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Michael P. Vandenbergh
Vanderbilt University Law School

Sharon A. Shewmake
Western Washington University

Abigail Okrent
U.S. Dept. of Agriculture

Lanka Thabrew
Vanderbilt Institute for Energy and the Environment

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Analysis

Predicting consumer demand responses to carbon labels☆

Sharon Shewmake [a,*], Abigail Okrent [b], Lanka Thabrew [c], Michael Vandenbergh [d]

[a] Department of Economics and Institute for Energy Studies, Western Washington University, United States
[b] Economic Research Service, United States Department of Agriculture, United States
[c] Vanderbilt Institute for Energy and the Environment, Vanderbilt University, United States
[d] Vanderbilt University Law School, United States

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ABSTRACT

Providing carbon footprint labels for all food products is a daunting and potentially infeasible project. Knowing how consumers substitute away from high carbon goods and what they choose as substitutes is essential for understanding which goods are likely to result in meaningful reductions in carbon emissions. This paper proposes a model to systematically estimate how consumers will respond to information from a carbon footprint label. Our model uses consumers' value of their individual carbon footprint with own- and cross-price elasticities of demand data on carbon emissions from life cycle analysis to simulate shifts in consumer demand for 42 food products and a non-food composite, and subsequent changes in carbon emissions from different labeling schemes. Our simulation results have several findings, including: (1) carbon labels can reduce emissions, but labeling only some items could lead to perverse impacts where consumers substitute away from labeled goods to unlabeled goods with a higher carbon footprint; (2) carbon labels can inform consumers such that their previous beliefs about carbon footprints matter; and (3) carbon labels on alcohol and meat would achieve the largest decreases in carbon emissions among the 42 food products studied.

Consumers are increasingly making civic and environmental statements through the products they purchase, especially food (Onozaka et al., 2010; Grebitus et al., 2013). Carbon footprint labels provide information about the global warming impacts of products, and thus may help concerned firms and consumers voluntarily reduce their carbon footprint. Research suggests consumers are more likely to take voluntary pro-environment actions when consumers are well informed about the environmental impact of their actions (Polonsky et al., 2012) and when environmentally friendly actions are easy (Green-Demers et al., 1997). If high carbon goods have low carbon alternatives that are substitutes with the same or lower prices, consumers are more likely to respond to these labels (Vlaeminck et al., 2014; Lanz et al., 2014). In this paper we develop the Environmental Impacts of Changes in Consumer Demand (EI-CCD) model to predict the environmental impact of labeling products by quantifying own- and cross-product substitution possibilities.

The EI-CCD model uses own- and cross-price elasticities of demand, current prices and quantities of consumer products, and the carbon footprint of consumer products as inputs to predict shifts in consumer demand. The EI-CCD model helps policy makers and others interested in maximizing the impact of labels to identify which products would provide the largest decreases in carbon emissions. The EI-CCD model is also a tool that can be used by other researchers to quickly quantify cross-product effects using already available data. We provide an example of how the EI-CCD model can be applied to food, but the model can be used for a much wider array of consumer products. Given the expansion of environmental labeling and information schemes (Gruère, 2015) we believe a model that predicts the environmental effectiveness of labeling schemes, using pre-existing data, will be a useful tool to both policy makers and researchers.

A large literature on life cycle analysis (LCA) has developed techniques to estimate carbon footprints. Economics is a central component of one of the main tools for calculating carbon footprints (Hendrickson et al., 2006), but economics is rarely used to predict whether firms and individuals are willing and able to act on the information that a

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* Corresponding author at: Department of Economics MS 9074, Western Washington University, 516 High Street, Bellingham, WA 98225, United States.
E-mail address: sharon.shewmake@wwu.edu (S. Shewmake).

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carbon footprint provides. For example, Weber and Matthews (2008) compare the carbon reductions from buying only locally sourced food[1] to a dietary shift from red meat and dairy to chicken, fish, eggs, or vegetables. The authors calculate the carbon impact of various food products but do not apply demand theory. Instead the authors make ad hoc assumptions such as a 24% reduction in expenditures on red meat would result in a 24% increase in expenditures on chicken. Many other academic papers do not fully develop the consumer substitution portion of their analysis (e.g., Carlsson-Kanyama et al., 2003; Garnett, 2008; Bin and Dowlatabadi, 2005; Jones and Kammen, 2011; Mungkung et al., 2012; Vieux et al., 2012), and most of the work on consumer substitution patterns from labels considers only individual products or small groups of products (Lanz et al., 2014; Matsdotter et al., 2014; Vlaeminck et al., 2014; Michaud et al., 2013; Onozaka et al., 2012; Vanclay et al., 2011). This gap has been noted in Edwards-Jones et al. (2009) and is further demonstrated in Table 1, which presents examples of the ad hoc methods that previous work has applied to consumer substitution patterns in food choices. Table 1 suggests how the EI-CCD model could have improved previous studies. Table 1 is not an exhaustive list of the food and climate change literature but an illustration of the types of research that could benefit from the EI-CCD model.

The EI-CCD model can be used to inform policy debates as well as research. Experts outside of academia frequently make statements about how changes in diet can produce changes in greenhouse gas emissions. Behind these statements are ad hoc assumptions about what foods consumers consider to be substitutes (and complements). David Friedberg, the CEO of the Climate Corporation, recently asserted "we are sending millions of tons of protein to China to feed hogs. We should really just skip the hogs and grow the quinoa" (Specter, 2013, pg. 43). However, researchers, policy makers, nutritionists and home cooks may argue that quinoa and pork are not substitutes. To address concerns about using such ad hoc assumptions in measuring the effects of carbon labels on consumer demand and carbon emissions, the EI-CCD model incorporates cross-price elasticities from the demand analysis literature that objectively capture substitute and complementary relationships between products.

The sign and the magnitude of the cross-price elasticity indicate whether two products are substitutes (positive cross-price elasticity), complements (negative cross-price elasticity) or unrelated (a cross-price elasticity of zero). Furthermore, demand theory allows a modeler to predict the size and overall direction of a change in the market of one good on markets for related goods. The EI-CCD model connects this economic information to LCA data on carbon emissions to capture the environmental effects of labels. Hence, the EI-CCD model can be used to calculate the environmental impacts of consumer responses that result from carbon footprint information and find which food products are most likely to produce reductions in carbon emissions. This will help researchers looking to account for the broader impacts of a label as well as policymakers and non-governmental organizations who are focused on reducing carbon emissions through the food supply (e.g., Environmental Working Group, 2011).

Generally, consumers like the idea of carbon labels (Hartikainen et al., 2014) and research has shown that consumers are responsive to carbon labels on coffee, apples, tomatoes, roses, and pet food (Nielsen, 2015, Onozaka et al., 2012; Michaud et al., 2013; Vanclay et al., 2011). However, labels can be most effective when consumers understand their message (Sharp and Wheeler, 2013; Polonsky et al., 2012), and evidence from focus groups suggests that this is not automatically the case (Hornibrook et al., 2013; Gadema and Oglethorpe, 2011; Upham et al., 2011). For example, Spaargaren et al. (2013) found that when labels were simply presented with no additional information element to explain what they mean, there was no significant change in CO_2 emissions. However, when accompanied with additional information, there was a significant 3% decrease in CO_2 emissions. In addition, consumers must also trust and understand how to use labels (Lyon and Montgomery, 2015; Thøgersen, 2000). Finally, a label must provide an opportunity for consumers to switch from goods with a high carbon footprint to those with a low carbon footprint. Whether consumers have green substitutes for brown products will determine whether this final criterion is met.

When Vanclay et al. (2011) labeled food products in a local supermarket, the researchers chose the products to label using the best advice available at the time, which was to pick "big items" that "exhibited high turnover and sufficient customer choice." One of those products was fresh milk. All the milk in this supermarket came from the same processing facility, so differences in the carbon footprints were a function of packaging, especially container size. Larger containers were given a green carbon footprint and smaller containers were given a black carbon footprint based on the per ounce carbon emissions.[2] While consumers were willing to switch between all other types of products that were labeled, consumers did not switch to larger containers of milk despite the environmental message. This finding is not unexpected in that Stockton and Capps (2005) found that the cross-price elasticity of milk container sizes is zero, implying that different package sizes of milk are not substitutes in consumption. Furthermore, Stockton and Capps (2005) estimated cross-price elasticities for other beverages with regard to container size, and found that these products were more substitutable across beverages (e.g., bottled water versus juice) and within container sizes. Hence, based on this economic evidence, it is unlikely that a proposal to label milk according to carbon emissions based on differences in containers would achieve any carbon reductions.

Many public and private initiatives have emerged to provide carbon footprint labels (Gruère, 2015). For example, Tesco supermarkets in the United Kingdom promised a "revolution in green consumption" in 2007 by pledging to carbon label all 70,000 of its products. This pledge was dropped in 2012 as it became apparent that the task was too difficult, with each product requiring "a minimum of several months' work" (Quinn, 2012; Vaughan, 2012). A more feasible plan may be to label a subset of products, using demand parameters and rough carbon footprint estimates to determine which groups of products will yield the highest carbon emission reductions (Shewmake et al., 2015). The EI-CCD model can identify which products would be the best to carbon label and which products may lead to perverse responses from substitution patterns that replace high carbon products (such as beef) with even higher carbon substitutes (lamb).

To our knowledge, this study is the first to apply a rigorous economic model to address the question of how consumers will respond to labels that tell consumers the carbon content footprint (measured in CO_2eq) of multiple goods. Previous studies have examined how consumers will respond to carbon footprint labels on individual items such as apples, roses, beef and subsets of goods[3] through surveys (Onozaka and Thilmany McFadden, 2011; Onozaka et al., 2012; Grebitus et al., 2013) or experiments (Michaud et al., 2013; Vanclay et al., 2011) (see Table 1) and the rebound effect from switching to vegetarian diets (Grabs, 2015), but these studies do not account for changes in the demand for complements and substitutes for the labeled product.

The EI-CCD model provides several intuitive findings that are nonetheless often neglected in the literature. The simulations based on the EI-CCD model suggest that goods with low-carbon substitutes, consumers with inaccurate beliefs about the carbon footprint of the good, and high-carbon goods that have large market shares are most likely to result in relatively large reductions in carbon emissions from carbon

[1] A reduction of approximately 0.36 tons of CO_2eq/household per year.

[2] Per ounce, a small container of milk has a higher environmental impact due to the packaging. Consumer psychologists have suggested that evaluative metrics are more effective in communicating environmental messages to consumers. Vanclay et al. hence used a black/yellow/green label where green was the lowest carbon option and black was the highest carbon option.

[3] Vanclay et al. (2011) examine the markets for milk, spreadable butter, canned tomatoes, bottled water, and non-perishable pet foods.

Table 1
Literature review of the impact of food choices on carbon footprint.

Study	Products examined or labeled	Method	Effects on CO_2 emissions	Behavioral substitution/complement effects
Studies comparing the carbon footprint of diet choices				
Carlsson-Kanyama et al. (2003)	150 food items.	Suggest more efficient meals based on carbon footprint information.	Not measured.	None.
Garnett (2008)	The greater food system.	Survey article on potential for abatement in the food system.	Not measured.	None.
Weber and Matthews (2008)	Aggregate footprints for food products from the EIO-LCA model.	Examine the impact of "buy-local" versus a dietary shift.	Buying all locally sourced food results in a smaller GHG reduction than shifting less than one day per week's worth of calories from red meat and dairy to chicken, fish, eggs, or a vegetable based diet.	Compare food based on expenditure and calories but do not use demand parameters.
Carlsson-Kanyama and González (2009)	22 foot items sold in Sweden.	Compared different meals with similar nutritional compositions.	"Changes toward a more plant-based diet could help substantially in mitigating emissions of GHGs." (pg. 1707S)	None. Meals were constructed to have similar nutritional characteristics but no attempt was made to understand whether consumers would consider these meals to be substitutes.
Jones and Kammen (2011)	Household actions including ones in transport, housing, food, goods, and services.	Examine the potential for 13 different mitigation actions.		None. However the EI-CCD model could have been applied to examine whether households are more willing to shift consumption between economic activities.
Vieux et al. (2012)	Population based diets in France.	Tested the impact of assumptions about reducing caloric intake and meat consumption.	Decreases in between 12% to an increase 2.7% depending on how calories are replaced.	None.
Studies examining the impacts of carbon footprint (or related) labels				
Bjørner et al. (2004)	Toilet paper, paper towels, and detergents	Panel data on consumer choices.	Not calculated.	None.
Grebitus et al. (2013)	Ground beef.	Survey with a choice attribute model.	Not calculated.	None.
Kortelainen et al. (2012)	Detergent.	Differences-in-differences estimate of the willingness-to-pay for carbon reduction using scanner data.	Not calculated.	None.
Michaud et al. (2013)	Roses.	Willingness-to-pay experiment.	Not calculated.	None.
Matsdotter et al. (2014)	Climate certified milk.	Randomized field experiment in 17 Swedish retail stores.	Not calculated, however a label increased demand for climate certified milk by 7%.	Substitution was within the milk category. Found climate certified milk was a substitute for organic milk.
Echeverría et al. (2014)	Fluid milk and bread.	Contingent valuation (survey) of Chilean consumers.	Not calculated.	None.
Studies examining the impact of a carbon footprint label on carbon emissions				
Vanclay et al. (2011)	37 products including milk, spreadable butter, canned tomatoes, bottled water, and non-perishable pet foods.	Experiment in Australian grocery store.	Not calculated.	None.
Onozaka et al. (2012)	Local, domestic and imported apples on and off-season.	Survey with an equilibrium displacement model.	A local designation label would increase net carbon emissions during the off-season but the effect is mitigated if it comes with a carbon label.	The equilibrium displacement model accounts for the shifts in demand and supply as a result of the label in the apple market but not in substitution and complement markets.
Spaargaren et al. (2013)	Prepared foods in a canteen at Wageningen University.	Experiment in two phases, light label and labels a comprehensive label.	Comprehensive label decreases CO_2 emissions per lunch by 3%.	Substitutions within canteen products were fully accounted for by labeling all products at the canter. The EI-CCD model could have been used to examine substitution between canteen food and FAH.
Vlaeminck et al. (2014)	Effect of various environmental impact labels on tomatoes, apples and proteins.	Experiment in a Belgian supermarket.	Increases in the shares of products with better eco-friendliness scores.	Authors studied which label was most effective in convincing shoppers to switch within groups only. The EI-CCD model could have been used to study the impacts of complements and substitutes to tomatoes, apples, and proteins.
Lanz et al. (2014)	Cola, milk, meat and spread (butter vs. margarine).	Experiment to study the impact of labels, subsidies and bans on consumer choices in a UK grocery store.	Not measured.	The authors found the substitutability of the good mattered as to how effective a label or subsidy would be to encourage the purchase of the low carbon option.

labels. We also find that how consumers calculate their carbon footprint in the absence of labels affects the relative success of a label.

This study is organized as follows. In the next section we construct an economic model (i.e., EI-CCD model) that predicts changes in carbon emissions as a result of carbon footprint labels. Next we describe parameters used in that model including elasticities of demand, carbon footprints and willingness to pay. We simulate two scenarios that account for differences in how consumers may calculate their carbon footprints. Finally we discuss the implications of the simulations for policy and future research.

1. The EI-CCD Model

We model the representative consumer's willingness to pay to reduce her personal carbon footprint as a disutility for personal carbon emissions. Without labels, the consumer may not know what their 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 a production function for perceived carbon footprint:

$$\max_{\{x_1,\ldots,x_n\}} \mathrm{U}\left(x_1,\ldots,x_n,\tilde{E}\right) s.t.\ M \ge x_1P_1 + \ldots + x_nP_n, \tilde{E} = x_1\tilde{E}_1 + \ldots + x_n\tilde{E}_n, \quad (1)$$

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, $E = x_1E_1 + x_2E_2 \ldots + x_nE_n$ but the consumer bases his or her utility on the perceived emission production function, $\tilde{E} = x_1\tilde{E}_1 + \ldots + x_n\tilde{E}_n$. This perceived emission production function relates how the consumer's beliefs about each item's carbon footprint, $\tilde{E}_i$, aggregates into the consumer's total perceived carbon footprint, $\tilde{E}$.

The first-order conditions for the utility maximization program are:

$$\begin{aligned} \frac{\partial \mathrm{U}}{\partial x_1} &= \lambda P_1 + \xi\tilde{E}_1, \\ &\vdots \\ \frac{\partial \mathrm{U}}{\partial x_n} &= \lambda P_n + \xi\tilde{E}_n, \\ \frac{\partial \mathrm{U}}{\partial \tilde{E}} &= \xi, \end{aligned} \quad (2)$$

where $\frac{\partial \mathrm{U}}{\partial x_i} > 0, \frac{\partial^2 \mathrm{U}}{\partial x_i^2} < 0 \forall i$, and $\frac{\partial \mathrm{U}}{\partial \tilde{E}} < 0$, 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 $\psi = \frac{\xi}{\lambda}$. This parameter has been estimated from stated preference and experimental studies (Diederich and Goeschl, 2014; Loschel et al., 2013; MacKerron et al., 2009; Brouwer et al., 2008). Using ψ, we can rewrite the first-order conditions in Eq. (2) with the ith condition being:

$$\frac{\partial \mathrm{U}}{\partial x_i} = \lambda\left(P_i + \psi\tilde{E}_i\right). \quad (3)$$

The conditions in Eq. (3) can be solved for demand functions that have as their argument $(P_1 + \psi\tilde{E}_1, P_2 + \psi\tilde{E}_2, \ldots P_n + \psi\tilde{E}_{n1})$. Thus instead of $\mathrm{D}_i(P_1, P_2, \ldots P_n, M)$, we can rewrite the demand for good i as:

$$\mathrm{D}_i\left(P_1 + \psi\tilde{E}_1, P_2 + \psi\tilde{E}_2, \ldots P_n + \psi\tilde{E}_n\right) = \hat{\mathrm{D}}_i\left(P_1, P_2, \ldots P_n, \tilde{E}_1, \tilde{E}_2, \ldots \tilde{E}_n\right) \quad (4)$$

where $\hat{\mathrm{D}}_i(\cdot)$ is the augmented demand for product i as a function of prices and perceived footprint.

1.1. Consumer Responses to Changes in Emissions

We are interested in how the demand for a product will change with a change in belief about the carbon footprint of a product due to the introduction of a label. The derivative of the ith demand function in Eq. (4) with respect to a change in the belief about emissions from good i is:

$$\frac{\partial \hat{\mathrm{D}}_i}{\partial \tilde{E}_i} = \left(\frac{\partial \mathrm{D}_i}{\partial P_i}\right)\psi, \quad (5)$$

where $\frac{\partial \mathrm{D}_i}{\partial P_i}$ is 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:

$$\eta_{Q_{i,},P_j} = \left(\frac{\partial D_i}{\partial P_j}\right)\left(\frac{P_j}{Q_i}\right), \quad (6)$$

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

$$\eta_{Q_{i,},P_j}\left(\frac{Q_i}{P_j}\right) = \frac{\partial \mathrm{D}_i}{\partial P_j}. \quad (7)$$

Hence, substituting Eqs. (6) and (7) into Eq. (5), the elasticity of demand for product i with respect to a change in beliefs about emissions in product j is:

$$\eta_{Q_{i,},\tilde{E}_j} = \left(\eta_{Q_{i,},P_j}\right)\left(\frac{Q_i}{P_j}\right)\psi\left(\frac{\tilde{E}_j}{Q_i}\right). \quad (8)$$

The elasticities of demand for products, $\eta_{Q_{i,},P_j}$, are parameters readily available in the demand analysis literature.[4] Thus, we use own- and cross-price elasticities of demand that have been previously estimated to predict the products that consumers may be willing to substitute away from and between.

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

$$E = E_1\hat{\mathrm{D}}_1\left(P_1, P_2, \ldots P_n, \tilde{E}_1, \tilde{E}_2, \ldots \tilde{E}_n\right) + E_2\hat{\mathrm{D}}_2(\cdot) + \cdots E_n\hat{\mathrm{D}}_n(\cdot). \quad (9)$$

A change in the consumer's belief about the carbon footprint of good i, $\tilde{E}_i$, results in a change of the total emissions for the representative consumer that is equivalent to:

$$\frac{\partial E}{\partial \tilde{E}_i} = E_i\left(\frac{\partial \hat{\mathrm{D}}_i}{\partial \tilde{E}_i}\right) + \sum\nolimits_{j \ne i} E_j\left(\frac{\partial \hat{\mathrm{D}}_j}{\partial \tilde{E}_i}\right). \quad (10)$$

The first term on the right-hand side is the direct effect of the label, or how a consumer alters her purchasing decisions as a result of knowing more about a good's carbon footprint. The second term is the indirect effect of the label, or the impact of a change in the consumer's belief about emissions on consumer choices for substitutes and complements. If we rearrange the order of goods in Eq. (10) 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:

$$\frac{\partial E}{\partial \tilde{E}_i} = E_i\left(\frac{\partial \hat{\mathrm{D}}_i}{\partial \tilde{E}_i}\right) + \sum\nolimits_{j=1}^{k} E_j\left(\frac{\partial \hat{\mathrm{D}}_j}{\partial \tilde{E}_i}\right) + \sum\nolimits_{j=k+1}^{n} E_j\left(\frac{\partial \hat{\mathrm{D}}_j}{\partial \tilde{E}_i}\right). \quad (11)$$

[4] Okrent and Alston (2011) and Andreyeva et al. (2010) provide comprehensive reviews of the demand analysis literature and summarize estimates of elasticities of demand for food.

Eq. (11) can be rewritten as:

$$\frac{\partial E}{\partial \tilde{E}_i} = E_i \psi \frac{\partial D_i}{\partial P_i} + \sum\nolimits_{j=1}^{k} E_j \psi \frac{\partial D_j}{\partial P_i} + \sum\nolimits_{j=k+1}^{n} E_j \psi \frac{\partial D_j}{\partial P_i}. \quad (12)$$

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 more carbon intensive than 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. Writing Eq. (12) as a total derivative, the effect of labeling good *i* is:

$$\Delta E = E_i \psi \frac{\partial D_i}{\partial P_i} \Delta \tilde{E}_i + \sum\nolimits_{j=1}^{k} E_j \psi \frac{\partial D_j}{\partial P_i} \Delta \tilde{E}_i + \sum\nolimits_{j=k+1}^{n} E_j \psi \frac{\partial D_j}{\partial P_i} \Delta \tilde{E}_i. \quad (13)$$

A good candidate for a carbon footprint label would be one for which

$$\left| E_i \frac{\partial D_i}{\partial P_i} + \sum\nolimits_{j=k+1}^{n} E_j \frac{\partial D_j}{\partial P_i} \right| \gg \left| \sum\nolimits_{j=1}^{k} E_j \frac{\partial D_j}{\partial P_i} \right|, \quad (14)$$

and

$$\left| \Delta \tilde{E}_i \right| \gg 0. \quad (15)$$

In other words, we want to label goods for which the direct effect and complementary indirect effects are greater in magnitude than the substitution indirect effect and a product where the consumer was relatively unaware of the product's carbon footprint. Note that Eq. (14) does not include ψ, the willingness to pay for reductions in the personal carbon footprint. While ψ influences the overall magnitude of the emission change (ΔE), ψ is not relevant to whether certain products are better candidates for others because ψ is the same for all goods. We have assumed that consumers value their overall carbon footprint and not which product substitutions create the change in carbon footprint. Because ψ enters Eq. (13) linearly, it has an impact on the overall magnitude of an effect but does not influence the direction of the effect. For example, if $\psi = \$0.03$ we find that labeling all products reduces emissions by approximately 5000 thousand tons of CO_2eq. If ψ is reduced by half (i.e., $\psi = \$0.015$), then carbon emissions would be reduced by half (to 2500 thousand tons of CO_2eq).

The effects of a carbon footprint 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.

2. Parameters for the Simulations Based on the Model

We include 42 food products and a non-food composite in our analysis.[5] We use publicly available price and quantity data and elasticities of demand from the demand analysis literature. We construct measures of carbon emissions for each product using data primarily from the Economic Input–Output Life Cycle Analysis (EIO-LCA) model for the U.S. but supplement this data with LCA databases such as CleanMetrics and ecoInvent v.2 database, and studies from the literature. These databases are the most comprehensive and most validated, and they are widely used by the LCA community.

[5] The inclusion of a non-food composite captures rebound effects similar to those in Grabs (2015), Druckman et al. (2011) and Herring and Sorrell (2009).

2.1. Price Elasticities of Demand, Prices, and Quantities

Recent comprehensive reviews of the food demand analysis literature summarize current estimates of elasticities of demand for foods in the United States from hundreds of studies (Andreyeva et al., 2010; Okrent and Alston, 2011). These reviews note that much of the coverage has been for aggregated food products, which may have limited use in policy analysis. In addition, more recent estimates of price elasticities of demand provide coverage of more disaggregated food products but do not explicitly model all foods. For example, Zhen et al. (2013) and Harding and Lovenheim (2014) model demand for 23 and 33 packaged food products, respectively, but do not include non-packaged food products and food purchased at restaurants. And since it has been shown that there is substitution between packaged foods purchased at grocery stores and foods purchased at restaurants (e.g., Park and Capps, 1997; Okrent and Alston, 2012; Richards and Mancino, 2013), then it is important to include all foods in the analysis of carbon labels.

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 footprint labeling on food consumption. They include 42 food products and a non-food composite at a level of disaggregation that allows us to simulate somewhat precisely the effects on demand and carbon emissions of a label that changes consumers' beliefs on carbon footprints. They also include all foods in their analysis, including non-packaged foods, restaurant foods and alcoholic beverages. An additional advantage to using the elasticities of demand from Okrent and Alston (2012) is that their estimates are consistent with demand theory (adding up, homogeneity, downward sloping demand) and many of their estimates are statistically significant. Lastly, the own-price and cross-price elasticities of demand are comparable in magnitude to others in the literature (e.g., Bergtold et al., 2004; Huang, 1993).

To estimate a demand system with such a large number of foods, Okrent and Alston (2012) used a two-stage budgeting framework.[6] As shown in Fig. 1, for the first stage, they estimated demand for eight broad categories—cereals & bakery products; dairy, meat and eggs; fruits & vegetables; nonalcoholic beverages; other foods purchased at grocery stores; restaurant foods and alcoholic beverages; and non-food. For the second stage, Okrent and Alston (2012) modeled demand for each of the seven broad food categories as weakly separable groups. For example, as shown in Fig. 1, Okrent and Alston (2012) estimate demand for disaggregated cereal and bakery products—flour and prepared flour mixes; breakfast cereals; rice and pasta; non-white bread; white bread; biscuits, rolls and muffins; cakes and cookies; and other bakery products—conditional on total expenditure on the broad food category of cereals and bakery products. Using estimates of elasticities of demand from the first and second stages, and following formulas derived by Carpentier and Guyomard (2001), they approximated 43 elasticities of demand for the 42 food items and the non-food composite.

Okrent and Alston (2012) estimated the first and second stages as shown in Fig. 1 using the Generalized Ordinary Differential Demand System (Eales et al., 1997) with monthly expenditure and price data between 1998 and 2010 from the Bureau of Labor Statistics. Okrent and Alston (2012) were constrained to the 42 foods included in this analysis because this was the finest level of disaggregation available in price and expenditure data (i.e., Consumer Expenditure Survey Public

[6] Because of data limitations, we limit our analysis to broad categories of foods such as 'citrus' or 'fish' and ignore seasonality. Also, with better information, we could expand our analysis to a third stage where we look at types of fish and types of beef. Broadly labeling products as 'fish' or 'apples' 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). For more information on seasonality and local versus imported issues for apples see Onozaka et al. (2012).

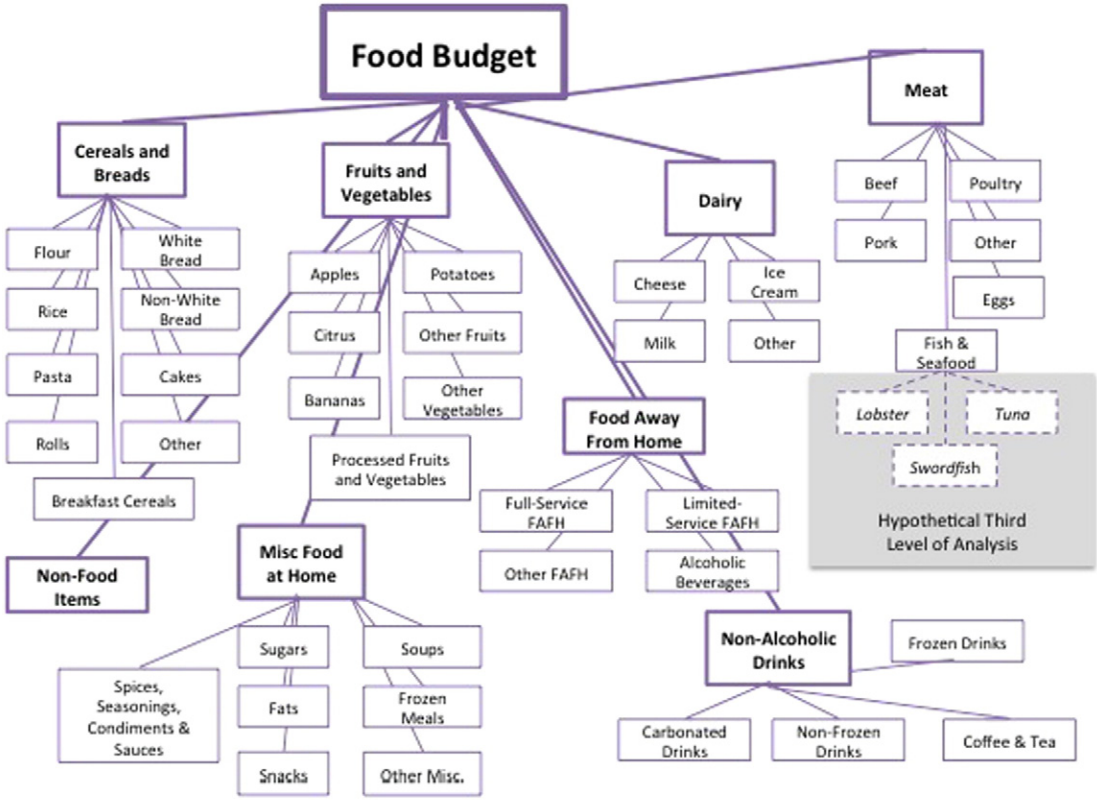

Fig. 1. Separable preference structure for representative consumer in a two-stage budgeting process.

Microdata; U.S. Department of Labor, Bureau of Labor Statistics, 2010b) and Consumer Price Index Database (U.S. Department of Labor, Bureau of Labor Statistics, 2010c).

The price and quantity data for the products are based on several sources. Most of the price data are from the Average Price Database (APD) published by the U.S. Department of Labor, Bureau of Labor Statistics (2010a) with supplemental information from the Quarterly Food-at-Home Price Database and the 2007–08 National Health and Nutrition Examination Survey (USDA ERS, 2011; CDC and NCHS, 2011, see Supplementary material A for more details on construction of the price and quantity data).

2.2. Willingness to Pay for Carbon Reductions

This paper assumes that consumers are willing to pay to reduce their personal carbon footprints. There is ample evidence for this assumption. Survey evidence suggests that most consumers are willing to pay more for a good with a lower carbon footprint (Shuai et al., 2014; Onozaka and Thilmany McFadden, 2011); surveys and experiments find that consumers are willing to pay for various carbon mitigation programs (Akter and Bennett, 2011; Lee et al., 2010; Carlsson et al., 2010; Cai et al., 2010; Johnson and Nemet, 2010; Solomon and Johnson, 2009; Viscusi and Zeckhauser, 2006; Roe et al., 2001); and when asked whether they are willing to pay for personally retiring 1-kg of carbon dioxide, consumers are willing to pay between \$8 and \$32 (Diederich and Goeschl, 2014; Loschel et al., 2013; MacKerron et al., 2009; Brouwer et al., 2008).

2.3. Carbon Footprint Data

Calculating the carbon footprint of seemingly basic foods such as apples and potatoes is a non-trivial task. Different assumptions about production, transportation, and the carbon footprint of fuels used may result in wildly different estimates. Consumer post-purchase choices—the way a potato is cooked, 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.

The carbon footprint of any good (i.e., E_i in our model) is measured in kilograms of equivalent carbon dioxide (CO_2eq), which includes the impact of other greenhouse gasses such as methane and nitrous oxide. The carbon footprint is composed of emissions from various life-cycle stages. These stages include production using raw materials, transportation, wholesaling and retailing, and use and final disposal by the consumer.[7] Indirect land use effects, such as clearing of additional rainforest for potato production or general changes in land use for the expansion of the potato crop, are viewed by the life cycle analysis literature to be too uncertain and unreliable. We do not include indirect land use effects in our estimates of carbon footprints, a common practice in the literature. We also limit our analysis to the retail level, thus excluding the use and disposal phases. This is for two reasons. The first is because consumers will confront labels at the retail stage, not once they have prepared and disposed of a meal. The second is that data on the disposal and use phases of food is limited and inconsistent.[8]

Considerable uncertainty exists in any carbon footprint estimation. Simply altering assumptions about the amount of a good imported (i.e., import fractions) and distance that the good is transported can

[7] Hendrickson et al. (2006) provide an excellent discussion of the intricacies of calculating carbon footprints.

[8] To demonstrate the difficulties in estimating the emissions from use and disposal of food consumption, we examine the potato as an example. We roughly know how potatoes are cooked using the 2007–08 National Health and Nutrition Examination Survey, which collects food intake data on more than 8000 different foods for nationally representative sample. Forty percent of the quantities of potatoes consumed were 'boiled', 'stewed', or in 'salads' which we assumed were cooked on the stove top, while 47% were 'roasted', 'baked', or 'scalloped,' which we assumed were cooked in the oven. Finally, 12% of potatoes were consumed as 'chips' and the cooking method is unclear. Understanding the use and disposal phases would need assumptions about the efficiency of appliances used, the fuel used (gas versus electric) and, in the case of electric, the carbon intensity of the electricity grid. This is beyond the scope of our analysis.

Table 2
Carbon footprints of food products.
Source: authors' calculations, Clean Metrics (2011), Swiss Centre for Life Cycle Inventories (2002), Carnegie Mellon University (2008), Colman and Paster (2009), Frischknecht et al. (2005) and CE Delft et al. (2006).

Food product	Mean carbon footprint	Median carbon footprint	Minimum carbon footprint	Maximum carbon footprint	Number of carbon footprint observations
Flour	1.41	1.39	0.72	2.22	7
Breakfast cereals	1.95	2.14	0.62	2.72	6
Rice	4.46	4.90	2.68	5.23	5
Pasta	2.06	2.06	1.40	2.72	5
White bread	1.23	1.53	0.60	1.53	6
Non-white bread	1.65	2.17	0.56	2.17	6
Rolls & muffins	1.30	1.60	0.68	1.60	6
Cake & cookies	2.76	3.24	0.85	3.24	5
Other bakery products	1.76	2.04	0.63	2.04	5
Beef	16.72	16.33	2.51	23.46	16
Pork	5.31	6.59	2.17	6.68	11
Other red meat	9.17	5.84	5.76	22.56	5
Poultry	3.67	3.85	2.35	5.14	7
Fish and seafood	8.94	8.86	0.08	15.06	22
Eggs	2.50	2.81	1.31	2.81	6
Cheese	12.30	14.15	6.54	14.73	6
Ice cream and frozen desserts	5.47	6.51	1.29	6.51	5
Milk	3.29	5.14	0.63	5.14	8
Other dairy	3.48	4.59	0.62	5.17	6
Apples	2.31	2.58	1.25	2.91	5
Bananas	1.44	1.46	0.96	1.79	5
Citrus	2.22	2.46	1.26	2.79	5
Other fresh fruits	3.35	3.85	1.34	4.18	5
Potatoes	1.22	1.40	0.16	1.78	6
Lettuce	1.95	2.12	1.24	2.45	5
Tomatoes	3.40	3.71	1.61	4.12	6
Other fresh vegetables	2.06	2.25	1.30	2.59	5
Processed fruits and vegetables	1.96	2.11	1.36	2.45	5
Carbonated juices and drinks	0.65	0.72	0.40	0.72	2
Frozen juices and drinks	0.69	0.77	0.36	0.77	2
Non-frozen, non-carbonated juices and drink	0.62	0.66	0.47	0.69	5
Coffee and tea	0.15	0.16	0.11	0.17	5
Soup	2.23	2.26	1.76	2.59	5
Other frozen foods	5.35	5.61	4.34	5.61	2
Spices, seasonings, condiments and sauces	1.91	1.58	1.58	3.27	2
Miscellaneous items	5.49	6.05	3.27	6.38	5
Sugars and sweeteners	1.43	0.79	0.71	4.60	6
Fats and oils	4.56	6.90	0.05	7.00	7
Full-service FAFH	3.29	3.97	0.58	3.97	2
Limited-service FAFH	2.44	2.91	0.58	2.91	2
Other FAFH	0.87	0.98	0.43	0.98	2
Alcohol	2.72	2.74	2.22	3.05	5
Non-food items	0.48	0.48	0.48	0.48	1

Note: Footprints are measured in kg of CO_2eq/kg of product with the exception of FAFH and non-food items which are measured in kg of CO_2eq/$ of product.

produce differing footprint results. This does not affect products such as meat very much as their production emissions are significantly greater than their transport emissions. However, fruits and vegetables have lower production emissions so assumptions about import fractions and transport distances have a greater effect (Weber and Matthews, 2008). Other sources of uncertainty in this method include geographic variation in production (energy and material use, technology, transport efficiencies in different countries), variation within one economic sector (e.g., white rice and brown rice will belong to the same category, grain farming, with emissions distinguished only by means of price differences), and time lag due to infrequent updates of economic databases (e.g., the most recent national input–output accounts are from 2002) (Hendrickson et al., 2006; Bauman and Tillman, 2004).

To model this uncertainty, we calculate carbon footprints using both a process based approach from various databases (ecoInvent v.2 database and ClimateMetrics data) and an economic input–output approach from the EIO-LCA model. We also use different assumptions about the carbon label by varying transportation emissions by plus or minus 25%. Table 2 shows the mean, median, minimum and maximum values from varying assumptions in estimation of the carbon footprints. We use the minimum and maximum values to characterize a uniform distribution around the carbon footprint for each food. We randomly draw 1000 carbon footprint values for each food based on these uniform distributions and re-estimate the model, holding all other parameters constant. To gauge the sensitivity of our point estimates to the EIO-LCA carbon footprint parameters, we report the posterior mean and the 10th and 90th percentiles from these 1000 draws.[9] One thousand draws is standard for drawing confidence intervals around simulated results (e.g., Piggott (2003), Hilmer et al. (2011)).

Finally, because our analysis encompasses 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, which would account for post-purchase decisions such as use and disposal, is described in the Discussion section. These

[9] Many of our results were significant at the 10th and 90th percentiles only. The 5th and 95th percentile intervals are presented in the supplementary materials.

phases are more likely to dominate products such as home appliances, electronics, and automobiles.

2.4. Current Carbon Beliefs

Labels give consumers better information about the carbon footprint of goods (Cohen and Vandenbergh, 2012). We model this information as a change in the belief about the carbon footprint. This change in belief is relative to a consumer's baseline beliefs about carbon footprints pre- and post-labeling. Sharp and Wheeler (2013) found that Australian consumers were unaware of the contribution of groceries to annual greenhouse gas emissions and that consumers struggled to identify activities that had relatively high and low carbon emissions. When asked to identify what percentage of their household emissions came from groceries, respondents gave answers between 0 to 100%. However consumers were able to rank products relative to one another in the correct order, with the exception of beer whose carbon footprint was underestimated. In addition, Sharp and Wheeler (2013) estimated the perceived carbon footprint of five food items: beef, cheese, bread, beer and potatoes. Most of the psychology literature provides only general guidance on how consumers respond to eco-labels (Thøgersen, 2000), but Sharp and Wheeler's methodology could be adopted for finding a better estimate of prior carbon footprints. At the moment, their five estimates of the perceptions of carbon footprints are not appropriate for our analysis since we apply the EI-CCD model to a greater number of goods and to the U.S. consumers. Further research is warranted in this area, perhaps by examining the willingness to pay for offsets, as some of our results are sensitive to how consumers initially calculate their carbon footprint.

In the first scenario, before consumers see the label, they assume that the carbon footprint per dollar spent on food is the same as the average carbon intensity of the U.S. economy, 0.48 kg/$ (International Energy Agency, 2011). Thus, for example, the consumer contemplating purchasing $1 worth of cheese (0.23 kg) would assume that this cheese results in 0.48 kg of CO_2eq. The label would inform the consumer that $1 worth of cheese actually had a carbon intensity of 2.83 kg.[10] We call this the "Expected Average Carbon Intensity" scenario. The second scenario that we evaluate is the case where before consumers see the label, they initially assume a zero carbon cost of consumption. We call this the "Expected Zero Carbon Footprint" scenario. The results of the expected zero carbon footprint scenario are mathematically identical to what would happen if the government were to implement a comprehensive carbon tax except where ψ is replaced by the actual carbon tax. These two scenarios represent the extremes of what consumers may believe about carbon footprints. If label i reduces overall emissions under both scenarios, then that label is likely a good candidate for a successful carbon labeling program. However, if label i reduces emissions under one scenario but not the other further research is warranted to better understand consumers' current beliefs about the carbon footprint of good i.

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

$$\psi^{-1} dE = \sum_{i=1}^{N} \left[\sum_{j=1}^{J} E_j \frac{\partial D_j}{\partial P_i} \right] d\tilde{E}_i. \tag{16}$$

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 $d\tilde{E}_i = 0$ for all other goods and estimate the impact of only changing the beliefs about 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 depends on the value of ψ, thus our results should be interpreted first as a way to rank categories of products and as absolute reductions for a particular value of ψ. For simplicity we assume that consumers are willing to pay three cents to reduce their carbon footprint by 1 kg, or $\psi = 0.03$. This is equivalent to a willingness to pay of $30 per ton. The expected average carbon intensity scenario is presented in column 1 of Table 3 and the impact of labeling groups of goods under this scenario is presented in column 1 of Table 4. The expected zero carbon footprint scenario is presented in column 2 of Table 3 and the impact of labeling groups of goods is presented in column 2 of Table 4.

3. Discussion

Tables 3 and 4 present changes in carbon emissions from simulating the impact of labeling each item (Table 3) or groups of items (Table 4) under two assumptions about the current carbon footprint beliefs held by consumers. The measurements assume a willingness to pay of $0.03 for a kilogram of personal CO_2eq reductions. The expected zero carbon footprint scenario works similarly to a carbon tax. If the carbon tax were smaller than $30 per ton, it would result in changes in emissions that are lower but linearly related to those in this scenario. In both scenarios, a lower willingness to pay for carbon footprint reductions would result in emission reductions that are smaller but linearly related to the results presented in Tables 3 and 4. The ordering of which products lead to the largest reductions would remain the same. Governments and private entities looking to reduce emissions through labels should be interested in the ordering of the best products to label as well as the magnitude of reductions.

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 both scenarios. The categories beef and other meats (which include many processed meats like sausage and hot dogs) 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 that pork has a similar carbon footprint, correcting this inaccurate belief so that consumers substitute away from beef and into pork could be an effective carbon mitigation scheme.

Labeling many products will result in an increase in carbon under one scenario but a decrease in the other scenario. White bread is an interesting example of this. When consumers believe that white bread has a carbon footprint of 0.48 kg/$, this translates into a prior carbon footprint belief of approximately 1.44 kg CO_2eq/kg, which is higher than the measured carbon footprint of 1.23 kg CO_2eq/kg. Thus the label tells consumers that white bread is not as carbon intensive as previously believed, and hence the consumer purchases more bread under this scenario (and less of its substitutes) but less bread (and more of its substitutes) under the other scenario. Labeling bread could lead to carbon emission increases, although this comes with the caveat that we have not estimated the use and disposal phases for these food products.

Under both scenarios, labeling of some foods, such as rice, increases emissions. In the expected average carbon intensity scenario,

[10] The carbon footprint for cheese is 12.30 kg of CO_2eq/kg, thus 0.23 kg of cheese would have a carbon footprint of $0.23 \times 12.30 = 2.83$ kg of CO_2eq. We acknowledge that this assumption may be problematic when we consider products that already make environmental claims. An example is organic and natural products, which are generally more expensive than their conventional substitutes. Consumers likely assume that organic and natural products have a lower environmental footprint. Thus our assumption that consumers believe all products have a carbon intensity of 0.48 kg/$ would be problematic since it suggests that consumers believe an organic apple has a higher carbon footprint than a cheaper non-organic apple. For an analysis on carbon labels for organic and natural versus their conventional substitutes, this would be an important flaw and we would require better information on the prior beliefs about carbon footprints. However in our aggregate analysis, the important substitution patterns are not between organic and conventional varieties but across products. Furthermore organic food sales represented only 3.7% of the 2009 U.S. food sales (OTA, 2010).

Table 3
Carbon emission impacts from labeling each food product under different assumptions about consumer beliefs of carbon footprints.
Source: authors' calculations.

	Expected average carbon intensity 0.48 kg/$	Expected zero carbon footprint
	Thousands of tons of CO_2eq	
Flour	170**	265**
	[56, 296]	[144, 405]
Breakfast cereals	−11	22
	[−39, 9]	[−44, 69]
Rice	524**	652**
	[324, 740]	[425, 888]
Pasta	153**	357**
	[60, 247]	[247, 478]
Non-white bread	12	−31*
	[−1, 33]	[−71, −1]
White bread	5	−21
	[−1, 12]	[−45, 0]
Rolls and muffins	−14	45**
	[−32, 0]	[27, 66]
Cake and cookies	−11	8
	[−40, 5]	[−30, 39]
Other bakery products	3	−60**
	[−22, 24]	[−116, −15]
Beef	−446	−469
	[−1680, 177]	[−2065, 412]
Pork	108	644**
	[−146, 352]	[392, 940]
Other red meat	−1988**	−2414**
	[−4498, −186]	[−5218, −304]
Poultry	−11	−2
	[−92, 42]	[−161, 133]
Fish and seafood	93	406**
	[−282, 435]	[86, 815]
Eggs	−19	−34
	[−54, 7]	[−90, 14]
Cheese	−125	−205
	[−296, 3]	[−464, 8]
Ice cream and frozen desserts	−2	3
	[−11, 5]	[−19, 24]
Milk	−19	−26
	[−64, 8]	[−114, 33]
Other dairy	3	52
	[−44, 45]	[−8, 113]
Apples	2	12
	[−4, 9]	[−10, 30]
Bananas	−3	−2
	[−32, 18]	[−52, 41]
Citrus	7	28
	[−7, 21]	[−16, 66]
Other fresh fruits	0	51
	[−26, 24]	[−7, 99]
Potatoes	−3	9
	[−17, 9]	[−14, 27]
Lettuce	−2	−1
	[−16, 9]	[−28, 24]
Tomatoes	10	33
	[−3, 26]	[−1, 66]
Other fresh vegetables	14	71**
	[−5, 36]	[10, 124]
Processed fruits and vegetables	12	48
	[−9, 32]	[−24, 112]
Carbonated juices and drinks	−5	29
	[−16, 2]	[−4, 62]
Frozen juices and drinks	−2**	2**
	[−3, −1]	[1, 3]
Non-frozen, non-carbonated juices and drinks	3	61
	[−8, 17]	[0, 125]
Coffee and tea	1	14**
	[−2, 3]	[4, 25]
Soup	−120	−335
	[−276, 9]	[−685, 27]
Other frozen foods	−141*	−421*
	[−290, −4]	[−817, −12]
Snacks	−11	−80**
	[−42, 8]	[−164, −14]

Table 3 (*continued*)

	Expected average carbon intensity 0.48 kg/$	Expected zero carbon footprint
	Thousands of tons of CO_2eq	
Spices, seasonings, condiments and sauces	259**	577*
	[45, 515]	[99, 1028]
Miscellaneous items	−4	57
	[−35, 23]	[−101, 192]
Sugars and sweeteners	−419	−450
	[−1528, 253]	[−1759, 412]
Fats and oils	15	96**
	[−76, 94]	[23, 182]
Full-service FAFH	−1183**	573**
	[−2102, −309]	[168, 995]
Limited-service FAFH	1122**	−948**
	[508, 1775]	[−1536, −430]
Other FAFH	−1	−126**
	[−26, 24]	[−206, −51]
Alcohol	−2030**	−3088**
	[−4433, −283]	[−6155, −711]
Non-food items	1	−463**
	[−93, 104]	[−822, −123]

Notes: Decreases measured from baseline of no labels. Estimates in brackets are the 10th and 90th percentiles of estimates. All calculations assume that consumers are willing to pay approximately $0.03 for a 1 kg of CO_2eq decrease in their personal carbon footprint.
** Indicates significance at the 5% level.
* Indicates significance at the 10% level.

consumers learn that rice has a higher carbon emission than previously thought, and while consumers will use less rice, they also increase consumption of substitutes to rice that are higher in carbon. This is the case with many items in the cereals and bakery category. One reason for this is because the cross-price elasticities between items in the cereals and bakery category and meat and FAFH and alcohol categories are generally positive. Labeling carbohydrates moves consumers from consuming these items and into consuming meats and FAFH and alcohol, items that have higher carbon footprints.

The impact of labeling all goods under both scenarios is similar, a reduction of 4.04 million tons of CO_2eq in the expected average carbon intensity and 4.55 million tons of CO_2eq in expected zero carbon footprint. To put these numbers in context, the U.S. economy emitted approximately 5.706 billion tons of CO_2 in 2010 (EPA, 2012).[11] If all food products were to be labeled as coarsely as our analysis, this could lead to a reduction of 0.08% of the US emissions (assuming $\psi = 0.03$). However, this number should only be taken as a rough approximation of the potential for CO_2eq reductions and perhaps even a lower bound because we ignore supply responses and other issues elaborated in the next section.

In addition to examining changes in emissions from labeling, we estimate changes in the quantities demanded of goods and their substitutes that result from labels.[12] Table 5 presents the assumed change in beliefs, $\Delta\tilde{E}_i$, under each scenario as well as the percentage change in quantity demanded for each meat product as a result of labeling products within the meat category. All meat products have an above average carbon footprint, which means $\Delta\tilde{E}_i$ is positive for each meat product in the expected average carbon intensity scenario. Not unexpectedly, the labels generally have the largest effect on the quantities demanded of the good that is labeled with the exception of a beef label on quantity demanded of pork in the expected average carbon intensity scenario. In this scenario, a label on beef causes a 2.33% increase in consumption of pork because beef and pork are substitutes and $\Delta\tilde{E}_i$ is relatively large (i.e., 12.89 kg of CO_2eq/kg of beef versus 1.76 kg of CO_2eq/kg of pork).

[11] Including sources and sinks and other GHG emissions, this number changes to 6.821 billion tons of CO_2eq.
[12] We could do this for all labels and quantities for both scenarios in all 43 by 43 label-quantity pairs but in the interest of brevity have limited our presentation to the meat category only.

Table 4
Carbon emission impact from labeling groups of food products under different assumptions about consumer beliefs of carbon footprints.
Source: authors' calculations.

	Expected average carbon intensity 0.48 kg/\$	Expected zero carbon footprint
	Thousands of tons of CO_2eq	
Breads and cereals	829**	1240**
	[471, 1212]	[800, 1700]
Meats and eggs	−2260*	−1870
	[−4638, −204]	[−4330, 304]
Dairy	−143*	−175
	[−314, −11]	[−406, 50]
Fruits and vegetables	37	249
	[−61, 138]	[−44, 541]
Non-alcoholic drinks	−4	106*
	[−19, 8]	[2, 213]
Miscellaneous FAH	−420	−557
	[−1626, 334]	[−2260, 710]
FAFH and alcohol	−2090*	−3590**
	[−4814, −10]	[−6860, −1040]
Label everything	−4050*	−5060**
	[−7260, −1050]	[−8410, −1920]

Notes: Decreases measured from baseline of no labels. Estimates in brackets are the 10th and 90th percentiles of estimates. All calculations assume that consumers are willing to pay approximately \$0.03 for a 1 kg of CO_2eq decrease in their personal carbon footprint.
** Indicates significance at the 5% level.
* Indicates significance at the 10% level.

Meanwhile, a carbon label on pork decreases consumption of pork by only 0.90% since $\Delta\tilde{E}_{pork}$ is relatively small.

Beef labels result in the largest change in emissions in both scenarios, because beef has a high carbon footprint (16.72 kg of CO_2eq/kg of product) and hence the impact of labeling beef corrects a very inaccurate assumed belief about the carbon footprint of its consumption by the consumer. Another interesting difference is that the effects of the label on consumption in the expected average carbon intensity scenario are smaller in absolute value than those in the expected zero carbon footprint scenario. Recall that in the average carbon intensity scenario, we assumed that consumers believed the carbon footprint of all goods is 0.48 kg/\$ before the carbon label. In the zero carbon footprint scenario, we assumed that consumers believed the carbon footprint of all goods is zero. Hence, $\Delta\tilde{E}_i$ is larger in the second scenario compared with the first. This is analogous to a situation where the tax on consumption is larger, and hence we see a larger shifts in consumption.

Table 5
Changes in quantities from labeling all meats as a result of changes in emission beliefs.
Source: authors' calculations.

	Effect of a label on						
	On emission beliefs	On quantity demanded					
		Beef	Pork	Other meat	Poultry	Fish	Eggs
	Kg of CO_2eq/kg	Percentage					
Expected average carbon intensity of 0.48 kg/\$ scenario							
Beef	12.89	−3.42	2.33	0.44	0.09	−0.89	−0.08
Pork	1.76	0.24	−0.90	0.23	0.22	−0.05	0.03
Other meat	6.25	0.12	0.63	−3.25	−0.09	1.54	−0.62
Poultry	1.65	0.01	0.33	−0.05	−0.95	0.33	0.17
Fish	4.13	−0.11	−0.06	0.70	0.29	−1.04	0.07
Eggs	1.54	−0.01	0.01	−0.17	0.09	0.04	−0.55
Expected zero carbon footprint scenario							
Beef	16.72	−4.44	3.02	0.57	0.11	−1.15	−0.10
Pork	5.31	0.72	−2.71	0.68	0.67	−0.14	0.08
Other meat	9.17	0.18	0.92	−4.76	−0.13	2.25	−0.90
Poultry	3.67	0.03	0.73	−0.10	−2.12	0.74	0.38
Fish	8.94	−0.25	−0.13	1.51	0.62	−2.24	0.16
Eggs	2.50	−0.01	0.02	−0.28	0.15	0.07	−0.89

Note: Calculations in columns 2 through 7 assume that consumers are willing to pay approximately \$0.03 for a 1 kg of CO_2eq decrease in their personal carbon footprint.

4. Extensions

Although we have used the best data available to parameterize the model, 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 footprint of 19.60 kg CO_2eq, and cod, which has a footprint of 1.19 kg CO_2eq. Our model is sufficiently flexible to accommodate any number of products. When information on elasticities of demand for more disaggregated products are available, more precise estimates of the effects of carbon labels can be estimated. 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 estimated by Carpentier and Guyomard (2001) and used by Okrent and Alston (2012) (Fig. 1). The parameters necessary to estimate this third stage are elasticities of demand for disaggregated seafood and fish products conditional on expenditure for seafood and fish; budget shares of the disaggregated seafood and fish products conditional on expenditure for seafood and fish; and the elasticities of demand from Okrent and Alston (2012). Hence, more precise estimates of the effects of carbon footprint labeling can be generated with additional information on the products of interest not included in this analysis. In this way, our model not only serves as a starting point for more detailed studies but is also a complement to studies that look at the willingness to pay for carbon footprint information on individual goods. For example, Onozaka et al. (2012) conduct a detailed analysis of the emission reductions that are possible from labeling apples. Their model, which takes into account supply shifts but not substitution and complementary relationships of other food products, could be imbedded as a third stage of our model.

Another extension to our analysis is the incorporation of carbon emissions from use and disposal of foods. 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. Consumers would then choose their disposal and cooking methods in a multi-stage process with the foods they purchase. For instance, a consumer might decide to purchase a potato and cook it in the microwave or boil it on the stovetop instead of cooking it in the oven where the carbon emissions are much higher. 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 and because carbon footprint labels often do not include use and disposal emission estimates for food. These phases are outside the scope of this study, however a survey or study using food diaries may be able to estimate these kinds of elasticities of demand.

Firms have responded to nutritional labels by reformulating their products to include more whole grains and fewer trans-fats (e.g., Ippolito and Matthios, 1990; Mancino et al., 2008; Unnevehr and Jagmanaite, 2008). We would expect a similar producer response where firms voluntarily reduce their carbon footprints in response to the label (Cohen and Vandenbergh, 2012; Loewenstein et al., 2013). The environmental literature has documented numerous cases where firms reduced their carbon footprints to differentiate their products (Kortelainen et al., 2012; Roe and Sheldon, 2007) to improve their reputation, to capture potential efficiency gains in supply chains, and other factors (Lenox and Eesley, 2009; Baron and Diermeier, 2007). While we do not explicitly model supply responses to a label, we would expect the largest supply responses to come from firms that stand to lose market share (or gain market share by being a low carbon product) due to consumer substitution of products.

Acceptance of and concern for climate change vary by ideology, race and gender (McCright and Dunlap, 2011) and similarly willingness to pay for environmentally friendly cars, homes, and electricity also varies by consumer segments in the U.S. (Kahn, 2007; Kahn and Vaughn, 2009; Dastrup et al., 2012; Kahn and Kok, 2014). Shuai et al. (2014) find that Chinese consumers who are wealthy, educated males from economically developed areas are more likely to respond to a carbon label, and we would expect a similar response in the United States. However, without knowing how and whether green consumers have different substitution patterns than brown consumers, we cannot incorporate this heterogeneity into our model.

5. Conclusion

Economists generally agree that carbon taxes and cap and trade systems are the most efficient way to reduce carbon emissions (Nordhaus, 2013; Metcalf, 2009; Stern, 2007). However, these measures are unlikely to be adopted and implemented in the near term in the United States. Furthermore most carbon taxes and cap and trade systems currently only regulate fossil fuel usage and industrial emissions, and exempt many of the emissions from agriculture and food production.[13] The United States Environmental Protection Agency's August 2015 Clean Power Plan only applies to existing electric power plants. Corporate Average Fuel Economy regulations and biofuel requirements affect greenhouse gas emissions from the transportation sector, but Congress has not adopted major legislation designed to reduce greenhouse gas emissions from agriculture.

Voluntary actions by firms and individuals[14] may be an important potential gap-filling and complementary measure (Vandenbergh et al., 2011; Dietz et al. 2009). Carbon labels will only reduce greenhouse gas emissions if consumers are willing to act on the labels and switch from high carbon goods to lower carbon goods, or if carbon labeling induces firms to reduce carbon emissions in response to more general reputation concerns or to capture efficiencies.

Our results suggest that although labels may be able to reduce carbon emissions, carbon footprint labels have the potential to incur the opposite effect, and thus should be implemented carefully. The study shows that it is important to account for consumer beliefs as well as complementary and substitute relationships if carbon footprint labels are to reduce carbon emissions. Failure to account for these factors may actually increase the carbon emissions of some goods.

The EI-CCD model combines information on elasticities of demand from the economics literature and carbon footprint estimates from the LCA literature to predict how consumers will respond to new information on carbon footprints by relating price elasticities of demand to carbon footprint elasticities. Previous work in the LCA literature relies on ad hoc assumptions about the willingness to change consumption patterns and what constitutes a substitute for high carbon items. Our model should improve this literature by showing how it is possible to use estimates of price elasticities of demand and willingness to pay to make these decisions and thus quantify the substitution and complementary relationships between products. This allows us to calculate reductions in emissions (Tables 3 and 4).

[13] Carbon taxes in British Columbia, Chile, Costa Rica, Denmark, Finland, France, Iceland, Ireland, Mexico, Japan, Norway, Sweden, Switzerland and the United Kingdom all either exempt agriculture or only cover fossil fuel and industrial sources of greenhouse gas emissions (World Bank, n.d.). The two largest trading programs, the European Emissions Trading System and California's trading market do not cover agriculture. The New Zealand Emissions Trading System was scheduled to be the first ETS to cover agriculture in 2015, however this deadline was extended indefinitely by the legislature (IETA and EDF 2014). Cap and trade programs often provide opportunities for agriculture to sell credits to other sectors and agriculture is impacted by increases in fuel prices and sometimes by regulation of fertilizer production plants.

[14] Voluntary actions may include purchasing 'green' goods, reducing energy usage through other means such as carpooling or turning off lights, purchasing green power, and switching to products with lower lifecycle carbon emissions.

We find that a carbon footprint label on meat and alcohol would yield the largest reductions in total emissions, but some caveats remain. We have used 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.

A comprehensive carbon tax may result in lower overall emissions, be less susceptible to mistakes from an incorrect carbon footprint estimate, and be more transparent than a carbon footprint labeling system. If a comprehensive carbon policy is not politically viable, private solutions such as labeling and educating consumers about carbon footprints may be a cost-effective second-best or interim strategy. However, those looking to reduce carbon emissions by introducing labels cannot neglect consumer demand. Ad hoc assumptions about which products are substitutes may be sufficient for comparing chicken versus beef but not for understanding substitutions among dairy, cereals, food away from home, and alcohol.

Researchers can predict consumer demand responses in two ways: they can conduct experiments where they label products and track the resulting behavior such as those in Vanclay et al. (2011); or they can model consumer behavior using existing information on price elasticities of demand. Both strategies are called for, but given the difficulty of labeling an entire grocery store (Quinn, 2012; Vaughan, 2012) a simulation approach can help identify promising groups of products. Potential uses for our model include predicting whether a campaign to educate consumers on the differences between the carbon footprints of products will be effective, or even choosing between which types of messaging (beef versus chicken or meat versus a vegetarian diet) would be most effective. Furthermore, with information on carbon footprints, budget shares, and elasticities of demand, our model can be expanded to analyze the impact of educating consumers on more difficult judgment calls such as hot-house versus imported tomatoes. The EI-CCD model would capture not just the substitution patterns between types of tomatoes, but also the impact on emissions from changes in consumption of non-tomato substitutes and complements. This should replace the need for ad hoc judgments and allow researchers to widen the boundary of label impacts by quantifying the changes in related markets. Ultimately, the EI-CCD model can guide those who want to use LCA information and carbon labels to products where this information will have the largest emission reductions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecolecon.2015.08.007.

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