Carbon Labeling for Consumer Food Goods

Sharon Shewmake
PhD Program in Law and Economics, Vanderbilt University Law School
Tel: (615) 343-9622; E-mail: sharon.shewmake@vanderbilt.edu

Abigail Okrent
Economic Research Service, United States Department of Agriculture

Lanka Thabrew
Vanderbilt Institute for Energy and the Environment, Vanderbilt University

Michael Vandenbergh
Vanderbilt University Law School

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association 2012 AAEA, Annual Meeting, Seattle, Washington August 12–14, 2012

The views expressed here are those of the authors and not necessarily those of the U.S. Department of Agriculture.

Abstract

We construct a model to predict how consumers will respond to better information about the carbon content of 42 foods and a nonfood composite as well as product categories through a label, and provide guidance as to what kinds of goods would provide the highest CO_2eq emission reductions through a labeling scheme. Our model assumes that consumers value their individual carbon footprint, allowing us to utilize estimates of own- and cross-price elasticities of demand from the literature on demand analysis. We make three different assumptions about how consumers currently value their carbon footprint and find that when a label informs consumers, their baseline perception matters. We also find that carbon labels on alcohol and meat would achieve the largest decreases in carbon emissions.

Keywords: Carbon emissions, food labeling
JEL Classification: Q53, D83, Q18

Introduction

Research suggests that minor adjustments to the mix and carbon content of consumer products may result in substantial carbon emission reductions (Dietz et al. 2009; Cohen and Vandenbergh 2012). While this research implies some changes to consumer behavior are politically feasible and would be acceptable to many consumers, rarely does this line of research employ demand analysis to calculate the consumer welfare impacts of these carbon mitigation behaviors or predict the likely substitutes for high carbon goods and services (e.g., Weber and Matthews 2008, Vanclay et al. 2011, EWG 2011). In this paper, we construct a model to predict how consumers will respond to better information about the carbon content of food products through a label, and we provide guidance as to the kinds of goods that would provide the highest emission reductions through a labeling scheme.

To our knowledge, this study is the first to apply a rigorous economic model to address the question of how consumers will respond to carbon labels. The evaluation of the impact of carbon labels on carbon emissions is addressed in the Life Cycle Assessment (LCA) literature, which typically presumes that a low-carbon good is a substitute for a high-carbon good (European Communities 2006, Bin and Dowlatabadi 2005, Jones and Kammen 2011). For example, chicken, which is produced with lower carbon emissions, is assumed to be a substitute for beef, which is produced with higher carbon emissions. However, chicken could be a substitute or a complement to many other foods as well. The responsiveness of demand for a product to changes in its own price and prices of complements and substitutes has been rigorously evaluated and quantified in the demand analysis literature (i.e., elasticities of demand). In particular, the cross-price elasticities of demand quantify these trade-offs between related goods, such as chicken and beef, and thus are a natural input into understanding consumer responsiveness to information on carbon footprints.

We develop a model that integrates elasticities of demand with LCA information on the carbon emissions of different products, and we apply this model to U.S. food products. We find that goods where consumers have a low carbon substitute, an inaccurate belief about the carbon footprint of the good, and where high carbon goods have a large market share are most likely to result in large reductions in carbon just from being labeled.

Background

The market for products with labels that include "sustainable," "environmentally friendly" and "eco" have been increasing over time. In 2009, almost 7,000 products on U.S. shelves included some sort of environmental claim (Mintel Group 2011, quoted in Cohen and Vandenbergh 2012). These product labels lower the cost of information about the environmental attributes of goods, and thus may help consumers voluntarily reduce their carbon footprint. The prospects for adoption of a comprehensive international carbon tax or cap and trade system over the next decade are slim, however, and public or private carbon labeling systems are emerging as a gap-filling measure in the interim (Vandenbergh et al. 2010). These systems can affect global supply chains prior to adoption of international or domestic carbon-pricing measures and can complement these measures after they are adopted.

Although carbon labels may be able to reduce carbon emissions from the production of consumer goods, they may have additional impacts, such as a rebound effect whereby consumers decrease other expenditures on environmental protection (Kotchen 2005, 2006), or a spillover effect where labels heighten awareness and cause consumers to increase their overall demand for environmental protection (Kals et al. 1999). The consumer response may be only half the story. Firms may reduce their carbon footprints for reasons beyond willingness to pay for carbon reductions, including boycott threats or more generalized reputational concerns, potential efficiency gains in supply chains, and other factors (Lenox and Eesley 2009, Baron and Diermeier 2007).

This paper assumes consumers are willing to pay to reduce their personal carbon footprints. This assumption is supported by evidence on the willingness to pay for various carbon mitigation programs (Akter and Bennett 2010, Lee et al. 2010, Carlsson et al. 2010, Cai et al. 2010, Johnson and Nemet 2010, Solomon and Johnston 2009, Viscusi and Zeckhauser 2006) and direct measures of mean willingness to pay for a 1-kg reduction in carbon dioxide that range between \$8 and \$32 (Diederich and Goeschl 2011, Loschel et al. 2010, MacKerron et al. 2009, Brouwer et al. 2008).[1] One finding of these surveys is the existence of 'fat tails' for willingness to pay for reductions in carbon dioxide, and that the median is lower than mean values for climate change mitigation. While some respondents are willing to pay large amounts to reduce greenhouse gas emissions, a large mass of the distribution is willing to pay nothing or even negative amounts. This heterogeneity is a problem if it is correlated with food consumption. For instance, if individuals who consume relatively large quantities of beef and are relatively responsive to the change in price of beef are also not concerned about climate change or have a low willingness to pay for carbon reductions, then our model will overstate the gains to labeling beef. We acknowledge this shortcoming and propose that future studies estimate elasticities of demand for products of interest separately, depending on whether they have a high or low willingness to pay for personal carbon footprint reductions.[2]

Calculating the carbon footprint of an apple or potato is a non-trivial task. Different assumptions about production, transportation, and the carbon content of fuels used may result in wildly different estimates. Consumer post-purchase choices—the way

---

[1] The mean willingness to pay for a 1-kilogram reduction in carbon dioxide emissions in these studies are originally reported in euros and we assumed 1 euro is worth \$1.277 USD.
[2] This could be accomplished using current data by using organic food purchases as a proxy for green sentiment.

a potato is cooked[3], how intensively a device is used, the source of electricity for a device, or whether material is recycled—can also change the carbon impact significantly. In response to the growing need for consistent emissions calculations and reporting of products, many ongoing efforts around the world are compiling databases of product emissions and impacts in a consistent manner. However, the focus of these standards is performance tracking of products over time, rather than product comparison, comparative assertions, or product labeling. Key issues remain unresolved, including the standards for manufacturer and supplier cooperation in data sharing, drawing an exact boundary for carbon assessment across companies, incorporating very uncertain land-use change related carbon, and for addressing the unknown life cycle paths of complex products such as consumer electronics produced in Southeast Asia (WRI/WBCSD, 2010).

This is not a paper on establishing carbon footprints, but rather an effort to integrate information on carbon footprints with consumer behavior. We use what we believe are the best, but not final, estimates of the carbon footprint of food products. Because of data limitations, we limit our analysis to broad categories of foods such as 'citrus' or 'fish'. Figure 1 shows the level of analysis we use, and how it could be expanded into a hypothetical third stage of analysis. Broadly labeling products as 'apples' or even 'fish' misses major opportunities for carbon reductions, such as modeling substitutions between seasonal and off-season produce or very different carbon footprints within categories such as fresh lobster (19.60 kg CO_2eq/kg) and fresh herring (1.34 kg CO_2eq/kg), which in our analysis are lumped together as fish (8.86 kg CO_2eq/kg).[4] Fortunately, our model can be expanded when new information becomes available on product carbon footprints and the associated consumer elasticities of demand.

The Economic Model

We model the representative consumer's willingness to reduce her personal carbon footprint as a disutility for personal carbon emissions. Without labels, the consumer may not know what her carbon emissions are but has a perceived footprint, $\tilde{E}$, which may not be the same as the actual footprint, E. Thus the consumer maximizes utility over goods x_1 through x_n, and $\tilde{E}$ subject to a budget constraint and an emissions constraint:

$$\max U\left(x_1, x_2, .. x_n, \tilde{E}\right)$$
$$s.t.$$
$$M \geq x_1P_1 + x_2P_2 .. + x_nP_n$$
$$\tilde{E} = x_1\tilde{E}_1 + x_2\tilde{E}_2 .. + x_n\tilde{E}_n,$$

[3] http://www.carbon-label.com/our-news/case-studies/tesco

[4] ecoinvent v.2 database (Frischknecht et al. 2005; Swiss Center for Life Cycle Inventories 2012)

where P_n is the market price for product n, and M is total expenditure on all market goods and services for the representative consumer. The actual emissions from each consumer is E and is based on the actual carbon footprint of each item, $E = x_1E_1 + x_2E_2..+x_nE_n$. We solve the consumer maximization problem by setting up a Lagrangian with two constraints:

$$\mathcal{L} = U(x_1, x_2, ..x_n, E) + \lambda(M - x_1P_1 - x_2P_2..-x_nP_n) + \xi(\tilde{E} - x_1\tilde{E}_1 - x_2\tilde{E}_2..-x_n\tilde{E}_n).$$

Taking the derivative of $\mathcal{L}$ with respect to x_1 through x_n, and $\tilde{E}$results in n + 1 first order conditions:

$$\partial u/_{\partial x_1} = \lambda P_1 + \xi\tilde{E}_1,$$
$$\vdots$$
$$\partial u/_{\partial x_i} = \lambda P_i + \xi\tilde{E}_i,$$
$$\vdots$$
$$\partial u/_{\partial x_n} = \lambda P_n + \xi\tilde{E}_n,$$

$$\partial u/_{\partial E} = \xi,$$

where $\frac{\partial U}{\partial x_i} > 0, \frac{\partial^2 U}{\partial x_i^2} < 0 \;\; \forall\, i$ and $\frac{\partial U}{\partial \tilde{E}} < 0$, λ is the marginal utility of income and ξ is the marginal disutility of emissions. The shadow values λ and ξ can be combined to equal the value consumers' place on personally reducing a unit of emissions, which we denote $\psi = \xi/\lambda$. This parameter has been estimated from stated preference and experimental studies (Diederich and Goeschl 2011, Loschel et al. 2010, MacKerron et al. 2009, Brouwer et al. 2008). Using ψ, we can rewrite the first-order conditions with the ith condition being:

$$\partial u/_{\partial x_i} = \lambda(P_i + \psi\tilde{E}_i).$$

These conditions can be solved for demand functions that have as their argument $(P_1 + \psi\tilde{E}_1, P_2 + \psi\tilde{E}_2, ... P_n + \psi\tilde{E}_{n1})$. Thus instead of $\mathrm{D}_i(P_1, P_2, ... P_n, M)$, we can rewrite the demand for good i as:

$$\mathrm{D}_i(P_1 + \psi\tilde{E}_1, P_2 + \psi\tilde{E}_2, ... P_n + \psi\tilde{E}_n) = \widehat{\mathrm{D}}_i(P_1, P_2, ... P_n, \tilde{E}_1, \tilde{E}_2, ... \tilde{E}_n).$$

Consumer Responses to Changes in Emissions

Ultimately, we are interested in how the demand for a product will change with a change in perceived emissions due to carbon labels. The derivative of the demand function with respect to a change in the perceived emissions of good i will be:

$$\frac{\partial\widehat{\mathrm{D}_\iota}}{\partial\tilde{E}_i} = \left(\frac{\partial \mathrm{D}_i}{\partial P_i}\right)\psi,$$

where $\frac{\partial \mathrm{D}_i}{\partial P_i}$ can be deduced from conventional estimates of elasticities of demand for product *i*. For example, the elasticity of demand for product *i* with respect to price of *j* is:

$$\eta_{Q_{i,},P_j} = \left(\frac{\partial \widehat{\mathrm{D}_i}}{\partial P_j}\right)\left(\frac{P_j}{Q_i}\right) ,$$

which implies that the slope of demand for product *i* with respect to price *j* is:

$$\eta_{Q_{i,},P_j}\left(\frac{Q_i}{P_j}\right) = \frac{\partial \widehat{\mathrm{D}_i}}{\partial P_j}.$$

Hence, the elasticity of demand for product *i* with respect to a change in perceived emissions in product *j* is:

$$\eta_{Q_{i,},\tilde{E}_j} = \left(\frac{\partial \widehat{\mathrm{D}_i}}{\partial \tilde{E}_j}\right)\left(\frac{\tilde{E}_j}{Q_i}\right) = \left(\frac{\partial \mathrm{D}_i}{\partial P_j}\right)\psi\left(\frac{\tilde{E}_j}{Q_i}\right) = \left(\eta_{Q_{i,},P_j}\right)\left(\frac{Q_i}{P_j}\right)\psi\left(\frac{\tilde{E}_j}{Q_i}\right).$$

The elasticities of demand for products, $\eta_{Q_{i,},P_j}$, are parameters readily available in the demand analysis literature. Thus, we may use own- and cross-price elasticities of demand that have been previously estimated to predict which products consumers may be willing to substitute away from and between.

To understand what total emissions are, we can sum the product of each good and its actual emissions, E_i, such that:

$$E = E_1\widehat{\mathrm{D}_1}\left(P_1, P_2, \ldots P_n, \tilde{E}_1, \tilde{E}_2, \ldots \tilde{E}_n\right) + E_2\widehat{\mathrm{D}_2}(\cdot) + \cdots E_n\widehat{\mathrm{D}_n}(\cdot).$$

A change in the perceived emissions of good *i*, $\tilde{E}_i$, results in a change of the total emissions for the representative consumer that is equivalent to: j

$$\frac{\partial E}{\partial \tilde{E}_i} = E_i\left(\frac{\partial \widehat{\mathrm{D}_J}}{\partial \tilde{E}_i}\right) + \sum_{j\neq i} E_j\left(\frac{\partial \widehat{\mathrm{D}_J}}{\partial \tilde{E}_i}\right).$$

The first term on the left-hand side is the own-price effect, or how a consumer alters her purchasing decisions as a result of knowing more about a good's carbon content. The second term is the impact of a change in perceived emissions on consumer choices for substitutes and complements. If we rearrange the order of goods such that the first *k* goods are substitutes for *i*, and the last *n* – *k* – 1 goods are complements for *i*, we can rewrite this equation as:

$$\frac{\partial E}{\partial \tilde{E}_i} = E_i\left(\frac{\partial \widehat{D_J}}{\partial \tilde{E}_i}\right) + \sum_{j=1}^{k} E_j\left(\frac{\partial \widehat{\mathrm{D}_J}}{\partial \tilde{E}_i}\right) + \sum_{j=k+1}^{n} E_j\left(\frac{\partial \widehat{\mathrm{D}_J}}{\partial \tilde{E}_i}\right).$$

This can be rewritten as:

$$\frac{\partial E}{\partial \tilde{E}_i} = E_i \psi \frac{\partial D_i}{\partial P_i} + \sum_{j=1}^{k} E_j \, \psi \frac{\partial D_j}{\partial P_i} + \sum_{j=k+1}^{n} E_j \, \psi \frac{\partial D_j}{\partial P_i}.$$

If consumers value a reduction in their personal carbon emissions, then the first term will be negative, the second term will be positive, and the last term will be negative. For example, if a consumer learns that beef is much more carbon intensive then previously thought, she will reduce her beef consumption to decrease her carbon emissions; however, her personal emissions from substitutes for beef will increase and her personal emissions for complements for beef will decrease. The net effect is ambiguous, unless we know that the emissions from substitutes are small or emissions from complements are large. A good candidate for a carbon label would be one for which:

$$\left| E_i \frac{\partial \mathrm{D}_i}{\partial P_i} + \sum_{j=k+1}^{n} E_j \frac{\partial \mathrm{D}_j}{\partial P_i} \right| \gg \left| \sum_{j=1}^{k} E_j \frac{\partial \mathrm{D}_j}{\partial P_i} \right|.$$

In other words, goods for which the own-price and complementary effects are greater in magnitude than the substitution effect.

The effects of a carbon label on emissions can be simulated using this model for any number of products. The only constraint on the number of products chosen to model these effects is the data necessary to parameterize the model, which include elasticities of demand, prices and quantities for products included in the analysis, and the retail-level carbon emissions from each product. In the next section, we discuss the parameterization of the model.

Parameters for the Simulations Based on the Model

We include 42 food products and a nonfood composite in our analysis. We use publicly available price and quantity data and elasticities of demand from the demand analysis literature, and we construct measures of carbon emissions for each product using data primarily from LCA databases such as CleanMetrics and ecoinvent, but supplemented with additional data from studies from the literature.

Price Elasticities of Demand for Food Products

Okrent and Alston (2012) estimated demand for 43 disaggregated products, using a two-stage budgeting framework (figure 1). For the first stage, they estimated demand for six food-at-home (FAH) product groups (cereals & bakery products, dairy, meat & eggs, fruits & vegetables, nonalcoholic beverages, and other FAH), a food-away-from-home (FAFH) and alcoholic beverages group, and a nonfood group. They then modeled the second-stage allocation of expenditures on the seven food groups as weakly separable groups, including: (i) flour & prepared flour mixes, breakfast cereals, rice & pasta, nonwhite bread, white bread, biscuits, rolls & muffins, cakes & cookies, and other bakery products, (ii) beef, pork, other red meat, poultry, fish & seafood, and eggs, (iii) milk, cheese, ice cream & frozen desserts, and other dairy products, (iv) apples, bananas, citrus, other fresh fruits, potatoes, lettuce, tomatoes, other fresh vegetables, and processed fruits & vegetables, (v) frozen, noncarbonated juices & drinks, nonfrozen, noncarbonated juices & drinks, carbonated drinks, and coffee & tea, (vi) sugars & sweeteners, fats & oils, soups, frozen meals, snacks, spices, seasonings, condiments & sauces, and other miscellaneous foods, and (vii) full-service FAFH, limited-service FAFH, other FAFH, and alcoholic beverages. Using estimates of elasticities of demand from the first- and second-stage allocations, they approximated elasticities of demand conditional on total expenditure for all goods and services.

To estimate the first and second stages, Okrent and Alston (2012) used the Generalized Ordinary Differential Demand System (Eales et al. 1997) with expenditure and price data from the Bureau of Labor Statistics. First, using the 1998–2010 diary portion of the Consumer Expenditure Surveys, they constructed a monthly time series of household expenditures by aggregating detailed weekly expenditure data into 43 products (i.e., three FAFH products, 38 FAH products, alcoholic beverages, and a nonfood composite) and then averaged these data over households for a given month (Bureau of Labor Statistics 2010b). They then matched the average monthly expenditures to monthly consumer price indexes (Bureau of Labor Statistics 2010c).

Following Carpentier and Guyomard (2001), they approximated the unconditional elasticities using the first- and second-stage elasticities of demand to approximate the unconditional elasticities of demand. The superscript denotes the composite group and the subscript denotes the elementary good. The authors then approximated the unconditional Marshallian expenditure (η_{iM}) and price (η_{ij}) elasticities of demand as

$$\eta_{iM} \approx \eta_{iM}^{I}\,\eta^{IM}, \tag{1}$$

$$\eta_{ij} \approx \delta^{IJ}\,\eta_{ij}^{I} + w_j^J \eta_{iM}^{I}\,\eta_{jM}^{J}\left(\delta^{IJ} / \eta_{jM}^{J} + \eta^{IJ}\right) + w_j^J w^J\,\eta^{IM}\,\eta_{iM}^{I}\left(\eta_{jM}^{J} - 1\right), \tag{2}$$

where

η_{iM}^{I} = expenditure elasticity for good $i \in I$ conditional on expenditure for group I,

η^{IM} = expenditure elasticity for composite group I with respect to total expenditure, M,

η_{ij}^{I} = Marshallian elasticity of demand for good $i \in I$ with respect to price $j \in J$ conditional on $I = J$,

η^{IJ} = Marshallian elasticity of demand for composite group I with respect to composite price J,

w_j^J = budget share for good $j \in J$ conditional on J,

w^J = budget share for composite group J,

$$\delta^{IJ} = \begin{cases} 1, \text{if } I = J \\ 0, \text{otherwise} \end{cases}$$

To date, the elasticities of demand estimated by Okrent and Alston (2012) are the most comprehensive set of elasticities for investigating the effects of a policy like carbon labeling on food consumption. They include a large number of foods at a level of disaggregation that allows us to simulate somewhat precisely the effects on demand and carbon emissions of a label that changes carbon perceptions. Comparable studies to Okrent and Alston (2012) do not have the level of disaggregation appropriate for the simulations. Also, most of the own-price elasticities are negative, which is consistent with demand theory, and statistically different from zero at the 10% level of significance.

Prices and Quantities of Food and Nonfood Products

The price data for the FAH products are based on several sources (Table 1). Most of the price data are from the Average Price Database (APD) published by U.S. Department of Labor, Bureau of Labor Statistics (2010a). The APD contains monthly national average prices for many basic FAH products that are used in the construction of the Consumer Price Indexes. We first use a simple average of the monthly prices for calendar year 2008 for the FAH products in the APD. We then constructed expenditure share-weighted average prices for many of the foods using the disaggregated prices in this database. For example, the price for poultry is the weighted average price per pound of (1) chicken, fresh, whole, (2) chicken breast, bone-in, (3) chicken legs, bone-in, (4) chicken breast, boneless, and (5) turkey, frozen, whole, with the expenditure shares for each poultry component as weights. The expenditure shares for each component disaggregated product are derived from the 2008 Consumer Expenditure Survey (U.S. Department of Labor, Bureau of Labor Statistics 2010b).

Because the APD does not cover all FAH products, we also used the Quarterly Food-at-Home Price Database (QFAHPD), which contains household expenditure-weighted prices for 52 food groups across 30 market areas (U.S. Department of Agriculture, Economic Research Service 2011). We calculated the price levels of FAH products using these data as a simple average across markets and quarters in 2008.

Quantities for the FAH products are derived as average annual household expenditures for a particular FAH product in 2008 (Column 2 in Table 2) divided by the average price per unit of measure (Column 1 of Table 2). The 2008 average annual household expenditures are derived from the 2008 Consumer Expenditure Survey public microdata (U.S. Department of Labor, Bureau of Labor Statistics 2010b). Most of the quantities are in pounds, except for carbonated beverages, frozen drinks, eggs, and milk. To make these quantities compatible with the carbon footprint information, we convert them to kilograms in the simulation.

The prices of and quantities for FAFH and alcohol products are derived somewhat differently than the prices of and quantities for the FAH products. For these products, expenditures and quantities are available but prices are not. We calculated the prices of the FAFH and alcohol products as total annual household expenditures on FAFH products in 2008 using the Consumer Expenditure Survey public microdata (U.S. Department of Labor, Bureau of Labor Statistics 2010b) divided by the quantities of FAFH products consumed by households. The quantities of FAFH and alcohol products consumed are based on the 2007-08 National Health and Nutrition Examination Survey. In this survey, individuals are asked to recall the type, quantity, and source of foods they consumed in a 24-hour period. For example, average daily consumption of food from limited-service FAFH for an individual in 2007-08 was 198.53 grams (Table 2). We then converted individual daily consumption into household annual consumption by multiplying Column 1 in Table 2 by 365 days and the average household size in 2008, which was 2.5 persons. The price per pound is then annual household expenditures for each FAFH and alcohol product in 2008 divided by pounds of each product consumed by a household.

Carbon Footprints Data

The carbon footprint of any good is composed of emissions from various life cycle stages and is measured in kilograms of carbon dioxide equivalency (CO_2eq) which includes other greenhouse gasses such as methane and nitrous oxide. The first stage is production. We use information primarily from the ecoinvent v.2 database (Swiss Center for Life Cycle Inventories), CleanMetrics[5] (CleanMetrics 2011), Meat Eater's Guide (Environmental Working Group 2011), and the Economic Input-Output Life Cycle Assessment (EIO LCA) Online database (Carnegie Mellon University Green Design Institute 2008). Additional information was obtained from SAI Platform (Mordini et al. 2009), Jungbluth (2005), and Coca-Cola Corporate Responsibility (Coca-Cola Enterprise, 2011). Most of these studies include raw material extraction and processing but ignore any indirect land use effects. The second stage is post-production, which generally consists of packaging. We use information from CleanMetrics and Meat Eater's Guide, which provides per kilogram emissions factors for packaging. The third stage is transportation. Calculating transportation emissions requires many simplifying assumptions as transportation emissions are a result of the distance traveled, the mode of travel used, and the carbon intensity of that mode. We obtained average distance traveled and mode for products from CleanMetrics and Meat Eater's Guide. We assumed the most frequent mode used was the only mode used. We used transportation emissions factors from CE Delft and GHG Protocol. The most common mode was trucking, but we also included container shipping, rail, refrigerated container shipping, and air cargo.

[5] CleanMetrics is a meta-analysis on US-specific food products.

Finally, because we are looking at emissions at the retail level only, we ignore use and disposal emissions. This is partially because of lack of data, partially to capture consumer response at the point of purchase, and also because for some foods (such as meats) the production phase dominates the use and disposal phases. An extension to our model is described in the Discussion section which would better account for post-purchase decisions such as use and disposal. These phases are more likely to dominate products such as home appliances, electronics, and automobiles.

LCA tends to focus on individual products and specific geographies (for instance tomatoes in Britain) since the emissions from any product can be highly sensitive to whether they are transported, the source of electricity, how much waste there is in the process, etc. Estimating elasticities of demand, however, requires a certain level of aggregation. Thus we find the economic data cover wide groups of products such as 'non-alcoholic carbonated beverages' while the carbon footprint of a liter of any soda may depend on whether it is delivered in a 375 mL glass bottle or a 2-liter plastic bottle. Thus to integrate these two data sources, we made simplifying assumptions to calculate the carbon content of broad product categories. For instance, we have separate carbon intensities for brown rice and white rice, which could differ further depending on how they are produced and where they are produced geographically. We thus take an average transportation distance and average the carbon footprint of brown rice and white rice since the quantities consumed of white and brown rice were not available. For other groups, such as other fruits, we used the top groups in these categories for which carbon intensities were available. For other fruits, these were strawberries, peaches, and grapes. We then calculated a weighted average for the aggregated carbon intensity. Ice cream and ice milk had no carbon footprints available for average products but Ben & Jerry's had calculated their individual footprint per pint. We assumed the density of ice cream was 0.8 grams/mL and calculated the carbon footprint of a pound of ice cream assuming Ben & Jerry's footprint was representative. For all types of FAFH, we used Carnegie Mellon's EIO-LCA web model, a sector-based aggregated estimate that calculates emissions on a per dollar basis. The assumption in this model is that the emissions are linearly related to the economic activity.

Current Carbon Perceptions

Labels give consumers better information about the carbon content of goods. We model this information as a change in perception. This change in perception is relative to a baseline perception of how consumers perceived carbon footprints pre- and post-labeling. We are unaware of research that documents consumer perceptions of carbon footprints without labels and thus we make a range of plausible assumptions and test the various scenarios. Further research is warranted in this area, as the results are sensitive to how consumers initially calculate their carbon footprint.

We evaluate the effects of carbon labels under three scenarios about current perceptions of carbon footprints. In the first scenario, consumers assume that the carbon footprint per dollar spent on food is the same as the average carbon intensity of the US economy, 0.48 kg/$ (IEA 2011). Thus the consumer contemplating purchasing 0.23 kg of cheese for $1 would assume that this cheese results in 0.48 kg of CO_2eq. The label would inform the consumer that 0.23 kg of cheese actually had a carbon intensity of 2.20 kg. The second scenario we test is that consumers have a general idea of which products are carbon intensive but the labels make the carbon cost more salient, which results in an across-the-board 1% increase in the carbon cost of goods. The third scenario we evaluate is the case where consumers initially assume a zero carbon cost of consumption. These assumptions, much like other parts of our model, are meant to be demonstrative of the process and not a definitive statement of the impact of carbon labels on consumer food decisions.

Scenario 1: Consumers assume the carbon footprint across all goods is 0.48 kg/$

To understand the impact of the carbon label we look at the total derivative of emissions with respect to the changes in the perceived emissions of goods:

$$\psi^{-1} dE = \sum_{i=1}^{N} \left[E_i \frac{\partial D_i}{\partial P_i} + \sum_{j=1}^{J} E_j \frac{\partial D_j}{\partial P_i} \right] d\tilde{E}_i. \qquad (3)$$

This equation specifies the total change in emissions from labeling all goods. If we wanted to know the impact of labeling cheese, we could set $\mathrm{d}\tilde{E}_i = 0$ for all other goods and estimate the impact of only changing the perceived emissions from cheese. If we wanted to know the impact of labeling all dairy products, we could set $d\tilde{E}_i = 0$ for all non-dairy products. The total amount of emissions is dependent on the value of ψ, thus our results should be interpreted as a way to rank categories of products but not absolute reductions. For simplicity we assume consumers are willing to pay one cent to reduce their carbon footprint by 1 kg, or $\psi = 0.01$.[6] This is presented in Column 1 of Table 4 and the impact of labeling groups of goods is presented in Column 1 of Table 5.

Scenario 2: 1% Increase in the Carbon Cost of All Goods

This scenario corresponds to the case where consumers roughly know what the carbon impacts of goods are, but the labels make the impacts more salient. Since we are assuming that consumers are willing to pay $0.01 to reduce their carbon impact by a kg, this is equivalent to a 0.01% increase in the price of all goods. This is likely an unrealistic assumption to make, but helps bound the actual impact of a carbon label. This is presented in Column 2 of Table 4 and the impact of labeling groups of goods is presented in Column 2 of Table 5.

---

[6] This is approximately equal to a willingness to pay of $10/ton of CO_2eq reductions.

Scenario 3: Consumers assume a zero carbon cost of goods

In this scenario we assume consumers have been ignoring the carbon cost of all goods, and only take the carbon impact into account once confronted with a label. This is also an extreme assumption to make, but the truth may lie somewhere in between these three scenarios. This is presented in Column 3 of Table 4 and the impact of labeling groups of goods is presented in Column 3 of Table 5.

Discussion

Tables 4 and 5 present simulation results from looking at the impact of labeling each item (Table 4) or groups of items (Table 5) under various assumptions about the current perceptions of carbon footprints. The measurements assume a willingness to pay of $0.01 for a kilogram of person CO_2eq reductions, which is lower than what has been measured in the literature.

We first look at the products associated with the largest reductions in emissions from the label. For instance labeling alcohol (which has a high carbon footprint) results in the largest reduction across all three scenarios. Other meats, which includes many processed meats like sausage and hot dogs, and beef are also good candidates for labeling. In contrast, labeling pork alone results in an increase in emissions since consumers substitute away from pork and into other products that are higher in carbon emissions. However, if consumers are already aware that beef has a relatively large carbon footprint and assume pork has a similar carbon footprint, correcting this misperception so that consumers substitute away from beef and into pork could be an effective carbon mitigation scheme.

Many products will result in an increase in carbon under some scenarios but a decrease in others. Wheat bread is an interesting example of this. When consumers believe that wheat bread has a carbon footprint of 0.48 kg/$, this translates into a perceived carbon footprint of approximately 1.44 kg CO_2eq/kg which is higher than the measured carbon footprint of 0.65 1.44 kg CO_2eq/kg. Thus the label tells consumers that wheat bread is not as carbon intensive as previously believed and hence the consumer consumes more bread under this scenario (and less of its substitutes) but less bread (and more of its substitutes) under the other scenarios.

Labeling certain other items, such as rice, increase emissions under all scenarios. Even in scenario 1, consumers learn that rice has a higher carbon emission than previously thought and so while they use less rice they consume more of the substitutes for rice that are higher in carbon. This is the case with many items in the bread section. One reason for this is because the cross-price elasticities between bread items and meats and FAFH are generally positive. Increasing the mental price of carbohydrates moves consumers from eating these items and into meats and FAFH which have higher carbon footprints.

Extensions

A drawback of our analysis is that the products included are composed of product groups that are heterogeneous in terms of carbon footprints. For example, the product fish and seafood contains lobster, which has a 19.60 kg CO_2eq global warming factor, and cod, which has a 1.19 kg CO_2eq global warming factor. Our model and the set of parameters used can be extended to include more disaggregated products. For the lobster and cod example, assuming that a household chooses these products as a third stage in the budgeting process, one can construct a third stage of lobster, cod, and other fish and seafood using equations (1) and (2) (Figure 1). The parameters necessary to estimate equations (1) and (2) are (a) elasticities of demand for disaggregated seafood and fish products conditional on expenditure for seafood and fish, (b) budget shares of the disaggregated seafood and fish products conditional on expenditure for seafood and fish, and (c) the elasticities of demand from Okrent and Alston (forthcoming). Hence, more precise estimates of the effects of carbon labeling can be estimated with additional information on the products of interest not included in this analysis.

This analysis has ignored use and disposal emissions. A further effort could build a multi-stage analysis where consumers learn the carbon consequences of disposing of food items and packaging as well as cooking and usage patterns depending on cooking method and fuel usage. For instance, a potato cooked in the oven has three times the carbon emissions of a potato cooked in the microwave or boiled on the stovetop (EWG 2011). This can vary by the carbon intensity of fuel sources. We ignore this analysis because we do not have elasticities of demand for potatoes that are baked versus those that are cooked in the microwave. However a survey or study using food diaries may be able to estimate these kinds of elasticities of demand.

Conclusion

This paper is the first to combine information on elasticities of demand and carbon footprints to predict how consumers will respond to new information on carbon footprints. Previous work in the LCA literature has relied on ad hoc assumptions about the willingness to change consumption patterns and what constitutes a substitute for high carbon items. Our model relies on price elasticities of demand to make these decisions and quantifies the substitution and complementary relationships between products, which allows us to calculate reductions in emissions (Tables 4 and 5).

We find that a carbon label on meat and alcohol would yield the largest reductions on total emissions, but some caveats remain. We have ignored consumer heterogeneity and use a fairly aggregated level of analysis. Further disaggregating the analysis to allow consumers to choose between disaggregated products within each food group (e.g., cod versus herring instead of fish versus beef) would likely incur even greater reductions in carbon emissions. In general, we find that goods where consumers have a low carbon substitute, an inaccurate belief about the carbon footprint of the good, and where high carbon goods have a large market share are the products that are most likely to result in large reductions in carbon just from being labeled.

This paper should not be construed as an argument that carbon labels should replace a carbon tax or cap and trade. Labeling only certain items (e.g. bananas) may have perverse effects in that the label may actually increase total carbon emissions. Labeling also may have spillover effects that result in greater than expected emissions reductions. A comprehensive carbon tax would result in lower overall emissions, be less susceptible to mistakes from an incorrect LCA, and be more transparent than a carbon label system. A carbon label system could however be a complement to an economic instrument or substitute for an economic instrument until more comprehensive climate policy is adopted.

References

Akter, S. and Bennett, J. 2011. "Household perceptions of climate change and preferences for mitigation action: The case of the carbon pollution reduction scheme in Australia." *Climatic Change*, 1–20.

Alston, J., Norton, G., Pardey, P. 1995. *Science Under Scarcity: Principles and Practice for Agricultural Research Evaluation and Priority Setting*. Ithaca: Cornell University Press.

Baron, D. and D. Diermeier. 2007. "Strategic Activism and Nonmarket Strategy." *Journal of Economics and Management Strategy,* 16, 599-634.

Ben & Jerry's. 2011. Social and Environmental Assessment Report. Available at: http://www.benjerry.com/company/sear/

Bin, S. and H. Dowlatabad. 2005. "Consumer lifestyle approach to US energy use and the related CO_2 emission." *Energy Policy*. 33, 197–20.

Brouwer, R., Brander, L. and P. Van Beukering. 2008. '"A convenient truth': Air travel passengers willingness to pay to offset their CO_2 emissions." *Climatic Change* 90(3), 299-313.

Busser, S. and N. Jungbluth. 2011. "LCA of Ready-to-Serve Goulash Soup Packed in Stand-Up Pouches." ESU-services Ltd. Uster, Switzerland. Commissioned by European Aluminium Foil Association e.V., Düsseldorf, Germany. Available at: http://www.alufoil.org/tl_files/sustainability/ESU%20-%20Goulash%20(2011)%20Exec%20Sum.pdf

Busser, S. and N. Jungbluth. 2009. "LCA of Chocolate Packed in Aluminium Foil Based Packaging. ESU-Services Paper." SU-services Ltd. Uster, Switzerland. Commissioned by

European Aluminium Foil Association e.V., Düsseldorf, Germany. Available at: http://www.alufoil.org/tl_files/sustainability/ESU_-_Chocolate_2009_-_Exec_Sum.pdf

Cai, B., Cameron, T. and G. Gerdes. 2010. "Distributional preferences and the incidence of costs and benefits in climate change policy." *Environmental and Resource Economics* 46(4), 429-458.

Carlsson, F., Kataria, M., Krupnick, A., Lampi, E., Lofgren, A., Qin, P., Chung, S. and T. Sterner. 2010. "Paying for mitigation: A multiple country study." Resources for the Future, Discussion Papers.

Carnegie Mellon University. 2008. Economic input-output life cycle assessment (EIO-LCA), U.S. 2002 industry benchmark model. *Carnegie Mellon University Green Design Institute*. www.eiolca.net. Accessed May 16, 2012

Carpentier, A., and H. Guyomard. 2001. "Unconditional Elasticities in Two-Stage Systems: An Approximate Solution." *American Journal of Agricultural Economics* 83(1), 222–229.

CDC, NCHS. 2011. "National Health and Nutrition Examination Survey Data." Hyattsville, MD: U.S. Department of Health and Human Services, 2007–2008. Available at: http://www.cdc.gov/nchs/nhanes/nhanes_questionnaires.htm, Accessed May 16, 2012.

Clean Metrics. 2011. "Product LCA and Carbon Footprint Analysis." http://www.cleanmetrics.com/html/carbon_footprints.htm, Accessed May 16, 2012.

Coca-Cola Enterprise, 2011. "Product Carbon Footprint." http://www.cokecorporateresponsibility.co.uk/big-themes/energy-and-climate-change/product-carbon-footprint.aspx, Accessed May 16, 2012.

Cohen, M. and M. Vandenbergh. 2012. "The Potential Role of Carbon Labeling in a Green Economy." *Environmental Economics,* forthcoming.

Colman, T. and P. Paster. 2007. "Red, White and 'Green': The Cost of Carbon in the Global Wine Trade." AAWE Working Paper No. 9.

Diederich, J. and T. Goeschl. 2011. "Willingness to Pay for Individual Greenhouse Gas Emissions Reductions: Evidence from a Large Field Experiment." University of Heidelberg, Department of Economics, Discussion Paper Series, No. 517. Available at: http://www.uni-heidelberg.de/md/awi/forschung/dp517.pdf.

Dietz, T., J. Gardner, J. Gilligan, P. Stern, and M. Vandenbergh. 2009. "Household action can provide a behavioral wedge to rapidly reduce U.S. carbon emissions." *Proc. Natl. Acad. Sci.* 106, 18452–18456.

Eales, J., C. Durham, and C. Wessells. 1997. "Generalized Models of Japanese Demand for Fish." *American Journal of Agricultural Economics.* 79(4), 1153–1163.

Environmental Working Group. 2011. "Meat Eater's Guide to Climate and Health." Available at: http://www.ewg.org/meateatersguide/, Accessed May 16, 2012.

European Communities. 2006. *Environmental Impact of Products (EIPRO) Analysis of the life cycle environmental impacts related to the final consumption of the EU-25*, Technical Report EUR 22284 EN: European Commission Joint Research Center.

Frischknecht, R. et al., 2005. The ecoinvent Database: Overview and Methodological Framework. *The International Journal of Life Cycle Assessment*, 10, pp.3-9. Available at: www.ecoinvent.org/fileadmin/documents/en/01_OverviewAndMethodology.pdf, accessed February 2012.

Grant , T. and T. Beer. 2008. "Life Cycle Assessment of Greenhouse Gas Emissions From Irrigated Maize and Their Significance in the Value Chain." *Australian Journal of Experimental Agriculture.* 48, 375–381.

Humbert, S., Y. Loerincik, V. Rossi, M. Margni, O. Jolliet. 2009. "Life cycle assessment of spray dried soluble coffee and comparison with alternatives (drip filter and capsule espresso)." *Journal of Cleaner Production* 17 1351–1358.

International Energy Agency. 2011. "CO_2 Emissions From Fuel Combustion: Highlights. 2011 Edition."

Johnson, E. and G.F. Nemet. 2010. "Willingness to pay for climate policy: A review of estimates." La Follette School Working Paper No. 2010-011. LaFollette School of Public Affairs at the University of Wisconsin-Madison.

Jones, C.M. and D. M. Kammen. 2011. "Quantifying Carbon Footprint Reduction Opportunities for U.S. Households and Communities." *Environmental Science & Technology.* 45(9), 4088–4095.

Jungbluth N. 2005. "Comparison of the Environmental Impact of Tap Water vs. Bottled Mineral Water." ESU- services and the Swiss Gas and Water Association (SVGW): Uster, Switzerland.

Lee, J., Yoo, S. and S. Kwak. 2010. "Public willingness to pay for preventing climate change." *Applied Economics Letters.* 17(4-6), 619–622.

Lenox, M. and C. Eesley. 2010. “Private Environmental Activism and the Selection and Response of Firm Targets.” *Journal of Economics and Management Strategy.* 18(1), 45–73.

Loschel, A., Sturm, B. and C. Vogt. 2010. “The demand for climate protection: an empirical assessment for Germany.” ZEW Discussion Papers (10-068). Centre for European Economic Research (ZEW), Mannheim.

MacKerron, G. J., Egerton, C., Gaskell, C., Parpia, A. and S. Mourato. 2009. “Willingness to pay for carbon offset certification and co-benefits among (high) flying young adults in the UK.” *Energy Policy* 37(4), 1372–1381.

Mordini, M., T. Nemecek, and G. Gaillard. 2009. “Carbon & Water Footprint of Oranges and Strawberries: A Literature Review.” Sustainable Agriculture Initiative Working Group on Fruit. Available at: http://www.saiplatform.org/uploads/Library/WG%20Fruit%20-%20ART%20Final%20Report.pdf

Okrent, A. and J. Alston, *The Demand for Disaggregated Food-Away-from-Home and Food-At-Home Products*. *forthcoming*, Economic Research Report. Washington, D.C.: U.S. Department of Agriculture.

Ruini, L. and M. Marino. 2009. “LCA of Semolina Dry Pasta Produced by Barilla.” Working Paper. Conference Paper, Available online at: http://ec.europa.eu/research/sd/conference/2009/papers/3/massimo_marino_-_lca_barilla.pdf

Solomon, B. D. and N. Johnson. 2009. “Valuing climate protection through willingness to pay for biomass ethanol.” *Ecological Economics* 68(7), 2137–2144.

Swiss Centre for Life Cycle Inventories. 2002. Ecoinvent v.2 Database. edited by S. C. f. L. C. Inventories. Hamburg: Swiss Centre for Life Cycle Inventories. Available on-line at: http://www.ecoinvent.org/database, accessed, May 15, 2012.

U.S. Department of Agriculture, Economic Research Service. 2011. Quarterly Food-at-Home Price Database. Available at: http://www.ers.usda.gov/Data/QFAHPD/qfahpd2.htm, Accessed May 16, 2012.

U.S. Department of Labor, Bureau of Labor Statistics. 2010a. Average Price Database. Available at: http://www.bls.gov/cpi/. Accessed on January 29, 2011.

U.S. Department of Labor, Bureau of Labor Statistics. 2010b. Consumer Expenditure Survey Public Microdata, 2008: Detailed Expenditure Files. Washington, DC: U.S. Department of Labor, Bureau of Labor Statistics.

U.S. Department of Labor, Bureau of Labor Statistics. 2010c. Consumer Price Index Database. Available at: www.bls.gov/cpi/#data. Accessed on March 10, 2010.

Vandenberg, M., T. Dietz, and P. Stern. 2011. "Time to Try Carbon Labeling." *Nature Climate Change*. 1.

Viscusi, W. and R. Zeckhauser. 2006. "The perception and valuation of the risks of climate change: A rational and behavioral blend." *Climatic Change* 77(1), 151−177.

Weber, C. and H. Matthews. 2008. "Food-Miles and the Relative Climate Impacts of Food Choices in the United States." *Environmental Science and Technology*. 42, 3508-3513.

World Resources Institute and World Business Council for Sustainable Development. *Product Accounting and Reporting Standard*. Draft, 2010.

Table 1. 2008 Prices and Quantity Parameters and Sources for Deriving Price Parameters

	Price	Annual household expenditure	Quantity	Unit of measure	Price source
	(1)	(2)	(3)=(2)/(1)	(4)	(5)
Flour & flour mixes	0.51	22.18	43.77	lb	Average of 2008 monthly prices (APD)
Breakfast cereals	1.42	105.13	73.80	lb	No average price available; used average price for all cereals and bakery
Rice & pasta	0.73	28.36	38.71	lb	Average of 2008 monthly prices (APD)
Non-white bread	1.12	34.26	30.59	lb	Average of 2008 monthly prices (APD)
White bread	1.94	69.03	35.63	lb	Average of 2008 monthly prices (APD)
Biscuits, rolls, muffins	1.37	41.39	30.29	lb	Average of 2008 monthly prices (APD)
Cakes & cookies	1.42	55.18	38.73	lb	No average price available; used average price for all cereals and bakery
Beef	2.88	97.40	33.77	lb	Weighted average of 2008 monthly prices of cuts of beef (APD)
Pork	3.36	150.19	44.71	lb	Weighted average of 2008 monthly prices of cuts of pork (APD)
Other red meat	2.76	151.56	54.96	lb	Average of 2008 monthly prices of bologna (APD)
Poultry	1.91	178.11	93.01	lb	Weighted average of 2008 monthly prices of cuts of poultry (BLS)
Fish & seafood	4.56	143.20	31.43	lb	Average across markets and quarters in 2008 (QFAHPD)
Egg	1.99	57.18	28.79	dozen	Average of 2008 monthly prices (APD)
Cheese	4.38	150.03	34.22	lb	Weighted average of 2008 monthly prices of types of cheeses (APD)
Ice cream	4.21	67.75	16.09	lb	Average of 2008 monthly prices (APD)
Milk	3.80	167.82	44.22	1/2 gal	Average of 2008 monthly prices (APD)
Other dairy	1.80	51.14	28.37	lb	Average across markets and quarters in 2008 (QFAHPD)

Table 1. 2008 Prices and Quantity Parameters and Sources for Deriving Price Parameters (continued)

	Price	Annual household expenditure	Quantity	Unit of measure	Price source
	(1)	(2)	(3)=(2)/(1)	(4)	(5)
Apples	1.80	51.14	28.37	lb	Average of 2008 monthly prices (APD)
Bananas	1.32	44.88	34.01	lb	Average of 2008 monthly prices (APD)
Citrus	0.61	36.27	59.53	lb	Weighted average of 2008 monthly prices of types of citrus (APD)
Other fresh fruit	2.12	118.94	56.00	lb	Average of 2008 monthly prices for pears, peaches, strawberries, grapes, and cherries (APD)
Potatoes	0.63	42.36	67.14	lb	Average of 2008 monthly prices (APD)
Lettuce	0.91	29.43	32.51	lb	Average of 2008 monthly prices (APD)
Tomatoes	1.74	41.26	23.66	lb	Average of 2008 monthly prices (APD)
Other fresh vegetables	1.37	124.19	90.81	lb	Average of 2008 monthly prices for cabbage, carrots, peppers, and broccoli (APD)
Processed fruits & vegetables	1.21	140.44	116.00	lb	Average of 2008 monthly prices (APD)
Carbonated drinks	1.34	149.70	111.69	2 liter	Average of 2008 monthly prices (APD)
Frozen drinks	2.54	6.75	2.66	12 oz	Average of 2008 monthly prices (APD)
Nonfrozen noncarb. drinks	0.51	133.97	261.64	lb	Average across markets and quarters in 2008 for noncarbonated caloric beverages (QFAHPD)
Coffee & tea	0.28	93.04	329.39	lb	Average across markets and quarters in 2008 for coffee and tea (QFAHPD)
Soups	1.19	51.30	43.13	lb	Average across markets and quarters in 2008 for canned soups, sauces, and prepared foods (QFAHPD)
Frozen foods	3.15	157.44	49.97	lb	Average across markets and quarters in 2008 for frozen foods (QFAHPD)
Snacks	4.02	157.33	39.12	lb	Average of 2008 monthly prices (APD)

Table 1. 2008 Prices and Quantity Parameters and Sources for Deriving Price Parameters (continued)

	Price	**Annual household expenditure**	**Quantity**	**Unit of measure**	**Price source**
	(1)	**(2)**	**(3)=(2)/(1)**	**(4)**	**(5)**
Spices, seasonings, cond.	1.19	137.83	115.86	lb	Average across markets and quarters in 2008 for canned soups, sauces, and prepared foods (QFAHPD)
Miscellaneous FAH	3.75	255.45	68.10	lb	Average across markets and quarters in 2008 for ready-to-eat meals and deli items (QFAHPD)
Sugar & sweets	0.51	144.72	281.30	lb	Average of 2008 monthly prices for types of sugar (APD)
Fats & oils	2.43	140.82	57.98	lb	Weighted average of 2008 monthly prices of types of fats and oils (APD)

Notes: APD=Average Price Database (U.S. Department of Labor, BLS 2010a), QFAHPD=Quarterly Food-at-Home Price Database (U.S. Department of Agriculture, ERS 2011).

Table 2. Derivation of Prices and Quantities for FAFH and Alcohol Products

	Individual daily consumption	**Household annual consumption**	**Household annual expenditures**	**Price**
	grams	*pounds*	*dollars*	*dollars/pound*
Limited service	198.53	416.17	1103.22	2.65
Full service	165.42	346.77	1254.69	3.62
Other FAFH	83.16	174.32	155.28	0.89
Alcohol	135.68	284.43	417.77	1.47

Source: Individual daily consumption derived from the 2007-08 NHANES and household annual expenditures based on the 2008 Consumer Expenditure Survey.
Notes: Pounds of FAFH and alcohol consumed are calculated as average daily grams of each food or drink consumed multiplied by 365 days and 2.5 persons per household.

Table 3. Correspondence Between Economic Elasticities of Demand, Quantities, and Prices and Carbon Footprint Information

Economic category	Carbon footprint information	Carbon footprint source
Flour	Wheat Flour	CleanMetrics 2010
Breakfast Cereals	Oat Flakes	ecoinvent V.2
Rice	White Rice and Brown Rice	CleanMetrics 2010
Pasta	Dry Semolina, Barilla Brand	Ruini and Marino 2009
Non-White Bread	Wheat and Rye Bread	ecoinvent V.2 database
White Bread		ecoinvent V.2 database
Rolls		ecoinvent V.2 database
Cakes	Same as Rolls	ecoinvent V.2 database
Cakes and Bread, Other	Same as Rolls	ecoinvent V.2 database
Beef		CleanMetrics 2010; Meat Eater's Guide
Pork		CleanMetrics 2010; Meat Eater's Guide
Meat, Other	Lamb and Veal	CleanMetrics 2010; Meat Eater's Guide
Poultry	Turkey and Chicken	CleanMetrics 2010; Meat Eater's Guide
Fish	Cod, Flatfish, Skinke, Herring, Mackerel, Mussels, Shrimp	ecoinvent V.2 database
Cheese	Cheese	CleanMetrics 2010
Ice Cream and Ice Milk	Ben & Jerry's Ice Cream	Ben & Jerry's (2012)
Milk	Skim Milk, Low Fat, Whole, Cream, Milk Powder, Whole	ecoinvent V.2 database
Dairy, Other	Yogurt	CleanMetrics 2010
Apples		CleanMetrics 2010
Bananas		CleanMetrics 2010
Citrus	Oranges	CleanMetrics 2010
Other Fruits	Strawberries, Peaches, Grapes	CleanMetrics 2010
Potatoes		CleanMetrics 2010
Lettuce		CleanMetrics 2010
Tomatoes		CleanMetrics 2010

Table 3. Correspondence Between Economic Elasticities of Demand, Quantities, and Prices and Carbon Footprint Information (continued)

Economic category	Carbon footprint information	Carbon footprint source
Other Vegetables	Carrots, Cabbage, Sweet Peppers, Broccoli	CleanMetrics 2010
Processed Fruits and Vegetables	All in study	Multiplied by 1.2 to account for packaging.
Non-Alcoholic Carbonated Beverages	14 Different Types of Coca-Cola Products (in various sizes)	Coca-Cola Enterprise 2011
Non-Alcoholic Frozen	Frozen Concentrated Orange Juice	Mordini et al. 2009
Non-Alcoholic Non-Frozen	Non-Refrigerated and Refrigerated Bottled Water	Jungbluth 2005
Coffee	Drip Filter and Capsule Espresso	Humbert et al. 2009
Soups	Ready-to-eat Goulash	Busser and Jungbluth 2001
Freezer Meals	All food products	Multiplied by 1.2 to account for packaging and processing.
Snack Foods	Corn Chips	Grant & Beer 2008
Seasonal Products	All food products	
Miscellaneous Other Products	All food products	
Eggs		CleanMetrics 2010
Sugars	Foil Wrapped Milk Chocolate	Busser and Jungbluth 2009
Fats	Butter, Peanut Butter, Vegetable Oil	CleanMetrics 2010
Alcohol	Beer and Wine	Colman and Paster, 2007
FAFH- Full Service	Food Services and Drinking Places	Carnegie Mellon University. 2008
FAFH- Quick Service	Food Services and Drinking Places	Carnegie Mellon University. 2008
FAFH- Vending Machines	Food Services and Drinking Places	Carnegie Mellon University. 2008
Non-Food Products	Average Carbon Intensity of the U.S. Economy	IEA 2011

Table 4: Carbon Emission Impact from Labeling Each Food Product Under Different Assumptions about Consumer Perceptions of Carbon Footprints

	Scenario 1 0.48 kg/$	**Scenario 2 1% increase**	**Scenario 3 Zero Carbon Footprint**
Flour	1.01	-0.42	-0.34
Breakfast Cereals	0.00	-0.16	-0.10
Rice	6.91	-0.27	-0.73
Pasta	3.76	-0.17	-0.28
White Bread	0.01	-0.12	-0.07
Wheat Bread	0.15	-0.17	-0.11
Rolls	-0.67	-0.15	-0.11
Cake	-0.86	-0.09	-0.07
Other Cakes & Breads	0.35	-0.18	-0.11
Beef	-5.33	-0.29	-4.82
Pork	8.78	-0.25	-1.55
Other Meats	-87.47	-0.38	-8.46
Poultry	-1.22	-0.51	-2.61
Fish	7.11	-0.18	-1.62
Cheese	-2.93	-0.42	-4.10
Ice Cream	0.01	-0.43	-0.56
Milk	0.02	-0.48	-0.56
Other Dairy	-0.62	-0.99	-0.94
Apples	-0.07	0.31	0.39
Bananas	0.58	0.65	0.90
Citrus	-0.05	0.33	0.41
Other Fruits	-1.19	0.19	0.26
Potatoes	0.37	0.64	0.87
Lettuce	0.14	0.45	0.56
Tomatoes	-0.17	0.23	0.37
Other Vegetables	-0.26	0.28	0.37
Pro. Fruits & Veg.	0.13	0.33	0.45
Carbonated Drinks	-0.73	-0.28	-0.12
Frozen Drinks	-0.09	-0.08	-0.03

Table 4: Carbon Emission Impact from Labeling Each Food Product Under Different Assumptions about Consumer Perceptions of Carbon Footprints (continued)

	Scenario 1 0.48 kg/$	**Scenario 2 1% increase**	**Scenario 3 Zero Carbon Footprint**
Non-Frozen Drinks	-0.42	-1.16	-11.01
Coffee	-0.10	-0.91	-0.10
Soup	-5.53	1.11	4.14
Other Frozen Foods	-2.55	0.41	1.54
Snacks	-0.24	0.33	0.59
Seasonal Items	11.77	1.14	1.14
Miscellaneous Items	-0.57	0.35	1.01
Eggs	-0.97	-0.04	-0.10
Sugars	-16.66	1.05	2.72
Fats	-0.96	-0.13	-0.21
Full-Service FAFH	-37.27	32.19	18.67
Quick-Service FAFH	30.90	-44.65	-25.90
Other FAFH	8.92	58.40	33.87
Alcohol	-85.41	-42.09	-115.11
Non-Food Items	0	-23.34	-11.21

Notes: Decreases measured from baseline of no labels, in millions of tons of CO_2eq.

Table 5: Carbon Emission Impact from Labeling Groups of Food Products Under Different Assumptions about Consumer Perceptions of Carbon Footprints

	Scenario 1 0.48 kg/$	**Scenario 2 1% increase**	**Scenario 3 Zero Carbon Footprint**
Breads	10.65	10.48	20.05
Meats	-78.13	-0.22	-19.07
Dairy	-3.53	0.04	-6.16
Fruits and Veg.	-0.51	8.30	4.57
Non-Alcoholic Drinks	-1.34	12.66	-11.26
Misc.	2.87	-2.25	8.42
Eggs	-0.97	-0.66	-0.10
Sugars	-16.66	0.10	2.72
Fats	-0.96	0.98	-0.21
FAFH	-82.86	3.86	-11.73
Label Everything	-171.45	33.29	-152.29

Notes: Decreases measured from baseline of no labels, in millions of tons of CO_2eq.