.4: Change (negative PAR_{2c} , %) in the incidence of coronary heart disease as a result of the sugar tax.

All	-3 (-1.4, -4.8)		
By sex:	-2.3 (-1.1, -3.7) (males)	-3.7 (-1.6, -5.8) (females)	
By education:	-3.2 (-1.3, -5.2) (basic education)	-3.1 (-1.5, -4.7) (secondary)	-2.8 (-1.4, -4.3) (tertiary)
By household income:	-4.9 (-2.0, -7.4) (low income)	-0.7 (1.9, -3.7) (middle income)	-2.5 (0.6, -5.2) (high income)
Notes: The calculations are based on average elasticities for different sexes and educational groups and on income-dependent elasticities for households at different income levels.			

Table 4.5: Effect of different sources of uncertainty on the confidence intervals of the estimated effect of the sugar tax on T2D incidence.

Health 2000	RR	DC	Point estimate -13.4
Yes	No	No	(-14.1, -12.6)
No	Yes	No	(-14.6, -12.2)
Yes	Yes	No	(-14.6, -12.0)
No	No	Yes	(-19.3, -6.4)
Yes	No	Yes	(-19.5, -6.4)
No	Yes	Yes	(-19.4, -6.34)
Yes	Yes	Yes	(-19.4, -6.24)

Notes: Change (negative PAR_{2c} , %) in the incidence of T2D as a result of the sugar tax, and the corresponding confidence intervals based on different sources of uncertainty in parentheses. The uncertainty in the estimated the prevalence, the change in demand (DC) , and the relative risks (RR) of T2D are accounted for, if the corresponding columns 'Health 2000', RC, and RR contain 'Yes', otherwise not

The **Aboa Centre for Economics (ACE)** is a joint initiative of the economics departments of the Turku School of Economics at the University of Turku and the School of Business and Economics at Åbo Akademi University. ACE was founded in 1998. The aim of the Centre is to coordinate research and education related to economics.

Contact information: Aboa Centre for Economics, Department of Economics, Rehtorinpellonkatu 3, FI-20500 Turku, Finland.

www.ace-economics.fi

ISSN 1796-3133