Use of a Carbon Tax on Food Purchases to Reduce Greenhouse Gas Emissions in the U.S.

Giulia Tiboldo, PhD Student, University of Connecticut, giulia.tiboldo@uconn.edu

Rebecca L. Boehm, University Postdoctoral Fellow, University of Connecticut, rebecca.boehm@uconn.edu

Elena Castellari, Assistant Professor, Università Cattolica del Sacro Cuore, elena.castellari@unicatt.it

Farhed Shah, Associate Professor, University of Connecticut, farhed.shah@uconn.edu

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1. Introduction

During the last few decades, rising concerns about the negative impacts of climate change on agriculture, the environment, health, and the economy as a whole have led several developed countries to put the reduction and mitigation of Greenhouse Gases Emissions (GHGEs) on their political agenda. In 2015, the United States reported to the United Nations Framework Convention on Climate Change (UNFCCC) its target of reducing total emissions by 26-28% below 2005 levels by 2025 (The White House 2015). While recognizing the essential role of agriculture in sustaining human life, it is important to also acknowledge that this sector contributes directly and indirectly to about 20% of global GHGEs (IPCC - Intergovernmental Panel on Climate Change).

The U.S. may choose among several policy alternatives to get agriculture to contribute towards its desired emissions target, such as price-based approaches, cap and trade policies, as well as tax exemptions or direct subsidies. According to the conventional economic wisdom, taxing emissions would be optimal to address the discrepancy between the private and social cost of production due to the negative externalities associated with GHGEs. However, taxes on output are preferable when the monitoring costs are high, the potential for technological advances in emissions control is limited and output can be easily substituted by consumers. These conditions typically hold in the case of GHGEs from food production in developed countries (Wirsenius, Hedenus, and Mohlin 2011).

As a consequence, in this paper, we focus on analyzing the use of a tax on consumer food purchases to reduce carbon emissions from the production and distribution of food in the U.S. Taxing consumers rather than producers is preferable to avoid the so called "carbon leakage", that is, the increase in GHGEs in foreign countries due to the U.S. effort to reduce its own GHGEs. More specifically, a carbon tax on production may lead to "emission leakage" as it would become more profitable for the U.S. producers to move production abroad to avoid the tax. Moreover, this kind of policy may harm domestic producers, as consumers would have more incentives to buy relatively cheaper foreign products (Edjabou and Smed 2013). So, taxing food consumption rather than production would be more cost-effective in this situation. To avoid trade distortions, we assume that an export tariff is also charged on domestic agricultural production which is equivalent to the carbon tax for each food product. In the absence of the export tariff, producers would be incentivized to increase their export, therefore leaving the domestic market underserved.

As indicated, our primary goal is to investigate how a carbon tax on food purchases would contribute to the achievement of the 2025 U.S. GHGEs reduction target. To accomplish this goal, we first estimate the demand for and the GHGEs from the main food product categories purchased by U.S. consumers (milk, milk substitutes and yogurt; cheese; meat; poultry; fish; eggs; rice, pasta, bread and cereals; sweets; fruit; vegetables and plant based protein foods; fats, oils and condiments; mixed dishes; non-alcoholic beverages and alcoholic beverages). Food demand is specified according to the Almost Ideal Demand System (AIDS) model developed by Deaton and Muellabuer (1980) and is estimated using the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) data[1]. Following the approach by Boehm et al. (2016), GHGEs for each food group are estimated using the "Economic Input-Output Life Cycle Assessment" (EIO-LCA) method (Carnegie Mellon University). The economic data required for the EIO-LCA implementation are derived from the 2007 input-output tables for 389 industries provided by the Bureau of Economic Analysis (BEA), augmented with the Environmentally Extended Input Output model of the U.S. Economy (USEEIO) elementary flows developed by the Environmental Protection Agency (EPA) [2].

Next, we compute a suitable carbon tax for each food category, proportional to the social cost of GHGEs generated across the product's entire life cycle. We use the U.S. Environmental Protection Agency (EPA)'s social cost per metric ton of carbon dioxide emissions estimated with a 3% discount rate (US EPA) as our base case. We also conduct a sensitivity analysis to see how our results vary with different discount rates. Using the own-price and cross-price elasticity values recovered from the estimated demand parameter and the post-tax prices, we then simulate the new market equilibrium under the scenario of carbon taxes implemented simultaneously on domestic purchases and on exports of food products. This allows us to evaluate changes in U.S. consumer purchasing behavior as well as in the total GHGEs from food acquisition.

The rising concerns about GHGEs has prompted empirical studies that evaluate carbon taxes on food purchases and their impact on social welfare (Edjabou and Smed 2013; Briggs et al. 2013;

[1] Data last accessed on October 14, 2016. For more information about FoodAPS, please see the USDA, ERS website at: https://www.ers.usda.gov/data-products/foodaps-national-household-food-acquisition-and-purchase-survey/
[2] Data last accessed on May 10, 2017. For more information about USEEIO data, please see the EPA website at: https://catalog.data.gov/dataset/useeio-elementary-flows-and-life-cycle-impact-assessment-lcia-characterization-factors

Caillavet, Fadhuile, and Nichèle 2016). Our research builds on them by integrating them in a unique framework. To the best of our knowledge, this represents the first attempt to evaluate the deployment of such a carbon tax to reduce GHGEs from the U.S. Moreover, the use of FoodAPS data allows for the analysis of Food-Away-From-Home (FAH) purchases, which have been not been accounted for in previous studies evaluating the use of carbon taxes on food purchases. Finally, unlike previous surveys, FoodAPS emphasizes SNAP and low-income non-SNAP households, allowing for a more thorough analysis on the potential recursive effect of the carbon tax.

The rest of the paper is organized as follows. In section 2 we describe the food purchases and GHGEs data we employed in this study. Section 3 presents the demand model and the estimation method. Our simulation approach is introduced in section 4, while preliminary results are reported in section 5.

2. Data

2.1 Food purchases data

Food purchases data are obtained from the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) Public Use Files (PUF)[3]. FoodAPS is a nationally representative survey which collects detailed information on food at home (FAH) and food away from home (FAFH) acquisition for 4,826 households over a seven-day period from April 2012 to January 2013. The households are grouped into four strata: household receiving Supplemental Nutrition Assistance Program (SNAP) benefits (n=1,581), non-SNAP households with incomes below 100% of the U.S. Federal poverty threshold (FPT) (n=434), non-SNAP households with income between 100% and 185% of FPT (n=878), and non-SNAP households with income above 185% of FPT (n=1,933) (USDA ERS 2016).

During the survey, participants were asked to report their food acquisitions into two books. The first book collects all the purchases of foods and drinks for consumption at home (FAH), while the second one reports information on foods and drinks consumed away from home or prepared foods

[3] Data last accessed on October 14, 2016. For more information about FoodAPS, please see the USDA, ERS website at: https://www.ers.usda.gov/data-products/foodaps-national-household-food-acquisition-and-purchase-survey/

brought to their homes (FAFH). For each shopping trip or FAFH meal, information was collected regarding the outlet category, the household's expenditure on each item as well as the total expenditure, the number of items which were bought, the package size and the grams per item.

Unlike previous surveys, SNAP and low-income non-SNAP households were oversampled in FoodAPS, allowing for the analysis of their food purchasing behavior with a sufficiently large sample size. Another important attribute of the FoodAPS dataset is that it includes detailed household sociodemographic and economic characteristics, as well as the nutrient content of each food.

Food group designations

We allocate foods to the following 14 groups: milk, milk substitutes and yogurt; cheese; meat; poultry; fish; eggs; rice, pasta, bread and cereals; sweets; fruit; vegetables and plant based protein foods; fats, oils and condiments; mixed dishes; non-alcoholic beverages and alcoholic beverages. A detailed description of the groups is reported in Table 1, while Table 2 shows the average market share and average price per kilogram for each group.

Household cohorts

Following Caillavet et al. (2016), we group households with similar demographic characteristics into cohorts. Specifically, we define 96 cohorts based on the household's income relative to the FPT (below or above 100% of FPT), participation to the SNAP program, size (1,2,3,4,5 or above 5 members) and number of children (1, 2 or above 2). This allows us to control for consumers' heterogeneity in food consumption and to evaluate the differential impact of the carbon tax on diverse socio-economic classes. Food at home (FAH) acquisitions are observed for 36 weeks, resulting in an unbalanced panel of 1,547 observations.

Table 1. Food groups definition.

Name	Description
Milk, milk substitutes and yogurt	Milk, flavored milk, dairy drinks and substitutes, yogurt
Cheese	Cheese, cottage/ricotta cheese
Beef and Pork meat	Meats and cold cuts and cured meats
Poultry	Chicken, turkey, duck and other poultry
Fish	Fish and shellfish
Eggs	Eggs and omelets
Rice, pasta, bread and cereals	Rice, pasta, cooked grains, breads, rolls, tortillas, quick breads, bread products, ready-to-eat cereals, cooked cereals, savory snacks, crackers
Sweets	Snack, meal bars, sweet bakery products, candy and chocolates, ice cream, pudding, other desserts, sugar, jams, syrups
Fruits	Fresh, canned and frozen fruits
Vegetables and plant-based protein foods	Fresh, canned and frozen vegetables, potatoes, plant based protein foods
Fats, oils and condiments	Fats and oils, condiments and sauces
Non-alcoholic beverages	100% juice, diet beverages, sweetened beverages, coffee and tea, plain water, flavored or enhanced water
Alcoholic beverages	Beer, wine, liquor and cocktails
Mixed dishes	Meat, poultry and seafood mixed dishes, pizza, sandwiches, soups, grain-based mixed dishes

Table 2. Average market share and price per kilogram by food group.

	Market share	Price
Milk	0.063	1.536
	(0.090)	(2.450)
Cheese	0.034	9.274
	(0.048)	(3.609)
Meat	0.093	9.745
	(0.108)	(6.452)
Poultry	0.084	8.195
	(0.093)	(4.325)
Fish	0.020	12.565
	(0.046)	(12.154)
Eggs	0.013	3.477
	(0.024)	(1.409)
Pasta	0.139	5.026
	(0.113)	(2.605)
Sweets	0.114	6.546
	(0.122)	(6.397)
Fruits	0.056	4.268
	(0.066)	(3.751)
Vegetables	0.090	3.972
	(0.085)	(3.579)
Fats	0.066	5.060
	(0.067)	(5.786)
Beverages	0.135	1.900
	(0.134)	(6.822)
Alcohol	0.021	5.849
	(0.070)	(6.945)
Mixed	0.074	6.524
	(0.093)	(4.590)

Standard errors are reported in parentheses below each estimated market share

2.2 Greenhouse gases emissions data

To estimate the greenhouse gases emissions (GHGEs) from food acquisition we use the Economic Input-Output Life Cycle Assessment (EIO-LCA) method (Carnegie Mellon University). According to the EIO approach, the relationship between the total industry output (X) and the final demand of a good (y) can be expressed as follows:

$$\mathbf{X}=(\mathbf{I}-\mathbf{A})^{-1}\,\mathbf{y} \tag{1}$$

Where **X** is a *n* by 1 vector of the total suppliers output for the *n* industry in the economy, **I** is an *n* by *n* identity matrix, **A** is the *n* by *n* direct requirements matrix and ***y*** is an *n* by 1 vector of the final demand for the *n* goods in the market. The matrix $(\mathbf{I}-\mathbf{A})^{-1}$ is also known as the total requirements matrix. One of the advantages of the EIO approach is that all the matrices and vectors are expressed in dollar terms, allowing for comparison across industries.

As originally suggested by Leontif, the EIO model can be expanded to include non-economic impacts as follows:

$$\mathbf{B}=\mathbf{R}\mathbf{X}=\mathbf{R}(\mathbf{I}-\mathbf{A})^{-1}\,\mathbf{y} \tag{2}$$

Where **R** is an *n* by *n* diagonal matrix with the external output per dollar of economic activity of the *nth* industry along the diagonal, while **B** is *n* by *1* vector representing the total (direct and indirect) external impact per dollar for the industries in the economy. In our analysis, the **R** matrix reports the direct emission intensity factor (EIF) for each industry which is defined as the kilogram of carbon dioxide equivalents (CO_2e) per dollar of output.

The economic data for this study are derived from the 2007 total requirements table, $(I-A)^{-1}$, from the input-output (IO) tables for 389 industries provided by the Bureau of Economic Analysis (BEA), while the emissions intensity factors (EIFs) included in the **R** matrix are obtained from the USEEIO model satellite tables developed by the EPA[4]. Specifically, the EPA EIFs are computed utilizing the 2013 industry output instead of the 2007 industry output, therefore reflecting the economic conditions of 2013, when the FoodAPS survey took place.

As the USEEIO EIFs reflects the amount of external output (i.e. CO_2e) generated per dollar of the industry activity evaluated at the producers' price level, we convert them into the corresponding EIFs at the purchasers' price level. Following Suh (2005), we transform the producers' values into purchasers' values by accounting for the transportation costs and the retail and wholesale margins for each industry. In details, this is done using the 2007 margins table provided by the BEA. The EIFs for the industries involved in food and beverages production are reported in Table 3.

[4] Data last accessed on May 10, 2017. For more information about USEEIO data, please see the EPA website at: https://catalog.data.gov/dataset/useeio-elementary-flows-and-life-cycle-impact-assessment-lcia-characterization-factors

Following the approach developed by Boehm et al. (2016) food items are matched to the corresponding BEA industry using the USDA Food and Nutrient Database for Dietary Studies (FNDDS) and the 4-digit Food Pattern Equivalents Ingredients (FPID) food codes and descriptions. As each of the 14 food categories we defined includes foods produced by different industry with different EIFs, we derive an average EIF for each food group as the mean over the EIFs of the foods included in it.

Table 3. Average emissions intensity factor (EIF) by food industry.

Industry name	Industry code	EIF
Beef cattle ranching and farming, including feedlots and dual-purpose ranching and farming	1121A0	2.749
Dairy cattle and milk production	112120	2.295
Grain farming	1111B0	1.318
Animal production, except cattle and poultry and eggs	112A00	0.991
Other crop farming	111900	0.895
Wet corn milling	311221	0.769
Greenhouse, nursery, and floriculture production	111400	0.547
Oilseed farming	1111A0	0.407
Vegetable and melon farming	111200	0.310
Poultry and egg production	112300	0.271
Fruit and tree nut farming	111300	0.226
Sugar and confectionery product manufacturing	311300	0.129
Breakfast cereal manufacturing	311230	0.113
Fruit and vegetable canning, pickling, and drying	311420	0.107
Flour milling and malt manufacturing	311210	0.080
Seafood product preparation and packaging	311700	0.062
Frozen food manufacturing	311410	0.056
Dry, condensed, and evaporated dairy product manufacturing	311514	0.053
Snack food manufacturing	311910	0.051
Fats and oils refining and blending	311225	0.051
Bread and bakery product manufacturing	311810	0.048
Cookie, cracker, pasta, and tortilla manufacturing	3118A0	0.039
Soybean and other oilseed processing	31122A	0.037
Poultry processing	311615	0.037
Ice cream and frozen dessert manufacturing	311520	0.034
All other food manufacturing	311990	0.033
Animal (except poultry) slaughtering, rendering, and processing	31161A	0.031
Coffee and tea manufacturing	311920	0.030
Fluid milk and butter manufacturing	31151A	0.028
Breweries	312120	0.027
Cheese manufacturing	311513	0.025
Soft drink and ice manufacturing	312110	0.023
Flavoring syrup and concentrate manufacturing	311930	0.022
Seasoning and dressing manufacturing	311940	0.015
Distilleries	312140	0.013
Wineries	312130	0.011

3. Model and Methods

In our empirical application, food demand is modeled according to the Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer 1980) in its linear approximation (LA-AIDS) (Moschini 1995). The AIDS model has been widely employed in scientific literature as it provides with a first order approximation to any demand system functional form and it allows perfect aggregation over consumers (Deaton and Muellbauer 1980).

Under the weak separability assumption, the market share of each food category *i* at each time period *t* for each cohort *c* is defined as follows:

$$w_{ict} = \alpha_i + \sum_j \gamma_{ij} \ln p_{jct} + \beta_i \ln(x_{ct}/P_{ct}) \tag{1}$$

where w_{ict} is the budget share of food *i* over the households belonging to cohort *c* at time *t*, p_{jct} are the market prices for all the *jth* products included in the demand system, x_{ct} is total expenditure, and P_{ct} is the Stone Price index defined as:

$$\ln P_{ct} = \sum_j w_{jct} \ln(p_{jct}) \tag{2}$$

An additional advantage of the AIDS mode is that the properties of direct demand functions, that is, adding up (3), homogeneity (4) and symmetry (5), can be imposed through some parameters restrictions, as follows:

$$\sum_i \alpha_i = 1 \quad \sum_I \gamma_{ij} = 0 \quad \sum_i \beta_i = 0 \tag{3}$$

$$\sum_j \gamma_{ij} = 0 \tag{4}$$

$$\gamma_{ij} = \gamma_{ji} \tag{5}$$

The expenditure (ε_i) and the uncompensated ($\varepsilon_{i,j}$) and compensated ($\eta_{i,j}$) price elasticity are derived as follows :

$$\varepsilon_i = \frac{\beta_i}{w_i} + 1 \tag{6}$$

$$\varepsilon_{i,j} = \frac{\gamma_{ij}}{w_i} - \beta_i \frac{w_j}{w_i} - \delta_{ij} \tag{7}$$

$$\eta_{i,j} = \frac{\gamma_{ij}}{w_i} + w_j - \delta_{ij} \tag{8}$$

where δ_{ij} is the Kronecker delta and is equal to 1 when *i* is equal to *j* and 0 otherwise.

The demand system in (1) is estimated for (j-1) equations in STATA 14 by seemingly unrelated regression (SUR). Homogeneity and symmetry constraints are imposed in the system as in (4) and (5). The parameters of the jth omitted equation can be computed using the theoretical constraints of demand as in (3) and (5). Standard errors are clustered at the cohort level.

To carry out our estimate, we need to impute the missing prices due to zero consumption in some time periods. Following Heien et al. (1990), missing prices are estimated through a regression approach on observed prices. Specifically, prices are specified as a function of the cohort's demographic characteristics (average household size, number of children), income and participation in food assistance programs (e.g. SNAP), time and cohort specific dummies.

4. Carbon tax simulation

In our simulation, we apply a carbon tax on each food group proportional to the GHGEs generated across the product's entire life cycle. The optimal tax rate has to be equivalent to the monetary value of the externality generated to society by GHGEs. We therefore set our baseline carbon tax to \$36 per metric ton of carbon dioxide equivalents emissions, which corresponds to the social cost per metric ton of carbon estimated with 3% discount rate by the EPA (US EPA). We also conduct a sensitivity analysis to see how our results vary with different discount rate.

We then use the own-price and cross-price elasticity values recovered from the estimated demand parameter and the post-tax prices to simulate the new market equilibrium under the scenario of carbon taxes implemented simultaneously on domestic purchases and on exports of foods. To evaluate the potential contribution of the tax to the 2025 GHGEs reduction target, we compute the GHGEs generated under the simulated scenario and we compare those with the ones obtained from the pre-tax equilibrium. We also calculate the change in consumers' surplus as follows:

$$\Delta CS = \sum_{c}^{C} 0.5(p_t - p_o) \cdot (q_t - q_o) \qquad (9)$$

where p_t and p_0 and q_t and q_0 are the equilibrium prices and quantities under the tax scenario and the baseline scenario respectively (Diewert 1992).

5. Preliminary results

Table 4 and table 5 report the AIDS estimate results and the relative elasticity values for FAH acquisitions respectively

Discussion

Our study has some limitations that need to be addressed in subsequent research. For example, we assume that all food purchased is consumed by a household, which is probably not the case. Moreover, we assume no reactions from the supply side to the tax, while it is likely that producers will adopt more efficient technology to reduce their GHGEs, and, in turn, the negative impact on their sales. This means that our current approach is likely to underestimate the potential impact of the carbon tax on U.S. GHGEs from food purchases. Despite its shortcomings, we feel that our paper makes significant contribution towards understanding the role of carbon taxes on food purchases in reducing agriculture related GHGEs. This line of inquiry is particularly important for the case of the U.S. where control of GHGEs us urgently needed.

Table 4. Almost Ideal Demand System estimate results.

Prices	Market Shares													
	Milk	Cheese	Meat	Poultry	Fish	Eggs	Pasta	Sweets	Fruits	Vegetables	Fats	Beverages	Alcohol	Mixed
Milk	-0.063***	-0.005	-0.013	0.013**	0.006	0.069**	0.002	0.006	-0.007	-0.002	-0.001	-0.004	0.011**	-0.012
	(-0.009)	(-0.004)	(-0.008)	(-0.005)	(-0.006)	(0.022)	(-0.006)	(-0.008)	(-0.007)	(-0.005)	(-0.005)	(-0.007)	(-0.005)	(-0.008)
Cheese	-0.005	-0.103***	0.047***	-0.009	0.007	-0.004	0.036***	0.007	0.013*	-0.004	-0.002	-0.002	0.009**	0.01
	(-0.004)	(-0.021)	(-0.014)	(-0.008)	(-0.007)	(0.015)	(-0.012)	(-0.007)	(-0.007)	(-0.005)	(-0.005)	(-0.005)	(-0.004)	(-0.008)
Meat	-0.013	0.047***	-0.111***	0.000	0.014*	0.030	-0.015	0.004	0.022**	-0.014	-0.012	-0.01	0.019***	0.039***
	(-0.008)	(-0.014)	(-0.031)	(-0.009)	(-0.008)	(0.024)	(-0.017)	(-0.011)	(-0.01)	(-0.01)	(-0.008)	(-0.008)	(-0.006)	(-0.011)
Poultry	0.013**	-0.009	0.000	-0.022*	-0.013**	0.037**	0.006	-0.008	0.006	-0.012**	0.031*	0.078**	-0.028	0.007
	(-0.005)	(-0.008)	(-0.009)	(-0.011)	(-0.005)	(0.017)	(-0.007)	(-0.008)	(-0.006)	(-0.005)	(-0.016)	(-0.037)	(-0.022)	(-0.006)
Fish	0.006	0.007	0.014*	-0.013**	-0.020***	0.007	0.008	-0.003	-0.008	-0.006	-0.008	-0.005	0.005	0.016**
	(-0.006)	(-0.007)	(-0.008)	(-0.005)	(-0.007)	(0.014)	(-0.007)	(-0.007)	(-0.007)	(-0.005)	(-0.006)	(-0.004)	(-0.004)	(-0.007)
Eggs	0.069***	-0.004	0.03	0.037**	0.007	-0.009*	0.008	0.049*	0.009	0.062**	0.011*	-0.001	-0.003	-0.009
	(-0.022	(-0.015)	(-0.024)	(-0.017)	(-0.014)	(0.016)	(-0.021)	(-0.025)	(-0.023)	(-0.025)	(-0.006)	(-0.006)	(-0.004)	(-0.016)
Pasta	0.002	0.036***	-0.015	0.006	0.008	0.008	-0.091***	0.029***	0.019**	0.000	-0.005	-0.002	-0.006	0.012
	(-0.006)	(-0.012)	(-0.017)	(-0.007)	(-0.007)	(0.021)	(-0.018)	(-0.01)	(-0.008)	(-0.008)	(-0.006)	(-0.005)	(-0.005)	(-0.01)
Sweets	0.006	0.007	0.004	-0.008	-0.003	0.049**	0.029***	-0.063***	0.001	-0.006	-0.01	-0.008	-0.01	0.012
	(-0.008)	(-0.007)	(-0.011)	(-0.008)	(-0.007)	(0.025)	(-0.01)	(-0.014)	(-0.013)	(-0.007)	(-0.006)	(-0.006)	(-0.008)	(-0.011)
Fruits	-0.007	0.013*	0.022**	0.006	-0.008	0.009	0.019**	0.001	-0.092***	0.009**	0.011	0.001	-0.001	0.018*
	(-0.007)	(-0.007)	(-0.01)	(-0.006)	(-0.007)	(0.023)	(-0.008)	(-0.013)	(-0.013)	(-0.005)	(-0.006)	(-0.006)	(-0.006)	(-0.009)
Vegetables	-0.002	-0.004	-0.014	-0.012**	-0.006	0.062**	0.000	-0.006	0.009**	-0.039***	0.001	0.004	0.002	0.005
	(-0.005)	(-0.005)	(-0.01)	(-0.005)	(-0.005)	(0.025)	(-0.008)	(-0.007)	(-0.005)	(-0.006)	(-0.005)	(-0.005)	(-0.005)	(-0.006)
Fats	-0.001	-0.002	-0.012	-0.005	-0.008	0.031	-0.005	-0.01	0.011	0.001	-0.012*	-0.007**	0.008*	0.011*
	(-0.005)	(-0.005)	(-0.008)	(-0.004)	(-0.006)	(0.016)	(-0.006)	(-0.006)	(-0.006)	(-0.005)	(-0.006)	(-0.003)	(-0.004)	(-0.006)
Beverages	-0.004	-0.002	-0.01	-0.005	-0.005	0.078**	-0.002	-0.008	0.001	0.004	-0.007**	-0.033***	-0.007	-0.001
	(-0.007)	(-0.005)	(-0.008)	(-0.006)	(-0.004)	(0.037)	(-0.005)	(-0.006)	(-0.006)	(-0.005)	(-0.003)	(-0.009)	(-0.005)	(-0.006)
Alcohol	0.011**	0.009**	0.019***	0.006	0.005	-0.028	-0.006	-0.01	-0.001	0.002	0.008*	-0.007	-0.004	-0.003
	(-0.005)	(-0.004)	(-0.006)	(-0.005)	(-0.004)	(0.022)	(-0.005)	(-0.008)	(-0.006)	(-0.005)	(-0.004)	(-0.005)	(-0.008)	(-0.004)
Mixed	-0.012	0.010	0.039***	0.007	0.016**	-0.339	0.012	0.012	0.018*	0.005	-0.005	-0.005	0.006	-0.103***
	(-0.008)	(-0.008)	(-0.011)	(-0.006)	(-0.007)	(0.201)	(-0.01)	(-0.011)	(-0.009)	(-0.006)	(-0.004)	(-0.006)	(-0.005)	(-0.013)
Expenditure	-0.020***	-0.018***	-0.028***	-0.030***	-0.028***	0.383***	-0.027***	-0.043***	-0.026***	-0.028***	-0.023***	-0.035***	-0.056***	-0.021***
	(-0.003)	(-0.002)	(-0.003)	(-0.003)	(-0.003)	(0.014)	(-0.002	(-0.003	(-0.002	(-0.002)	(-0.002)	(-0.004)	(-0.008)	(-0.003)
Constant	0.138***	0.111***	0.245***	0.173***	0.080***	-1.211***	0.203***	0.277***	0.101***	0.211***	0.166***	0.308***	0.079***	0.119***
	(-0.016)	(-0.021)	(-0.02)	(-0.016)	(-0.016)	(0.085)	(-0.022)	(-0.023)	(-0.018)	(-0.017)	(-0.013)	(-0.019)	(-0.016)	(-0.017)

Standard errors are reported in parenthesis. Significance levels *10%, ** 5%, ***1%.

Table 5. Uncompensated price and expenditure elasticity.

	Milk	Cheese	Meat	Poultry	Fish	Eggs	Pasta	Sweets	Fruits	Vegetables	Fats	Beverages	Alcohol	Mixed	Expenditure
Milk	-1.441	-0.018	-0.063	0.122	0.052	0.327	0.045	0.080	-0.033	0.018	0.019	0.016	0.089	-0.069	0.857
	(0.100)	(0.028)	(0.057)	(0.048)	(0.045)	(0.135)	(0.047)	(0.062)	(0.054)	(0.038)	(0.035)	(0.049)	(0.042)	(0.058)	(0.024)
Cheese	-0.020	-1.911	0.466	-0.057	0.075	-0.233	0.359	0.111	0.130	0.003	0.006	0.031	0.098	0.106	0.835
	(0.036)	(0.142)	(0.176)	(0.072)	(0.064)	(0.162)	(0.085)	(0.072)	(0.064)	(0.047)	(0.047)	(0.038)	(0.044)	(0.066)	(0.037)
Meat	-0.039	0.205	-1.424	0.021	0.066	-0.017	-0.038	0.050	0.100	-0.033	-0.031	-0.005	0.088	0.171	0.884
	(0.034)	(0.060)	(0.116)	(0.038)	(0.034)	(0.089)	(0.069)	(0.046)	(0.041)	(0.038)	(0.032)	(0.028)	(0.023)	(0.046)	(0.015)
Poultry	0.101	-0.036	0.043	-1.095	-0.062	0.006	0.071	0.000	0.049	-0.034	-0.002	0.024	0.047	0.059	0.829
	(0.027)	(0.047)	(0.053)	(0.064)	(0.028)	(0.090)	(0.040)	(0.042)	(0.035)	(0.028)	(0.024)	(0.030)	(0.029)	(0.035)	(0.020)
Fish	0.119	0.125	0.260	-0.102	-1.221	-0.339	0.166	0.057	-0.061	0.001	-0.037	0.049	0.096	0.240	0.647
	(0.061)	(0.096)	(0.122)	(0.063)	(0.080)	(0.204)	(0.092)	(0.091)	(0.087)	(0.065)	(0.072)	(0.052)	(0.055)	(0.096)	(0.068)
Eggs	-0.013	0.038	0.052	0.024	0.019	-1.103	0.058	0.047	0.025	0.016	0.027	0.033	0.049	0.045	0.684
	(0.015)	(0.011)	(0.021)	(0.013)	(0.009)	(0.142)	(0.016)	(0.019)	(0.016)	(0.017)	(0.012)	(0.026)	(0.018)	(0.013)	(0.018)
Pasta	0.029	0.193	-0.043	0.054	0.048	-0.122	-1.423	0.180	0.108	0.028	-0.004	0.028	-0.019	0.074	0.869
	(0.031)	(0.069)	(0.083)	(0.038)	(0.036)	(0.104)	(0.105)	(0.056)	(0.040)	(0.037)	(0.031)	(0.026)	(0.024)	(0.053)	(0.016)
Sweets	0.041	0.043	0.054	-0.003	0.000	-0.009	0.136	-1.185	0.021	0.011	-0.010	0.019	-0.026	0.060	0.846
	(0.028)	(0.028)	(0.043)	(0.026)	(0.027)	(0.086)	(0.038)	(0.056)	(0.047)	(0.025)	(0.022)	(0.021)	(0.026)	(0.037)	(0.013)
Fruits	-0.029	0.153	0.276	0.099	-0.056	-0.226	0.242	0.087	-1.886	0.145	0.147	0.093	0.008	0.207	0.740
	(0.073)	(0.082)	(0.136)	(0.072)	(0.066)	(0.238)	(0.093)	(0.128)	(0.235)	(0.059)	(0.075)	(0.066)	(0.057)	(0.101)	(0.049)
Vegetables	0.010	-0.002	-0.034	-0.035	-0.017	0.135	0.027	0.008	0.057	-1.156	0.024	0.058	0.018	0.039	0.870
	(0.024)	(0.026)	(0.045)	(0.022)	(0.024)	(0.101)	(0.038)	(0.033)	(0.022)	(0.032)	(0.022)	(0.023)	(0.022)	(0.030)	(0.012)
Fats	0.015	0.001	-0.040	-0.007	-0.035	0.020	-0.003	-0.021	0.078	0.033	-1.051	0.002	0.062	0.085	0.861
	(0.029)	(0.032)	(0.047)	(0.024)	(0.035)	(0.090)	(0.038)	(0.036)	(0.039)	(0.029)	(0.040)	(0.021)	(0.027)	(0.037)	(0.015)
Beverages	0.003	0.005	-0.004	0.004	-0.006	0.115	0.015	0.007	0.016	0.037	-0.003	-1.070	-0.014	0.011	0.885
	(0.023)	(0.016)	(0.025)	(0.019)	(0.014)	(0.101)	(0.017)	(0.019)	(0.020)	(0.015)	(0.012)	(0.026)	(0.015)	(0.019)	(0.012)
Alcohol	0.232	0.197	0.418	0.195	0.125	-1.216	0.068	0.064	0.055	0.170	0.223	0.128	-0.996	0.044	0.292
	(0.079)	(0.078)	(0.133)	(0.087)	(0.062)	(0.443)	(0.067)	(0.093)	(0.068)	(0.068)	(0.070)	(0.065)	(0.104)	(0.056)	(0.136)
Mixed	-0.075	0.100	0.368	0.088	0.147	-0.295	0.136	0.147	0.168	0.079	0.125	0.047	-0.013	-1.845	0.822
	(0.070)	(0.076)	(0.128)	(0.059)	(0.070)	(0.161)	(0.094)	(0.099)	(0.078)	(0.050)	(0.057)	(0.043)	(0.035)	(0.173)	(0.040)

Standard errors in parenthesis.

References

Boehm, Rebecca, Parke E. Wilde, Michele Ver Ploeg, Christine Costello, and Sean B. Cash. 2017. "Is It Hot in Here or Is It Your Food Choices? Examining the Carbon Footprint of U.S. Household Food Spending and Opportunities for Emission Mitigation Strategies through Changes in Food Expenditures." Accessed May 18. http://ageconsearch.tind.io/record/236065.

Briggs, Adam D M, Ariane Kehlbacher, Richard Tiffin, Tara Garnett, Mike Rayner, and Peter Scarborough. 2013. "Assessing the Impact on Chronic Disease of Incorporating the Societal Cost of Greenhouse Gases into the Price of Food: An Econometric and Comparative Risk Assessment Modelling Study." *BMJ Open* 3 (10). doi:10.1136/bmjopen-2013-003543.

Caillavet, France, Adélaïde Fadhuile, and Véronique Nichèle. 2016. "Taxing Animal-Based Foods for Sustainability: Environmental, Nutritional and Social Perspectives in France." *European Review of Agricultural Economics* 43 (4): 537–60. doi:10.1093/erae/jbv041.

Deaton, Angus, and John Muellbauer. 1980. "An Almost Ideal Demand System." *The American Economic Review* 70 (3): 312–26.

Diewert, W. E. 1992. "Exact and Superlative Welfare Change Indicators." *Economic Inquiry; Huntington Beach* 30 (4): 565.

Edjabou, Louise Dyhr, and Sinne Smed. 2013. "The Effect of Using Consumption Taxes on Foods to Promote Climate Friendly Diets – The Case of Denmark." *Food Policy* 39 (April): 84–96. doi:10.1016/j.foodpol.2012.12.004.

Carnegie Mellon University "EIO-LCA Method-Economic Input-Output Life Cycle Assessment" Accessed May 17. http://www.eiolca.net/Method/eio-lca-method.html.

The White House. 2015. "FACT SHEET: U.S. Reports Its 2025 Emissions Target to the UNFCCC." Whitehouse.gov. March 31. https://obamawhitehouse.archives.gov/the-press-office/2015/03/31/fact-sheet-us-reports-its-2025-emissions-target-unfccc.

Heien, Dale, and Cathy Roheim Wessells. 1990. "Demand Systems Estimation with Microdata: A Censored Regression Approach." *Journal of Business & Economic Statistics* 8 (3): 365–71. doi:10.2307/1391973.

"IPCC - Intergovernmental Panel on Climate Change." 2017. Accessed May 19. http://www.ipcc.ch/ipccreports/tar/wg3/index.php?idp=115.

Moschini, Giancarlo. 1995. "Units of Measurement and the Stone Index in Demand System Estimation." *American Journal of Agricultural Economics* 77 (1): 63–68. doi:10.2307/1243889.

Sangwon Suh. 2005. "Developing a Sectoral Environmental Database for Input–output Analysis: The Comprehensive Environmental Data Archive of the US." *Economic Systems Research* 17 (4): 449–69. doi:10.1080/09535310500284326.

US Department of Commerce, B. E. A. "Bureau of Economic Analysis." Accessed May 17. https://www.bea.gov/industry/io_annual.htm.

US EPA, OAR. "The Social Cost of Carbon." Reports and Assessments. Accessed May 19. /climatechange/social-cost-carbon.

Wirsenius, Stefan, Fredrik Hedenus, and Kristina Mohlin. 2011. "Greenhouse Gas Taxes on Animal Food Products: Rationale, Tax Scheme and Climate Mitigation Effects." *Climatic Change; Dordrecht* 108 (1–2): 159–84. doi:http://dx.doi.org.ezproxy.lib.uconn.edu/10.1007/s10584-010-9971-x.