Combined fiscal policies to promote healthier purchases: effects on purchases and consumer welfare

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Abstract

Taxes on unhealthy foods and sweetened beverages, as well as subsidies to healthy foods, have become increasingly popular strategies to curb obesity. The existing evidence on the welfare effects of fiscal policies is mixed and almost uniquely focused on tax schemes. Using the 2016-2017 Household Budget Survey in Chile, we estimate an Exact Affine Stone Index (EASI) incomplete demand system and simulated changes in purchases, tax incidence and consumer welfare of three different policy scenarios: (1) an 18% tax on unhealthy food and sweetened beverages, (2) a subsidy defined as zero-rating fruits and vegetables from the current 19% value-added tax, and (3) a combined (tax and subsidy) policy. The combined scheme captures the incentives to switch purchases from both single-policy alternatives, creating almost no change in government revenue. In terms of welfare, low income households strictly benefit from a combined policy, while high income households experience a loss of consumer welfare, thus generating significant re-distributional effects.

Keywords: EASI Demand System, food policy, consumer welfare, household behavior.

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1 Introduction

The global prevalence of obesity has increased dramatically since 1980 (Ng et al. 2014). More than one in two adults and nearly one in six children are overweight or obese in the OECD area (OECD, 2017), with increased risk of several non-communicable diseases (Malik et al. 2010; Stanhope 2012). In response to the obesity crisis, governments have become increasingly interested on implementing fiscal policies to curb unhealthy food consumption. In recent years, over 40 locations including the United Kingdom, Saudi Arabia, Mexico, Finland, France, Chile, Peru, Ireland, South Africa and other countries and cities across the U.S. have implemented or modified the prevailing taxes on sweetened beverages or added sugar (WCRFI 2018). During the same period, other countries or states have discussed and/or implemented taxes on saturated fat or unhealthy foods, including Mexico (Batis et al. 2016), Denmark (Smed, Jensen, and Denver 2005), Japan and the state of Kerala in India (Strnad 2004). Moreover, countries such as Hungary, has opted for a broader taxation scheme referred to as the *public health product tax*, which levies a tax over a wider range of unhealthy foods (Bíró 2015). In addition, governments have also explored subsidies and/or tax earmarking options, such as the European Union subsidy scheme to provide free fruit and vegetables to children in schools, established in 2008 (WHO, 2015). Similarly, India and Egypt (among other countries) subsidize several healthy food groups, including pulses and other staple foods.

To date, most of the debate around food-related fiscal policies has focused on estimating their potential to change purchasing patterns towards improved nutritional health, based on simulated models or empirical evaluations. Simulations often estimate price elasticity of demand for different food groups and then project changes in purchases in response to different fiscal policy scenarios. Some studies also include potential health effects at the population level; changes in body mass index (BMI), prevalence of cardiovascular diseases (CVDs), prevalence of obesity and/or health care cost savings (Anand et al. 2015; Andreyeva, Long, and Brownell 2010; Smed and Jensen 2005; Nnoaham et al. 2009a). Fewer articles have extended the analysis to estimate the consumer and producer welfare effects of such food policies (Zhen et al. 2013; Allais, Etilé, and Lecocq 2015; Madden 2015; Thiele 2010). However, despite the growing interest in combined fiscal policies (i.e. implementing simultaneously taxes on unhealthy foods and subsidies on healthy foods), the heterogeneous effects on purchases and consumer welfare of such combined schemes remains unclear

(Sassi et al. 2018; Powell et al. 2013; Thow, Downs, and Jan 2014). Few studies have measured the health effects of combined fiscal policies, although providing limited evidence regarding the distribution of changes in welfare (Kotakorpi et al. 2012; Tiffin and Arnoult 2011; Nnoaham et al. 2009a). Theoretically, the combination of food taxes and subsidies can have substantial impacts on average household purchases while minimizing welfare losses, relative to a tax only scenario. However, due to variation in price sensitiveness and mean consumption across socioeconomic groups, the distributional welfare effects of combined fiscal policies remain as an empirical question. From a public policy perspective, estimating welfare effects across different sub-populations (by income, for example) is essential to the discussion on tax equity and political feasibility.

This study builds on previous evidence by measuring the joint effect of food-based, health-oriented combined fiscal reform on household purchases and consumer welfare across different socioeconomic groups. A combined food policy scheme could boost the difference in relative prices between healthy and unhealthy foods, while reducing the consumer welfare loss. Although we estimate changes in purchases across all food groups, our focus is to measure the change in consumer welfare due to a combined policy, in comparison to two similar policies: a tax on unhealthy foods and a subsidy on healthy foods. For this purpose, we estimate the compensated variation for each household. This is to say, how much income a household would need to receive (or give away) in order for them to maintain the same level of welfare than before policy implementation.

Chile is a compelling case study for several reasons. First, as a recently declared high-income country, Chile experienced a rapid raise in disposable income in the last decades, therefore policy analysis can be informative for many middle and high income countries. Second, Chile has a high prevalence of obesity (34.4% among population 15 years and older in 2016) and type 2 diabetes (12.3% in 2016) (MINSAL 2017). Third, Chile recently introduced a comprehensive suite of regulations around food labeling on the front-of-package, restrictions of food marketing to children and an adjustment to taxation of beverages based on sugar content (Corvalán et al. 2013). Finally, the prevalence of obesity and related chronic diseases have been found to be higher among lower socio-economic status individuals, proxied by educational attainment (MINSAL 2017). Therefore, fiscal policies that discourage consumption of unhealthier options an/or encourage consumption of healthier options might benefit lower-income households to a larger extent.

We use the Chilean Household Budget Survey (2016-2017) to analyze the impact of three relevant fiscal policies in order to present results in context. First, a 18% tax on sweetened beverages (SBs) and unhealthy foods (which includes sweet and salty snacks and desserts). This scheme uses the current Chilean SB tax to expand to other food groups. Second, we considered a healthy subsidy by zero-rating fruits, vegetables, and seafood from the current 19% value-added tax (VAT). Finally, we simulate the combination of both of these strategies. To simulate each scenario, we require food demand estimates. As such, we implement an incomplete censored demand system to determine households' own and cross-price elasticities of demand for several food groups. In particular, we estimate an Exact Affine Stone Index (EASI) implicit Marshallian demand system, introduced by Lewbel and Pendakur (2009). This demand system approach has two clear advantages for welfare estimation: Engel curves are not limited by functional form restrictions and error terms can be interpreted as consumer heterogeneity, similar to random effects. As noted in previous studies, Engel curves vary significantly in shape across different food groups. Ignoring such heterogeneity can cause important deviations on consumer welfare calculation. Moreover, while ignoring household unobserved heterogeneity does not significantly affect estimated parameters, it can have substantial impact on welfare estimates (Lewbel and Pendakur 2009; Zhen et al. 2013).

We find that using the full sample, the combined policy increases household fruit and vegetables purchases by 7.4 kilograms per month, decreases unhealthy food purchases by 2 kilograms per month, and reduce sweetened beverage purchases by 1.5 liters per month. The combined policy creates an average welfare gain of USD 2.35 per month per household (0.09% of monthly income). Taxes and subsidies produce meaningful changes in household food purchases in the expected direction, where the larger changes, in absolute terms, occur among higher income households (fifth quintile), but there is no significant difference in consumer response between low (first quintile) and high (fifth quintile) income households in relative terms (i.e., proportional to baseline household consumption). The combined policy is estimated to create welfare transfers from high income households (USD 4.58 per month or 0.06% of monthly income) to low income households (USD 1.65 per month or 0.29% of monthly income). As governments develop a stronger interest in fiscal policies to promote healthier purchases, we highlight the importance of considering combined strategies to address nutrition-related chronic diseases, not only to maximize the potential effects on consumer behavior, but also to mitigate welfare inequalities.

This article is organized as follows. Section 2 provides background on studies to date on fiscal policies on food purchases and consumer welfare, Section 3 describes the data and methods, Section 4 presents the results, and Section 5 discusses the findings and their policy implications.

2 Fiscal policies, food purchases and consumer welfare

Despite current widespread adoption, food- or nutrient-based fiscal policies remain controversial means to curb obesity and nutrition-related chronic disease trends. From an economic perspective, price incentives can be justified as a way to internalize the externalities due to obesity and related chronic diseases on the health care system (Griffith et al. 2016; Brownell et al. 2009). Individuals with obesity have larger risk of chronic diseases such as cardio-vascular diseases and diabetes that lead to higher health care costs, driving up average prices for medical services (Seuring, Archangelidi, and Suhrcke 2015; Finkelstein EA, Brown DS, and Popkin BM 2007). Obesity and related chronic diseases also generate indirect costs through lower labor market productivity due to lower labor force participation and amount worked by individuals as well as their caregivers (Finkelstein, Fiebelkorn, and Wang 2005). Fiscal policies targeting certain foods or nutrients have also been argued as instruments to facilitate individuals to address *internalities*, i.e. the long-term individual costs associated to current poor nutritional diet(O'Donoghue and Rabin 2006). Food and beverage taxation, particularly tax schemes based on the amount of critical nutrients of concern (such as sugar, sodium or saturated fats) per unit of volume or weight, can create incentives for product reformulation, improving the average nutritional quality of the food supply (Hawkes et al. 2015). Finally, additional fiscal revenues from taxes can be used to fund public health initiatives (Capacci and Mazzocchi 2011) and to compensate for undesired distributional effects from such policies (Sassi et al. 2018).

A key element of the global trend on food and beverage taxation is the emphasis on a rigorous evidence-based approach (WCRFI 2018; Hawkes et al. 2017). Such evidence often is translated on estimated changes on average household purchases, based on simulated models or empirical evaluations. Few articles have extended the analysis to estimate the economic welfare effects of food policies, with mixed results. Yaniv, Rosin, and Tobol (2009), have developed a theoretical model that simulates a joint policy: taxes on unhealthy food and subsidies for food inputs (under the assumption that healthy foods are often cooked, thus also requiring time inputs). Authors find that such a strategy could decrease welfare for healthier individuals with a higher opportunity cost of time. Lusk and Schroeter (2012) derived a simple model for high versus low calorie food demand, with utility explicitly depending on weight and physical activity. Based on their assumptions and previous results from other studies, they have concluded that for taxes to be welfare-increasing, the willingness to pay for weight reduction is remarkably high, around $1,500 per pound lost. However, this result depends strongly on the stability of the relationship between price increases and weight loss, which may vary depending on the tax size. Miao, Beghin, and Jensen (2013) have estimated welfare implications in a structural framework, aiming to calculate both consumer and producer welfare changes between a sales tax versus taxing inputs (e.g., sugar). They have found that taxing sweetener inputs is more efficient (lower surplus loss) than a sales tax, although strictly welfare reducing for consumers, as expected. On a similar note, Harding and Lovenheim (2017) have demonstrated that nutrient-specific taxes are likely to produce lower welfare losses, given the larger tax base, compared to product-specific taxes. In relation to alternative policies, Allais, Etilé, and Lecocq (2015) have determined that mandatory labelling has a substantial differential effect on both welfare and purchases, compared to fat taxes. To date, there is only study to date that explores the potential joint benefits of combining subsidies and taxes, reporting significantly larger health effects (compared to single policy strategies) but it does not present estimated changes in economic welfare (Härkänen et al. 2014).

In terms of heterogeneity on welfare effects by income sub-groups, Chouinard et al. (2007) have reported a large welfare variation in low income households when fat taxes are applied to dairy products; however, their analysis ignores substitutions and complementarities with other food groups. Nnoaham et al. (2009a) shows that combined tax and subsidy policies to promote healthy diets are regressive, based on data from the United Kingdom. However, this study does not recognize that households from different income levels can have different underlying preferences. Zhen et al. (2013) have revealed that SSB taxes would affect low income households disproportionately in the

United States, in a context where low income households are also the high-consumer group. This is consistent with high-consumers being less sensitive to prices but displaying larger absolute decreases compared to average consumers when facing a tax schedule (Etilé and Sharma 2015). In France, results based on simulation models indicate that taxing products high in sugar and fat are consistent with U.S. evidence (Allais, Etilé, and Lecocq 2015). Madden (2015) has also reported heterogeneous welfare effects for the different simulated policies, although using a fairly broad categorization of food products. In sum, welfare changes across socioeconomic sub-groups depend not only on price elasticity of demand but also on the initial level of consumption.

Whether low-income households are more or less sensitive to prices in the case of unhealthy foods and sweetened beverages is rather unclear, although evidence from middle income countries suggests low socioeconomic (SES) households are more responsive to taxes (Colchero, Molina, and Guerrero-López 2017). Evidence for Germany also suggests that fat taxes creates a higher burden on low income households more strongly, despite reporting larger price elasticity (Thiele 2010). A major limitation of the aforementioned studies is the strong restriction on Engel curves to be linear, which has been shown to have a strong impact on demand system estimates (Lewbel and Pendakur 2009). Finally, Muller et al. (2017) have provided experimental evidence suggesting that low income households face smaller price reductions due to taxes than high income households and perceive less benefits from the taxes, due to both an unhealthier pre-tax base consumption and because of their lower responsiveness to the price changes.

We contribute to the previous literature, by examining the heterogeneous welfare effects of combined (subsidy and tax) policies, using a demand system approach that allows for larger flexibility on the relationship between income and purchases. We estimate the demand system at each quintile of the income distribution separately, to recognize that different income groups might have different underlying preferences for foods and beverages. Our focus on combined policies lie in their potential to achieve average consumer welfare neutrality while creating a larger relative price differential, thus inducing a joint effect to reduce unhealthy and increase healthy purchases. As mentioned, we use an incomplete demand system approach, to recognize the importance of substitutions and complementarities across food groups. This is critical, since previous evidence suggests that households with a strong taste for sugar are expected to substitute SB with other sweet energy-dense foods (Caro et al. 2017; Griffith et al. 2016; Zhen et al. 2013).

3 Data and Methods

In order to simulate different policy scenarios, we need to estimate structural demand parameters. In particular, we estimate an Exact Affine Stone Index (EASI) demand system, introduced by Lewbel and Pendakur (2009). The EASI demand system has significant advantages over other demand system models. First, it allows Engel curves of any order, not being subject to the rank three limitation discussed by Gorman (1981)[1]. Previous evidence shows that, in general, Engel curves are quite non-linear, and therefore imposing strong functional form restrictions can have significant effects on estimates of consumer demand (Zhen et al. 2013). Second, since the EASI demand system is based on cost functions, welfare calculations are quite straightforward. Finally, error terms in the model can be interpreted as unobserved consumer heterogeneity, similarly to random effects, which has been proven to significantly affect welfare calculations(Lewbel and Pendakur 2009).

3.1 2016-2017 Household Budget Survey

In our analysis, we used the 2016-2017 Household Income and Budget Survey (EPF, Spanish acronym), which is an income and expenditure survey conducted by the National Institute of Statistics (INE, Spanish acronym) in Chile (*INE*). This survey is conducted every five years in major urban areas, representing 74% of the urban population. The EPF contains information regarding quantities and expenditure on all items used to construct the Consumer Price Index weights, and also reports socioeconomic and demographic information of the households (used to define poverty lines, among other applications). The EPS has a probabilistic, stratified, two stage sample design. The total sample size is 15,239 households. After excluding households with incomplete survey information, our analytic sample includes 15,184 households. There are two representative zones

[1]Gorman's rank restriction: no matter how many Engel curves are in the model, they must be expressed as linear combinations of at most three functions of expenditure.

identified in the survey: main capital (Santiago) and rest of the country. Food expenses are classified into food to be prepared and/or consumed at home, and food away from home. For the foods consumed at home, data includes name of the food item, expenditure, quantity and place of purchase[2].

[Table1 around here]

Table 1 shows the descriptive statistics for the full sample as well as for low and high income households. Hereon, low and high income refers to first and fifth quintile of income, respectively. [3] Low income households have a median income of 578 US dollars per month and mid-high income households have a median income of 7,762 US dollars per month (average exchange rate in the period: 660 CLP = 1 US), this is an income quintile ratio of 13.4. The large disparities across households highlights the importance of estimating household heterogeneous response in purchases, tax burden (or subsidy transfer) and welfare effects.

[Table 2 around here]

To estimate the demand system we divided food purchases into 11 groups that combine food products with similar nutritional content: (1) fruits, (2) vegetables, (3) carbohydrates, (4) sweets, desserts and salty snacks, (5) seafood, (6) poultry and red meats, (7) animal and vegetable fats, (8) dairy products, (9) (sugary and artificially) sweetened beverages , (10) coffee, tea and water, and (11) a numeraire good which includes all other foods consumed at home (condiments, for example) and foods away from home. Table 2 reports the descriptive statistics of the 11 food groups per household income group. For each household group, we reported the expenditure, unit values, quantity (in kilograms or liters), budget share, and share of zeros in purchases. To some extent, unit values can provide a proxy of relative quality across households, as well as differences in purchase place and package size. The share of zeros corresponds to the proportion of households that does not spend on a specific food group. High income households spend more on every food group,

[2] In some cases products that are registered by unit instead of volume or weight, INE impute quantities using the method of implicit prices. INE also corrects both expenditure and quantities for seasonal variation at the time the data was collected.

[3] Income distribution was calculated using nationally representative weights. As a result, sub-samples do not contain the same number of observations.

consume higher quantities, have a lower share of zeros and a higher unit value than low income households. We found that all variables have a significant statistical difference between the two income groups (note that, on average, high income households also have larger size). The only exceptions were the quantity purchased of carbohydrates and the budget share of poultry and red meat, and animal and vegetable fats.

3.2 Empirical Model

The EASI demand system is based on standard consumer theory, assuming that households maximize their utility subject to a linear budget constraint and face J vector of prices $p = [p^1, ..., p^j]$. The household has a total expenditure x after choosing a bundle of goods that is described by the J-vector of budget shares $w = [w^1, ...w^j]$. Therefore, let $x = C(p, u)$ be the cost function that provides the minimum nominal total expenditure to attain a utility level u, given prices p. These implicit Marshallian demands are hybrid demand functions of Marshallian and Hicksian demands that provide a direct approximation of household utility level as a function of observables. This way, we have been able to estimate the trade-off between income, price changes and utility. The model (its budget share form) is specified as follows:

$$w^j = \sum_{r=1}^{R} b_r^j (y)^r + \sum_{t=1}^{T} g_t^j z_t + \sum_{k=1}^{J} a^{jk} lnp^k + \varepsilon^j \tag{1}$$

where w^j is the budget share of good j, y is the implicit utility defined in equation 2, z_j is a vector of the households demographic characteristics, lnp^k is the index price log of good k and ε^j is a vector of unobserved preference or heterogeneity parameters. Finally, b_r^j, g_t^j and a^{jk} are parameters to be estimated, where b_r^j defines the shape of the Engel curve and R is the highest order of the polynomial y (third order, in our case). The implicit utility y is a log-money-metric representation of utility for a unit price vector[4] and is given by:

[4]Utility is equivalent to an affine function of the log of expenditure deflacted by the Stone Index. The Stone Index given by $\prod_{j=1}^{J} (p^j)^{w^j}$ is the exact deflactor that converts nominal expenditure x into real expenditures $exp(y)$, provided that we could call y the log real expenditure

$$y = lnx - \sum_{j=1}^{J} w^j lnp^j + 0.5 \sum_{j=1}^{J} \sum_{k=1}^{K} a^{jk} lnp^j lnp^k \quad (2)$$

Standard demand restrictions such as adding up, homogeneity and symmetry were imposed in the EASI model. Symmetry implies $a^{jk} = a^{kj}$, while homogeneity requires $\sum_{k=1}^{J} a^{jk} = 0$ for all j. As a result, we were able to produce a complete elasticity matrix per household. This allows us to have a distribution of elasticity estimates across households.

3.3 Endogeneity, price indexes and censoring

Implicit Marshallian demands have the dependent variable on both sides of the equation, which leads to endogeneity. This econometric problem is solved via instrumental variables. These instrumental variables, as suggested by Pendakur (2009), are functions of expenditure, prices and demographic variables, which are considered to be exogenous in this framework. However, as noted in previous studies, prices are not directly observed in this survey, rather unit values are constructed as proxy for prices, by dividing expenditure on quantity for each purchase (Caro et al. 2017). Due to the survey design, we do not have the required information to control for price endogeneity. Therefore, we exclude unit values as valid instruments in our estimation.

Another aspect to take into account is how price indexes are built, since price is only observed in households that purchase each specific good. To solve this, we have defined ten clusters based on income quintile and location (inside/outside the metropolitan region). First, we calculated the unit value (food group expenditure divided by its corresponding quantity) for the households that reported purchases. We replaced households with zero expenditure (households that did not report purchases for a specific food group) with the mean unit value of the cluster. We have assumed that households that do not report spending on a food group face a price that corresponds to the mean unit value of the cluster to which they belong, therefore unit values were imputed based on such rule. Finally, we winsorized extreme values (percentiles one and ninety-nine).

The original model specification by Lewbel and Pendakur (2009) does not take censored data into account. Since we are using cross sectional data at the household level and want to have a relatively large number of food groups in order to only aggregate similar food items, we needed to handle censored data. We have used the two-step approach developed by Heien and Wesseils (1990). The first step involves the estimation of a probit model describing the sample selection. Estimates from the probit model are used to calculate the inverse mills ratio (IMR) defined as the ratio of the probability density function to the cumulative distribution function for the budget share distribution of each food group. In the second step, estimates of the parameters of interest are obtained using a modified version of the EASI demand model, defined as:

$$w_j^i = \sum_{r=1}^{R} b_r^j (y)^r + \sum_{t=1}^{T} g_t^j z_t + \sum_{k=1}^{J} a^{jk} lnp^k + \delta_j IMR_j + \xi_j, \tag{3}$$

where ξ_j is the random error term with unknown distribution.

3.4 Estimation and simulation procedure

Following Pendakur (2008) we estimated the system of equations using an iterated linear method, given the sample size restrictions. This method can be described by the following steps:

1. Choose starting values for parameters a^{jk} to compute y_0 and select convergence criteria.
2. Estimate the linear system of equations in model defined by equation (3) by three-stage least squares. This step allows to instrument for endogeneity of budget shares as well as imposing symmetry and homogeneity.
3. Compute y_n using the estimated parameters in the previous step (n denotes the iteration number)
4. Repeat the previous steps, updating n until converge over y is achieved (based on the distance between y_n and y_{n-1} over all observations). Retain final estimated parameters once convergence is achieved.

Using the estimated parameters, we estimate average demand elasticities for all households and we use them to compute changes in the quantity demanded and tax burden (or subsidy transfer) for each of the ten food groups under each of the three fiscal policy scenarios. Finally, we computed the compensated variation for the household with median demographic characteristics under each policy scenario, which corresponds to the income that a household needs to receive in order to return to the original utility level after a price change. Standard errors are obtained via bootstrap, with 500 repetitions (see Appendix 6.2 for more details about the methodology). Using equivalences of scale, we predicted the welfare effect for the remaining households in the sample, in relation to the median household (this is the household with median demographic characteristics). The equivalence scale can be defined as a measure of the cost of living of a household of a given size and demographic composition, relative to the cost of living of a reference household, when both households attain the same level of utility or standard of living (Lewbel and Pendakur 2006).

3.5 Simulation scenarios

The EASI model above helps us to predict the quantity demanded change after a price change. We estimate changes in quantities, tax burden and consumer welfare for three policy scenarios. Policy 1 corresponds to a tax of 18% on sweets and desserts, salty snacks and chips (unhealthy foods) and SBs. At the time of the data collection, while unhealthy foods remained untaxed, SBs were already under a 10-18% specific tax depending on their sugar content. Based on reported average purchases by Caro et al. (2017), we estimate that SBs overall require 4 additional percent points [5]. Policy 2 corresponds to exempting the existing 19% VAT from fruits and vegetables. The VAT is currently applied to all foods in general. We choose this approach as previous evidence notes that zero-rating goods is more effective to induce changes in retail prices compared to a tax exemption ("Zero-rating versus Cash Transfers under the VAT"). Finally, policy 3 corresponds to the combination of policies 1 and 2. We assume that price changes due to these fiscal policies are fully transferred to consumers, however we present sensitivity analysis to this assumption in the Appendix.

We chose these policy scenarios with the aim of attaining more realistic values that could be informative for policy. Our first scenario is equivalent to extend the current tax rate on sugary beverages

[5] Purchase data in the EPF survey does not distinguish between sugary and artificially sweetened beverages

(SBs) in Chile (those with more than 6.25 grams per 100 milliliter) to unhealthy foods and other SBs. Unhealthy foods, similar to SBs, has been point out as a leading obesity determinant (Caro et al., 2017). Our second policy represents a net reduction on the price for healthy foods (fruits and vegetables), which has been proposed before in other studies (Härkänen et al. 2014; Nnoaham et al. 2009a). This scenario is consistent with evidence that most households do not meet the dietary guidelines for consumption of fruits and vegetables (MINSAL 2017).

4 Results

Using the estimated parameters from the EASI demand model for the full sample and each income quintile, we calculated the matrix of own-price and cross-price elasticities by food group. Appendix Table 5 presents the mean elasticities for the full sample. As expected, own price elasticities have a negative sign and cross-price elasticities were significant in most cases, particularly for the groups subject to policy simulation scenarios. Using the estimated elasticities, we computed the purchase variation for each group subject to each policy, measured as kilograms (or liters) per household, per month[6].

[Figure 1 around here]

Appendix Tables 5, 6 and 7 report the own-price and cross-price elasticities for the full sample, low and high income households respectively. In general we find that low income households have larger own-price demand elasticities (in absolute terms) compared to high income households, which is consistent with the literature. However, in terms of absolute changes in purchases across the food groups, our policy scenarios predict greater changes among high income households compared to low income households. The latter occurs because high income households have a larger baseline purchase quantity. Nonetheless, changes in relative terms are very similar, which is consistent with

[6]In this study we are not discussing the change in purchases for food categories not subject to fiscal policy changes. Dharmasena and Capps (2012) and Caro et al. (2017) have shown that increased purchases in other food groups could compensate the total reduction of sugar consumption. A simple analysis of our elasticity estimates indicate that calories from other sources will increase, but not in enough magnitude to overcome the positive effects of the simulated policies

very small differences in estimated elasticities across food groups.

Estimated changes in purchases are shown in Figure 1 and Appendix Table 4. Our estimates reveal that an 18% tax on unhealthy foods and beverages (Policy 1) would lead to an overall purchase decrease of 1.8 kg per household/month of sweets and salty snacks and 0.9 liters per households/month of sweetened beverages. There is also a substitution towards higher fruit purchases (+0.14 kg per household/month) and vegetable purchases (+0.47 kg per household/month) and dairies purchases (+0.25kg per household/month). A fruit and vegetable VAT zero-rating would lead to an overall increase of 1.6 kilograms of fruits and 5.1 kilograms of vegetables, with a decrease in sweets and snacks purchases (-0.18 kilograms per household/month) and SB purchases (-0.56 liters per household/month). Finally, the combined policy incorporates both effects, almost in an additive fashion, as expected in a model linear in prices. Thus, increases in fruit purchase are estimated to be +1.8 kilograms, vegetable purchase increases are estimated to be +5.6 kilograms, while sweet and snack purchases are estimated to fall by nearly 2 kg and SB purchases would decline by 1.5 liters per household/month.

Tax burden and welfare changes from different policies, under the baseline price pass-through scenario (100%), are presented in Table 3. The size of the tax burden and subsidy transfer from policies 1 and 2 are not statistically different. As a result, the combined policy is virtually revenue neutral. In terms of welfare, households have a much larger change in compensated variation from the subsidies, compared to the tax scheme, and therefore the combined policy results in a net gain for the average household (near to 0.1% of monthly income). As expected, a tax policy would lead to an average household tax burden significantly smaller than the welfare change in absolute terms. Implicitly, the difference is due to the dead weight loss of taxation.

[Table 3 around here]

Figures 2, 3 and Appendix Table 8 presents the estimated changes in tax burden and compensated variation for each quintile of the income distribution. There is significant heterogeneity in tax burden of a 18% tax on unhealthy food and SB between low and high income households. The lowest income (quintile 1) households report a much larger tax burden relative to income, than highest income (quintile 5) households (1.1% versus 0.4%). In the case of a 19% VAT reduction on fruits and vegetables, high income households would capture a smaller subsidy transfer (relative to income), than low income households (0.3% versus 1.1%). Finally, in the case of the combined policy simulation, we found that low income households receive a subsidy of 0.39% of income, while high income households face a negligible net cost of the policy (0.05% of income). In terms of welfare, a tax policy will put a lower welfare cost to high compared to low income households, relative to their average monthly income (0.24% versus 0.76%). In the case of the subsidy schedule, low income households receive a larger welfare benefit as a share of their income (1.05% versus 0.18%) compared to high income households). Finally, the combined policy will create welfare transfers from high income households (net welfare reduction of 0.06% income) to low income households (net welfare gain of 0.29% income). Moreover, the richest 40% of households experience a welfare loss from the combined policy, while poorest 40% experience a welfare gain from the combined policy. Households in the average of the income distribution do not experience significant change in welfare.

[Figure 2 around here]

[Figure 3 around here]

Finally, we report the results of our robustness checks and sensitivity analysis. We did not find relevant differences in the estimated parameters after comparing the results with and without unit value imputation and winsorizing techniques, which confirms the robustness of the model estimates. In addition, we found that our specification for income rank (Engel curves of third order) is significant for several food groups. In terms of censoring, the parameters δ_j are also statistically significant for food groups will largest fraction of households reporting zero purchases.

In terms of sensitivity of our estimates to supply-side responses, we conducted two alternative scenarios to the pass-through of fiscal policies to prices. First, we assumed 75% pass-through for both tax and subsidy, with the results shown in Appendix Table 9. Secondly, we imposed a 75% pass-through on the tax, but 50% on the subsidy, based on the idea that tax cuts are less likely to be passed to final consumers (Benzarti et al. 2017) whose results are shown in Appendix Table **??**. We found that reducing the expected size of the pass-through have two clear welfare implications.

If the pass-through is smaller for both the tax and subsidy, then our conclusions remain unchanged; only the size of the effects are smaller. However, if the subsidy does not translate into lower prices in the same way as the tax (i.e. a smaller pass-through), then the combined policy no longer creates welfare transfers across income groups, but rather puts the larger burden of welfare in the middle-high income households (and as such, is not regressive). Although not presented here, expected reduction in purchases will also be reduced proportionally (linear) to the size of the expected pass-though on prices.

5 Discussion and policy implications

In this study we present the estimates of the effects on purchases, tax burden (or subsidy transfer) and welfare variation of three different policy scenarios: a tax on unhealthy food and sweetened beverages (SB), a subsidy for fruits and vegetables, and a combination of these two fiscal policies. In order to do this, we used the EASI demand system developed by Lewbel and Pendakur (2009). We calculated the compensated variation and estimated a set of elasticities to simulate quantity, tax burden (or subsidy transfer) and welfare losses (or gains) under these three fiscal policy scenarios. We estimate the effects using the full sample, and also at every quintile of the income distribution, recognizing that households at different quintiles might express different preferences, as noted in the previous literature.

As a per-household average, the combined policy would lead to an increase of 7.4 kilograms of fruits and vegetables per month. If we assume that one average portion of fruits and vegetables corresponds to 80 grams, and given the average household size, the combined policy would lead to an increase of 1 portion of fruits and vegetables a day per person. While we found that the changes are greater for higher income households in Chile, among the low income households (quintile 1), monthly fruit and vegetable consumption is still estimated to increase 5.6 kilograms, which translates to an increase of 0.94 portion of fruits and vegetables a day per person. As a comparison, Capacci and Mazzocchi (2011) found that a public information campaign to promote fruits and vegetables consumption in the UK (5-a-day campaign) led to an increase of between 0.2 and 0.7

portions of fruits and vegetables a day. Furthermore, the combined policy reduces the consumption of unhealthy food by almost 2 kilograms and consumption of beverages by 1.5 liters, consistent with previous evidence (Caro et al. 2017).

A key issue of note in this study is our estimation of the welfare losses of gains under the three policy scenarios, and how this may vary by income quintile. We found that the combined policy results in welfare transfers from high income households (loss of 0.06% income among fifth quintile) to low income households (gain of 0.29% income among the first quintile). These results suggest that a combined policy can be one way for governments to not only improve dietary choices (and resultant health outcomes) of their population, but also helps redistribute resources to address equity concerns, without requiring direct transfers. We choose to compare relative to each income quintile because, at the time of the survey, poverty in Chile reached nearly 20%[7]. In fact, we can note that the welfare effects between the first and second quintile are significantly different.

To date, there are very limited studies that compare the welfare implications of various fiscal policy designs as applied to foods or nutrients to compare our findings to. Nnoaham et al. (2009b) is the closest study that presents a similar analysis, finding that a policy schedule in line with our combined policy scenario will be regressive, while our results suggests otherwise. However, this study uses a model that is linear in income and ignores differences in price elasticities across income groups. Such differences can account for the diverging conclusions. Härkänen et al. (2014) consider a sugar tax, a tax reduction for healthy foods and a combined policy in Finland on changes in energy and nutrient intake and extrapolate this to provide a range of estimates on health outcome changes. Akin to our findings, they found that there are significantly larger health effects with a combined policy compared to either single policy strategies, but their study did not estimate economic welfare changes. Härkänen et al. (2014) also found that the health effects were the most pronounced for low-income individuals, primarily because low-income individual have the most severe health problems to start with. Consequently, the authors conclude that these policies may help reduce health inequalities in Finland. In this paper, while we do not extrapolate our findings to health outcomes, we do find that the changes in purchases are not significantly different

[7]Currently, Chile measures poverty using a comprehensive set of indicators rather than just income. Poverty measure as income reached 7.3% in 2017

between income groups (in relative terms). However, given that the prevalence of obesity-related non-communicable diseases is larger in low socioeconomic groups, we can expect similar effects of health inequalities as presented in Härkänen et al. (2014) and MINSAL (2017).

Meanwhile, under the tax policy alone, the welfare loss represents 0.76% of income among the lowest income households, but the tax incidence is very large among the lowest income households (6.2% of income), indicating higher dead weight loss for these lowest income households, and that a tax policy alone in Chile is likely to be regressive and inefficient. Thus, these results together suggest that should a unhealthy food based tax policy be implemented in Chile, it may need to be accompanied by other forms of income transfers such as a healthy food price subsidy (i.e., a combined policy).

As mentioned earlier, we do not extrapolate our findings to potential changes in the health, productivity and reduced health care expenditures that could arise from the three policies and how they might vary across income quintiles, which is beyond the scope of this paper. However, under all three scenarios, given increases in fruit and vegetable consumption and reductions in sweetened beverages, sweets and snacks we should expect that the health and productivity effects and reduced health care expenditures should be strictly positive and sizable. However, whether this impacts are disproportional between income groups remains as a empirical question for future research. Likewise, we have ignored the potential environmental dimension; unhealthy food and sweetened beverage production leads to larger greenhouse emissions than fruits and vegetables production. In France, Caillavet, Fadhuile, and Nichèle (2016) found a beneficial synergy between environmental and nutritional effects across income and age groups, with a small regressive impact. In this sense, future work can explore the effects at the nutrient-level, as proxy to health effects, as well as potential environmental impacts. In any case, we argue that both tax incidence and welfare impact are relevant dimensions to consider as part of the debate around fiscal policies related to food and nutrition. Without estimates of potential health and labor productivity benefits from shifting away from unhealthier foods towards healthier ones, our analytic approach can only provide an economic welfare estimation based on the current purchase level; we are unable to quantify the welfare gain attributable to healthier purchases in the long run.

Our work presents some limitations. First, we were only able to analyze the demand for foods and beverages, and did not consider other substitution and income effects beyond this set of purchases, based on the assumption of staged budgeting, as noted in other studies (Zhen et al. 2013; Caro et al. 2017). Second, due to data limitations, we were not able to distinguish artificially sweetened beverages from sugar-sweetened beverages and were only able to look at sweetened beverages collectively. We additionally worked under the assumption of a uniform pass-through for both household income groups. In one of the few studies on tax pass-through, Colchero et al. (2015) found that the soda tax in Mexico has a different pass-through on price across beverages and regions. Thus, it could be the case that, to some extent, some income groups do not respond to price variations, as determined by Bertail and Caillavet (2008). Finally, in this framework, we have no means of providing enough information to compare the social benefits of the combined policy with other food-based welfare policies that not represent a direct cash transfer, such as the Chilean School Meal Program.

As governments are increasingly exploring fiscal policies to promote healthier purchases, we highlight the importance of considering multiple strategies to address this goal, as well as consider the welfare changes and tax incidence overall and across income groups and how these policies may alleviate or worsen inequities. Our findings suggest that a combined policy taxing less healthy foods and beverages at 18% with a subsidy/removal of the existing 19% VAT on fruits and vegetables in Chile is one potential way to improve dietary choices while also achieving redistributive goals.

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References

Allais, Olivier, Fabrice Etilé, and Sébastien Lecocq (2015). "Mandatory labels, taxes and market forces: An empirical evaluation of fat policies". In: *Journal of Health Economics* 43 (Supplement C), pp. 27–44.

Anand, Sonia S. et al. (2015). "Food Consumption and its Impact on Cardiovascular Disease: Importance of Solutions Focused on the Globalized FoodăSystem: A Report From the Workshop Convened by the WorldăHeartăFederation". In: *Journal of the American College of Cardiology* 66.14, pp. 1590–1614.

Andreyeva, Tatiana, Michael W. Long, and Kelly D. Brownell (2010). "The Impact of Food Prices on Consumption: A Systematic Review of Research on the Price Elasticity of Demand for Food". In: *Am J Public Health* 100.2, pp. 216–222.

Batis, Carolina et al. (2016). "First-year evaluation of Mexicos tax on nonessential energy-dense foods: an observational study". In: *PLoS medicine* 13.7, e1002057.

Benzarti, Youssef et al. (2017). *What Goes Up May Not Come Down: Asymmetric Incidence of Value-Added Taxes*. Working Paper 23849. DOI: 10.3386/w23849. National Bureau of Economic Research.

Bertail, Patrice and France Caillavet (2008). *Fruit and Vegetable Consumption Patterns: A Segmentation Approach*. SSRN Scholarly Paper ID 1146682. Rochester, NY: Social Science Research Network.

Bíró, Anikó (2015). "Did the junk food tax make the Hungarians eat healthier?" In: *Food Policy* 54, pp. 107–115.

Brownell, Kelly D. et al. (2009). "The Public Health and Economic Benefits of Taxing Sugar-Sweetened Beverages". In: *New England Journal of Medicine* 361.16, pp. 1599–1605.

Caillavet, France, Adélaïde Fadhuile, and Véronique Nichèle (2016). "Taxing Animal-Based Foods for Sustainability: Environmental, Nutritional and Social Perspectives in France". In: *Eur Rev Agric Econ*.

Capacci, Sara and Mario Mazzocchi (2011). "Five-a-Day, a Price to Pay: An Evaluation of the UK Program Impact Accounting for Market Forces". In: *Journal of Health Economics* 30.1, pp. 87–98.

Caro, Juan Carlos et al. (2017). "Designing a tax to discourage unhealthy food and beverage purchases: The case of Chile". In: *Food Policy* 71 (Supplement C), pp. 86–100.

Chouinard, Hayley H et al. (2007). "Fat Taxes: Big Money for Small Change". In: *Forum for Health Economics & Policy* 10.2.

Colchero, M. A. et al. (2015). "Price Elasticity of the Demand for Sugar Sweetened Beverages and Soft Drinks in Mexico". In: *Econ Hum Biol* 19, pp. 129–137.

Colchero, M. Arantxa, Mariana Molina, and Carlos M. Guerrero-López (2017). "After Mexico Implemented a Tax, Purchases of Sugar-Sweetened Beverages Decreased and of Water Increased: Difference by Place of Residence, Household Composition, and Income Level". In: *J. Nutr.* jn251892.

Corvalán, Camila et al. (2013). "Structural responses to the obesity and non-communicable diseases epidemic: the Chilean Law of Food Labeling and Advertising". In: *obesity reviews* 14, pp. 79–87.

Dharmasena, Senarath and Oral Capps (2012). "Intended and unintended consequences of a proposed national tax on sugar-sweetened beverages to combat the U.S. obesity problem". In: *Health Econ* 21.6, pp. 669–694.

Etilé, Fabrice and Anurag Sharma (2015). "Do High Consumers of Sugar-Sweetened Beverages Respond Differently to Price Changes? A Finite Mixture IV-Tobit Approach". In: *Health Econ.* 24.9, pp. 1147–1163.

Finkelstein, Eric, Ian C. Fiebelkorn, and Guijing Wang (2005). "The Costs of Obesity among Full-Time Employees". In: *Am J Health Promot* 20.1, pp. 45–51.

Finkelstein EA, Brown DS, and Popkin BM (2007). "Lifetime Medical Costs Associated with Obesity and Smoking". In:

Gorman (1981). "Some Engel Curves". In: *Essays in the Theory and Measurement of Consumer Behavior: In Honor of Sir Richard Stone*.

Griffith, Rachel et al. (2016). *Using Taxation to Reduce Sugar Consumption*. Institute for Fiscal Studies.

Harding, Matthew and Michael Lovenheim (2017). "The effect of prices on nutrition: Comparing the impact of product- and nutrient-specific taxes". In: *Journal of Health Economics* 53 (Supplement C), pp. 53–71.

Hawkes, Corinna et al. (2015). "Smart food policies for obesity prevention". In: *The Lancet* 385.9985, pp. 2410–2421.

Hawkes, Corinna et al. (2017). "Principles behind evaluations of national food and beverage taxes and other regulatory efforts". In: *Obesity Reviews* 18.11, pp. 1374–1375.

Heien, Dale and Cathy Roheim Wesseils (1990). “Demand systems estimation with microdata: a censored regression approach”. In: *Journal of Business & Economic Statistics* 8.3, pp. 365–371.

Härkänen, Tommi et al. (2014). “The Welfare Effects of Health-Based Food Tax Policy”. In: *Food Policy* 49, Part 1, pp. 196–206.

INE, ed. *INE*. `http://www.ine.cl/estadisticas/ingresos-y-gastos/epf`. Accessed: 2018-06-03.

Kotakorpi, Kaisa et al. (2012). *The Welfare Effects of Health-Based Food Tax Policy*. Discussion Paper 81. Aboa Centre for Economics.

Lewbel, Arthur and Krishna Pendakur (2006). “EQUIVALENCE SCALES Entry for The New Palgrave Dictionary of Economics, 2nd edition”. In:

— (2009). “Tricks with Hicks: The EASI Demand System”. In: *American Economic Review* 99.3, pp. 827–63.

Lusk, Jayson L. and Christiane Schroeter (2012). “WHEN DO FAT TAXES INCREASE CONSUMER WELFARE?” In: *Health Economics* 21.11, pp. 1367–1374.

Madden, David (2015). “The poverty effects of a 'fat-tax' in Ireland”. In: *Health Econ* 24.1, pp. 104–121.

Malik, Vasanti S. et al. (2010). “Sugar-Sweetened Beverages, Obesity, Type 2 Diabetes Mellitus, and Cardiovascular Disease Risk”. In: *Circulation* 121.11, pp. 1356–1364.

Miao, Zhen, John C. Beghin, and Helen H. Jensen (2013). “Accounting for Product Substitution in the Analysis of Food Taxes Targeting Obesity”. In: *Health Econ.* 22.11, pp. 1318–1343.

MINSAL, Departamento de Epidemiologia (2017). “Encuesta Nacional de Salud 2016-2017: Primeros resultados”. In: *Ministerio de Salud, Chile*.

Muller, Laurent et al. (2017). “Distributional Impacts of Fat Taxes and Thin Subsidies”. In: *Econ J* 127.604, pp. 2066–2092.

Ng, Marie et al. (2014). “Global, regional, and national prevalence of overweight and obesity in children and adults during 1980-2013: a systematic analysis for the Global Burden of Disease Study 2013”. In: *Lancet* 384.9945, pp. 766–781.

Nnoaham, Kelechi E. et al. (2009a). “Modelling Income Group Differences in the Health and Economic Impacts of Targeted Food Taxes and Subsidies”. In: *Int J Epidemiol* 38.5, pp. 1324–1333.

Nnoaham, Kelechi E et al. (2009b). “Modelling income group differences in the health and economic impacts of targeted food taxes and subsidies”. In: *International journal of epidemiology* 38.5, pp. 1324–1333.

O'Donoghue, Ted and Matthew Rabin (2006). “Optimal sin taxes”. In: *Journal of Public Economics* 90.10, pp. 1825–1849.

Oordt, Marius van. “Zero-rating versus Cash Transfers under the VAT”. In: *Fiscal Studies*.

Pendakur, Krishna (2008). *EASI made Easier*.

— (2009). “Chapter 7 EASI Made Easier”. In: *Contributions to Economic Analysis*. Ed. by Daniel J. Slottje. Vol. 288. Emerald Group Publishing Limited, pp. 179–206.

Powell, Lisa M et al. (2013). “Assessing the potential effectiveness of food and beverage taxes and subsidies for improving public health: a systematic review of prices, demand and body weight outcomes”. In: *Obesity reviews* 14.2, pp. 110–128.

Sassi, Franco et al. (2018). “Equity impacts of price policies to promote healthy behaviours”. In: *The Lancet*.

Seuring, Till, Olga Archangelidi, and Marc Suhrcke (2015). “The Economic Costs of Type 2 Diabetes: A Global Systematic Review”. In: *Pharmacoeconomics* 33.8, pp. 811–831.

Shonkwiler, J. Scott and Steven T. Yen (1999). “Two-Step Estimation of a Censored System of Equations”. In: *American Journal of Agricultural Economics* 81.4, pp. 972–982.

Smed, Sinne, Jorgen Dejgaard Jensen, and Sigrid Denver (2005). *Differentiated Food Taxes as a Tool in Health and Nutrition Policy*. 2005 International Congress, August 23-27, 2005, Copenhagen, Denmark 24579. European Association of Agricultural Economists.

Smed, Sinne and Jørgen Dejgaard Jensen (2005). “Food safety information and food demand”. In: *British Food Journal* 107.3, pp. 173–186.

Stanhope, Kimber L. (2012). “Role of Fructose-Containing Sugars in the Epidemics of Obesity and Metabolic Syndrome”. In: *Annual Review of Medicine* 63.1, pp. 329–343.

Strnad, Jeff (2004). *Conceptualizing the 'Fat Tax': The Role of Food Taxes in Developed Economies*. SSRN Scholarly Paper ID 561321. Rochester, NY: Social Science Research Network.

Thiele, Silke (2010). *Fat Tax: A Political Measure To Reduce Overweight? The Case Of Germany*. 115th Joint EAAE/AAEA Seminar, September 15-17, 2010, Freising-Weihenstephan, Germany 116393. European Association of Agricultural Economists & Agricultural and Applied Economics Association.

Thow, Anne Marie, Shauna Downs, and Stephen Jan (2014). "A systematic Review of the Effectiveness of Food Taxes and Subsidies to Improve Diets: Understanding the Recent Evidence". In: *Nutr Rev* 72.9, pp. 551–565.

Tiffin, Richard and Matthieu Arnoult (2011). "The public health impacts of a fat tax". In: *European journal of clinical nutrition* 65.4, p. 427.

Building momentum: lessons on implementing a robust sugar sweetened beverage tax (2018). Tech. rep.

Yaniv, Gideon, Odelia Rosin, and Yossef Tobol (2009). "Junk-food, Home Cooking, Physical Activity and Obesity: The Effect of the Fat Tax and the Thin Subsidy". In: *Journal of Public Economics* 93.5, pp. 823–830.

Zhen, Chen et al. (2013). "Predicting the Effects of Sugar-Sweetened Beverage Taxes on Food and Beverage Demand in a Large Demand System". In: *Am. J. Agr. Econ.*

Table 1: Household descriptive statistics

	Full sample		Low income (quintile 1)		High income (quintile 5)	
	Mean/SD	Ref.household	Mean/SD	Ref.household	Mean/SD	Ref.household
Years of education household head	11.452	12	9.008	10	15.483	17
	(6.147)		(5.804)		(4.313)	
Head of household men (share)	0.562	1	0.420	0	0.703	1
	(0.496)		(0.494)		(0.457)	
Number of children under 18	0.782	1	0.617	1	0.843	1
	(1.021)		(0.967)		(1.026)	
Number of adults	2.394	2	1.830	2	2.664	2
	(1.118)		(0.840)		(1.191)	
Number of men in the household	1.491	1	1.050	1	1.715	2
	(1.059)		(0.928)		(1.036)	
Household size	3.176	3	2.447	2	3.506	3
	(1.623)		(1.387)		(1.601)	
Share of households in Santiago	0.523	1	0.509	1	0.526	1
	(0.500)		(0.500)		(0.499)	
Household income ($USD)	2690.0	1694.9	575.9	600.0	7762.8	6056.1
	(3405.8)		(240.2)		(5335.5)	

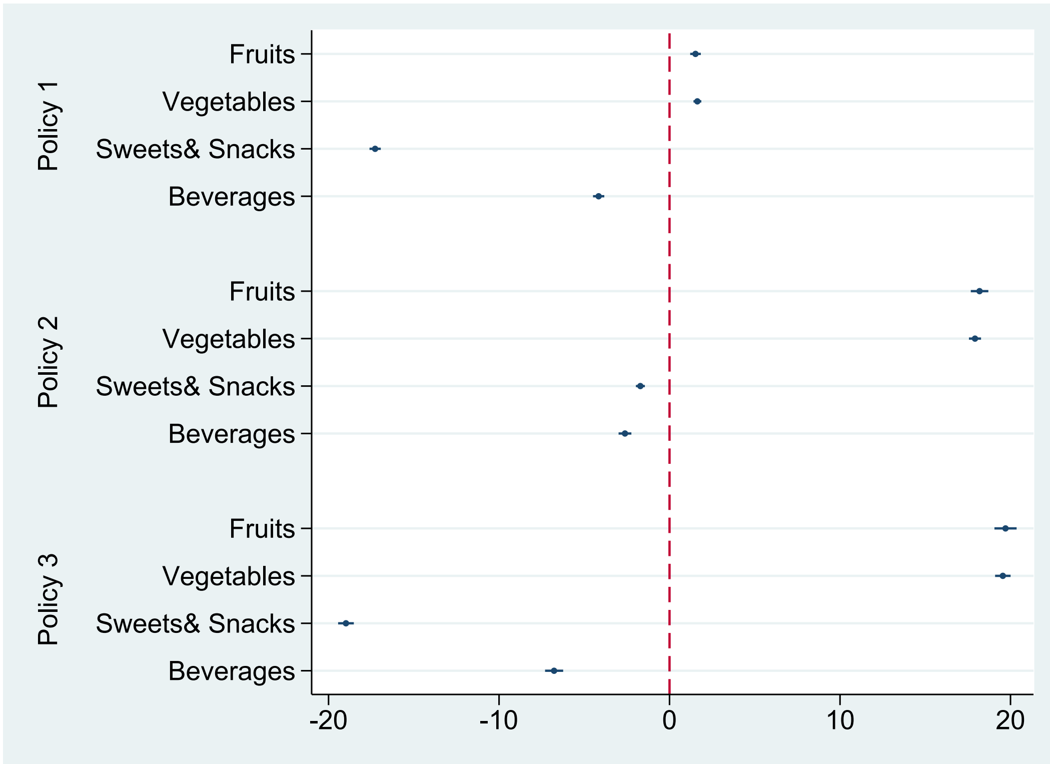
Notes: Weighted values using sampling weights. The reference household corresponds to a representative household with median values of all socio-demographic variables.

Table 2: Food group statistics by household income group

	Full sample(N=15,184)					Low income(quintile 1)					High income (quintile 5)				
	Expenditure	Unit values	Quantity	Share(%)	Zeroes(%)	Expenditure	Unit values	Quantity	Share(%)	Zeroes(%)	Expenditure	Unit values	Quantity	Share(%)	Zeroes(%)
Fruits	17.2	2.47	8.99	4.5	27.7	10.1	2.05	6.46	4.54	35.1	30.1	3.37	11.9	4.99	19.7
Vegetables	40.2	1.93	28.5	10.2	10.7	27.3	1.68	22.9	11.3	14.1	58	2.45	31.8	9.19	10.7
Carbohydrates	59.3	2.29	29.4	17.6	1.92	46.8	2.03	25.8	22.6	1.83	61.5	2.93	24.2	10.6	3.45
Sweets and snacks	45.9	5.8	10.3	10.8	11.3	20.7	5.23	5.85	8.57	21.2	90.5	7.03	16.4	14.9	4.29
Seafood	10.9	9.85	1.35	2.45	56.5	5.54	8.44	.849	2.16	65.5	20.2	12.5	1.82	3.02	48.2
Poultry and red meat	63.1	7.77	8.76	14.1	19.3	38.3	7.06	6.1	13.9	24.5	88.2	9.23	10.2	12.8	18.4
Animal and vegetal fat	28.7	7.42	4.75	7.05	13.6	18	6.49	3.54	7.44	17.7	42.7	9.53	5.37	6.65	12.8
Dairies	43.8	2.67	36.7	10.8	8.64	25.3	2.33	28.3	10.4	13.3	70.8	3.41	42.7	11.4	7.34
Sweetened beverages	29.2	1.54	21.5	7.63	14.7	15.4	1.38	13.3	6.76	25.1	42.2	1.87	26.5	7.27	9.73
Water, coffee and tea	10.4	9.63	12.9	2.61	42.1	5.47	14.2	6.53	2.38	54.2	19.4	5.41	23.3	3.35	27.1
Other	55.4	11.4	6.12	12.2	14.6	26.3	8.69	4.14	10	22.6	102	15.7	8.32	15.9	7.66

Notes: Expenditures and unit values are expressed in $USD. Quantities are measured in kilograms or liters depending on each food group. Shares and zeroes represent the fraction of the total budget and households reporting no purchases for each food group, respectively. Wilcoxon-Mann-Whitney's test was conducted to check whether there is a significant statistical difference between low income and high income households. We found that almost all variables have a significant statistical difference between the two income groups (first and fifth quintiles). The only exceptions were the budget share of poultry meat and animal fat, and total purchase of carbohydrates.

Figure 1: Average percentage change in household purchases (%)



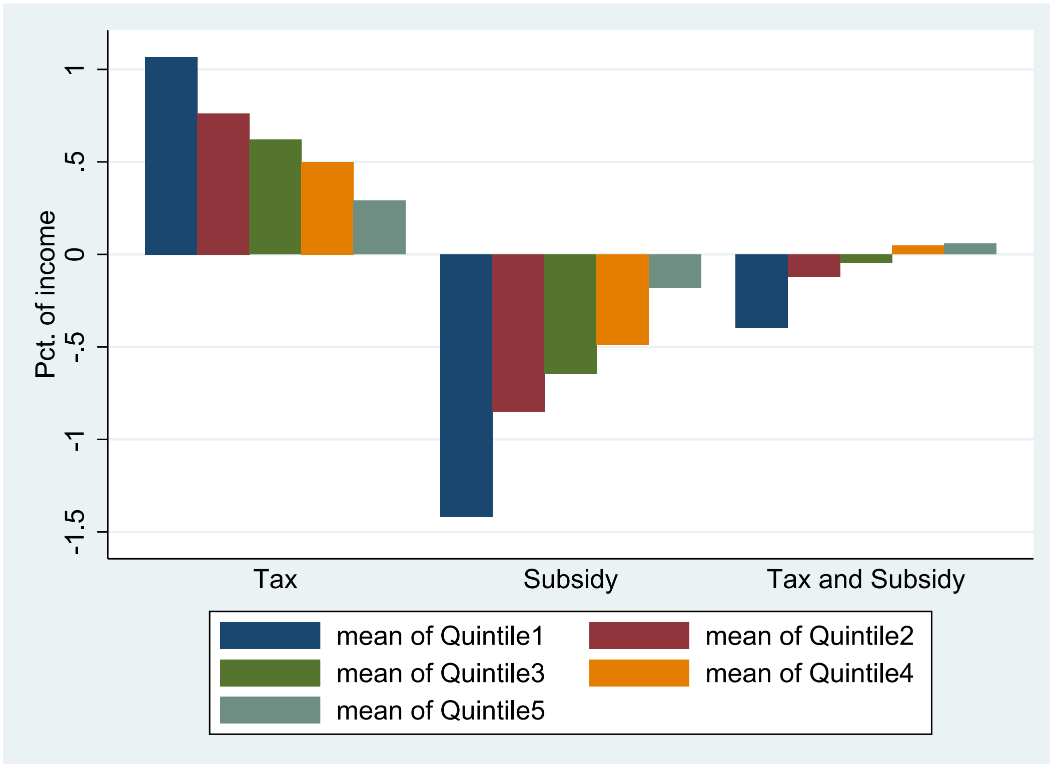
Results are shown only for food groups that are affected by taxes or subsidies. Standard errors were calculated using bootstrap method.

Table 3: Household compensated variation and tax burden/subsidy transfer in USD per month, assuming 100% pass through in prices (full sample)

	Welfare loss	Pct.	Tax burden	Pct.
18% tax on junk food	8.396	0.312	12.014	0.155
	(0.085)	(0.004)	(0.104)	(0.005)
19% fruit and vegetables VAT reduction	-10.741	-0.399	-12.252	-0.158
	(0.081)	(0.004)	(0.098)	(0.005)
Tax and Subsidy together	-2.345	-0.087	-0.662	-0.009
	(0.089)	(0.003)	(0.125)	(0.005)

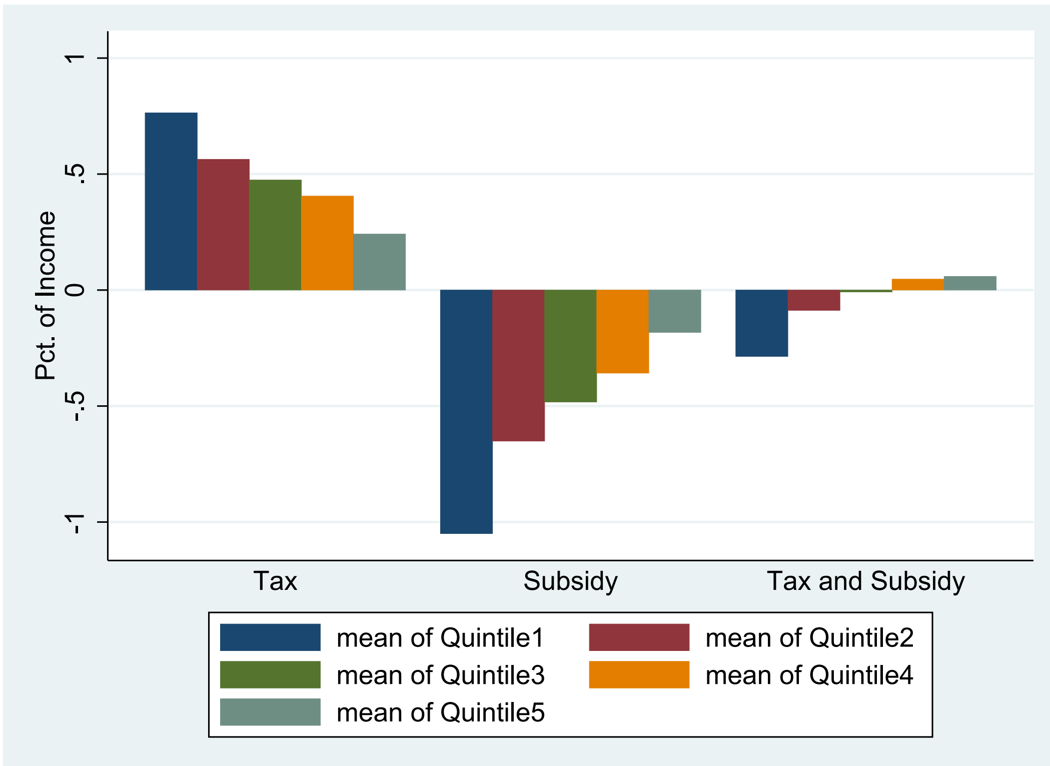
Notes:CV: compensated variation Standard errors in parenthesis. They were calculated using bootstrap method. Positive values denote welfare losses; and negative values denote welfare gains. Welfare losses and gains and tax burden are in US dollars. "Pct." is equivalent to percent of household income.

Figure 2: Household tax burden or subsidy transfer as percent of income



Notes: Positive values denote welfare losses; and negative values denote welfare gains. "Pct." is equivalent to percent of household income.

Figure 3: Household welfare loss or compensated variation as percent of income



Notes: Positive values denote welfare losses; and negative values denote welfare gains. "Pct." is equivalent to percent of household income.

6 Appendix

6.1 Price Elasticities

Following the procedure by Zhen et al. (2013), we calculated the compensated (Hicksian) elasticity of demand for good j with respect to the price of good k and expenditure elasticities. Then, using the Slutsky equation, we computed uncompensated (Marshallian) price elasticities [8].

Compensated (Hicksian) elasticity of demand for good j with respect to price of good k is,

$$\xi = \varpi^{-1}A + \Omega\varpi - I \tag{4}$$

where ξ is a JxJ matrix of compensated demand elasticities, ϖ is an identity matrix where the ones have been replaced by the food groups budget shares, Ω is an JxJ matrix of ones and I is an identity matrix. Expenditure elasticities are calculates as follows:

$$\eta = \varpi^{-1}(I + BP')^{-1}B + 1_j) \tag{5}$$

where η is an J vector of expenditure elasticities and B is the derivative of equation 3 (model corrected by Shonkwiler and Yen (1999)) with respect to the real expenditures y_l, whose jth elements equal $\sum_{r=1}^{3} rb_{ir}y^{r-1}$, P is the $JX1$ vector of log prices, and 1_j is a $Jx1$ vector of ones.

Uncompensated (Marshallian) price elasticity is recovered from the Slutsky equation,

$$E = \eta - \xi * S \tag{6}$$

[8] We dropped extreme values (7 out of 10,485 households/observations)

6.2 Welfare Analysis

Based on the cost function $C(p_0, u, z, \varepsilon)$, we evaluated the cost to an individual of a price change based on Pendakur (2009). In order to obtain that result, we used the log cost of living index as a consumer surplus measure for the price change from p_0 to p_1 which, for the cost function, is given by:

$$\begin{aligned} \ln\left(\frac{C(p_1, u, z, \varepsilon)}{C(p_0, u, z, \varepsilon)}\right) &= \sum_{j=1}^{J} w_0^j(\ln p_1^j - \ln p_0^j) \\ &+ \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} a^{jk}(\ln p_1^j - \ln p_0^j)(\ln p_1^j - \ln p_0^j). \end{aligned} \tag{7}$$

The first term of the equation 7 is the Stone index for the price change, which captures the first order effects driven by expenditure shares. The presence of the second term allows one to explicitly model substitution effects (or second order effects). The welfare calculated by equation 7 is related to the reference household. However, the interpretation of the error terms as unobserved preference heterogeneity allows the estimation of a distribution of welfare, instead of only the average welfare effect.

Finally, based on Lewbel and Pendakur (2009) we adjusted our welfare estimations with an equivalence scale for households with different demographic characteristics. These equivalence scales allow inter-household comparisons of the welfare effect. The equivalence scale is given by:

$$\ln E(p, u, z, e) = \sum_{t=1}^{T} g_t^j z_t + \sum_{t=1}^{T}\sum_{j=1}^{J} lnp^j(g_t^j z_t + \varepsilon^j) + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} a^{jk} lnp^j lnp^k, \tag{8}$$

where d are the coefficients of demographic variables, z is the vector of demographic variables, p is the vector of price index and A are price coefficients.

6.3 Appendix:Tables and Figures

Table 4: Average change in household purchases in kilograms or liters per month

	Full sample			Low Income (Quintile 1)			High Income (Quintile 5)		
	Policy 1	Policy 2	Policy 3	Policy 1	Policy 2	Policy 3	Policy 1	Policy 2	Policy 3
	Mean/Std error	Mean/Std error	Mean/Std error	Mean/Std error	Mean/Std error	Mean/Std error	Mean/Std error	Mean/Std error	Mean/Std error
Fruits	0.137	1.634	1.771	0.094	1.160	1.255	0.136	2.090	2.225
	(0.014)	(0.030)	(0.036)	(0.017)	(0.041)	(0.047)	(0.046)	(0.080)	(0.098)
Vegetables	0.466	5.112	5.578	0.360	3.983	4.343	0.491	5.724	6.215
	(0.034)	(0.072)	(0.086)	(0.045)	(0.115)	(0.136)	(0.101)	(0.191)	(0.232)
Bread,flour,pasta,potato	0.031	0.131	0.163	-0.010	0.183	0.174	0.034	0.164	0.198
	(0.034)	(0.046)	(0.058)	(0.055)	(0.064)	(0.088)	(0.087)	(0.104)	(0.119)
Sweets and Snacks	-1.787	-0.177	-1.964	-1.046	-0.122	-1.168	-2.678	-0.237	-2.915
	(0.026)	(0.014)	(0.032)	(0.033)	(0.016)	(0.039)	(0.087)	(0.041)	(0.103)
Seafood	-0.001	-0.011	-0.013	-0.002	-0.011	-0.013	-0.011	-0.013	-0.024
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.008)	(0.010)
Poultry and Red meat	-0.091	-0.029	-0.120	-0.039	0.011	-0.028	-0.101	-0.006	-0.108
	(0.010)	(0.011)	(0.016)	(0.011)	(0.015)	(0.018)	(0.028)	(0.032)	(0.045)
Animal and Vegetable fat	-0.043	-0.109	-0.152	-0.034	-0.080	-0.114	-0.053	-0.114	-0.168
	(0.006)	(0.009)	(0.011)	(0.009)	(0.012)	(0.016)	(0.019)	(0.021)	(0.029)
Dairies	0.246	-0.025	0.221	0.125	0.002	0.127	0.112	-0.040	0.073
	(0.032)	(0.039)	(0.052)	(0.046)	(0.060)	(0.080)	(0.104)	(0.106)	(0.156)
Beverages	-0.895	-0.563	-1.458	-0.543	-0.358	-0.901	-1.026	-0.811	-1.836
	(0.038)	(0.042)	(0.061)	(0.040)	(0.048)	(0.067)	(0.112)	(0.130)	(0.185)
Water,coffee,tea	-0.098	-0.136	-0.234	-0.046	-0.068	-0.114	0.009	-0.319	-0.310
	(0.015)	(0.016)	(0.023)	(0.011)	(0.013)	(0.018)	(0.095)	(0.084)	(0.126)
Others	-0.076	0.161	0.085	-0.039	0.113	0.073	-0.136	0.189	0.053
	(0.005)	(0.005)	(0.007)	(0.007)	(0.009)	(0.011)	(0.019)	(0.017)	(0.021)

Notes: Each policy is defined in table **??**. Standard errors in parenthesis. They were calculated using bootstrap method.

Table 5: Mean Marshallian Price Elasticities, **Full sample**

	with respect to the price of										
	Fruits	Vegetables	Carbohydrates	Sweets and Snacks	Seafood	Red and Poultry meat	Fats	Dairies	Beverages	Water, coffee, tea	Others
Fruits	-0.991	-0.148	-0.067	0.066	0.026	0.020	0.074	0.016	0.074	0.000	-0.067
	(0.014)	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)	(0.008)	(0.004)	(0.003)
Vegetables	-0.095	-1.028	-0.072	0.075	0.026	0.060	0.062	-0.005	0.065	0.027	-0.156
	(0.009)	(0.010)	(0.007)	(0.006)	(0.008)	(0.006)	(0.009)	(0.005)	(0.009)	(0.006)	(0.005)
Bread,flour,pasta,potato	-0.014	-0.014	-0.704	0.009	0.065	0.034	0.019	-0.010	-0.011	0.048	-0.111
	(0.014)	(0.011)	(0.015)	(0.009)	(0.012)	(0.009)	(0.012)	(0.007)	(0.015)	(0.009)	(0.006)
Sweets and Snacks	0.037	0.070	-0.038	-0.953	-0.002	-0.050	-0.026	0.036	-0.024	-0.026	-0.057
	(0.008)	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)	(0.007)	(0.005)	(0.009)	(0.006)	(0.004)
Seafood	0.020	0.033	0.102	-0.009	-1.168	-0.019	-0.008	0.004	0.019	-0.003	-0.037
	(0.008)	(0.005)	(0.006)	(0.004)	(0.014)	(0.004)	(0.007)	(0.003)	(0.008)	(0.004)	(0.002)
Red and Poultry meat	-0.002	0.023	-0.038	-0.048	-0.010	-1.013	-0.029	0.005	0.005	0.026	-0.049
	(0.012)	(0.010)	(0.010)	(0.009)	(0.011)	(0.012)	(0.011)	(0.007)	(0.012)	(0.009)	(0.006)
Animal and vegetable fat	0.061	0.083	-0.014	-0.040	-0.005	-0.044	-0.984	0.033	-0.044	0.002	-0.097
	(0.009)	(0.006)	(0.006)	(0.005)	(0.007)	(0.005)	(0.012)	(0.004)	(0.009)	(0.005)	(0.003)
Dairies	0.008	-0.004	-0.065	0.038	0.006	0.032	0.025	-1.014	-0.005	-0.002	-0.054
	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)
Beverages	0.065	0.099	-0.038	-0.013	0.026	-0.034	-0.025	0.012	-0.888	0.011	-0.063
	(0.010)	(0.007)	(0.008)	(0.007)	(0.008)	(0.006)	(0.010)	(0.005)	(0.016)	(0.006)	(0.003)
Water,coffee,tea	0.004	0.063	0.118	-0.046	0.001	0.113	0.010	0.005	0.015	-1.183	-0.030
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)
Others	-0.038	-0.127	-0.182	-0.055	-0.019	-0.049	-0.058	-0.049	-0.059	-0.018	-0.444
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.007)

Notes: Bootstrap standard errors in parenthesis (500 repetitions).

Table 6: Mean Marshallian Price Elasticities, **Low income: quintile 1**

	with respect to the price of										
	Fruits	Vegetables	Carbohydrates	Sweets and Snacks	Seafood	Red and Poultry meat	Fats	Dairies	Beverages	Water,coffee,tea	Others
Fruits	-1.027	-0.097	-0.057	0.062	0.049	-0.023	0.076	0.003	0.077	0.012	-0.055
	(0.026)	(0.011)	(0.011)	(0.010)	(0.014)	(0.010)	(0.014)	(0.007)	(0.015)	(0.008)	(0.006)
Vegetables	-0.066	-1.020	-0.121	0.072	0.028	0.040	0.054	-0.002	0.060	0.021	-0.134
	(0.018)	(0.019)	(0.012)	(0.012)	(0.013)	(0.011)	(0.016)	(0.010)	(0.017)	(0.010)	(0.011)
Bread,flour,pasta,potato	-0.009	-0.036	-0.705	0.004	0.084	0.029	0.018	-0.014	-0.024	0.032	-0.078
	(0.027)	(0.021)	(0.031)	(0.021)	(0.026)	(0.019)	(0.025)	(0.014)	(0.028)	(0.015)	(0.013)
Sweets and Snacks	0.042	0.088	-0.044	-0.991	-0.009	-0.020	-0.030	0.028	-0.006	-0.030	-0.044
	(0.014)	(0.010)	(0.011)	(0.020)	(0.010)	(0.010)	(0.013)	(0.009)	(0.015)	(0.009)	(0.008)
Seafood	0.042	0.038	0.162	-0.015	-1.239	0.025	-0.003	-0.018	0.002	0.003	-0.042
	(0.015)	(0.009)	(0.012)	(0.008)	(0.031)	(0.009)	(0.015)	(0.007)	(0.013)	(0.006)	(0.005)
Red and Poultry meat	-0.021	0.010	-0.055	-0.029	0.008	-1.081	-0.018	0.012	0.012	0.024	-0.028
	(0.023)	(0.017)	(0.019)	(0.018)	(0.020)	(0.025)	(0.023)	(0.014)	(0.023)	(0.014)	(0.013)
Animal and vegetable fat	0.064	0.078	-0.018	-0.039	-0.002	-0.013	-1.026	0.039	-0.058	-0.004	-0.068
	(0.016)	(0.011)	(0.011)	(0.011)	(0.016)	(0.010)	(0.021)	(0.008)	(0.015)	(0.008)	(0.006)
Dairies	-0.001	0.001	-0.085	0.025	-0.011	0.049	0.031	-1.024	-0.002	0.005	-0.030
	(0.010)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.010)	(0.011)	(0.010)	(0.007)	(0.007)
Beverages	0.070	0.098	-0.071	0.004	0.009	-0.011	-0.042	0.013	-0.938	0.011	-0.026
	(0.018)	(0.013)	(0.013)	(0.013)	(0.015)	(0.011)	(0.016)	(0.008)	(0.026)	(0.008)	(0.007)
Water,coffee,tea	0.016	0.049	0.078	-0.043	0.007	0.096	0.002	0.017	0.015	-1.166	-0.011
	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.008)	(0.003)
Others	-0.039	-0.131	-0.182	-0.044	-0.028	-0.024	-0.050	-0.032	-0.034	-0.012	-0.526
	(0.009)	(0.008)	(0.007)	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.006)	(0.013)

Notes: Bootstrap standard errors in parenthesis (500 repetitions).

Table 7: Mean Marshallian Price Elasticities, **High income: quintile 5**

	with respect to the price of										
	Fruits	Vegetables	Carbohydrates	Sweets and Snacks	Seafood	Red and Poultry meat	Fats	Dairies	Beverages	Water, coffee, tea	Others
Fruits	-0.937	-0.168	-0.068	0.041	0.018	0.052	0.070	-0.008	0.092	-0.003	-0.110
	(0.025)	(0.013)	(0.017)	(0.009)	(0.018)	(0.012)	(0.017)	(0.009)	(0.022)	(0.012)	(0.006)
Vegetables	-0.114	-1.013	-0.043	0.070	0.030	0.001	0.057	-0.005	0.064	0.030	-0.189
	(0.020)	(0.022)	(0.019)	(0.012)	(0.020)	(0.015)	(0.018)	(0.011)	(0.022)	(0.016)	(0.013)
Bread,flour,pasta,potato	-0.031	-0.011	-0.738	0.004	0.042	0.005	-0.023	0.053	0.015	0.042	-0.130
	(0.026)	(0.019)	(0.039)	(0.014)	(0.026)	(0.016)	(0.026)	(0.011)	(0.028)	(0.018)	(0.009)
Sweets and Snacks	0.024	0.067	-0.012	-0.908	-0.003	-0.005	-0.010	0.016	-0.009	-0.007	-0.082
	(0.020)	(0.017)	(0.019)	(0.022)	(0.019)	(0.015)	(0.019)	(0.013)	(0.023)	(0.022)	(0.012)
Seafood	0.010	0.035	0.032	-0.027	-0.969	-0.096	-0.033	-0.000	-0.030	0.012	-0.040
	(0.022)	(0.016)	(0.020)	(0.010)	(0.038)	(0.014)	(0.020)	(0.009)	(0.023)	(0.015)	(0.005)
Red and Poultry meat	0.012	-0.008	-0.035	-0.040	-0.046	-0.904	-0.056	0.008	0.008	0.022	-0.085
	(0.030)	(0.026)	(0.027)	(0.017)	(0.031)	(0.027)	(0.029)	(0.015)	(0.034)	(0.026)	(0.014)
Animal and vegetable fat	0.057	0.077	-0.060	-0.041	-0.030	-0.107	-0.869	0.049	-0.055	0.010	-0.130
	(0.020)	(0.014)	(0.020)	(0.010)	(0.020)	(0.013)	(0.027)	(0.009)	(0.021)	(0.015)	(0.006)
Dairies	-0.002	0.008	0.026	0.013	0.008	0.043	0.040	-1.030	0.007	-0.001	-0.094
	(0.015)	(0.012)	(0.013)	(0.011)	(0.013)	(0.010)	(0.014)	(0.013)	(0.016)	(0.015)	(0.009)
Beverages	0.086	0.106	0.012	-0.007	-0.017	-0.082	-0.037	0.024	-0.848	0.023	-0.122
	(0.025)	(0.018)	(0.021)	(0.012)	(0.022)	(0.015)	(0.021)	(0.011)	(0.037)	(0.016)	(0.007)
Water,coffee,tea	0.005	0.081	0.080	-0.007	0.030	0.114	0.030	0.012	0.037	-1.202	-0.031
	(0.009)	(0.008)	(0.009)	(0.007)	(0.010)	(0.008)	(0.009)	(0.006)	(0.010)	(0.013)	(0.005)
Others	-0.041	-0.102	-0.097	-0.075	-0.010	-0.049	-0.051	-0.064	-0.066	-0.015	-0.390
	(0.013)	(0.010)	(0.013)	(0.011)	(0.010)	(0.011)	(0.010)	(0.009)	(0.013)	(0.013)	(0.016)

Notes: Bootstrap standard errors in parenthesis (500 repetitions).

Table 8: Household compensated variation and tax burden/subsidy transfer as percent of income, assuming 100% pass through in prices (by household quintile)

	18% tax		19% subsidy		Tax and Subsidy	
	Tax burden	Welfare loss	Tax burden	Welfare loss	Tax burden	Welfare loss
Quintile 1	1.067	0.764	-1.418	-1.050	-0.396	-0.286
	(0.022)	(0.014)	(0.024)	(0.018)	(0.028)	(0.020)
Quintile 2	0.762	0.564	-0.852	-0.651	-0.121	-0.087
	(0.015)	(0.010)	(0.015)	(0.012)	(0.019)	(0.014)
Quintile 3	0.623	0.474	-0.646	-0.483	-0.044	-0.008
	(0.011)	(0.009)	(0.011)	(0.009)	(0.015)	(0.010)
Quintile 4	0.505	0.405	-0.488	-0.358	0.003	0.047
	(0.008)	(0.006)	(0.008)	(0.006)	(0.011)	(0.008)
Quintile 5	0.291	0.242	-0.240	-0.183	0.043	0.059
	(0.006)	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)

Notes: Standard errors in parenthesis calculated using bootstrap method (500 repetitions). Positive values denote tax burden and negative values denote subsidy transfer.

Table 9: Household compensated variation as percent of income, assuming 75% pass through in prices (by quintile)

	18% tax		19% subsidy		Tax and Subsidy	
Quintile 1	0.573	(0.011)	-0.787	(0.014)	-0.214	(0.015)
Quintile 2	0.423	(0.008)	-0.488	(0.009)	-0.066	(0.010)
Quintile 3	0.356	(0.006)	-0.362	(0.007)	-0.006	(0.008)
Quintile 4	0.304	(0.005)	-0.269	(0.005)	0.035	(0.006)
Quintile 5	0.181	(0.004)	-0.137	(0.003)	0.044	(0.003)

Notes: Standard errors in parenthesis calculated using bootstrap method (500 repetitions). Positive values denote welfare losses and negative values denote welfare gains.

Table 10: Household compensated variation as percent of income, assuming 75% pass through for tax and 50% pass through on subsides (by quintile)

	18% tax		19% subsidy		Tax and Subsidy	
Quintile 1	0.573	(0.011)	-0.525	(0.009)	0.048	(0.012)
Quintile 2	0.423	(0.008)	-0.326	(0.006)	0.097	(0.009)
Quintile 3	0.356	(0.006)	-0.241	(0.004)	0.115	(0.007)
Quintile 4	0.304	(0.005)	-0.179	(0.003)	0.125	(0.005)
Quintile 5	0.181	(0.004)	-0.091	(0.002)	0.090	(0.003)

Notes: Standard errors in parenthesis calculated using bootstrap method (500 repetitions). Positive values denote welfare losses; and negative values denote welfare gains.

Table 11: Estimated coefficients

	Constant		**Implicit utility 1**		**Implicit utility ^2**		**Implicit utility ^3**	
Budget share	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*
Group 1	0.054	*0.004*	-0.001	*0.001*	0.002	*0.001*	0.001	*0.000*
Group 2	0.123	*0.004*	0.006	*0.001*	-0.002	*0.001*	0.000	*0.000*
Group 3	0.190	*0.004*	-0.069	*0.003*	0.002	*0.002*	-0.001	*0.001*
Group 4	0.070	*0.007*	0.005	*0.002*	0.004	*0.002*	0.001	*0.001*
Group 5	0.039	*0.004*	0.007	*0.001*	0.001	*0.001*	0.000	*0.000*
Group 6	0.134	*0.008*	0.045	*0.002*	-0.006	*0.001*	-0.002	*0.000*
Group 7	0.059	*0.004*	0.006	*0.001*	-0.001	*0.001*	0.000	*0.000*
Group 8	0.084	*0.006*	0.005	*0.001*	-0.002	*0.001*	0.000	*0.000*
Group 9	0.086	*0.004*	-0.019	*0.002*	0.004	*0.002*	0.001	*0.001*
Group 10	0.044	*0.002*	-0.005	*0.001*	0.000	*0.001*	0.000	*0.000*
Group 11	0.118	*0.011*	0.020	*0.002*	-0.002	*0.002*	0.000	*0.001*

	Price group 1		**Price group 2**		**Price group 3**		**Price group 4**	
Budget share	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*
Group 1	0.001	*0.001*	-0.012	*0.001*	-0.005	*0.001*	0.005	*0.001*
Group 2	-0.012	*0.001*	-0.003	*0.001*	-0.008	*0.001*	0.010	*0.001*
Group 3	-0.005	*0.001*	-0.008	*0.001*	0.045	*0.003*	-0.004	*0.001*
Group 4	0.005	*0.001*	0.010	*0.001*	-0.004	*0.001*	0.007	*0.001*
Group 5	0.002	*0.001*	0.003	*0.001*	0.010	*0.001*	0.000	*0.001*
Group 6	0.001	*0.001*	0.008	*0.001*	-0.002	*0.002*	-0.006	*0.001*
Group 7	0.006	*0.001*	0.008	*0.001*	-0.001	*0.001*	-0.003	*0.001*
Group 8	0.001	*0.000*	0.000	*0.001*	-0.008	*0.001*	0.005	*0.001*
Group 9	0.006	*0.001*	0.009	*0.001*	-0.006	*0.001*	-0.003	*0.001*
Group 10	0.000	*0.000*	0.004	*0.000*	0.007	*0.001*	-0.003	*0.000*
Group 11	-0.005	*0.000*	-0.019	*0.001*	-0.027	*0.001*	-0.007	*0.001*

	Price group 5		**Price group 6**		**Price group 7**		**Price group 8**	
Budget share	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*
Group 1	0.002	*0.001*	0.001	*0.001*	0.006	*0.001*	0.001	*0.000*
Group 2	0.003	*0.001*	0.008	*0.001*	0.008	*0.001*	0.000	*0.001*
Group 3	0.010	*0.001*	-0.002	*0.002*	-0.001	*0.001*	-0.008	*0.001*
Group 4	0.000	*0.001*	-0.006	*0.001*	-0.003	*0.001*	0.005	*0.001*
Group 5	-0.015	*0.001*	-0.001	*0.001*	0.000	*0.001*	0.001	*0.000*
Group 6	-0.001	*0.001*	0.003	*0.003*	-0.003	*0.001*	0.005	*0.001*
Group 7	0.000	*0.001*	-0.003	*0.001*	0.002	*0.001*	0.004	*0.000*
Group 8	0.001	*0.000*	0.005	*0.001*	0.004	*0.000*	-0.001	*0.001*
Group 9	0.002	*0.001*	-0.006	*0.001*	-0.004	*0.001*	0.000	*0.001*
Group 10	0.000	*0.000*	0.007	*0.001*	0.000	*0.000*	0.000	*0.000*
Group 11	-0.003	*0.000*	-0.006	*0.001*	-0.008	*0.000*	-0.006	*0.001*

Table 11 (Continued)

	Price group 9		Price group 10		Price group 11		Gender hh head	
Budget share	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*
Group 1	0.006	*0.001*	0.000	*0.000*	-0.005	*0.000*	0.000	*0.001*
Group 2	0.009	*0.001*	0.004	*0.000*	-0.019	*0.001*	-0.005	*0.001*
Group 3	-0.006	*0.001*	0.007	*0.001*	-0.027	*0.001*	0.002	*0.003*
Group 4	-0.003	*0.001*	-0.003	*0.000*	-0.007	*0.001*	-0.009	*0.003*
Group 5	0.002	*0.001*	0.000	*0.000*	-0.003	*0.000*	-0.001	*0.001*
Group 6	-0.006	*0.001*	0.007	*0.001*	-0.006	*0.001*	0.007	*0.002*
Group 7	-0.004	*0.001*	0.000	*0.000*	-0.008	*0.000*	0.001	*0.001*
Group 8	0.000	*0.001*	0.000	*0.000*	-0.006	*0.001*	-0.011	*0.002*
Group 9	0.010	*0.002*	0.001	*0.000*	-0.008	*0.001*	0.004	*0.001*
Group 10	0.001	*0.000*	-0.012	*0.000*	-0.002	*0.000*	-0.001	*0.001*
Group 11	-0.008	*0.001*	-0.002	*0.000*	0.093	*0.001*	0.011	*0.004*
	Education hh head		**Zone**		**Equivalent adults**		**Number of men in hh**	
Budget share	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*	Coef.	*(Std. Err)*
Group 1	0.000	*0.000*	-0.003	*0.001*	-0.004	*0.001*	-0.003	*0.001*
Group 2	0.000	*0.000*	-0.007	*0.001*	-0.005	*0.002*	-0.005	*0.001*
Group 3	-0.002	*0.000*	-0.008	*0.003*	0.009	*0.002*	0.009	*0.002*
Group 4	0.005	*0.000*	0.022	*0.003*	0.016	*0.002*	-0.011	*0.002*
Group 5	0.000	*0.000*	0.003	*0.001*	-0.005	*0.000*	0.001	*0.000*
Group 6	-0.002	*0.000*	-0.009	*0.002*	-0.007	*0.002*	0.004	*0.001*
Group 7	-0.001	*0.000*	0.004	*0.001*	-0.002	*0.001*	0.002	*0.001*
Group 8	0.002	*0.000*	0.002	*0.002*	0.010	*0.002*	-0.004	*0.002*
Group 9	0.000	*0.000*	-0.012	*0.001*	0.000	*0.001*	0.007	*0.001*
Group 10	-0.001	*0.001*	-0.001	*0.001*	-0.001	*0.001*	-0.001	*0.001*
Group 11	-0.001	*0.000*	0.004	*0.004*	-0.008	*0.003*	0.001	*0.003*

Notes: Food groups i: (1) Fruits, (2) Vegetables (3) Carbohydrates, (4) Sweets and Snacks, (5) Seafood, (6) Poultry and Red meat (7) Animal and Vegetable fat (8) Dairies (9) Beverages (10) Water, coffee, tea (11) Other.