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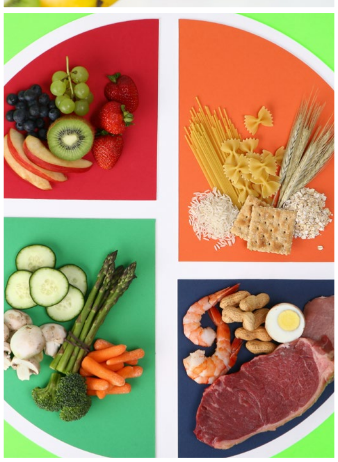
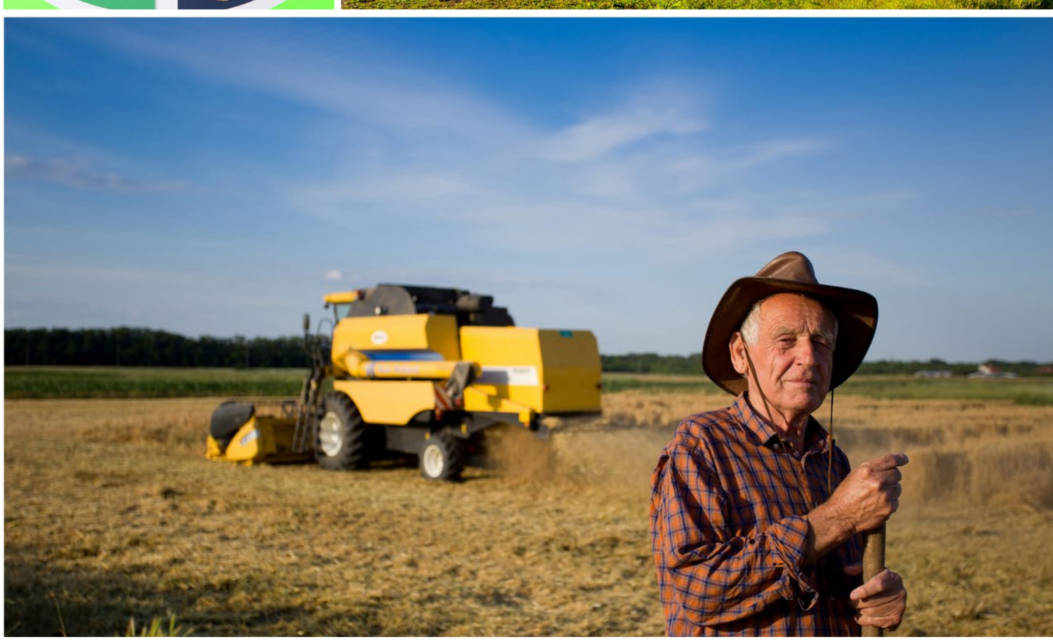
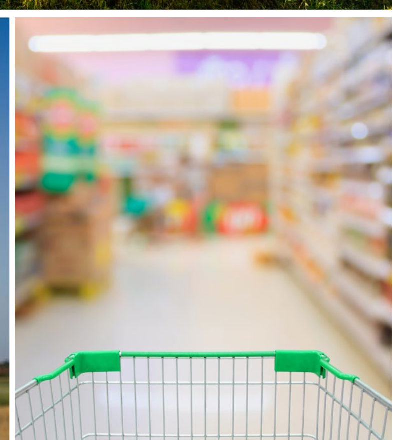
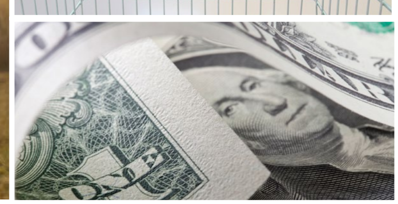
The Role of Fossil Fuels in the U.S. Food System and the American Diet

Patrick Canning, Sarah Rehkamp, Arnold Waters, and Hamideh Etemadnia

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Errata

On March 8, 2017, ERS corrected a few errors made in the calculation of data reported in Figure 14 (p. 32) and in the calories columns in Table 5 (p. 34). References to these data were updated in the text on pages 31-33 and p. 42. Also, a superscript on q on p. 89 was changed from a 1 to 0.

The Role of Fossil Fuels in the U.S. Food System and the American Diet

Patrick Canning, Sarah Rehkamp, Arnold Waters, and Hamideh Etemadnia

Abstract

The food system accounts for a large share of fossil fuel consumption in the United States, and energy accounts for a substantial and highly variable share of food costs. This intersection between food and energy markets suggests that public and private decisions affecting one market will have spillover effects in the other. For example, would increasing the share of population having diets that align with Federal dietary guidance reduce fossil fuel use in the U.S. food system? Would a carbon dioxide (CO_2) tax improve diet quality? To address these issues, we use the most recent data available to integrate the material-flows accounting framework adopted by the United Nations Statistical Commission into the existing food-system accounting structure of the ERS Food Dollar accounts. Then, we use mathematical optimization to model healthy diets. Our research indicates that U.S. agri-food industries are more sensitive to energy price changes than nonfood industries. We find that in 2007, fossil fuels linked to U.S. food consumption produced 13.6 percent of all fossil fuel CO_2 emissions economywide. Our study of alternative diets shows there are many ways to meet the Dietary Guidelines for Americans. If Americans made a minimal dietary shift to eat healthy, we find food-system energy use would decrease by 3 percent. By making greater changes from current consumption, we find food-system energy use could be reduced by as much as 74 percent. A tax on CO_2 emissions from fossil fuels would increase the cost of a typical meal by an average of 1.7 percent, with estimates ranging between 0.2 and 5.4 percent.

Keywords: Carbon emissions tax, Dietary Guidelines for Americans, energy prices, environmental input-output model, food policy, fossil fuels, food prices, greenhouse gases, healthy diet, sustainability, U.S. food system

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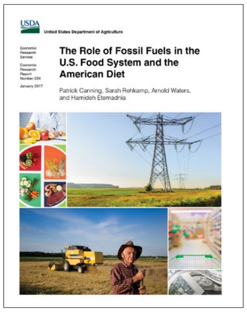
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What Is the Issue?

The consumption of fossil fuels, nuclear power, and renewable energy by the ***U.S. food system*** was on par, in 2002, with the ***entire national energy budget*** for India and exceeded the combined energy budgets of all African nations. In addition, energy costs are a substantial and highly variable share of U.S. food costs. This intersection of food and energy commodity markets raises questions about how changing food choices (such as through nutrition promotion) and changing energy prices (such as through a CO_2 emissions tax on fossil fuels) relate. Our research addresses limitations of previous studies by examining the relationship between energy prices and food-system energy use over time and measuring the CO_2 emissions associated with fossil fuel use in the food system. With this information, we analyze whether potential outcomes of nutrition promotion and a hypothetical CO_2 tax are interrelated.

What Did the Study Find?

- **Changing energy prices are the principal cause of year-to-year changes in food-related energy use between 1993 and 2012.**

  Food industries are more sensitive to energy price changes than are nonfood industries. This helps explain why food-related energy use accounted for more than half of the increase in total U.S. energy use between 1997 and 2002 (a period of generally declining energy prices). This also helps explain why food-related energy use declined 7 percent between 2002 and 2007 as energy prices and total U.S. energy use were increasing.

- **Use of fossil fuels to produce the foods and beverages consumed by Americans in 2007 accounted for 13.6 percent of economywide CO_2 emissions from fossil fuels.**

  Domestic fossil fuel use linked to U.S. food consumption produced 817 million of the nearly 6 billion metric tons of CO_2 emissions economywide from fossil fuels in 2007. This disproportionate total is attributed to the food system's above-average reliance on fossil fuel energy sources. Whereas 86 percent of nationwide energy consumption in 2007 came from fossil fuels, the share of U.S. food-system energy from fossil fuels was 93 percent.

ERS is a primary source of economic research and analysis from the U.S. Department of Agriculture, providing timely information on economic and policy issues related to agriculture, food, the environment, and rural America.

- **Diet-related energy use in the United States could be reduced by 3 percent if average diets changed minimally to meet the Dietary Guidelines for Americans.**

  Many potential diets would meet the 2010 Dietary Guidelines for Americans (DGA), each with varying energy requirements, measured in British thermal units (Btu). We focus on two diets. The ***Realistic Healthy Diet*** results from a model that formulates a diet requiring minimal change from typical diets (as of 2007-2008) to meet the DGA. The Realistic Healthy Diet reduces diet-related energy use in the U.S. food system by 3 percent. To put this in context, this reduction is equivalent to the annual gasoline consumption of 3.7 million U.S. vehicles. The ***Energy Efficient Diet*** is predicated on a diet requiring the minimum energy necessary to meet the caloric and nutrient targets in the DGA, with no consideration for how much diets will actually change. In this diet, energy use (in Btu) is reduced by 74 percent.

- **For each $100 spent on food and beverages, a tax on CO_2 emissions from fossil fuels— reflecting the wide range of current estimates on the social cost of those emissions—results in an average cost increase of $1.70 for both current and Realistic Healthy Diets or $1.90 for the Energy Efficient Diet.**

  Our research indicates that a typical meal would cost 0.2 to 5.4 percent more with the CO_2 tax. This wide range reflects the uncertainty about the social cost of CO_2 emissions, with the average increase over this range at 1.7 percent for both the current and the Realistic Healthy Diets. Although the tax rate averages 1.9 percent for the Energy Efficient Diet, resulting tax revenue is substantially lower due to the food system's reduced reliance on fossil fuels as an energy source. If faced with the CO_2 tax, U.S. producers and consumers would adjust their behaviors in order to mitigate the higher costs. Given the U.S. food system's sensitivity to energy prices, a CO_2 emissions tax would likely result in reduced energy use.

How Was the Study Conducted?

To facilitate a joint analysis of nutrition promotion and fossil fuel CO_2 taxation, we have integrated the material-flows accounting framework adopted by the United Nations Statistical Commission into the existing food-system accounting structure of the ERS Food Dollar accounts. The result is a first-of-its-kind U.S. environmentally extended input-output data system and model called the Food Environment Data System (FEDS). We conduct regression analysis to examine how the intensity of electricity use throughout the food system adjusts to changes in energy prices.

Then, we use mathematical optimization to model healthy diets based on numerous data sources and model specifications. The Realistic Healthy Diet is obtained from a maximum likelihood model designed to identify a diet that meets the DGA and is closest to the average American diet as reported in the National Health and Nutrition Examination Survey (NHANES) in 2007-2008, the years that correspond with the most recent benchmark year of data in FEDS. Using the same modelling approach and data sources, the Energy Efficient Diet results from a model that minimizes energy use while meeting the caloric and nutrient targets in the DGA. The diet modeling was linked to FEDS for the integrated sustainable diet analysis.

Next, the study traced the total cost that would be passed on to food consumers from a carbon dioxide emissions tax. The tax rate reflects the range of current Federal estimates for social costs from CO_2 emissions. We assume that all taxes levied to fossil fuel users are completely passed on to consumers.

Abbreviations

bBtu	Billion British thermal unit
BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
bmt	Billion metric tons
Btu	British thermal unit
CES	Constant elasticity of substitution
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalents
DGA	Dietary Guidelines for Americans
DRI	Dietary Reference Intakes
EIO	Environmental Input-Output
ERS	Economic Research Service
FEDS	Food Environment Data System
FNDDS	Food and Nutrient Database for Dietary Studies
FP	Food Patterns
FPED	Food Patterns Equivalents Database
GAMS	General Algebraic Modeling System
GDP	Gross domestic product
GHG	Greenhouse gases
IAWGSCC	Interagency Working Group on the Social Cost of Carbon
IO	Input-output
Kg	Kilogram
LCA	Life-cycle assessment
MJ	Megajoule
MEIO	Multiregional environmental input-output
NAICS	North American Industry Classification System
NHANES	National Health and Nutrition Examination Survey
OECD	Organisation of Economic Cooperation and Development
qBtu	Quadrillion Btu
SCC	Social cost of carbon
SEDS	State Energy Data System
SoFAS	Solid fats and added sugars
SR	Standard Reference
UL	Tolerable Upper Intake Level
UN	United Nations
WWEIA	What We Eat in America

The Role of Fossil Fuels in the U.S. Food System and the American Diet

Introduction

In 2002, the last year energy in the food system was analyzed by ERS, U.S. food-related energy use was about 14 quadrillion British thermal units (qBtu) (Canning et al., 2010). This level is roughly equal to all energy use (food and nonfood related) for India in 2002, the world's sixth-leading primary energy consumer that year, and exceeded that year's combined energy budgets of all African nations (U.S. Department of Energy, Energy Information Administration, 2016). In turn, energy costs have represented a substantial and highly variable share of food costs, growing from 3.5 cents of each dollar spent in U.S. grocery stores in 1998 up to 7.5 cents in 2008 and then down to 5.7 cents in 2014 (U.S. Department of Agriculture, Economic Research Service, 2016). This intersection of food and energy commodity markets portend a strong relationship between changing food choices (e.g., through nutrition promotion) and changing energy prices (e.g., through fossil fuel carbon dioxide (CO_2) taxes), which may lead to spillover effects to both market outcomes.

Substantial gaps in basic data on food-system energy use and energy prices have led to a paucity of cross-commodity food and energy market research. Specifically, there is no single source of consistent and comprehensive time series data on energy use and prices by fuel source (fossil, nuclear, and renewable fuels) that distinguish between which energy services are used throughout the agri-food chain. An accurate assessment of energy use throughout the food system requires a more detailed breakout of energy uses and prices, by both food commodity groups (e.g., meats, dairy products, grain products, fruits, vegetables, nuts, etc.), and agri-food chain stages including (i) farm production, (ii) food processing, (iii) packaging, (iv) transportation, (v) marketing (wholesaling and retailing), and (vi) meal preparation and cleanup (in home kitchens and at foodservice establishments).

It is also important to consider the spatial attributes of energy use in the food system when assessing possible effects on commodity prices and the environment. A case in point is electricity, which is an important source of energy services such as running refrigeration equipment. The primary fuels used for electric power generation vary substantially across different regions of the country. For example, in 2012, 97 percent of electric power generation in West Virginia came from coal, whereas in Rhode Island 98 percent came from natural gas, in Vermont 76 percent came from nuclear power, and in Idaho 75 percent came from hydroelectricity (U.S. Department of Energy, 2015). Electric power generation from different fuel sources is subject to different price pressures and can have very different environmental implications. Aside from electric power, refined petroleum products and natural gas are also important sources of energy services in the food system, from the production of farm inputs through the preparation of meals at foodservice establishments and in home kitchens. Thus, it is also important to have an accurate depiction of how the production economy, household expenditures, and diets are all linked together.

To that end, we developed a data product to fill these information gaps and assess whether potential outcomes from two distinct issues prominent in private and public discussions—nutrition promotion and fossil fuel CO_2 taxation—are unrelated or codependent. To achieve this, a national system of food-related energy use and price accounts is developed for the years 1993-2012. The physical flow accounting framework (United Nations et al., 2014) is followed with adaptations that accommodate the accounting structure in the U.S. system of national accounts. With these data, we are able to address the following questions:

1. Is energy intensity[1] in the U.S. food system sensitive to energy prices?
2. How much of U.S. CO_2 emissions from fossil fuels is linked to American diets?
3. Would adherence to the Dietary Guidelines for Americans reduce food-system energy use?
4. Would a CO_2 emissions tax influence dietary choice through cost and price effects?

[1] Energy intensity is the quantity of energy use per unit of production.

Background

Energy in the U.S. Food System

A systematic allocation of food-system energy use becomes increasingly complicated when processes are interconnected. The input-output (IO) table is a means to understanding these interconnections. This table, used in IO material flow analysis—also called environmental input-output (EIO) analysis—can be used to allocate fossil fuel consumption and subsequent carbon dioxide emissions systematically from production processes to final products (Bullard and Herendeen, 1975). In 2003, the United Nations, the European Commission, the International Monetary Fund, the Organisation for Economic Co-operation and Development (OECD), and the World Bank jointly issued a handbook that provides economic accounting guidelines for member nations and recommends the EIO approach as a best practice for achieving "a consistent analysis of the contribution of the environment to the economy and of the impact of the economy on the environment" (United Nations et al., 2003, p. iii).

Among the few U.S. and numerous international studies of food-related energy use using the EIO method,[2] two closely related studies 36 years apart applied the EIO framework to the latest U.S. benchmark IO accounts at the time in order to assess energy use linked to all domestic food expenditures. Hirst (1974) found that 12 percent of the 1963 U.S. energy budget was attributed to the food system, with household energy use making up the largest portion of this total. The U.S. food system studied by Hirst produced 13.7 percent of total 1963 U.S. gross domestic product (GDP), whereas the 2002 food system studied by Canning et al. (2010) produced 8.7 percent of 2002 GDP.[3] Although the food economy share of GDP fell by more than a third between the two study periods, Canning et al. (2010) found a one-fifth increase in the food system's share of the national energy budget to 14.4 percent in 2002. About half of the growth in food-related energy use between 1997 and 2002 was explained by a shift from human labor toward a greater reliance on energy services. Per capita food availability growth and population growth each accounted for one-quarter of the increase. Limitations of both the Hirst and the Canning et al. studies are that (i) neither study examines energy use by U.S. region, and therefore they are not able to distinguish between fossil fuel and non-fossil fuel use, and (ii) only 1 (Hirst, 1974) or 2 (Canning et al., 2010) years are studied in these reports, which does not allow for regression analysis of time series data in order to measure food-system energy demand elasticities. Such measures can inform public and private discussions where outcomes depend on the relationship between energy prices and the level of energy use.

A different analytical approach to measuring food-system energy use—which is outside of the economic accounting structures of EIO analysis—is known as process-based life-cycle assessment, or process-based LCA. Whereas the boundary of analysis for the EIO approach is the entire domestic economy, a process-based LCA study will typically identify a narrower boundary comprising the salient domestic processes within the food-system life cycle. Within these boundaries, a piecemeal approach to compiling primary and secondary data sources for measuring direct energy use is carried out, and often involves making informed assumptions about the application

[2] A review of several studies using the EIO method and other types of life-cycle assessments discussed in text is found in Heller, Keoleian, and Willett (2013).

[3] Based on 1963 and 2002 GDP data reported in U.S. Bureau of Economic Analysis, "Table 1.1.5 (line 1)," and "Table 2.4.5 (lines 26 and 82)," www.bea.gov/iTable/index_nipa.cfm.

of more narrowly defined data to processes outside of its own boundary definitions. If the boundaries are carefully defined and reliable data sources are available, results from applying the EIO and process-based LCA methods to the same research question should converge. Two studies using a LCA approach—Heller and Keoleian (2000) and Pimentel et al. (2008)—ask a similar research question, but their results differ.

Heller and Keoleian (2000) use data from the mid-1990s and find that the U.S. food system used 10.2 qBtu, or roughly 11 percent of the average mid-1990s annual U.S. energy budget. This study found that household operations accounted for the largest share of total food-related energy flows and the combined energy flows through food processing and packaging industries are similar to the 1997 figures in Canning et al. (2010). Heller and Keoleian attribute greater energy flows to the farm and farm-input industries than Canning and colleagues and lower flows through the foodservice and food retailing industries. Aside from the two studies using different data sources and covering different time periods, their definitions of supply chain stages are also different. For example, transportation-related energy flows represent the combined flows through the commercial freight industry and household food-related travel in Heller and Keoleian's (2000) work, whereas Canning et al. (2010) treat the latter as part of household-related energy flows.

Another LCA study by Pimentel et al. (2008) uses data from the mid-2000s and reports that total food-related energy flows through the U.S. food system represented 19 percent of the national energy budget. This figure, however, is somewhat higher than Canning and colleagues' 2002 estimates.

These two studies also do not extend their analysis to the disaggregated U.S. regional level, which would more accurately measure the specific fuel sources (e.g., fossil versus nonfossil fuels) used by the U.S. food system. Both are also single-period studies. Further, since no economic markets are defined by this approach, price and quantity information linked to specific energy market transactions are not compiled.

Sustainable Diets

Rather than focus solely on energy use in the food system, a number of studies have assessed the environmental impacts and sustainability of dietary choices. As defined by the Food and Agriculture Organization of the United Nations,

> "Sustainable Diets are those diets with low environmental impacts which contribute to food and nutrition security and to healthy life for present and future generations. Sustainable diets are protective and respectful of biodiversity and ecosystems, culturally acceptable, accessible, economically fair and affordable; nutritionally adequate, safe and healthy; while optimizing natural and human resources." (2010, p. 7)

While environmental impacts depend on where (i.e., locally, domestically, internationally) and how (i.e., conventionally, organically) foods are produced (Baroni et al. 2007; Saxe et al., 2013), a common approach to assess sustainability is to focus on specific food products. This line of research typically finds that animal-based products, such as meat or dairy, are more resource-intensive compared to plant-based products (Carlsson-Kanyama and Gonzalez, 2009; Eshel and Martin, 2006; Macdiarmid et al., 2012; Saxe et al., 2013; Tukker et al., 2011; Vieux et al., 2013; Wallen et al., 2004). However, Carlsson-Kanyama et al. (2003) find variation in energy embodied in different food products, even products that fall into the same food category. For example, energy inputs for meat range from 13 megajoules (MJ)[4] per kg for chicken stew up to 220 MJ/kg for shrimp. Swedish fresh chicken and beef fall within this range, using 35 and 70 MJ/kg, respectively. By comparison, the energy inputs for vegetables range from 2.7 MJ/kg for carrots to 66 MJ/kg for greenhouse tomatoes, while sweets can range from 18 MJ/kg for candies to 44 MJ/kg for chocolate. Another sweetener, honey, requires 1.3 MJ/kg of energy inputs.

However, focusing solely on energy use may not accurately depict environmental impacts. As such, greenhouse gases (GHG) are another frequently used metric to assess sustainability. For example, energy derived from the burning of fossil fuels to generate electricity emits carbon dioxide (CO_2) into the atmosphere and contributes to climate change. Eshel and Martin (2006) consider the energy and GHG emissions associated with the average U.S. diet and four hypothetical, isocaloric diets by decomposing the diets into their animal-based and plant-based components and applying energy use efficiencies. In their scenario analysis, they find that omnivorous diets containing fish or poultry and a lacto-ovo vegetarian diet are associated with fewer emissions than the average U.S. diet. Another study by Marlow et al. (2009) considers multiple environmental metrics using a survey of consumption patterns by food group and use efficiencies. The authors compare an omnivorous diet to a lacto-ovo vegetarian diet in California and find the omnivorous diet uses more fertilizer, water, primary energy, and pesticides by factors of 13, 2.9, 2.5, and 1.4, respectively.

Others extend the scope of their research beyond environmental impacts to include another element of sustainable diets: human health. There are studies exploring both the environmental and health impacts of omnivorous diets in the United States (Eshel et al., 2014; Heller and Keoleian, 2015; Tom et al., 2015), the United Kingdom (Macdiarmid et al., 2012), Sweden (Wallen et al., 2004), France (Vieux et al., 2013), Denmark (Saxe et al., 2013), across Europe (Tukker et al., 2011), and on a global scale (Tilman and Clark, 2014). In this line of research, healthy diets are typically characterized as diverse diets with reduced meat consumption and increased fruit and vegetable consumption (Macdiaramid et al., 2012; Saxe et al., 2013). While results are mixed due to the data sources, types of models, units of measurement, and definitions of healthy, these studies largely find that healthier diets are associated with fewer environmental impacts.

Macdiarmid et al. (2012) use a linear programming diet model to identify healthy diets in the United Kingdom. They find that GHG emissions may decrease 36 to 90 percent when shifting to a healthier diet. Using a consequential life-cycle assessment approach in Denmark, Saxe et al. (2013) also find that the healthy diet decreases GHG emissions, but by 27 percent. The healthier diet scenarios evaluated using an EIO model across Europe by Tukker et al. (2011) moderately lowered (by 8 percent) the aggregated environmental impacts of food. On a global scale, Tilman and Clark (2014) report that environmental impacts such as GHG emissions, land clearing, and species extinction could be reduced with alternative diets by comparing LCAs.

Two recent U.S. studies look at the GHG emissions[5] associated with healthy diets, as defined by the 2010 Dietary Guidelines for Americans (DGA). Both Heller and Keoleian (2015) rely on USDA's Loss-Adjusted Food Availability data as a proxy for food consumption while Tom et al. (2015) calculate calories using a system of equations. Heller and Keoleian and Tom et al. rely on LCA data from the literature and link these emissions factors to food groups. Heller and Keoleian observe a 1-percent decrease in GHG emissions when eating healthy and reducing caloric intake to the recom-

[4] 1 megajoule = 1×10^6 Joules and 1 Joule = 9.4782×10^{-4} Btu.

[5] In addition to GHG emissions, Tom et al. (2015) also study life-cycle energy use and the blue water footprint of diets.

mended level. In Tom et al.'s (2015) dietary scenario that meets the 2010 DGA in composition and caloric intake, energy use increases from the baseline by 38 percent and GHGs increase by 6 percent. Vieux et al. (2013) also find that a diet of high nutritional quality increases GHG emissions by 9 percent for men and 22 percent for women. Alternatively, Wallen et al. (2004) find a negligible effect on energy use and, thus, GHG emissions given a shift to a healthier diet. Wallen et al. (2004) use energy data on food products from multiple sources for the estimates, primarily relying on existing LCAs as Heller and Keoleian and Tom et al. do. In each of these studies, costs of alternative diets are not considered.

Taxing Carbon Emissions

The U.S. food system is one source of GHG emissions among many others. GHG emissions in the United States totaled 6,673 million metric tons CO_2 equivalents[6] (CO_2e) in 2013 (U.S. Environmental Protection Agency, 2013). Additionally, the World Meteorological Organization (2015) reports that the global average CO_2 concentration has now surpassed the 400-parts-per-million threshold.

One approach designed to curb emissions is a carbon tax. First, a tax rate is determined based on the additional cost to society not reflected in market prices due to increased carbon emissions, such as changes in net agricultural productivity, human health, property damages from increased flood risk, and reduced value of ecosystem services due to climate change (Interagency Working Group on the Social Cost of Carbon (IAWGSCC), 2015). Such measures are subject to uncertainty, and this is reflected in the wide range of estimates on the social cost. Fossil fuels are then taxed proportionally to the quantity of carbon emitted when burned (Baranzini et al., 2000). A carbon tax can be easily translated to a CO_2 emissions tax,[7] and using a 3-percent average discount rate, estimates ranged from $6 per ton of CO_2 to $123 per ton (IAWGSCC, 2015) in 2015. The tax raises the price of polluting and provides an economic incentive to reduce emissions by producing differently (i.e., substituting toward cleaner fuel sources) or producing less. In France, carbon taxes effectively reduced CO_2 emissions by 2 percent between 1990 and 1999 (Bruvoll and Larsen, 2004). Currently, there is neither a global carbon tax nor a nationwide carbon tax in the United States as some other countries have adopted (World Bank, n.d.).

One can easily imagine a demand response to increased fuel prices, but fossil fuels are also embodied in consumer goods such as food. Symons et al. (1994) measure the distributional effect of a carbon tax on the economy in the United Kingdom. In their study, the authors first use an IO framework to model the effects of a fossil fuel carbon tax on economic sectors and then estimate the effects of the tax on consumer demand, fossil fuel use, and CO_2 emissions. They consider five scenarios that reduce CO_2 emissions by approximately 20 percent and find that food prices increase in four of the five scenarios, but other goods, such as household energy or transport, are affected more than food by the tax. Following the same approach using a different demand system, Cornwell and Creedy (1996) study the effects of a carbon tax in Australia and find a relatively large price increase in food compared to other sectors due to a 10-percent tax rate on food purchases. Creedy and Sleeman (2006) also find that a carbon tax increases food prices in New Zealand.

[6] A CO_2 equivalent is a standardized measurement unit for GHGs that accounts for differences in global warming potential.

[7] Carbon and CO_2 emissions are proportional: 1 ton of carbon = 3.67 tons of CO_2 (Baranzini et al., 2000).

Wirsenius et al. (2011) research the effect of a GHG-weighted consumption tax on animal-based foods in the European Union. Using a tax base of €60 per ton of carbon dioxide equivalent (CO_2e), the authors estimate the effect of a tax on foods based on the average production emission intensities. The results indicate that GHG emissions could be reduced by 32 million tons of CO_2e due to the tax and shifts in demand between foods.

These empirical studies at the intersection of diet, fossil fuel consumption, and the environment provide several insights that can help inform important issues. Where findings cover similar time periods and measure overlapping outcomes, they produce mostly reinforcing results. However, the combined insights of these studies still create an incomplete accounting of where fossil fuels are used throughout the agri-food chain over time and what the alternative diets will cost. To address this gap in the empirical research, this study uses the newly compiled Food Environment Data System (FEDS).

Role of Fossil Fuels in the U.S. Food System

FEDS is a system of national environmental economic accounts that is organized into a food system life-cycle framework. To compile FEDS for the years 1993 to 2012, the starting point is the ERS Food Dollar accounts (Canning, 2011), which are compiled primarily from two main data sources: the benchmark IO accounts published in 5-year intervals by the Bureau of Economic Analysis (BEA) (2007) and annual IO tables (1993 to 2012) published by the Bureau of Labor Statistics (BLS). The ERS Food Dollar accounts reconfigure the IO accounting structure to better represent salient attributes of the U.S. food system and incorporate other primary data sources into the estimation process. A detailed documentation of the first edition Food Dollar accounts is reported in a separate ERS report (Canning, 2011); updates and changes to these accounts are reported in the online documentation to the Food Dollar data product (www.ers.usda.gov/data-products/food-dollar-series.aspx) (see Appendix B).

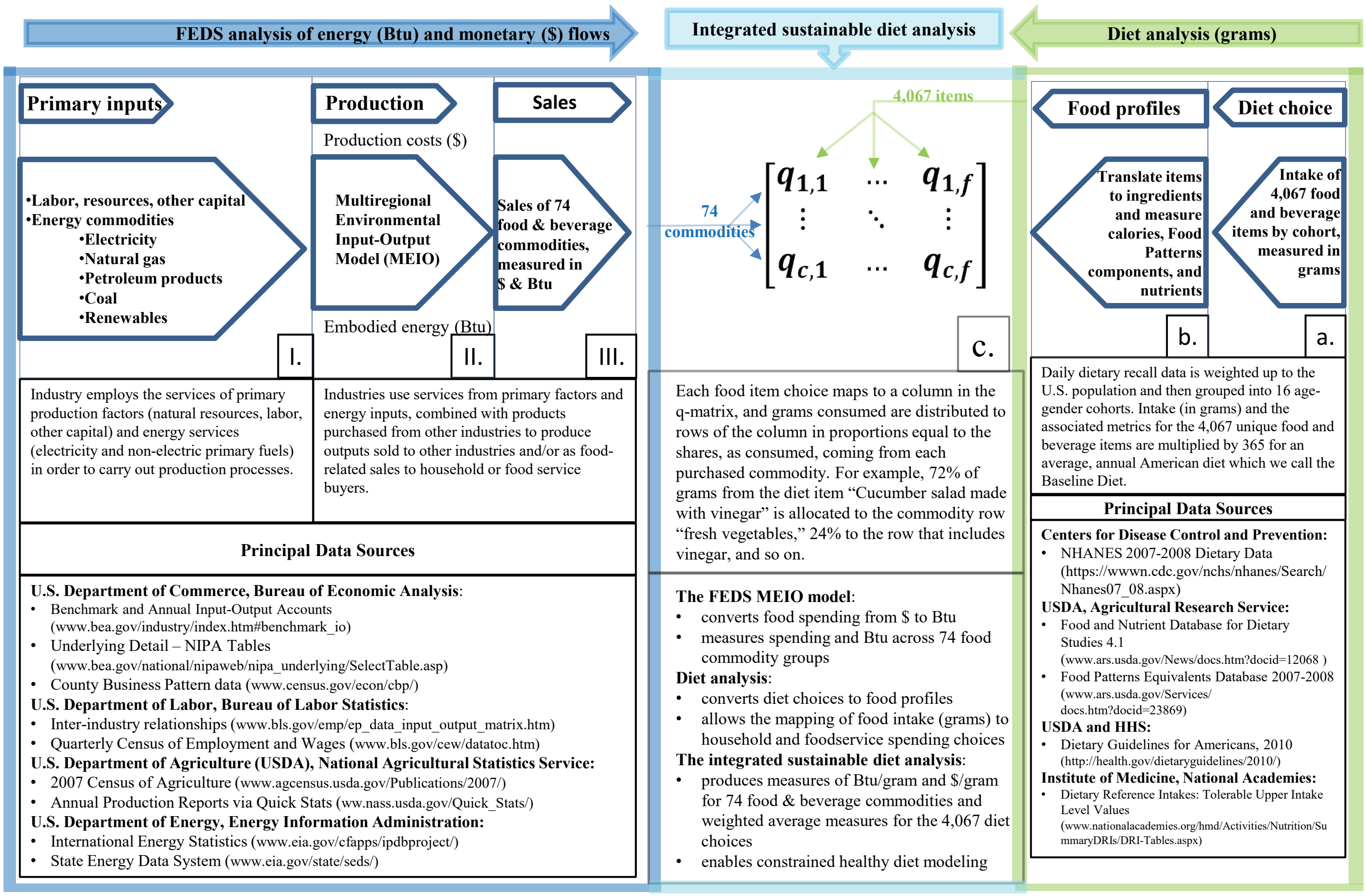
To facilitate the analysis, we must integrate and link the FEDS data and EIO models to diet recall data, nutrition data, and a healthy diet model (discussed below). A detailed description of our modeling approaches and data sources is provided in Appendices B and C. Here, we present a logic model[8] that describes our integrated approach to diet/energy analysis. Figure 1 depicts our approach for the baseline scenario, which represents the 2007 U.S. food system and the diet choices of all U.S. food consumers ages 2 and above in 2007-2008, using the most recent detailed data available from BEA.

Starting from the top left corner (figure 1), boxes labeled from left to right as I, II, and III describe the inputs, activities, and outputs related to the multiregional environmental input-output (MEIO) model analysis of monetary and energy flows through the U.S. food system. From the top right corner, boxes labeled from right to left as a, b, and c describe the inputs, activities, and outputs related to the baseline diet analysis. The Baseline Diet is the average American consumption as measured by the diet recall data.

The inputs to the MEIO model described in box I are the primary production factors including labor, capital (e.g., resources, equipment, buildings), and several types of energy commodities. The primary factors create value when they are used by industry (see list of the 344 industries in appendix table A2). Each of the energy commodities listed in box I are recorded in the MEIO accounts (box II) in physical units (Btu), whereas all other primary production factors are recorded in the MEIO accounts in monetary units ($). For most energy commodities, there is an underlying primary resource that is recorded in monetary units as part of the capital accounts. For example, the energy commodity natural gas is the output of the natural gas distribution industry, and it is purchased by many of the 344 model industries as well as by final market buyers (box III). These transactions are recorded in Btu. The industry that is producing the main ingredient of this commodity (oil and gas extraction, or FEDS benchmark commodity 013) is extracting this natural gas resource as a primary production factor, and this is recorded in monetary units as part of that industry's capital accounts. Boxes of the logic model in figure 1 directly below box I and boxes II and III describe the actions or processes taking place in the boxes above. For example, the description below boxes II and III notes that the MEIO model records all industry-to-industry transactions. These transactions represent purchased inputs that, when combined with the services each industry

[8] A logic model is "a conceptual tool for planning and evaluation which displays the sequence of actions that describes what the science-based program is and will do" (USDA/National Institute of Food and Agriculture, 2015).

Figure 1
Logic model of integrated sustainable diet analysis



Source: USDA, Economic Research Service.

obtains from their primary production factors, leads to the production of an industry output. Box III shows that a subset of the industry outputs characterized in box II are sold in both food retailing and foodservice outlets as food and beverage commodities. A list of these commodities is provided in appendix table A.1 (final demand benchmark commodities 01 to 74). Recalling that both monetary and physical units are recorded in the MEIO, the 74 commodity sales are reported in both market values and Btu of embodied energy by type of energy commodity. The box at the bottom of the logic model in figure 1 below boxes I to III list all of the principal data sources. Other ancillary data sources used to compile the FEDS accounts and models are discussed in appendix B.

The inputs to the diet analysis are described in box a of the logic model in figure 1. To characterize current American diets, we use What We Eat in America (WWEIA), the dietary intake portion of the National Health and Nutrition Examination Survey (NHANES), 2007-2008. This cycle of the survey corresponds with the 2007 FEDS analysis of food system energy. Then, the diets of survey respondents are weighted to represent the U.S. population and grouped into 16 age-gender cohorts (appendix table A.3). These data allow for a summary of the average daily intake, in grams, of 4,067 different food and beverage items. With this information, box b of the logic model in figure 1 describes the conversion of each cohort's food consumption in grams to measures on nutrient, caloric, and Food Patterns content to facilitate a dietary assessment of each cohort group's average daily diet choices. These translations coincide with recommendations jointly developed by USDA and HHS in the Dietary Guidelines for Americans. Principal data sources for input and outcome boxes (a and b) in the logic model are listed at the bottom of the column below these boxes. Ancillary data sources and a detailed description of the inputs and activities represented in boxes a and b are found in appendix C.

Box c of the logic model in figure 1 describes both the output of the diet analysis and the activities of the integrated sustainable diet analysis. The output carried over from activities in box b are the total annual grams consumed by all cohorts combined of the 4,067 food and beverage items. These values represent the control totals for the corresponding 4,067 columns of the q-matrix. The box below box c describes the activities for filling in the rows of the q-matrix. This activity assigns the total grams consumed across each food item to 1 or more of the 74 rows in the matrix. Each row in the q-matrix represents 1 of the 74 commodities for which expenditures and embodied Btu were measured for the same time period as an output of box III. Finally, the inputs and outputs of the integrated sustainable diet analysis are summarized in the bottom of the column below box c. The final output listed—weighted-average measures of Btu per gram and $ per gram across each of the 4,067 food items—are used to carry out the analysis reported in this section and the following section. We consider both primary energy (Btu) and food energy (calories) and reference their respective units instead of energy to avoid confusion.

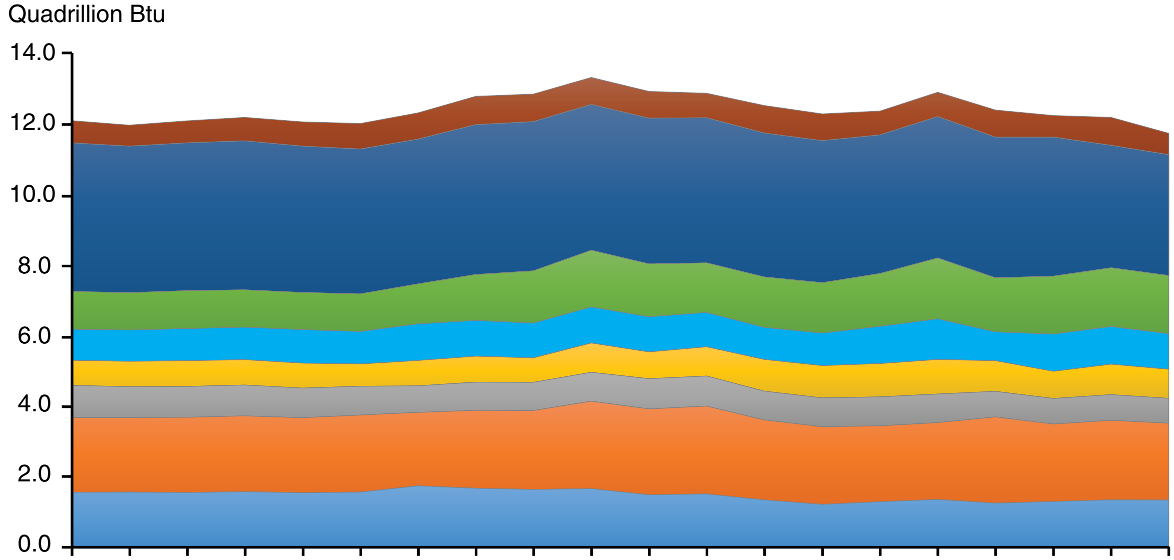
Trends Over Time

FEDS then yields a complete accounting of all food-related-energy market transactions throughout the domestic economy, broken out by supply chain stage and energy commodity. It is computed across 21 annual final demand categories (see appendix table A.1 for list of final demand categories) for the period 1993-2012. Figures 2 and 3 report the combined results summing across all 21 categories of final demand. (See box, "Accounting for the Energy Embodied in Food-Related Imports and Exports," for a discussion of international energy use linked to this study.)

Figure 2 shows the annual energy flows embodied in all food-related final demand expenditures aggregated over all energy commodities and broken out by agri-food chain stage. Focusing first on overall food-related energy flows, we find totals were slightly above 12 qBtu between 1993 and 1998, with only the household foodservice stage changing more than 0.1 qBtu over the interval, declining from 4.3 to 4.1 qBtu. Over the next 4 years, food-related energy flows rose sharply, reaching 13.5 qBtu in 2002, which is a 12-percent increase and represents about 14 percent of the 2002 national energy budget. Drilling down by supply chain stage, we see that leading this increase were the food-service, food processing, and commercial transportation industry groups with a combined increase of 1.0 qBtu, or about 71 percent of the overall change. In 8 of the remaining 10 years covered in this study, year-to-year measures of food-related energy flows were either unchanged or decreased and by 2012 reached the lowest total over the 20-year study period, 11.9 qBtu. Leading this decline from 2002 to 2012 was household foodservice, which dropped or was unchanged in each year, falling 0.7 qBtu over the interval. Food processing and farm production also trended downward over this period, both declining 0.3 qBtu by 2012.

Figure 2

Annual food-related energy commodity consumption by supply chain stage, 1993 to 2012



	1993	94	95	96	97	98	99	2000	01	02	03	04	05	06	07	08	09	10	11	12
Nat'l energy budget	87.5	89.0	91.0	94.1	94.7	95.0	96.6	98.8	96.2	97.6	98.0	100.1	100.3	99.7	101.4	99.4	94.8	98.3	97.6	95.2
Total food-related	12.2	12.1	12.2	12.3	12.2	12.1	12.4	12.9	13.0	13.5	13.1	13.0	12.6	12.4	12.5	13.0	12.5	12.4	12.3	11.9
Household transportation	0.6	0.6	0.6	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.7	0.8	0.8	0.7	0.7	0.8	0.6	0.8	0.6
Household food service	4.3	4.2	4.2	4.3	4.2	4.1	4.1	4.3	4.3	4.2	4.2	4.2	4.1	4.1	4.0	4.0	4.0	4.0	3.5	3.5
Food service	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.3	1.5	1.6	1.5	1.4	1.4	1.4	1.5	1.7	1.5	1.7	1.7	1.7
Wholesale/retail	0.9	0.9	0.9	0.9	1.0	0.9	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.1	1.2	0.8	1.1	1.1	1.0
Transportation	0.7	0.7	0.7	0.7	0.7	0.6	0.7	0.7	0.7	0.8	0.8	0.8	0.9	0.9	1.0	1.0	0.9	0.8	0.9	0.8
Packaging	0.9	0.9	0.9	0.9	0.8	0.8	0.8	0.8	0.8	0.8	0.9	0.9	0.8	0.8	0.8	0.8	0.7	0.7	0.7	0.7
Food processing	2.1	2.1	2.1	2.2	2.1	2.2	2.1	2.2	2.3	2.5	2.5	2.5	2.3	2.2	2.2	2.2	2.5	2.2	2.3	2.2
Farm production	1.6	1.6	1.6	1.6	1.6	1.6	1.8	1.7	1.7	1.7	1.5	1.5	1.4	1.2	1.3	1.4	1.3	1.3	1.4	1.4

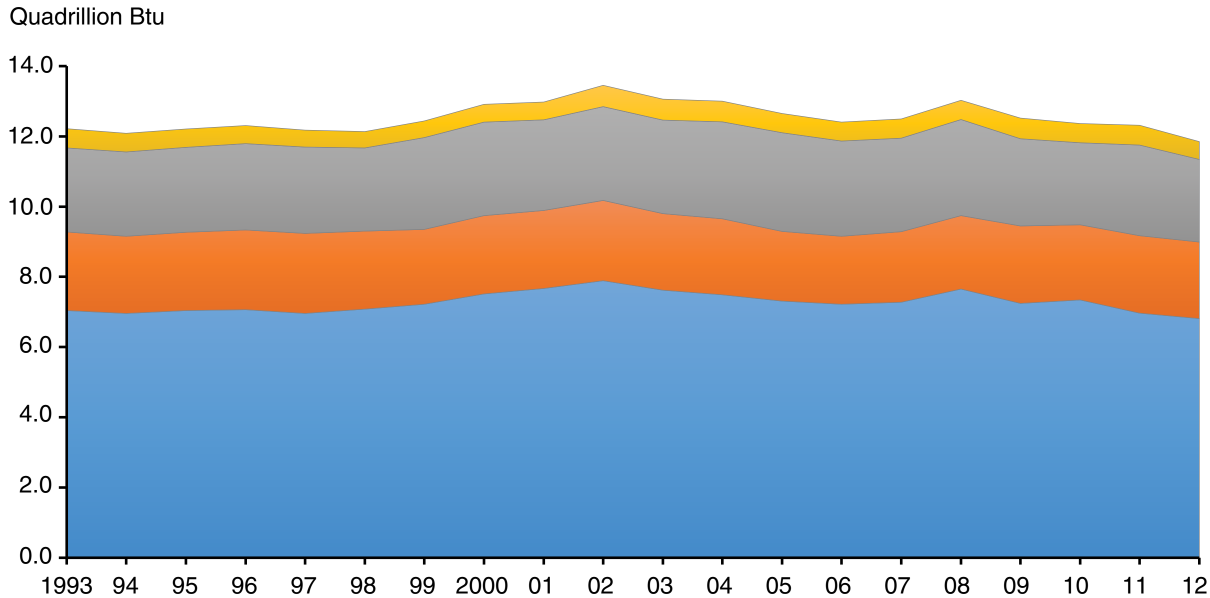
Source: USDA, Economic Research Service.

In figure 3, annual energy flows embodied in all food-related final demand expenditures are aggregated over all agri-food chain stages[9] and broken out by energy commodities.[10] Reported this way, we have the same three intervals of change—flat from 1993 to 1998, increasing from 1999 to 2002, declining from 2003 to 2012—but the reported indicators of change are energy commodities such as petroleum, natural gas, and electricity. Of these fuel commodities, electricity is the dominant source in the food system. For example, in 2012, 57 percent of food-related energy use was in the form of electricity. Over the 1993-1998 period of little overall change, the same can be said about change by energy commodity, as no single energy commodity had a year-to-year change of more than 0.1 qBtu. Over the 1998-2002 period of increasing overall food-related energy use, electricity and petroleum products accounted for about the same shares of total energy use at the beginning and end of this period. While the natural gas share fell from 18 percent to 17 percent of the total, the "other" energy commodities share rose from 4 to 5 percent due entirely to increased coal use. In the period

[9] Recall that stages in the agri-food chain include farm production, food processing, packaging, transportation, wholesale/retail, food service, household food service, and household transportation.

[10] Energy commodities include coal, natural gas, electricity, refined petroleum, ethanol for vehicle fuel blends, and self-supplied renewable fuels.

Figure 3
Annual food-related energy consumption by energy commodity, 1993 to 2012



	1993	94	95	96	97	98	99	2000	01	02	03	04	05	06	07	08	09	10	11	12
Nat'l energy budget	87.5	89.0	91.0	94.1	94.7	95.0	96.6	98.8	96.2	97.6	98.0	100.1	100.3	99.7	101.4	99.4	94.8	98.3	97.6	95.2
Total food-related	12.2	12.1	12.2	12.3	12.2	12.1	12.4	12.9	13.0	13.5	13.1	13.0	12.6	12.4	12.5	13.0	12.5	12.4	12.3	11.9
Other	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.5	0.5	0.5	0.6	0.6	0.5	0.6	0.5
Petroleum	2.4	2.4	2.4	2.5	2.5	2.4	2.6	2.7	2.6	2.7	2.7	2.8	2.8	2.7	2.7	2.7	2.5	2.3	2.6	2.4
Natural gas	2.2	2.2	2.2	2.3	2.3	2.2	2.1	2.2	2.2	2.3	2.2	2.2	2.0	1.9	2.0	2.1	2.2	2.1	2.2	2.2
Electricity	7.0	7.0	7.0	7.1	7.0	7.1	7.2	7.5	7.7	7.9	7.6	7.5	7.3	7.2	7.3	7.7	7.2	7.3	7.0	6.8

Note. "Other" includes coal, ethanol for vehicle fuel blends, and self-supplied renewable fuel.
Source: USDA, Economic Research Service

of declining food-related energy use from 2002 to 2012, electricity and petroleum-product use saw periods of decline and increase, but both ended the period more than 10 percent below their 2002 levels. For natural gas and other energy commodities, there was very little measured change in use over the 2002-2012 period. Although annual use of all energy commodities both rose and fell over the 1993-2012 period, use of nearly all energy commodities returned to 1993 levels by 2012. Only electricity was below its 1993 level in 2012, by 0.2 qBtu.

Drivers of Change

We now explore instruments of change to determine which are driving U.S. food-system energy use. We focus on four specific categories: (i) total population, (ii) per capita food availability, (iii) the commodity content of food availability (i.e., changes to the variety of foods on a typical food plate), and (iv) the energy intensity of food-system production technologies.

With respect to changes in ***total population***, the annual percentage growth in resident U.S. population ranged between 1.0 and 1.2 percent between 1993 and 2002, and in the 2003-2012 period ranged between 0.7 and 0.9 percent (U.S. Department of Commerce, Census Bureau, 2012). These figures indicate a small and steady upward pressure on the population-driven change in food-related energy consumption.

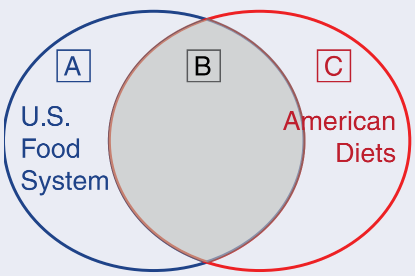
Accounting for the Energy Embodied in Food-Related Imports and Exports

To measure the energy embodied in American diets, one should consider both domestic and imported production of goods and services. For example, when fresh produce is imported into the United States, the energy required to transport and market this produce from its port of unlading to its point of purchase is embodied in American diets. In addition, all energy used to grow this imported produce in the country of origin and transport it to a U.S. port of unlading is also reflected in the energy embodied in American diets. The total energy embodied in American diets is represented by the red circle in the Venn diagram below.

To measure the energy embodied in the U.S. food system, all energy consumption linked to U.S. production that is marketed to domestic food consumers or sold in export markets should be included. Identifying what export commodities are food related is difficult. Clearly, exported food commodities are food related; however, products such as exported packaging materials and exported farm machinery are likely to be embodied in the food production of other countries. Whichever criteria are used to identify exported food system outputs, the total energy embodied in the U.S. food system is represented by the blue circle in the Venn diagram depicted below.

With the present study, only energy use at the intersection of the U.S. food system and American diets are measured. The reason for this approach is that this study examines interactions between domestic diet outcomes and domestic energy consumption. This intersection is depicted by shaded area B in the Venn diagram below. For example, the analysis in this report finds that, in 2007, area B totaled 12.5 qBtu.

Venn diagram: Overlapping food-related energy use



Area A—Domestic energy use of food system outputs exported to other countries: To approximate the energy embodied in U.S. food system exports, we consider food commodities produced in the U.S. and sold in export markets. These transactions are directly measurable in the FEDS accounts, and embodied energy for these exports is measured in the same way as the computations of area B in this study.

Area C—International energy use of food-related direct and embodied imports: To approximate the energy embodied in area C, we treat all direct and embodied imports as if they are produced in the United States and measure the domestic energy requirements to produce these commodities. Because domestic transportation and marketing energy requirements of the imports are already measured in area B, these should not be included in estimates of area C. This approach is accurate provided the technologies used in the countries that the United States is sourcing these imports from is similar to U.S. technologies.

Total food-related energy use, 2007 (qBtu)

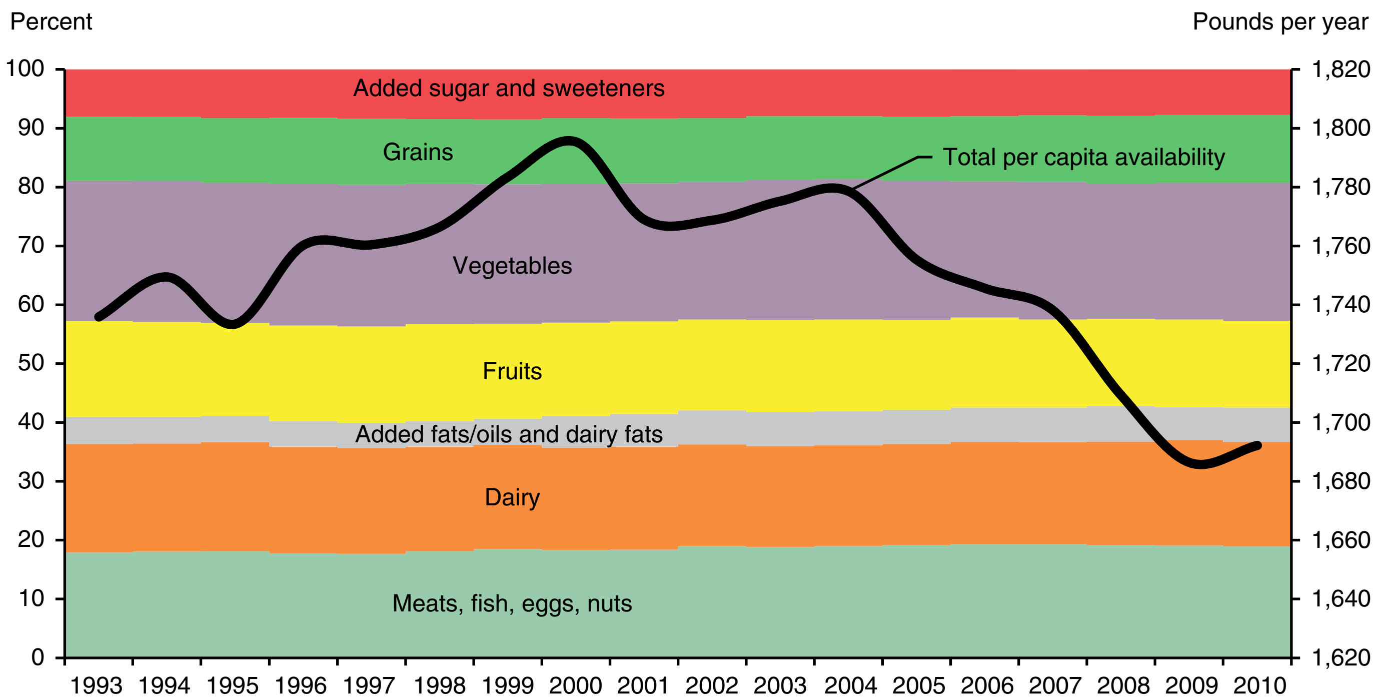
Area A	Area B	Area C
0.9	12.5	0.5

A summary of total food-related energy use in 2007 is reported in the adjacent table. It shows that energy embodied in areas A and C totaled 1.4 qBtu, or a little over 10 percent of the energy embodied in area B.

The influence of changes to ***per capita food availability***—absent changes in the commodity content of food availability—should be the same as population change. In other words, higher per capita availability should produce a proportionally similar increase in energy use and vice versa. Figure 4 reports data from the ERS food availability data system for the years 1993-2010, covering most of the period of our analysis. The solid line in the figure (linked to the secondary y-axis) depicts the annual average per capita total food availability, reported in pounds of farm weight for crop-based food products plus carcass weight where applicable. For 1993-1998, the change in the annual per capita food availability averaged 0.4 percent. This would add to the modest upward pressures on energy use from population change in this period, where overall yearly change in food-related energy use was measured as flat, indicating that other factors offset modest upward population and availability-induced pressures. For 1998-2002, annual per capita availability totals averaged no change. Combined with the modest upward pressures from population change, this suggests that other factors were behind the more than 10-percent increase in food-related energy use. For the 2002-2010 period, change in annual per capita food availability averaged -0.5 percent. This about offsets population pressures over this period, again pointing to other factors for the downward trend in overall energy use over this period.

Changes to the ***commodity content of food*** may be driving changes in food-system energy use. Evidence of this is depicted by the shaded areas of figure 4, which represent the annual shares of total food availability across seven different broad categories of food commodities, defined by the data source. We cannot formulate any expectations on the likely impact of these commodity content changes on energy use without measurements of energy use per pound. However, the data show that the availability share for any of the seven food categories had an annual change of more than

Figure 4
Share of food availability by commodity group and total per capita food availability, 1993-2010



Source: Economic Research Service Food Availability (Per Capita) Data System (www.ers.usda.gov/data-products/food-availability-(per-capita)-data-system/.aspx).

0.5 percent in only 2 of the 119 (7 commodities × 17 years) observations of change—a 0.9-percent increase in the availability share of fats in 2000 and a 0.6-percent increase in the availability share of meats, fish, eggs, and nuts in 2002. Any upward pressures this may have had on food-system energy use in this period of substantial overall increases would have been largely muted by the simultaneous drop in overall food availability.

A more indepth look at how changes in commodity mix may impact energy use will be presented later in this report (when looking at the relationship between diets and energy use). Anecdotally, the evidence does not indicate that these factors were driving the observed changes in our study period.[11] This suggests that changes in food-system production technologies are a primary factor of change in U.S. food-system energy use. This leads to our first research question—do changes in energy prices lead to changes in energy intensity in the U.S. food system?

Is Energy Intensity in the U.S. Food System Sensitive to Energy Prices?

Before examining the relationship between carbon taxes and dietary outcomes, we first need to establish that changing the relative price of energy would lead to changes in energy use in the food system. We begin with the hypothesis that energy intensity in the U.S. food system increases as the price of energy decreases relative to the price of labor and capital, and vice versa. Energy intensity is measured as the quantity of energy used per unit of production. A negative relationship between the price of a product and the demand for that product is typically assumed, but the lack of time series data on food-system energy use has precluded any empirical demonstration of the existence and strength of this relationship between energy prices and food-system energy intensity.

In agri-food chain analysis, production is measured as the net output at each agri-food chain stage. A widely used economic modeling approach for assessing energy use in production is to specify a constant elasticity of substitution (CES) production function where energy inputs like electricity and petroleum fuels are used with other primary production factors such as labor and capital (e.g., Bosetti et al., 2006; Paltsev et al., 2005). Using this approach, one can identify the optimal mix of energy, capital, and labor inputs as a problem of minimizing the production costs of meeting current market demand. From a CES production function specification, expressions describing the level of energy use, as well as the use of composite capital-labor inputs, can be derived as functions of all input prices and technology parameters. Taking a ratio of the demand expressions for the use of energy ($\boldsymbol{\varepsilon}$) and composite quantity of capital and labor ($\boldsymbol{qv}$) by production stages through point of purchase produces the measure of industry energy intensity (omitting superscripts that indicate supply chain stages):

$$(1) \qquad \left(\frac{\boldsymbol{\varepsilon}}{\boldsymbol{qv}}\right)^{*} = \frac{\alpha_{\varepsilon}}{\alpha_{qv}} \times \left(\frac{\boldsymbol{p\varepsilon}}{\boldsymbol{pv}}\right)^{\sigma},$$

where intensity of energy use relative to other production factors ($\boldsymbol{\varepsilon/qv}$) is sensitive to the unit price of energy ($\boldsymbol{p\varepsilon}$) relative to the composite unit price of capital and labor ($\boldsymbol{pv}$). The α expressions in (1) are factor-specific productivity parameters. The exponent, σ, is the elasticity of substitution, which translates a percentage change in the ratio of energy prices to capital-labor prices into a percentage change in the energy intensity of production. For example, a value of $\sigma = -1$ would imply that each

[11] Canning et al. (2010) included a structural decomposition of factors affecting change in energy use between 1997 and 2002 and attributed 25 percent of the change to population change, 25 percent to changes in the level and mix of food availability, and 50 percent to changes in food-system energy intensity.

10-percent increase in the price of energy relative to the price of the composite capital-labor inputs would result in a 10-percent decline in energy intensity. For absolute values of σ greater (less) than 1, the decline in energy intensity would be over (under) 10 percent. The * exponent on the left side of the equality in equation (1) signifies an optimal or longrun energy intensity, which reflects the recognition that transitions to new energy intensity levels in response to changes in relative factor prices occurs over several investment cycles.

If we denote the natural log of $\boldsymbol{\varepsilon/qv}$, $\alpha_{\varepsilon}/\alpha_{qv,}$ and $\boldsymbol{p\varepsilon/pv}$ as *a*, *b0*, and *c* respectively, and let b1 = σ, the energy intensity expression can be restated in natural log form as:

(2) $a^* = b0 + b1 \times c.$

Nerlov supply response models (Nerlov, 1958) are a widely used method of measuring period-to-period changes to industry energy intensity while recognizing transitions occur over more than one period. It is applied here by introducing a weighting parameter, $0 \leq b2 \leq 1$, that reflects the rate of transition as follows (see pp. 261-62 in Theil, 1971):

(3) $a^{t} = b2 \times a^* + (1\text{-}b2) \times a^{t-1}$,

where a^t is the current period's energy-intensity outcome and a^{t-1} is the previous period's outcome, such that values of *b2* approaching 1 (0) indicate a rapid (slow) transition. Plugging the expression for *a** from equation (2) into equation (3) yields the expression from which the unknown parameters (*b0*, *b1*, and *b2*) can be measured based on the observed parameters (a^t, a^{t-1}, and c^t):

(4) $a^{t} = (b0 \times b2) + (b1 \times b2) \times c^{t} + (1\text{-}b2) \times a^{t-1}$.

The FEDS accounts provide annual observations for a^t and c^t over the 1993-2012 interval.[12] Nonlinear least-squares estimates of equation (4) with data on electricity use intensities[13] by agri-food chain stage produce sample sizes ranging from 171 to 266 using pooled data across all food-commodity-expenditure categories relevant to each production stage. For example, unprocessed food commodities are omitted from the processing stage regressions because they do not contribute energy use data to the food-processing-stage regression. A lagged dependent variable (a^{t-1}) appears on the right side of the equation, so autocorrelation is likely to be present. This undermines use of standard t-statistics, so the Durbin-h (dh) statistic is used to test for its presence (Durbin, 1970). Results by supply chain stage are reported in table 1.

As expected, autocorrelation is found to be present in the pooled results, with dh statistics of 2.45 or higher.[14] In the pooled data, multiple food-commodity supply chains are producing net industry outputs from overlapping sets of industry groups, increasing the likelihood for serial correlation of error terms. One exception is the pooled data results of the retail/wholesale stage, where the best

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[12] Observations for a^t are from estimations of Equation B.9 (Appendix B) and a quantity index of capital labor composite derived from the real (2005 prices) food dollar industry group series (www.ers.usda.gov/data-products/food-dollar-series.aspx). Observations for c^t come from U.S. Department of Energy, Energy Information Administration (www.eia.gov/state/seds/) and the capital-labor composite price index, which is derived from the ratio of the nominal and real food dollar industry group series.

[13] Electricity is singled out based on the assessment above that it is both the most widely used energy commodity throughout the food system and is the energy commodity showing the most change in use over the study period.

[14] The Durbin-h statistic has a standard normal distribution with a critical value slightly under 2.0 such that a dh statistic below this value signals a rejection of the presence of autocorrelation in regression error terms.

Table 1
Nonlinear least square regression results by production stage

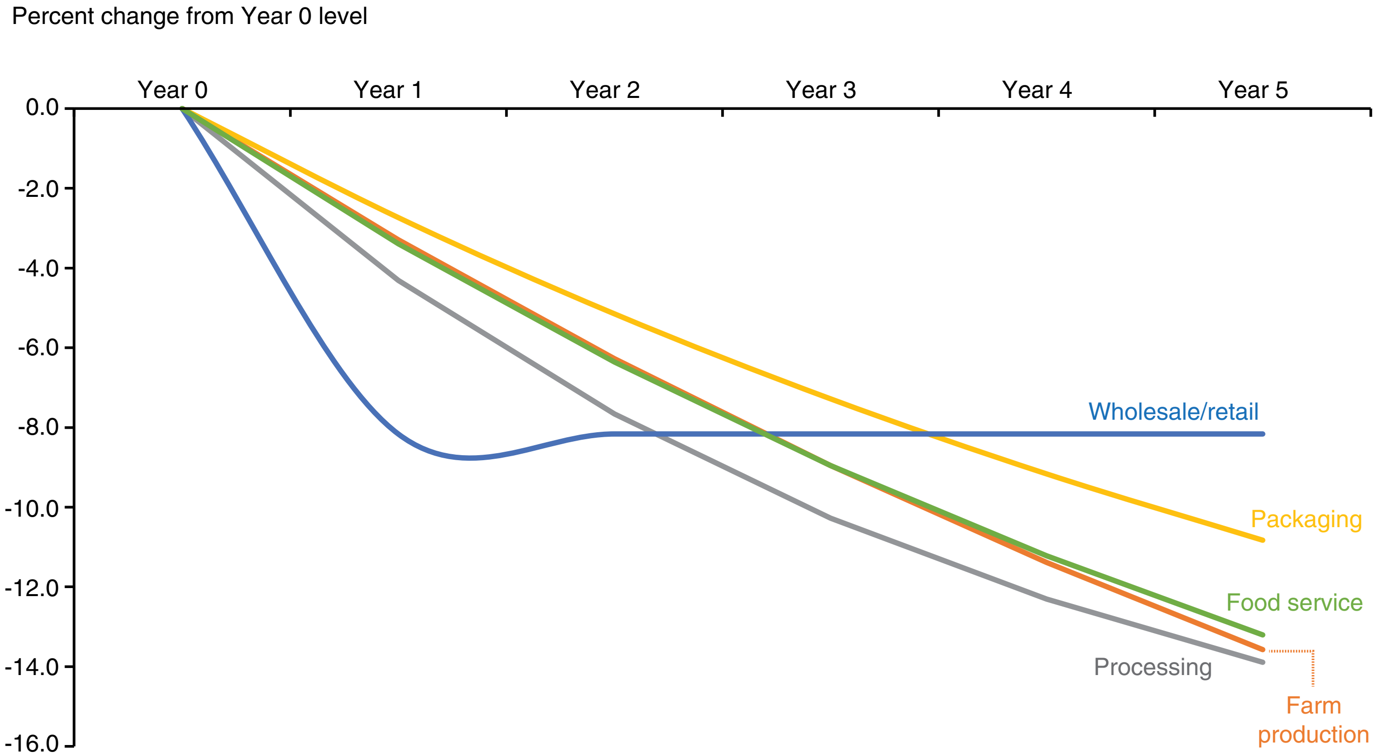
Stage	Sample	b0	b1	b2	Adj. R2	Durbin-H	Observa-tions
Farm production	Pooled data	47.999	-3.388	0.097	0.920	7.933	209
	(t-stat)	(3.90)	(-2.64)	(3.45)			
	Processed fruits and vegetables	71.988	-5.869	0.280	0.765	0.922	19
	(t-stat)	(2.75)	(-2.17)	(2.24)			
Food processing	Pooled data	34.055	-1.946	0.221	0.900	7.490	171
	(t-stat)	(9.28)	(-5.12)	(5.99)			
	Meats	32.484	-1.730	0.363	0.653	0.870	19
	(t-stat)	(4.14)	(-2.15)	(2.38)			
Packaging	Pooled data	38.774	-2.340	0.117	0.921	2.723	266
	(t-stat)	(6.00)	(-3.51)	(4.53)			
	Fresh seafood	39.329	-2.423	0.260	0.961	1.254	19
	(t-stat)	(9.09)	(-5.50)	(3.70)			
Food service	Pooled data	42.445	-2.698	0.126	0.945	2.448	266
	(t-stat)	(8.74)	(-5.69)	(6.76)			
	Other foods	36.400	-2.110	0.401	0.815	1.429	19
	(t-stat)	(6.00)	(-3.55)	(2.72)			
Retail/wholesale trade	Pooled data	23.196	-0.816	na	0.860	na	266
	(t-stat)	(10.10)	(-3.59)	na			

Note. T-statistics indicate that all estimates are statistically significant at a 5-percent level.
Source: USDA, Economic Research Service

results came from imposing a value of 1 for the b2 parameter such that full adjustment occurred in the first time period. Since the lagged dependent term drops out of this equation, the standard Durbin-Watson statistic is used and produces a value of 1.96, which indicates the absence of autocorrelation.

Table 1 also reports results from an unpooled subset of the data for each agri-food chain stage that represents electricity use and net output for specific food-commodity supply chains. In each case the food-commodity-group results reported account for a substantial portion of the pooled-data net output totals. Regression results with these data do not exhibit the presence of autocorrelation, with all dh statistics well below 1.5. Reported t-statistics indicate that all parameter estimates are highly significant and show the same relationships as their pooled counterparts. There were no single-commodity regression results that produced significant parameter estimates of the opposite direction, either with or without the presence of autocorrelation. Since presence of autocorrelation does not lead to a bias in the parameter estimates (Kelejian and Oates, 1981), we view the combined findings of the pooled and unpooled estimates as compelling evidence of a strong relationship between energy intensity and energy prices and thus do not reject our hypothesis that energy use is significantly linked to energy prices.

Figure 5
Electricity use response to 10-percent price increase in Year 1



Source: USDA, Economic Research Service.

The pooled data results indicate the magnitude and pace of a food industrywide response to energy price movements. Figure 5 demonstrates how a one-time 10-percent increase in electricity prices, while holding the price of capital and labor constant, would affect the energy intensities over a 5-year period in each of the supply chain stages. In the first year, all stages decrease their electricity use intensity from between 2 and 5 percent except the retail/wholesale stage, which decreases intensity by 8.2 percent. In the absence of any other price changes by the fifth year after the 10-percent electricity price increase, all stages lower electricity use intensity by between 8 and 14 percent, with food processors declining the most and retail/wholesale the least.

This evidence (on the pace of price-induced adjustments to electricity intensity in production throughout the food system) is more accelerated than other empirical studies on the economywide average annual rates. For example, a survey of several prominent climate change models (van der Werf, 2008) identifies 4 models that employ the identical nested CES production function used in this study, which notably is the model specification found to “fit the data best” in van der Werf’s own analysis of data from 12 OECD countries (see p. 2976 in van der Werf, 2008). These four models, plus van der Werf’s analysis, report elasticity of substitution parameter estimates for energy in the -0.4 to -0.5 range, and all of the models assume full adjustment in the year of the price shock. By comparison, table 1 results indicate first-year elasticity parameters in the -0.3 to -0.8 range (see table 1, b1*b2 in pooled data rows) and further adjustments in subsequent years.

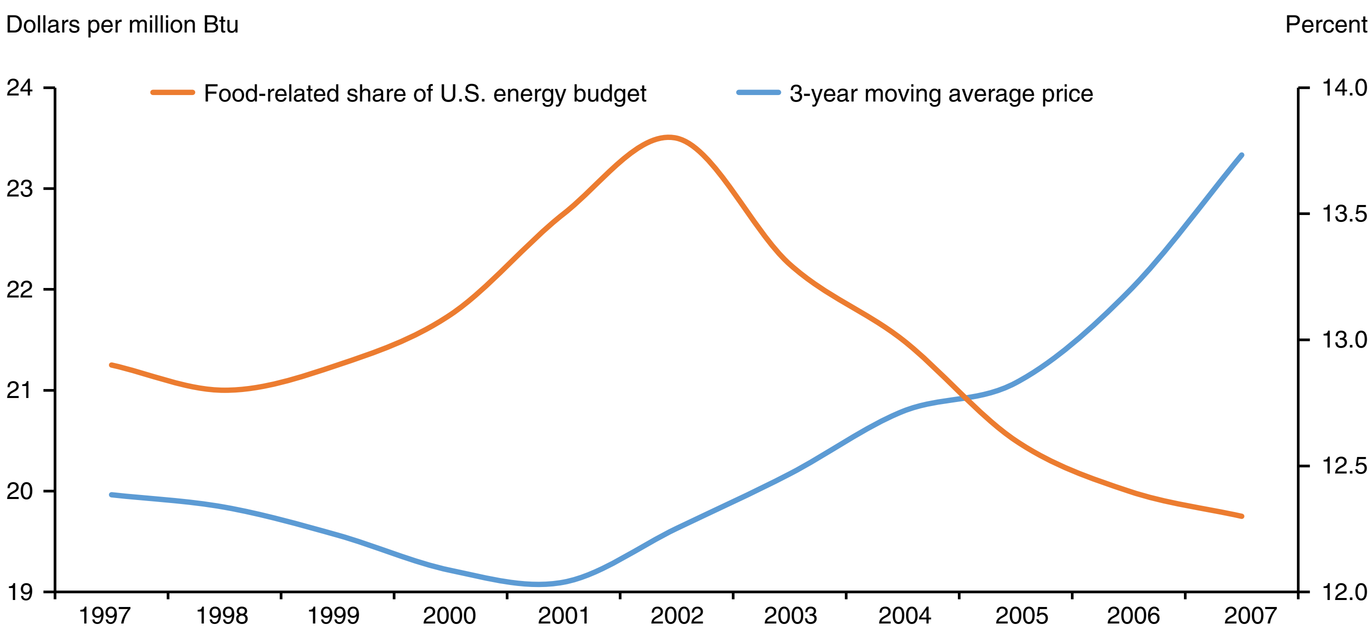
A food system whose energy intensity is more price-sensitive then the economywide average would be consistent with an economy where the food system gains a greater share of the national energy budget during sustained periods of declining energy prices and loses share during sustained periods of increasing energy prices. We use our electricity market analysis to make inferences about overall energy use in the U.S. food system because electricity represents well over half of the total energy use in the food system. Figure 6 shows just this pattern for the U.S. economy over 1997-2007, from the first to the last benchmark years of data available. In the figure, electricity prices are reported as a 3-year moving average since our estimates in equation (4) indicate a multi-period adjustment to energy price changes. Figure 6 confirms the negative relationship between energy prices and the food system's energy intensity, showing a clear pattern of growing national energy budget share during a sustained decrease in electricity prices in the late 1990s and a declining share during the steep increase in electricity prices during the 2000s.

How Much of U.S. CO_2 Emissions From Fossil Fuels Is Linked to American Diets?

Now that we have established that energy taxes could reduce energy use, we need to establish the level of CO_2 emissions that are due to current dietary patterns in the United States. One approach is to use the national average conversion rate to convert food-system energy use to CO_2 emissions. This approach would mean that the food system share of CO_2 emissions from fossil fuels is the same as its share of the national energy budget, which has ranged between 12 and 14 percent from 1993 to 2012. For example, in 2007, 59 metric tons of CO_2 emissions were produced from each bBtu of energy consumption (www.eia.gov/environment/). To use this ratio when converting food-system energy consumption to CO_2 emissions, the food system's reliance on each fossil fuel type should be the same as the national average. In 2007, 86 percent of national energy consumption was from fossil fuels, with the percentages attributed to coal, natural gas, and petroleum being 22.4 percent, 23.4 percent, and 39.8 percent, respectively (www.eia.gov/totalenergy/data/annual/). In order to test

Figure 6

Electricty prices and food-related share of U.S. energy budget, 1997 to 2007



Source: Average prices paid across U.S. food system in 3 previous years are ERS calculations using electricity price data from EIA, SEDS (www.eia.gov/state/seds); food-system energy use series are ERS calculations.

this relationship, we use the FEDS MEIO model, which is compiled with the 2007 benchmark year accounts (see discussion of multiregional input-output models in Appendix B). Recall from figure 3 that electricity is the most widely used energy commodity in the U.S. food system and, as previously mentioned, fuel sources used for electric power generation vary by region.

Table 2 reports the share of electricity output by State that is produced from each of the fossil fuel sources. These values in table 2 are used to convert measures of direct electricity requirements to the more detailed measure that will allow us to compute electricity use by fossil fuel source (see equation B.10 in appendix B).

Table 2

Percent of 2007 electricity output by fuel source

State	Coal	Natural Gas	Petroleum	State	Coal	Natural Gas	Petroleum
AK	9.3	61.6	10.0	MT	65.4	0.3	2.5
AL	57.9	13.0	0.1	NC	61.4	3.1	0.2
AR	50.3	12.4	0.2	ND	94.3	0.0	0.2
AZ	40.1	27.1	0.0	NE	61.0	3.2	0.1
CA	1.3	47.5	1.2	NH	19.3	17.8	1.7
CO	70.6	23.7	0.1	NJ	17.9	26.0	0.4
CT	12.6	23.5	4.5	NM	78.7	16.6	0.1
DC	0.0	0.0	100.0	NV	27.2	61.4	0.1
DE	78.7	18.0	2.6	NY	15.2	28.7	5.8
FL	33.8	38.7	10.0	OH	85.9	2.4	0.8
GA	64.6	9.1	0.1	OK	50.9	42.0	0.2
HI	15.4	0.0	76.3	OR	8.6	21.0	0.0
IA	77.4	5.1	0.8	PA	54.7	6.5	0.6
ID	0.0	12.2	0.0	RI	0.0	96.0	0.4
IL	47.6	3.1	0.1	SC	39.3	5.0	0.2
IN	96.5	2.9	0.1	SD	44.7	6.7	1.3
KS	72.4	4.8	0.5	TN	62.3	0.8	0.2
KY	93.1	1.9	3.3	TX	43.2	41.5	0.4
LA	35.8	33.4	3.6	UT	84.7	13.4	0.1
MA	27.9	45.2	7.6	VA	46.8	11.7	2.5
MD	58.7	4.8	2.2	VT	0.0	0.0	0.1
ME	3.1	30.9	3.9	WA	8.8	5.6	0.0
MI	59.2	10.3	0.5	WI	65.5	8.5	1.5
MN	60.0	6.2	0.8	WV	98.3	0.4	0.2
MO	83.5	4.5	0.1	WY	96.4	0.4	0.1
MS	38.4	39.9	0.9	US	51.6	17.4	1.6

Source: U.S. Energy Information Administration: https://www.eia.gov/state/seds/

Note. Percentages may not add to 100 percent because of non-fossil fuel sources of electricity in each State.

Next, conversion factors are needed to translate fossil fuel consumption into tons of CO_2 emissions. The national CO_2 conversion factors for each sector—such as transportation, commercial, and electric power—by primary fossil fuel are reported in table 3. For coal and natural gas, national average emission coefficients across all commodity types and end users are applied. For petroleum products, each end user's emission coefficient is computed as a weighted average from more detailed fuel uses, where the weights are the 2007 consumption totals by detailed petroleum fuels and end user. For example, the residential petroleum coefficient (153.44) is the weighted average of butane/propane mix (141.1), home heating and diesel (161.3), and kerosene (159.4). The weights are the shares of 2007 residential Btu consumption by fuel: 0.386, 0.579, and 0.035 for butane/propane mix, home heating and diesel, and kerosene, respectively.

A complete accounting of all 2007 food-related CO_2 emissions from fossil fuels is computed for each agri-food chain stage and across all 83 benchmark-year, food-related final demand categories. Table 4 reports all food-related CO_2 emissions from the consumption of coal, natural gas, and petroleum products in 2007. The results in table 4 are compiled from summations of appendix equation B.10. Results are reported in both consumption units (million Btu) and emission units (metric tons of CO_2). Total food-related CO_2 emissions reach almost 817 million metric tons per year with 332 million from coal, 282 million from natural gas, and 202 million from petroleum production.

While 2007 food-related energy use represents 12.3 percent of that year's national energy budget, we find that food-related CO_2 emissions from fossil fuels accounted for 13.6 percent of the 5.99 billion metric tons of CO_2 emissions from fossil fuel consumption in the United States (see table 12.1 in www.eia.gov/totalenergy/data/monthly/pdf/sec12.pdf). The difference indicates that use of national average conversion rates misses the actual food-related CO_2 emissions by 11 percent. In other words, the carbon footprint of the U.S. food system is 1.1 times larger than its energy footprint.

While fossil fuels account for 93 percent of total food-related energy use, they account for only 86 percent of the 2007 national energy budget. Higher-than-average reliance on fossil fuel sources helps to explain the higher-than-expected CO_2 emission totals. Within the fossil fuel category, CO_2 emissions from natural gas consumption in the food system are nearly a quarter (23 percent) of the 1.24 billion metric tons (bmt) emitted nationally from natural gas. This disproportionate reliance on natural gas among fossil fuels serves to mitigate the emission impacts of the food system's fossil fuel reliance. For coal, the food system share was 15 percent of the 2.17 bmt national emissions from

Table 3

Pounds of CO_2 emissions per million Btu by type of fossil fuel

End user	Coal	Natural gas	Petroleum
Transportation sector		117.00	158.62
Commercial sector	210.20	117.00	158.59
Electric power sector	210.20	117.00	185.41
Industrial sector		117.00	157.11
Coke plants	210.20		
Organic chemicals	210.20		
Residential sector	210.20	117.00	153.44

Source: U.S. Energy Information Administration: www.eia.gov/environment/emissions/co2_vol_mass.cfm
Note. Coal and natural gas are national averages while petroleum is broken out by end user.

Table 4
Food-related annual fossil fuel consumption and carbon dioxide emissions, 2007

State	Fossil fuel consumption			Fossil fuel CO_2 emissions		
	Coal	Natural gas	Petroleum products	Coal	Natural gas	Petroleum products
		(million Btu)			*(metric tons)*	
Alabama	75,392,269	84,343,997	44,791,792	7,140,311	4,452,626	3,198,043
Alaska	1,909,832	14,134,324	9,303,885	181,133	746,388	665,556
Arizona	55,043,250	93,597,446	43,109,647	5,217,768	4,939,806	3,083,260
Arkansas	47,403,478	70,994,455	45,061,028	4,503,610	3,757,851	3,223,317
California	36,094,727	880,366,259	280,467,095	3,434,307	46,589,665	20,059,107
Colorado	87,741,488	56,649,635	42,445,734	8,335,716	2,997,343	3,036,253
Connecticut	11,033,739	76,770,705	20,855,569	1,047,872	4,058,537	1,491,644
Delaware	18,218,424	10,575,916	8,863,052	1,726,750	558,975	632,844
District of Columbia	85,616	1,720,683	15,550,544	8,024	90,581	1,109,282
Florida	134,003,656	291,793,559	155,664,814	12,724,726	15,428,140	11,138,992
Georgia	160,834,065	147,301,629	84,126,635	15,255,857	7,785,691	6,015,207
Hawaii	5,190,041	8,886,337	32,218,848	492,306	469,971	2,302,085
Idaho	2,657,248	24,369,913	22,366,987	253,127	1,290,791	1,597,287
Illinois	170,741,293	269,825,840	123,322,080	16,217,505	14,273,913	8,822,924
Indiana	176,967,424	58,941,759	72,114,585	16,796,018	3,120,979	5,157,721
Iowa	90,614,831	72,304,935	70,383,319	8,609,478	3,830,017	5,025,692
Kansas	64,801,852	52,082,371	51,552,621	6,154,179	2,756,611	3,681,566
Kentucky	119,153,475	36,557,984	53,663,493	11,309,907	1,936,277	3,838,384
Louisiana	40,006,121	99,901,748	57,042,734	3,791,735	5,277,365	4,079,684
Maine	2,622,020	34,214,220	12,461,441	249,515	1,810,996	890,807
Maryland	72,401,674	65,546,750	35,516,143	6,873,974	3,465,190	2,541,123
Massachusetts	44,838,273	124,963,929	47,019,327	4,259,535	6,609,397	3,364,164
Michigan	143,793,598	147,619,962	71,889,575	13,642,007	7,801,216	5,138,659
Minnesota	98,380,902	108,439,622	66,566,269	9,342,991	5,737,534	4,755,945
Mississippi	28,612,062	62,325,949	31,254,729	2,712,518	3,291,612	2,232,363
Missouri	135,844,787	74,835,401	62,390,652	12,892,366	3,960,338	4,461,701
Montana	16,839,976	7,134,803	14,744,794	1,595,581	377,441	1,052,939
Nebraska	42,628,800	49,899,219	52,740,150	4,063,130	2,647,610	3,771,474
Nevada	16,270,416	44,756,891	15,274,689	1,544,414	2,365,208	1,092,964
New Hampshire	6,281,033	27,506,231	6,996,560	595,548	1,451,991	499,599
New Jersey	40,743,458	210,349,554	62,866,982	3,869,922	11,122,790	4,502,165
New Mexico	33,674,483	17,129,439	15,420,374	3,192,005	904,754	1,101,770
New York	71,574,497	336,117,072	128,162,568	6,790,534	17,752,481	9,161,597
North Carolina	142,395,059	138,642,117	79,391,248	13,513,560	7,329,874	5,673,934
North Dakota	22,466,502	9,712,423	18,387,564	2,126,930	514,164	1,311,826

—continued

Table 4
Food-related annual fossil fuel consumption and carbon dioxide emissions, 2007—continued

State	Fossil fuel consumption			Fossil fuel CO_2 emissions		
	Coal	Natural gas	Petroleum products	Coal	Natural gas	Petroleum products
	(million Btu)			*(metric tons)*		
Ohio	267,585,205	125,836,344	101,646,551	25,396,614	6,658,621	7,269,038
Oklahoma	47,067,515	62,018,059	36,851,707	4,467,458	3,278,940	2,634,295
Oregon	11,974,831	53,370,155	36,057,599	1,137,981	2,824,390	2,578,268
Pennsylvania	184,170,937	220,295,948	100,177,817	17,479,383	11,646,085	7,164,118
Rhode Island	377,625	27,332,727	5,319,283	35,949	1,447,958	381,101
South Carolina	45,622,029	94,823,830	36,805,369	4,323,164	5,005,769	2,627,568
South Dakota	12,264,464	10,270,029	18,742,770	1,164,900	543,802	1,337,395
Tennessee	106,281,653	104,422,111	61,327,967	10,124,133	5,538,057	4,397,638
Texas	255,371,886	449,687,987	222,505,059	24,263,287	23,792,296	15,922,367
Utah	54,636,659	24,059,736	25,698,086	5,191,802	1,273,950	1,841,378
Vermont	694,397	18,395,030	4,920,897	66,055	970,261	351,044
Virginia	88,207,351	124,436,164	60,132,276	8,372,429	6,576,760	4,301,975
Washington	19,473,190	72,256,658	64,871,228	1,852,908	3,828,490	4,641,615
West Virginia	53,845,912	10,619,847	18,136,053	5,091,976	561,312	1,294,961
Wisconsin	120,226,630	117,614,512	70,580,473	11,419,252	6,225,552	5,046,775
Wyoming	16,868,586	4,776,815	10,429,622	1,592,677	252,487	745,165
United States	3,501,929,239	5,330,529,029	2,828,190,284	332,444,827	281,928,853	202,246,579

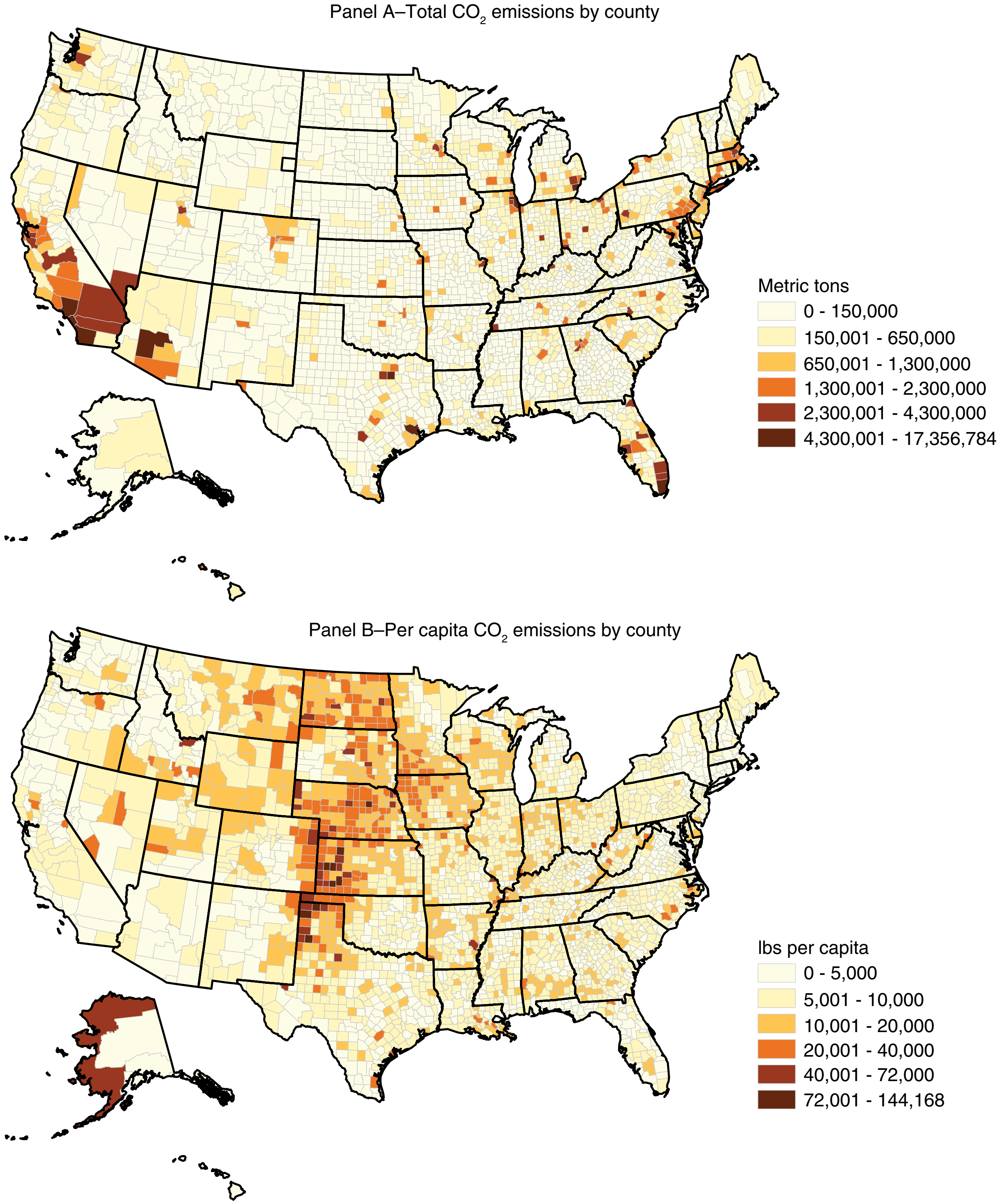
Source: USDA, Economic Research Service.

coal in 2007; for petroleum products, the food system's share was 8 percent of the 2.58 bmt national emissions associated with petroleum products.

Figure 7 shows the spatial distribution of annual CO_2 emissions down to U.S. counties, indicating the source of food-system emissions. This figure depicts data that are based on an assumption that electric power generation in each county derives the same shares of power by fossil fuel sources as the statewide average and also assumes that statewide energy use by type of industry is spatially distributed to counties in proportion to the share of that industry's labor force in each county. Finally, the county emissions data split the allocation of emissions from the commercial transportation industry between the counties where vehicles, vessels, and railcars are most likely to have been launched and the counties where they are most likely to have terminated. These are strong assumptions that will misallocate a small percentage of the overall emission locations, but they expected to be representative of the spatial disposition of overall 2007 food-system CO_2 emissions from fossil fuel consumption. For example, food-related energy consumption by the commercial transportation industry represented 8 percent of total food-related energy use in 2007, and the share of emissions from this energy consumption that was neither in the origin or destination counties of all shipments was a small fraction of this total.

Both total CO_2 emissions (panel A) and per capita CO_2 emissions (panel B) are depicted in figure 7. The 10 highest emitting counties list differs across the two metrics. In terms of total emissions

Figure 7
Food-related carbon dioxide emissions by county, 2007



Note: CO_2 emissions are assigned to counties where fossil fuels are used in production, such as electric power plants and household-kitchen natural gas ovens.
Source: USDA, Economic Research Service.

(panel A), 8 of the 10 highest emitting counties are also among the top 10 most populated counties, and the other two top-emitting counties are among the top 20 most populous U.S. counties. These results are not surprising given that household food services and transportation, along with commercial food services, account for about half of total food-related energy use (figure 2). Thus, the most populated counties will also have the largest number of home kitchens and be likely to have more commercial kitchens (foodservice establishments).

The story is very different on a per capita basis (panel B). Of the 10 highest per capita emitting counties, 8 are in Kansas (5) or Texas (3), 6 are in counties with population totals in the bottom 10 percent nationally, and all 10 are in counties with population totals in the bottom 20 percent. These counties are disproportionately farming- and/or food-processing-intensive areas, and are more fossil fuel intensive than other farming and processing areas.

Since CO_2 emissions quickly mix with other gases in the atmosphere, the location of the sources for these emissions are not as important as the quantity of emissions in terms of climate change implications. However, knowledge of the locations where fossil fuels are being used does help in assessing how regional economies are affected by different approaches designed to reduce CO_2 emissions.

We draw a few key points from this section. First, overall food-related energy use remained slightly above 12 qBtu between 1993 and 1998. Electricity represented the most-used energy commodity in the U.S. food system, and household kitchen operations were the largest energy user among agri-food chain stages. Because the national energy budget rose steadily over this period while the food-related energy budget remained flat, the food-related share of the national energy budget declined from 14.0 percent in 1993 to 12.8 percent by 1998. From 1998 to 2002, however, the opposite trend occurred. Food-related energy use rose steadily while the national energy budget remained flat. This led to a rebound in the food-related share, reaching 13.8 percent by 2002. Over the remainder of the study period, both the national energy budget and the food-related energy budget first rose with steeply rising energy prices and then fell with highly volatile energy prices. The net result was a falling food-related energy budget share that declined to 12.4 percent by 2012.

Our econometric analysis of year-to-year changes in the intensity of electricity use throughout the food system produced evidence of a strong and statistically significant relationship between the intensity of electricity use and the relative price of electricity. These results help to explain the macro trends in food system energy use. In comparison to evidence of economywide price response in the literature, our results indicate that energy use is more responsive to price in the food system.

An extension of the energy flow analysis to U.S. States (see table 4) facilitated the estimation of carbon dioxide emissions from the use of fossil fuels. This analysis shows that the 2007 U.S. food system had a more fossil-fuel-intensive energy use profile than did the national system. As a result, the U.S. food system had a carbon footprint that was 11 percent larger than its energy footprint. Projecting food-related CO_2 emission estimates out to U.S. counties, we find that the top 10 counties in terms of food-related CO_2 emissions were all among the top 20 most populated counties, whereas the 10 highest per capita CO_2 emission counties were among the least populated counties. The analysis in this section could be extended to more recent years as data become available.

Evaluating Nutrition Promotion and a CO_2 Emissions Tax

To assess whether nutrition promotion through the 2010 DGA and a hypothetical CO_2 emissions tax tied to the social cost of carbon are complementary, we use data and analysis from the previous section to analyze the effects of each program on aggregate diet quality and total energy use. We begin with an examination of Federal nutrition promotion.

Would Adherence to the Dietary Guidelines for Americans Reduce Food-System Energy Use?

For nutrition promotion, we focus on the DGA, which are published every 5 years by USDA and the U.S. Department of Health and Human Services. The DGA aim to improve the health and well-being of Americans by providing dietary recommendations informed by current nutrition science for Americans age 2 and above. Nutrition promotion is a desirable public effort because a healthy diet along with physical activity can help Americans manage their weight and reduce their risk of chronic diseases (U.S. Department of Agriculture and U.S. Department of Health and Human Services, 2010).

Diets are influenced by many factors, including prices, cultural and ethnic norms, socioeconomic circumstances, climate, and food availability, all of which are broadly represented in the diversity of current American diets. We begin with the hypothesis that increasing the number of Americans following the 2010 DGA would decrease the energy embodied in our diets. For this to hold, current diets must be more energy intensive than the diets resulting from all Americans aligning their food consumption with the DGA. For the likelihood of diets to be objectively determined, evidence of the statistical probabilities for alternative healthy diets is required. Since this is beyond the scope of the data and models available for this research, our approach is to employ a mathematical programming model that determines the minimum required change from average diets for each of 16 different age/gender cohorts (see appendix table A.3) that is necessary to meet the DGA under alternative scenario assumptions, and apply a transparent ad hoc probability-based assessment of the likelihood for the different scenario outcomes.

By analyzing the 2010 DGA, we are able to compare our results to those of others in the literature who also used the 2010 DGA as a yardstick to measure healthy diets (Heller and Keoleian, 2015; Tom et al., 2015). Also, we found minor differences when comparing the 2010 DGA to the 2015 DGA, which were released as we finished this report.

To compile the model data, we follow a methodology similar to the *Thrifty Food Plan, 2006* (Carlson et al., 2007). First, data from WWEIA, the dietary intake component of the 2007-2008 NHANES, characterize a baseline American diet. NHANES is a nationally representative survey that is done in 2-year cycles. The NHANES data provide food and beverage consumption by Americans and also the nutrient and caloric content of each item. The 2007-2008 data correspond with the 2007 benchmark accounts, the most recent data that characterize the U.S. economy by detailed sector, used in FEDS.

The USDA Food Patterns recommend consumption by food group at 12 caloric levels, which serve as an example of how to follow the DGA. Food groups such as vegetables or grains are called Food Pattern (FP) components; subgroups include dark-green vegetables or whole grains. We use the Food

Patterns Equivalents Database 2007-2008 (FPED), which converts the food and beverage items from NHANES to the FP components outlined in the USDA Food Patterns.

Next, we link the foods and beverages consumed in NHANES to commodity groups that are based on food expenditure categories from FEDS. To do this, we use the Food and Nutrient Database for Dietary Studies (FNDDS 4.1), which breaks food items into ingredients. With the grams of food as consumed organized by commodity group, we are able to compute 38 energy[15] pathways with unique Btu-per-gram ratios. These 38 pathways are obtained from combinations of the 74 food commodity groups in FEDS (appendix table A.1). The combinations were made to eliminate some ambiguities about correct mappings of NHANES food items to FEDS commodity groups. We map these ratios back to each food item using a weighted average of the commodity makeup. Just as we can trace Btu back to each food item, we can also do this with dollars and calculate the cost for each food item based on FEDS. See Appendix C for more information on the input data sources and description of this methodology.

With the input data compiled, we shift our focus to the model constraints. All of the constraints are weighted based on the age and gender demographics of NHANES participants. First, we assume a moderately active activity level for caloric needs, which we allow to vary by 5 percent above or below the target to give the model flexibility (see Appendix 6 in U.S. Department of Agriculture and U.S. Department of Health and Human Services, 2010). Second, we include the FP components using the subcomponents for grains, vegetables, and protein foods (see Appendix 7 in U.S. Department of Agriculture and U.S. Department of Health and Human Services, 2010). Daily alcohol limits are also included and are set at zero for those under the legal drinking age. Last, we impose 33 nutrient targets as constraints (as listed in Appendix 5 of the 2010 DGA, derived mostly from the Institute of Medicine (2016)). These are supplemented by Tolerable Upper Intake Levels (ULs) when necessary (Institute of Medicine, n.d.). A complete list of the constraints is available in appendix table C.2, and further details are provided in Appendix C. Appendix C also formally states the mathematical optimization model.

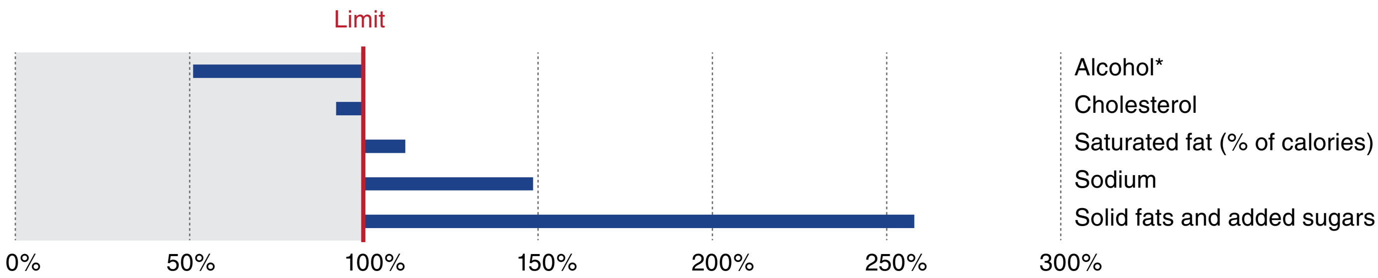
Assessment of the Baseline Diet shows that average consumption in the United States is not in line with the 2010 DGA. Figures 8-10 show all of the dietary constraints and where the baseline falls relative to these constraints. The shaded area is recommended levels of consumption; consumption should be at or above the goal (lower bound) and below the limit (upper bound). Figure 8 shows the dietary constraints with only a consumption limit and shows that the average American exceeds three out of five of these limits. Figure 9 shows the dietary constraints with only a consumption goal. In this case, there is underconsumption in 14 of the 24 dietary components in the Baseline Diet. Those nutrients with both a goal and a limit on consumption are shown in figure 10; there are no FP components with both a goal and a limit. Overall, the Baseline Diet misses the mark on 6 of these 20 constraints.

We run several versions of the diet optimization model, each with a unique combination of constraint sets and objective functions. The constraint sets, objective functions, and model results are described in Appendix C. We chose to highlight two diets from the modeling, which we refer to as the Realistic Healthy Diet and the Energy[16] Efficient Diet.

[15] Recall that we consider both primary energy (Btu) and food energy (calories). We reference their respective units instead of energy to avoid confusion.

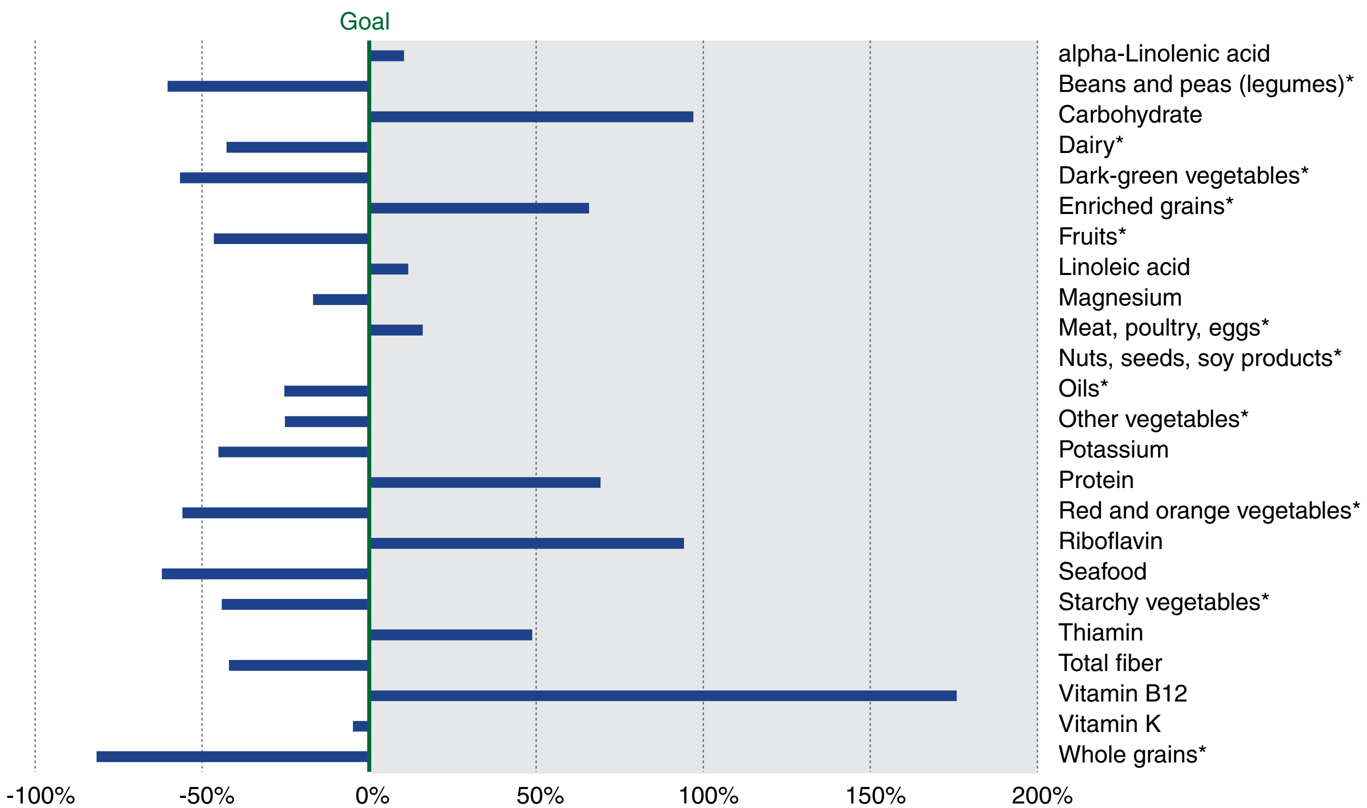
[16] Energy means embodied Btu in this case.

Figure 8
Baseline consumption of nutrients and Food Patterns components with a limit on consumption only



Note: Food Patterns components are indicated with an asterisk (*).

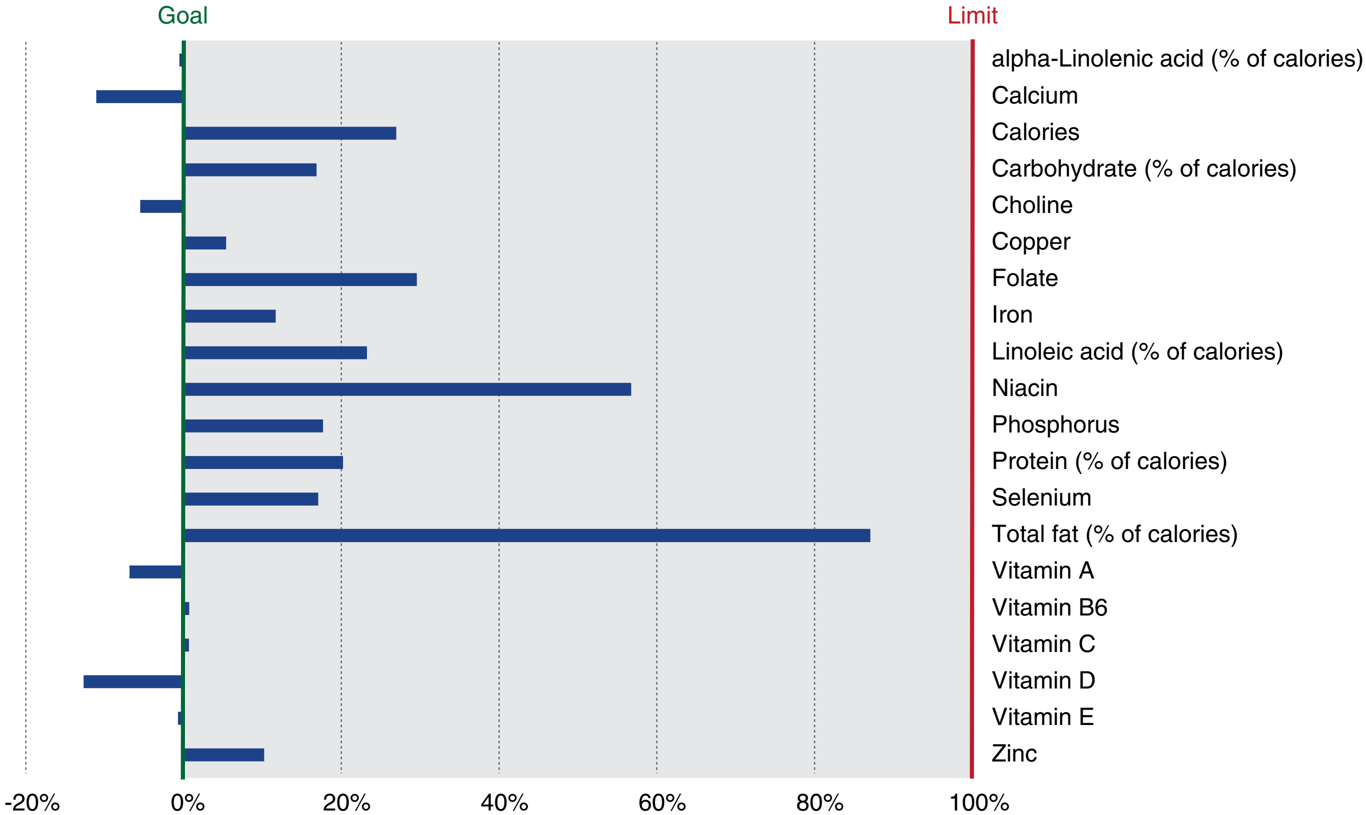
Figure 9
Baseline consumption relative to nutrient and Food Patterns components with a consumption goal only



Note: Food Patterns components are indicated with an asterisk (*).

The Realistic Healthy Diet is output from a model in which the objective is to minimize the changes one would have to make from baseline consumption patterns; in other words, it is the shortest route to eating healthy (appendix equation C.1). The constraints in the model include all dietary constraints and the cost constraint. This is the most restrictive constraint set because it ensures that caloric and nutrient targets are met; forces individuals to eat a diverse, omnivorous diet

Figure 10
Baseline consumption of nutrients with a consumption goal and limit



Note: There are no Food Patterns components with both a goal and a limit. There is only a limit for calories, but we allow calories to vary by 5 percent above or below this goal for flexibility in the model.

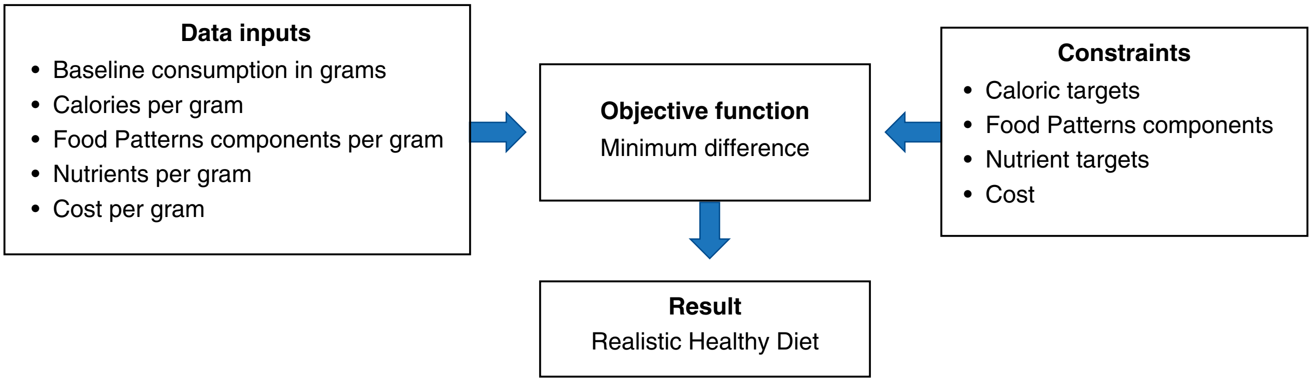
due to the FP components; and maintains a daily wholesale food budget of $4.65 per capita. Figure 11 diagrams the modeling approach. We call the model results the Realistic Healthy Diet because the model minimizes the change from the Baseline Diet, resulting in many of the same food items being consumed and costing the same or less than the Baseline Diet. The maximum-likelihood properties of this diet model make the Realistic Healthy Diet the most representative diet among Americans who are currently aligned with the 2010 DGA (see appendix C). This model results in 2,541 distinct food items being consumed.

We call results from the second model the Energy Efficient Diet (figure 12). This model's objective is to minimize Btu while shifting to a healthy diet (appendix equation C.3). In this case, we allow greater changes from the Baseline Diet. We include only the caloric and nutrient constraints in this model. The cost constraint is unnecessary since all of the resulting diets cost less than the Baseline Diet. This model has the flexibility to make more than a minimal change from baseline consumption and is not restricted by the FP components. This means that any food items in the NHANES data can be selected if caloric and nutritional needs are met. There are 85 distinct food items consumed in this diet.

Figure 13 compares the results from both models for the total population using two metrics: Btu and cost. The Realistic Healthy Diet reduces Btu by 3 percent while the cost is the same as in the

Figure 11

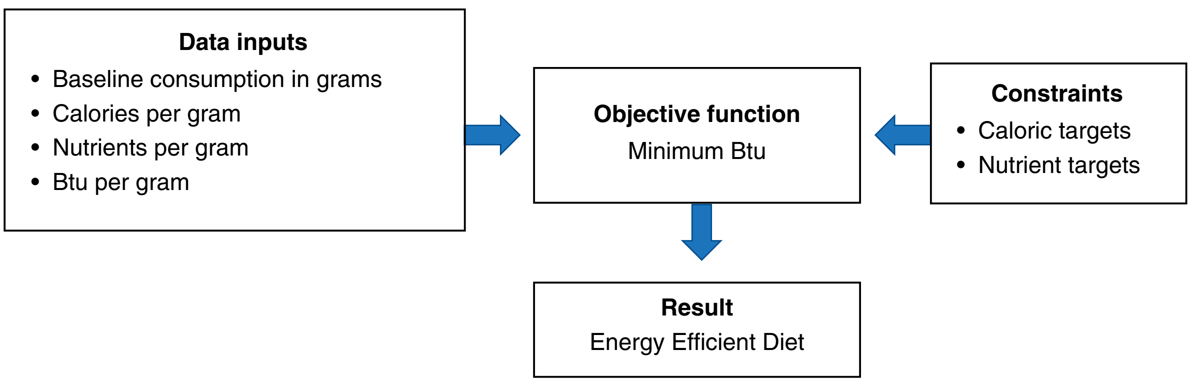
Model diagram for the Realistic Healthy Diet



Source: USDA, Economic Research Service.

Figure 12

Model diagram for the Energy Efficient Diet



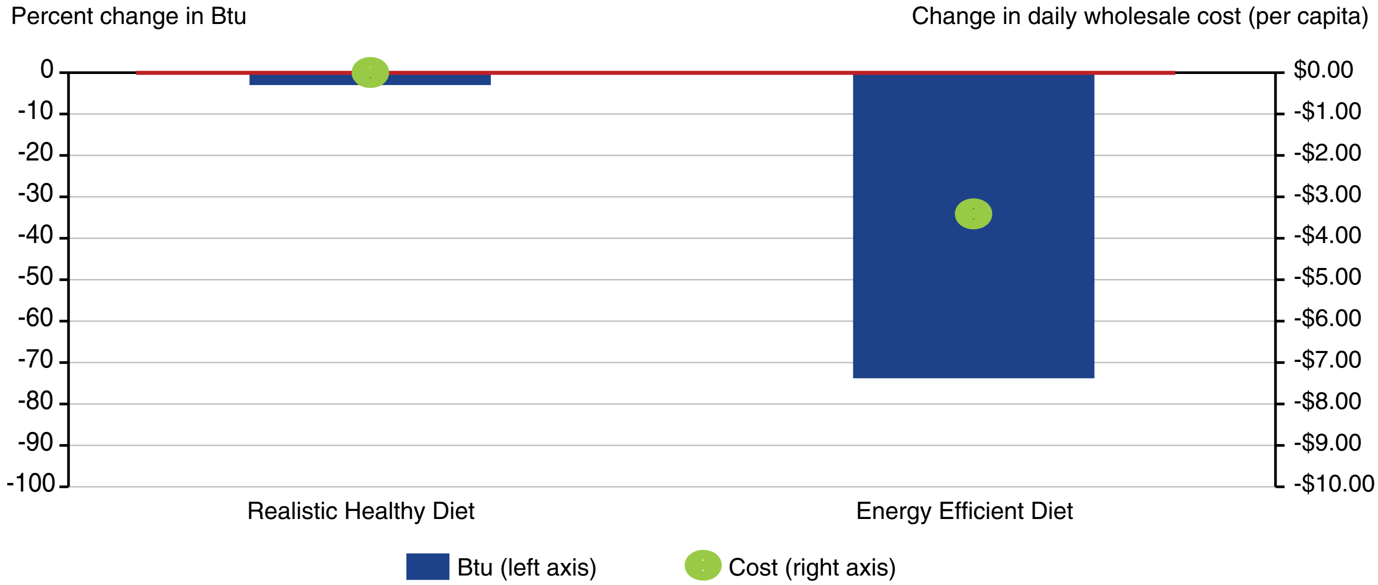
Source: USDA, Economic Research Service.

Baseline Diet. To put this in context, a 3-percent reduction in total 2007 diet-related[17] energy use is equivalent to the annual gasoline consumption of 3.7 million U.S. vehicles.[18] In the Energy Efficient Diet, wholesale costs decrease by $3.41 per person per day and Btu decrease by 74 percent compared to the Baseline Diet. Having the Energy Efficient Diet become the new average diet among all Americans would represent an extreme change in the food choices of average Americans. To put this in context, a 74-percent reduction in total 2007 diet-related energy use is equivalent to the

[17] We use "diet-related" as a subset of total food-system energy use, which excludes the kitchen operation energy use and grocery trips.

[18] This was calculated by multiplying the Btu embodied in the Baseline Diet by the percentage change. Then, we divide by 120,476, the Btu in a gallon of gasoline (U.S. Energy Information Administration, 2015). Next, we multiply by 25.2, the average miles per gallon reported for October 2015 (University of Michigan, 2016). Finally, we divide by 13,472, the total average annual miles driven in the United States (U.S. Department of Transportation, 2015).

Figure 13
Selected model results relative to Baseline Diet



Source: USDA, Economic Research Service.

annual gasoline consumption of 90 million vehicles, or more than one-third of the vehicles in the United States.[19]

We report detailed results for the Realistic Healthy Diet and the Energy Efficient Diet relative to the Baseline Diet. Figures 14 and 15 present the results in calories[20] and Btu, respectively. We aggregate foods into 9 food groups by the first digit of the USDA food code (see Appendix B in U.S. Department of Agriculture, Agricultural Research Service, Food Surveys Research Group, 2010b). In the Baseline Diet, the most calories come from grain products. While grain products account for 724 calories, or 35 percent of the total, they account for only 21 percent of Btu. The largest contributor to Btu in the Baseline Diet is sugar, sweets, and beverages with 2.13 qBtu, or 27 percent of total Btu.

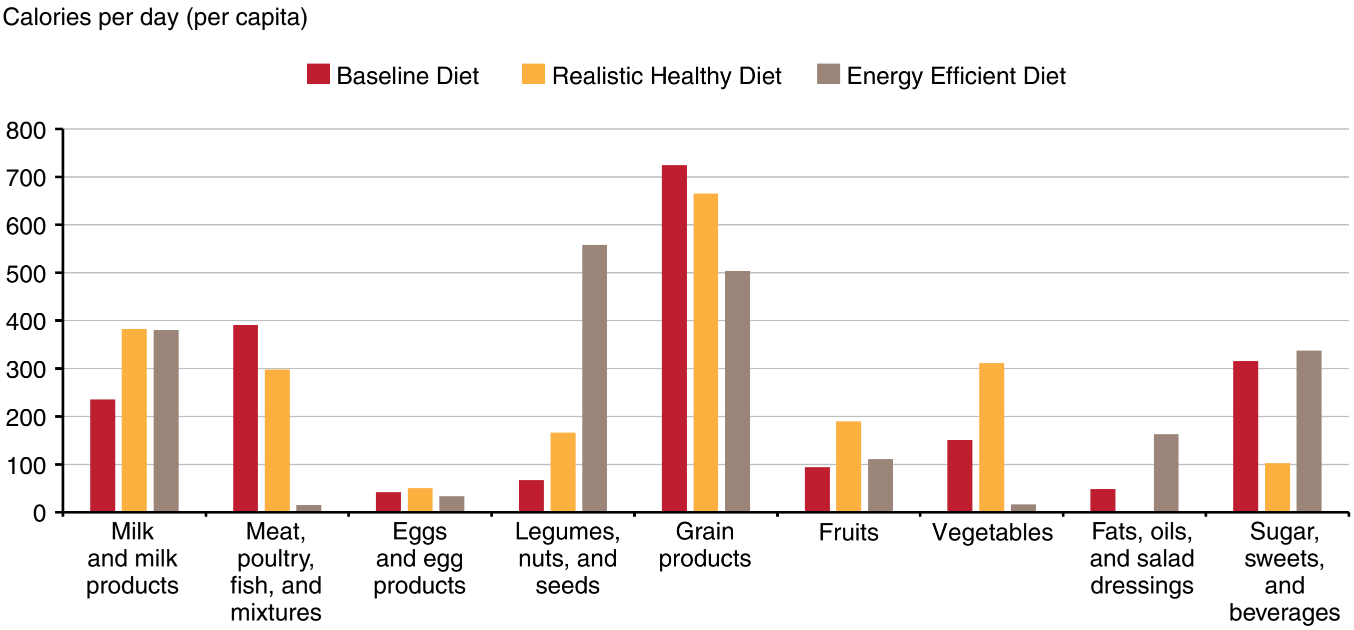
In the Realistic Healthy Diet, although calories from grain products are reduced to 665 calories, grain products are still the largest contributor to total caloric intake at 31 percent. However, grain products contribute a lesser share (16 percent) to total embodied Btu (1.22 qBtu). Similar to the Baseline Diet, the most Btu embodied in the Realistic Healthy Diet come from meat, poultry, fish, and mixtures. Meat, poultry, fish, and mixtures represent 30 percent of total Btu while only supplying 298 calories, or 14 percent of total calories.

The Energy Efficient Diet results in a different ranking of food groups. Legumes, seeds, and nuts are the largest contributor to calories with 558 (26 percent of the total), followed closely by grain products with 503 calories (24 percent of the total). Grain products contribute 0.46 qBtu, or 22 percent of

[19] Calculated same as in footnote 18, except with a 74-percent change. There were 255.8 million registered highway vehicles in 2013 (U.S. Department of Transportation, Bureau of Transportation Statistics, n.d.).

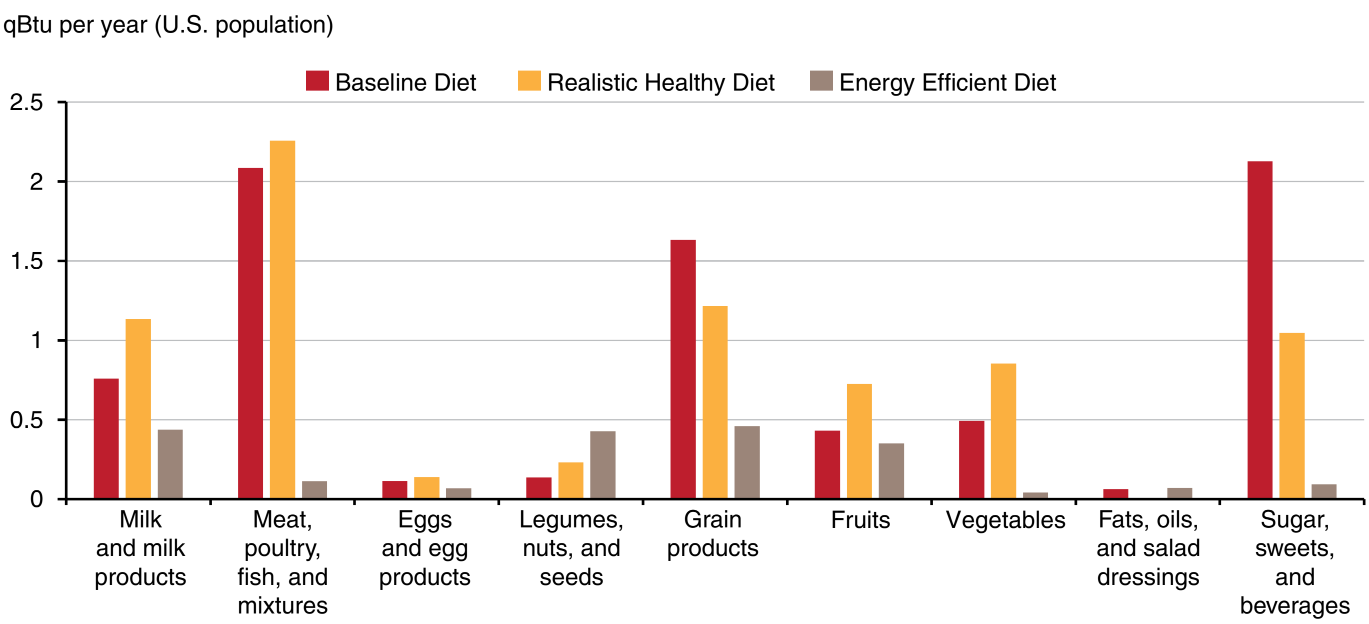
[20] In our work, 1 calorie refers to a kilocalorie, or food calorie, equivalent to 4,184 joules.

Figure 14
Calories by food group in Baseline, Realistic Healthy, and Energy Efficient Diets



Source: USDA, Economic Research Service.

Figure 15
Btu by food group in Baseline, Realistic Healthy, and Energy Efficient Diets



Source: USDA, Economic Research Service.

total Btu, in the Energy Efficient Diet. The legumes, nuts, and seeds and milk/milk products categories each contribute 21 percent of embodied Btu in this diet.

When looking at the detailed food items in the Energy Efficient Diet, the model chooses much less variety, but more nutrient-dense items. Even if an item does not have the lowest Btu per gram, it may be able to meet more nutrient goals and thus be favored by the model. The Energy Efficient Diet is a pescatarian diet,[21] meaning the model did not choose any meat or poultry items.

It may be counterintuitive that calories from milk and milk products increase in the Energy Efficient Diet while the Btu decrease relative to the Baseline Diet. We see this relationship because dietary composition changes both in terms of food groups as well as composition of food items within the food groups. The results indicate that, in the Energy Efficient Diet, the combination of milk and milk products is less energy intensive than in the Baseline Diet. In other words, Energy Efficient Diet favors the milk and milk products that have a lower energy requirement (per gram) across all production stages and are still able to conform to the caloric and nutrient targets in DGA.

This highlights the importance of interpreting the results correctly. The models choose a different product mix, not just different quantities. To provide another example, bananas are the most-consumed fresh fruit on a caloric basis in both the Baseline Diet and the Realistic Healthy Diet. In the Energy Efficient Diet, the most-consumed fresh fruit in terms of calories is an avocado. This does not mean that the avocado is the most efficiently produced fruit. Rather, it means that the avocado is an energy efficient source of nutrients, as a part of a total diet that conforms to the caloric and nutrient targets in the DGA.

Another way to examine a shift to the Realistic Healthy and Energy Efficient Diets is percentage change from the Baseline Diet (table 5). Overall, substantial changes in each food category are required in both the Realistic Healthy Diet and the Energy Efficient Diet.

If shifting from the Baseline to the Realistic Healthy Diet, the largest increase in calories (147 percent) is required in legumes, nuts, and seeds; whereas the largest reduction in calories (96 percent) is in the fats, oils, and salad dressings category. If shifting to the Energy Efficient Diet, calories from legumes, nuts, and seeds need to again increase the most; this time the increase is sevenfold from Baseline Diet consumption. Foods that fall in the meat, poultry, fish, and mixtures category are reduced by 96 percent, the largest caloric decrease in the Energy Efficient Diet.

In terms of Btu relative to the Baseline Diet, vegetables increase most in the Realistic Healthy Diet (73 percent) resulting from the small quantities currently consumed in these food categories; quantities that are well below the DGA's recommended level. Legumes, nuts, and seeds increase the most in the Energy Efficient Diet (212 percent). The largest reduction in Btu is 94 percent for fats, oils, and salad dressings in the Realistic Healthy Diet; the largest reduction in Btu in the Energy Efficient Diet is for sugar, sweets, and beverages, at 96 percent.

Recalling our hypothesis that Btu reductions are more likely under healthy diets, such assessments are possible under the following conditions:

i. More Americans would adopt the Realistic Healthy Diet than other healthy diets;

ii. The range of possible healthy diets are normally distributed from low to high Btu outcomes; and

[21] A pescatarian diet is a plant-based diet that includes dairy, eggs, fish, and seafood, but excludes meat and poultry.

Table 5
Percentage change by food group from Baseline Diet

	Realistic Healthy Diet		Energy Efficient Diet	
	Calories	Btu	Calories	Btu
Milk and milk products	63%	49%	62%	-42%
Meat, poultry, fish, and mixtures	-24%	8%	-96%	-95%
Eggs and egg products	21%	22%	-20%	-41%
Legumes, nuts, and seeds	147%	69%	728%	212%
Grain products	-8%	-26%	-31%	-72%
Fruits	102%	68%	18%	-19%
Vegetables	106%	73%	-89%	-92%
Fats, oils, and salad dressings	-96%	-94%	233%	11%
Sugar, sweets, and beverages	-67%	-51%	7%	-96%

Source: USDA, Economic Research Service

iii. Virtually all Americans adopt diets within four standard deviations of the most common diet.

Under these assumptions, the Z-statistic for the Baseline Diet is 0.17, implying Pr(Z<Baseline) = 0.57.[22] This means that among Americans who align their diets with the DGA, three in five of these healthy diets would reduce food-system energy use relative to the Baseline Diet.

A result worth highlighting is that all of the alternative diets include animal products, suggesting that animal products may be part of a healthy and energy-efficient diet. The healthy diets including food items from the meat, poultry, fish, and mixtures category may reduce Btu compared to the Baseline Diet, depending on the amount and type of food items in this category. While the Energy Efficient Diet—the diet that reduces Btu the most—does not include meat and poultry, it does include fish, eggs, and dairy products.

In their paper, Barosh et al. (2014) find the diet that is both healthy and sustainable to be more expensive for each of the five demographic groups they study. The most disadvantaged group faces the largest proportional increase in diet cost, at 30 percent. However, our results show that a healthy diet that also reduces Btu may have the same wholesale cost as the Baseline Diet, or be even less expensive, although in our model there is no price response from changes in demand.

We also assume that these diets are produced with 2007 food-system technologies since this is the most recent year of detailed data that we have in FEDS. Additionally, implicit in the IO models is the assumption of perfectly elastic supply curves. This means that we assume the U.S. food system could supply any amount of the food items that are part of the healthy diets without affecting prices and that extends to import products too. A limitation of these assumptions if major shifts in American diets take place is that supply constraints may occur for certain foods, leading to price changes that affect affordability, purchasing choices, and the role of imports in the food system.

[22] Measured as $Z = (X-\mu)/\sigma$ where X is Btu in the Baseline Diet, μ is Btu in the Realistic Healthy Diet, and σ is 0.25*(minBtu - realistic), where “realistic” is shorthand for food-system energy (Btu) required by the Realistic Healthy Diet and “minBtu” is shorthand for energy used by the Energy Efficient Diet.

There are other limitations to the analysis in this section. As mentioned, underreporting in NHANES is documented (Subar et al., 2015), so we acknowledge that the Baseline Diet is likely the lower bound of consumption. Therefore, the Btu embodied in the Baseline Diet and the Btu savings by switching to one of the alternative diets may be underestimated. Additionally, we assume that each of the items or ingredients are mapped to the linear combinations of 74 energy pathways that are further aggregated to 38, and this limits the measured variation in Btu per gram across different diet choices. Also, the assumptions imposed to estimate the likelihood of individuals choosing among possible healthy diets would benefit from further research to determine whether our underlying assumptions are realistic. Finally, our scenario that all Americans will shift to a healthier diet is hypothetical. Even if less energy-intensive diets exist, there are many challenges surrounding dietary change. Americans make dietary choices based on tastes, preferences, habits, culture, convenience, and price, among other things.

Would a CO_2 Emissions Tax Influence Dietary Choice Through Cost and Price Effects?

Now we address a CO_2 emissions tax in relation to dietary patterns. Prices paid for a food or beverage product reflect the total value added by all industries that participate in making this product available for final market purchase. This is stated formally in appendix equation B.3, where value added represents the compensation for the use of materials and services from primary factors such as labor, capital, and resources like fossil fuels. This compensation to primary factors typically must at least cover the costs to the owners of those factors for making their materials and services available for use. In addition, factor owners will charge an economic rent that reflects market value to the purchaser from the use of that factor in production. The outcome of this market structure is that for any primary factor, unit price equals unit supply costs plus a unit rental cost.

Like other primary factors, fossil fuels are associated with environmental externalities whose costs are not reflected in this "costs plus rent" price formulation. One of these externalities from the use of fossil fuels is the emission of carbon dioxide into the atmosphere. Worldwide emissions are occurring at rates higher than the natural rates of assimilation that remove these gasses from the atmosphere. The net impact of this situation is increasing accumulations of CO_2 into the atmosphere, thus contributing to the greenhouse effect of rising temperatures worldwide (Karl et al., 2009). Climate scientists studying this effect produce measures of economic costs from rising temperatures, and the uncertainty in these measures is reflected in the wide range of cost estimates (IAWGSCC, 2015). However, the cost-plus-rent price formation mechanism for primary factors described above does not incorporate these societal costs into the formation of market prices.

Economists have long recognized that the internalization of external costs, such as through taxation, can lead to more efficient market outcomes if the government can accurately gauge the social cost (Pigou, 1920). For example, consider an industry's decision to purchase fossil fuels at a price that does not reflect external costs. Like other inputs, the industry will purchase the amount of this fuel that maximizes the expected profits from its use. Next, suppose the industry is charged for the societal costs of its use of fossil fuels. This charge will offset the expected profits such that the industry will be able to increase net profits by decreasing its use of fossil fuels, since this will reduce costs faster than it will reduce revenues. This reduction in use will continue until the point where both costs and revenues fall by the same amount. If all users of fossil fuels are accurately charged for the true external costs, one can analytically show that fossil fuel use will occur at its socially optimal level. Both the measurement of social costs from fossil fuel use and the appropriate mechanism for internalizing this cost in energy markets are the two great challenges facing the United States and other nations seeking to reduce their carbon emissions.

In our research, we broaden the consideration of what constitutes the socially optimal cost of fossil fuel use by assessing the potential spillover effects of higher fuel costs on American diets. Current estimates of the social costs of CO_2 emissions in the United States were recently published by the IAWGSCC (Interagency Working Group on the Social Cost of Carbon, 2015). We consider a hypothetical implementation of a fossil fuel CO_2 tax that reflects the wide range of current estimates of the social cost of CO_2 emissions and measure the food costs and relative commodity price effects of this tax.

In 2010, the IAWGSCC developed its original estimates on the social costs of carbon (SCC) in order to allow agencies to incorporate the social benefits of reducing carbon dioxide emissions into cost-benefit analysis of regulatory actions that impact cumulative global emissions. In July 2015, the original 2010 estimates were revised (IAWGSCC, 2015). Here, we consider three hypothetical CO_2 tax rates on fossil fuel use representing the 5th percentile, average, and 95th percentile of SCC estimates when ordered from low-cost to high-cost values.[23] Costs represent present discounted values of current and future monetized damages (2007 dollars) from carbon emissions that are not reflected in any market transactions. Examples include human health, agricultural productivity, increased flood risk, and property damages. The low, average, and high tax-rate assumptions are $6, $42, and $123 respectively per metric ton of CO_2 emissions. These costs assume a year 2020 implementation, a 3-percent discount rate, and use of the 5th, 95th, and average cost estimates from 150,000 model simulations spanning 3 models and 5 scenarios (IAWGSCC, 2015); the range of results we consider reflects 90 percent of the potential SCC estimates from these models. These tax rates are in 2007 U.S. dollars, in order to correspond to the 2007 data used in the energy and dietary analysis.

Modeling the price impacts and behavioral adjustments along the U.S. agri-food chain from a hypothetical CO_2 tax is a complex research challenge. For example, a recent study of alternative CO_2 taxes on electric power generation in the United States found that if such a tax were based on the IAWGSCC 2010 cost estimates, it would induce the industry to substitute natural gas or wind and nuclear fuel sources for coal, depending on whether the tax rate is based on the lower or higher cost estimates of the IAWGSCC (Paul et al., 2013). Using the results from estimating the relationship between food-system energy intensity for electricity and changes in electricity prices, we demonstrate a similar response by agri-food chain industries (figure 5). In both cases, industries facing the new tax reduce their use of the higher priced energy source to mitigate price impacts. Similar behaviors are anticipated for non-electricity energy markets such as natural gas and petroleum products, both of which have substantial roles in the U.S. food system. Further, any tax-induced price impacts that do get passed on to consumers in the form of retail food prices will likely cause consumers to adjust their food purchasing behaviors in order to further mitigate the cost impacts of the tax.

Rather than accounting for all of the behavioral changes that are induced by the introduction of a tax on fossil fuel CO_2 emissions, we trace the total cost of such a tax that would be passed onto food consumers. This assumes that no behavioral adjustments occur and that all tax burdens levied to fossil fuel users are completely passed on to buyers of the energy-using industry outputs. Using our estimates on food-related CO_2 emissions (table 4), we trace contributions of the tax on fossil fuel

[23] The SCC ranges come from the output of 3 different models, each running 10,000 simulations for 5 different model scenarios (see appendix table A.3 in IAWGSCC, 2015).

CO_2 emissions to retail costs for each individual food commodity represented in the FEDS model (see appendix table A.1). With the measures of embodied CO_2 emissions already in metric ton units, we multiply these emission measures by the lower, upper, and average 2020 SCC tax rates per metric ton of CO_2 emissions to produce a range of estimates of the total potential tax burden on each food commodity market. Then, dividing this figure by total grams consumed in each commodity group produces an average CO_2 tax rate range per gram consumed for each of the 4,000-plus food items consumed in each of the diets examined in this study.

Table 6 reports the range of potential tax burdens on the Baseline Diet, the Realistic Healthy Diet, and the Energy Efficient Diet. In the first three columns, total annual potential tax revenues are reported under the assumption that each of the three diets represents the annual average diet of all Americans age 2 and older in the study period of 2007. The numbers indicate that total diet purchases of all Americans in 2007 would have cost between \$3.0 billion and \$62.2 billion in CO_2 taxes under the Baseline Diet, with the average expected tax revenue of \$21.2 billion. Under the Realistic Healthy Diet scenario, between \$3.0 billion and \$60.5 billion in CO_2 taxes would be paid, with the average expected revenue of \$20.7 billion. Whereas total embodied Btu from all energy sources under the Realistic Healthy Diet is 3 percent lower than in the Baseline Diet, total tax revenue between the two diets is slightly closer, as revenues under the Realistic Healthy Diet are 2.7 percent lower than Baseline Diet revenues. This divergence between Btu and CO_2 tax revenues is attributed to the result that embodied energy in Realistic Healthy Diets has a slightly higher (0.3 percent on average) carbon content than in Baseline Diets. Under the Energy Efficient Diet scenario, between \$0.8 billion and \$15.7 billion in CO_2 taxes would be paid, with an average expected revenue of \$5.4 billion. In this case, the embodied energy has a lower (3.8 percent on average) carbon content than in Baseline Diets.

Columns 4 to 6 translate these total tax burdens into percentages of their pre-tax retail costs. Viewed in this way, the numbers indicate that a meal would cost between 0.2 and 5.0 percent more with the tax for both the Baseline and Realistic Healthy Diets, and the average expected cost increase of both diets is 1.7 percent. For example, for each \$100 spent on food and beverages, the CO_2 tax would add between 20 cents and \$5, with an average expected cost increase being \$1.70 for both the Baseline and Realistic Healthy Diets. Although the Realistic Healthy Diet has a slightly lower tax rate if reported to the second decimal, the two diets have ostensibly the same tax rate. This apparent contradiction of unequal tax revenues and equal tax rates is explained by the fact that the Realistic Healthy Diet had an overall retail price tag that was 2.3 percent lower even though the wholesale price tags were about the same. Recall that the budget constraint in the Realistic Healthy Diet model was wholesale costs.[24] It turns out that the foods in the Healthy Diets model had a slightly lower average retail-markup rate, roughly equal to the percent decrease in tax revenues in the same diet. This outcome led to both diets having roughly equal tax rates. This result is even more pronounced when comparing the Baseline and Energy Efficient Diets. Energy Efficient Diets have a wholesale price tag that is about 72 percent lower and a retail price tag that is about 75.5 percent lower than the Baseline Diet wholesale and retail price tags. Since tax revenues are down slightly under 75 percent for this diet, the average tax rate per retail dollar is actually higher, averaging 1.9 percent.

[24] Wholesale cost constraints were used in the Realistic Healthy Diet model to avoid the outcome of having healthy diet choices disproportionately reduce foods more often purchased at food service establishments, since such purchases have a larger retail markup. This outcome would represent a large behavioral change and so be less "realistic" (see Appendix C).

Table 6

Potential annual revenues and average tax rates from a range of (per metric ton) CO_2 tax levels on fossil fuel use

Item	Baseline Diet	Realistic Healthy Diet	Energy Efficient Diet	Baseline Diet	Realistic Healthy Diet	Energy Efficient Diet
	CO_2 tax revenues (million dollars)			*Average CO_2 tax rate (percent)*		
	Average SCC tax rate ($42 per metric ton of CO_2 emissions)					
Total Diet	**21,233**	**20,659**	**5,359**	**1.7**	**1.7**	**1.9**
Milk and milk products	2,083	3,133	1,205	1.8	2.1	2.0
Meat, poultry, fish, and mixtures	5,794	6,233	308	1.7	1.5	1.2
Eggs and egg products	324	398	194	2.3	2.5	2.7
Legumes, nuts, and seeds	370	625	1,150	1.8	1.7	1.9
Grain products	4,329	3,123	1,091	1.9	1.9	2.1
Fruits	1,169	1,974	855	1.7	1.6	1.7
Vegetables	1,340	2,331	112	1.7	1.6	1.6
Fats, oils, and salad dressings	168	10	192	1.7	1.5	1.7
Sugars and sweets	547	48	0	2.0	1.9	0.0
Beverages	5,110	2,785	251	1.5	1.6	1.4
Kitchen operations/grocery trips	**13,067**	*	*	**10.1**	*	*
	5th Percentile SCC tax rate ($6 per metric ton of CO_2 emissions)					
Total Diet	**3,033**	**2,951**	**766**	**0.2**	**0.2**	**0.3**
Milk and milk products	298	448	172	0.3	0.3	0.3
Meat, poultry, fish, and mixtures	828	890	44	0.2	0.2	0.2
Eggs and egg products	46	57	28	0.3	0.4	0.4
Legumes, nuts, and seeds	53	89	164	0.3	0.2	0.3
Grain products	618	446	156	0.3	0.3	0.3
Fruits	167	282	122	0.2	0.2	0.2
Vegetables	191	333	16	0.2	0.2	0.2
Fats, oils, and salad dressings	24	1	27	0.2	0.2	0.2
Sugars and sweets	78	7	0	0.3	0.3	0.0
Beverages	730	398	36	0.2	0.2	0.2
Kitchen operations/grocery trips	**1,867**	*	*	**1.4**	*	*
	95th Percentile SCC tax rate ($123 per metric ton of CO_2 emissions)					
Total Diet	**62,182**	**60,502**	**15,694**	**5.0**	**5.0**	**5.4**
Milk and milk products	6,099	9,175	3,530	5.2	6.1	5.9
Meat, poultry, fish, and mixtures	16,968	18,253	902	5.0	4.4	3.5
Eggs and egg products	949	1,166	569	6.7	7.5	7.9
Legumes, nuts, and seeds	1,083	1,830	3,367	5.3	5.1	5.7
Grain products	12,678	9,145	3,195	5.5	5.6	6.3

—continued

Table 6

Potential annual revenues and average tax rates from a range of (per metric ton) CO_2 tax levels on fossil fuel use—continued

Item	Baseline Diet	Realistic Healthy Diet	Energy Efficient Diet	Baseline Diet	Realistic Healthy Diet	Energy Efficient Diet
	CO_2 tax revenues (million dollars)			*Average CO_2 tax rate (percent)*		
	95th Percentile SCC tax rate ($123 per metric ton of CO_2 emissions)					
Fruits	3,423	5,780	2,505	4.9	4.7	5.0
Vegetables	3,923	6,826	329	5.0	4.8	4.7
Fats, oils, and salad dressings	492	30	562	5.0	4.5	4.8
Sugars and sweets	1,602	141	0	5.7	5.7	0.0
Beverages	14,965	8,155	735	4.4	4.7	4.2
Kitchen operations/grocery trips	**38,267**	*	*	**29.6**	*	*

Note. Kitchen operations and grocery trips are indeterminate under the "Realistic" and "Energy Efficient" healthy diet scenarios.
Source: USDA, Economic Research Service.

For all three diets, eggs and egg products have the highest tax rates, ranging from 2.3 to 2.7 percent on average. The food groups with the lowest tax rates vary by diet. In the Baseline Diet, beverages have the lowest tax rate at 1.5 percent on average, while the "meat, poultry, fish, and mixtures" plus "fats, oils, and salad dressings" categories both have the lowest tax rates in the Realistic Healthy Diet, at 1.5 percent on average. For the Energy Efficient Diet, the lowest tax rate also falls on meat, poultry, fish and mixtures, but is even lower at 1.2 percent on average.

Potential CO_2 tax burdens on home kitchen operations and household food-related transportation are not associated with the alternative diets since we do not have sufficient information to determine how kitchen operations would change under the alternative diet scenarios. The data indicate that the CO_2 tax is at a substantially higher rate for home kitchen operations, with an average tax rate of about 10.1 percent of the pre-tax cost to operate these home kitchens, and lower and upper ranges of 1.4 and 29.6 percent, respectively. But whether this result would encourage households to eat out more often depends on how households view the value of their efforts spent on home food preparation. To explain, consider an identical meal that is one day prepared at home and the next day purchased at a restaurant. It is likely that the embodied energy and, by extension, the total CO_2 tax bill of the two meals will be very similar. However, the cost of the meal eaten away from home will likely be higher as well, such that the tax rate (tax as a percent of pre-tax cost) on the meal away from home will be lower. Thus whether the consumer views the roughly equal total tax on both meals as an incentive to increase or decrease the number of times he or she eats out depends on the value each consumer places on his or her home kitchen services (including consumers' own time and effort). If they equate this value to the extra cost of purchasing the meal at a restaurant, they will likely view the tax rate as equal, and so the CO_2 tax will be neutral in terms of the eating-at-home versus eating-out decision.

Related to this issue, our research does not account for any changes in the amount of home kitchen services that are associated with the healthy diet scenarios. If the mix of food products in the healthy diet scenarios include far less processed foods, these healthier diets might require more post-purchase processing and, thus, more home kitchen services. However, this logic may not hold up to a closer examination. For this reason, this study does not attempt to predict how a CO_2 tax or nutrition promotion might affect decisions about food preparation.[25]

Although the rates of taxation on different food groups have clear differences, the overall rate of taxation on the typical Baseline meal and the typical Realistic Healthy meal are virtually the same. In addition, after markets react to the tax, price and cost impacts will be lower. To gauge by how much, consider that without market reactions, our calculations represent 13.6 percent of total CO_2 tax revenues, since the food system accounts for that percentage of total CO_2 emissions from fossil fuels economy-wide. This implies that the total annual tax revenue would have been $252.2 billion ($34.3 bil./0.136). Economists at Resources for the Future (2012) studied this issue and concluded that a tax of $25 per ton of CO_2 would raise approximately $125 billion annually after factoring in market reaction.[26] If we scaled our analysis to a $25 tax rate, we would expect approximately $150 billion in annual tax revenues (252 * 25/42). This "back of the envelope" calculation suggests that market reactions to the tax would lower overall tax revenues by about 17 percent.

Turning to our research question, we ask whether a CO_2 emissions tax on fossil fuel use will have a significant influence on diet outcomes. The SCC estimates are wide-ranging, reflecting the uncertainty in measuring these costs. Estimates on the low-cost end produce very low tax rates on food. Estimates on the high end are about 20 times larger than the low-end estimate and the average SCC estimate is 7 times larger. But, making a case that these higher cost estimates will influence diet outcomes is still difficult. For example, the Baseline Diet in this study is the average diet across all Americans ages 2 and above and is a diet that is statistically the most likely to reflect actual diets of more Americans than other healthy diets. Given the maximum likelihood properties of the Realistic Healthy Diet (see appendix C), it is also likely that many Americans are currently choosing this diet. Tax economists have long argued that taxing economic choices at a flat rate has a "neutral" effect on those choices since it does not affect their relative prices (Slemrod, 1990). From a complete diet perspective, the hypothetical carbon tax results reported in table 6 suggest that those Americans consuming the Baseline Diet and those consuming the Realistic Healthy Diet would both face the same tax rate, which averages 1.7 percent, and should have a neutral effect on those choosing between the two diets.

But diets are made up of many choices, and the data in this study identify over 4,000 choices. In table 6, tax rates on those choices are summarized for 10 food groups. On the low-cost end of possible SCC estimates, tax rates range from 0.2 to 0.3 percent across the 10 food groups (0.4 for egg products in the Energy Efficient Diet), and this again does not suggest a substantial influence on diet choices. On the high-cost end of possible SCC estimates, tax rates range between 4.4 and 6.7 percent for the Baseline Diet, and between 4.4 and 7.5 percent for the Realistic Healthy Diet. These ranges are likely to induce diet changes. But answering whether these changes lead to more or less healthy diets requires a more indepth study, such as demand systems analysis, which was not undertaken in this study. For average SCC estimates, tax rates range between 1.5 and 2.5 percent, which is nearly a flat range of tax rates; however, each of these food groups represents an average of 4,000 different food and beverage items, and food group averages can mask a wider range of tax rates across items.

[25] We recognize that this may not be a realistic assumption, but this is an empirical question that is left for future research.

[26] See analysis summarized on the Resources for the Future website at www.rff.org/blog/2012/considering-carbon-tax-frequently-asked-questions.

From these findings, the evidence suggests that a CO_2 emissions tax on fossil fuel use that reflects SCC estimates on the low end of the ranges reported in the IAWGSCC study (2015) are unlikely to affect diet outcomes, whereas taxes reflecting high-end SCC estimates from this study are likely to affect food choices. Further research along the lines of a detailed demand systems analysis is required to assess whether overall diets would become more or less healthy, or if the outcomes are ambiguous in response to the high-end tax. This analysis should seek a balance which recognizes that greater commodity detail in the demand analysis comes with diminished data reliability both in terms of behavioral parameters used in a demand systems analysis and in measures of carbon content across detailed food commodities. Additionally, researchers could use different SCC estimates to evaluate the damages of CO_2 emissions beyond 2020.

Conclusion

The findings from this research can be used to inform discussions at the intersection of health, diet, energy, and environmental issues. Our empirical research addresses four related questions that are fundamental to understanding the relationships between nutrition promotion and a hypothetical CO_2 emissions tax.

First, our research shows that changing energy prices are the principal cause of year-to-year changes in food-related energy use between 1993 and 2012 using available Bureau of Labor Statistics data. Our analysis produced significant statistical evidence that agri-food chain industries, from farm production and food processing to food retailing and food services, are more sensitive to electricity price changes than non-food industries throughout the U.S. economy. Electricity accounts for nearly 60 percent of all energy use in the food system. This finding helps explain why the food system accounted for more than 50 percent of the increase in the total U.S. energy budget between 1997 and 2002—a period of generally declining energy prices. This finding also helps explain why per capita food-related energy use declined by 11 percent between 2002 and 2007 compared to a 1 percent decline per capita economy-wide—a period of steeply increasing energy prices.

Second, using the most recent year of detailed Bureau of Economic Analysis data, our analysis shows that fossil fuels linked to all 2007 U.S. food consumption produced 817 million metric tons of CO_2 emissions. This total amounts to 13.6 percent of the almost 6 billion metric tons of CO_2 emissions economy-wide from fossil fuel consumption in 2007. Our analysis attributes this higher-than-expected total to the food system's higher-than-average reliance on fossil fuel energy sources. Had the percent of total food-system energy use from each fossil fuel source mirrored national energy use, then diet-related CO_2 emissions would have been about 10 percent lower. When food-related CO_2 emission estimates were shared out to U.S. counties, it showed that population density was driving the spatial allocation of food-related CO_2 emissions because of home and restaurant kitchen-energy consumption. More recent analysis of the food system's CO_2 footprint is possible as data become available.

Third, American diets are diverse, and there are many food combinations that individuals may choose that meet the Dietary Guidelines for Americans. Using national dietary data from 2007-2008 to correspond with our above analysis, we find a moderate Btu reduction of 3 percent is the most likely of many possible outcomes when shifting to a healthier diet—we denote this the Realistic Healthy Diet. In the Realistic Healthy Diet, calories from grain products are reduced relative to the Baseline Diet, but grain products are still the largest contributor to total caloric intake at 31 percent. However, grain products contribute a lesser share to total embodied Btu. Similar to the Baseline Diet, the most Btu embodied in the Realistic Healthy Diet come from meat, poultry, fish, and mixtures, representing 30 percent of total Btu while only supplying 298 calories, or 14 percent of the total calories. If all Americans met the DGA, we estimate that about 60 percent of the diets that Americans chose to get to the DGA would reduce food-system Btu requirements. Overall, this would reduce food-system energy use by 3 percent, or equivalent to the annual gasoline consumption of 3.7 million U.S. vehicles. These results are based on 2007 food-system technologies.

Last, we trace the total cost that would be passed on to food consumers from a range of CO_2 emissions tax rates on fossil fuel use, again in 2007 dollars. Our research indicates that an average meal would cost between 0.2 and 5.0 percent more with the CO_2 tax for both the Baseline Diet and the

Realistic Healthy Diet, depending on the assumed social costs of carbon emissions used to set the tax rate. For the average rate over this range, the estimated increase in the cost of an average meal would be 1.7 percent. From these findings, the evidence suggests that a CO_2 emissions tax on fossil fuel use that reflects SCC estimates on the low end of the ranges reported in the IAWGSCC study (2015) is unlikely to affect diet outcomes. Taxes reflecting average or high-end SCC estimates from this study are likely to affect food choices, but further research along the lines of a detailed demand systems analysis is required. It should be recognized that greater commodity detail in the demand analysis comes with diminished data reliability.

Upon the completion of the research for this report, the 2015 DGA were released. Although the 2015 DGA provide important insights based on new scientific evidence, the report states, “While the Healthy U.S.-Style Pattern is substantially unchanged from the base USDA Food Pattern of the 2010 edition of the *Dietary Guidelines*, small changes in the recommended amounts reflect updating the Patterns based on current food consumption and composition data” (see Appendix 3 in U.S Department of Agriculture and U.S. Department of Health and Human Services, 2015). To examine how these changes would impact the findings in this report, the model that produces the Realistic Healthy Diet was re-run based on the 2015 DGA. We found only minimal differences in the energy requirements of healthy diets. We conclude that our findings in this report can apply to both the 2010 and 2015 DGA, but by using the 2010 DGA, our results can be compared to related research described in the background section of this report.

Future research could consider other sustainability metrics in addition to energy use. For example, water, land, and other greenhouse gases also have major roles in the U.S. food system. Food-system water withdrawals, soil erosion, and other GHG emissions are also likely to change under alternative U.S. diets. Each of these important natural resources and production byproducts are the subject of many current and proposed Federal approaches to issues. Just as it would be considered incomplete to study only one of the many dietary recommendations in the Dietary Guidelines for Americans, the same can be said for a consideration of only one of the metrics of food system sustainability.

Another area of future research on this topic is to consider how international markets for U.S. food products may respond to changes in the terms of trade brought on by the issues considered in this report. For example, if consumers more fully align their diets with the DGA, the farm and food products that U.S. consumers no longer demand could find alternative international markets, and so food-system energy use may not decline. Or U.S. dietary changes could be part of an international trend such that producers of the food products no longer consumed will shift to producing the newly popular foods or exit the industry.

This report has expanded our understanding of the relationships between food and energy commodity markets. By design, our analytical framework, data system development, and food-system modeling approaches are foundational for broader considerations of diet and food system sustainability.

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Appendix A: Underlying Detailed Tables

Appendix Table A.1—Benchmark year and annual food-related final demand categories		
FEDS Final Demand Benchmark Series Code	**Representative Products in Category**	**FEDS Final Demand Annual Series Code**
01	Rice and Packaged Rice Products	07
02	Flour, Cornmeal, Malt, Dry and Refrigerated/Frozen Flour Mixes (biscuits pancakes, cakes, etc.) Made in Mill	07
03	Breakfast Cereals and Oatmeal	07
04	Macaroni and Noodle Products with Other Ingredients and Nationality Foods (not canned or frozen)	10
05	Noodle Pasta and Dry Soup Mixes with Other Ingredients plus Fresh Pasta and Packaged Unpopped Popcorn	04
06	Popcorn Wild Rice (not canned or processed)	01
07	Grits and Soy Flour	07
08	Dry Pasta, Dry Noodles, and Flour Mixes from Purchased Flour	08
09	Bread, Rolls, Cakes, Pies, Pastries (including frozen)	08
10	Cookies, Crackers, Biscuits, Wafers, Tortillas (except frozen)	08
11	Beef and Veal (fresh or frozen/not processed canned or sausage)	12
12	Pork (fresh or frozen/not canned or sausage)	12
13	Boxed Cooked and Processed (lunch) Meats plus Lamb & Other Meats (including game)	03
13	Boxed Cooked and Processed (lunch) Meats plus Lamb & Other Meats (including game)	12
14	Fresh Frozen or Processed Poultry (except soups)	12
15	Fresh Frozen or Prepared Fish & Shellfish (incl. canned and soups)	02
15	Fresh Frozen or Prepared Fish & Shellfish (incl. canned and soups)	03
15	Fresh Frozen or Prepared Fish & Shellfish (incl. canned and soups)	13
16	Fresh Milk	11
17	Natural and Processed Cheese	11
18	Dry Condensed and Evaporated Dairy	11
19	Ice Cream, Custards, Frozen Yogurt, Sherbets, Frozen Pudding	11
20	Cottage Cheese, Yogurt, Milk Substitutes, Sour Cream, Butter, Milk, Eggnog	11
21	Shell Eggs	02
22	Dried Frozen or Liquid Eggs	04
23	Corn Oils	07
24	Margarine, Shortening, Oilseed, Oils	07
25	Peanut Butter	04
26	Mayonnaise, Salad Dressings, Sandwich Spreads	04

Appendix Table A.1—Benchmark year and annual food-related final demand categories		
FEDS Final Demand Benchmark Series Code	**Representative Products in Category**	**FEDS Final Demand Annual Series Code**
27	Oilseed, Oils, and Other Oilseed Products	07
28	Butter and Butter Oils	11
29	Lard and Other Animal Oils	12
30	Fresh Fruits	01
31	Fresh Vegetables	01
32	Mushrooms and Other Vegetables Grown Under Cover	01
33	Fresh Herbs and Spices	01
34	Fruit Flours Made in Grain Mills	07
35	Frozen Fruits and Vegetables	10
36	Canned or Dried & Dehydrated Fruits or Vegetables	10
37	Processed Vegetables and Fruits Packaged with Other Products (e.g., noodles)	04
38	Dry Beans and Peas (not canned)	01
39	Corn Sweeteners (e.g., Karo syrup & sugar substitutes)	07
40	Sugar and Chocolate Products, Non-Chocolate Bars, Gums, and Candies	09
41	Jams, Jellies, and Preserves	10
42	Dessert Mixes, Sweetening, Syrups, Frostings	04
43	Almonds and Other Fresh Tree Nuts	01
44	Fresh Peanuts	01
45	Granola	07
46	Frozen Dinners, Nationality Foods, Other Frozen Specialties (excl. seafood)	10
47	Catsup and Other Tomato Sauces (e.g., spaghetti sauce)	10
48	Pickles and Pickled Products	10
49	Canned Soups and Stews (excl. frozen or seafood) and Dry Soup Mixes	10
50	Dry and Canned Milk plus Dairy Substitutes	11
51	Nuts and Seeds	04
52	Chips and Pretzels	04
53	Vinegar, Condiments, Sauces (excl. tomato-based), Semi-Solid Dressings, and Spices	04
54	Baking Powder and Yeast	04
55	Refrigerated Lunches	04
56	Refrigerated Pizza (fresh, not frozen)	04
57	Bagged Salads	04
58	Value Added Fresh Vegetables	04
59	Fresh-Cut Fruits	04
60	Fresh Tofu	04
61	Coffee, Tea, and Related Beverage Materials	04

Appendix Table A.1—Benchmark year and annual food-related final demand categories		
FEDS Final Demand Benchmark Series Code	**Representative Products in Category**	**FEDS Final Demand Annual Series Code**
61	Coffee, Tea, and Related Beverage Materials	14
62	Soft Drinks and Ice	14
63	Bottled Water	14
64	Frozen and Canned Fruit Drinks	10
65	Frozen and Canned Vegetable Drinks	10
66	Spirits, Flavorings, and Cocktail Mixes	04
66	Spirits, Flavorings, and Cocktail Mixes	14
67	Wine and Brandy	14
68	Beer	14
69	Food on Farm, Vegetables	01
70	Food on Farm, Fruits and Tree Nuts	01
71	Food on Farm, Dairy	02
72	Food on Farm, Beef	02
73	Food on Farm, Meats Except Beef and Poultry	02
74	Salt, Fatty Acids, and Organic Chemical Food Flavorings	05
74	Salt, Fatty Acids, and Organic Chemical Food Flavorings	06
75	Household: Natural Gas	15
76	Household: Electricity	16
77	Household: Petro for Cooking	17
78	Household: Appliances	18
79	Household: Kitchen Equipment	19
80	Household: Motor Vehicles and Parts	20
81	Household: Auto Repair and Leasing	20
82	Household: Auto Insurance	20
83	Household: Auto Fuels, Lubricants, and Fluids	21
84	All Other Final Demand	22

Source: USDA, Economic Research Service

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
001	Oilseed farming	1
002	Grain farming	1
003	Vegetable and melon farming	1
004	Fruit and tree nut farming	1
005	Greenhouse nursery and floriculture production	1
006	Other crop farming	1
007	Dairy and beef cattle	2
008	Poultry and egg production	2
009	Animal production except cattle and poultry and eggs	2
010	Forestry and logging	3
011	Fishing hunting and trapping	5
012	Support activities for agriculture and forestry	6
013	Oil and gas extraction	7
014	Coal mining	8
015	Fossil fuels for electric power generation	193
016	Copper nickel lead and zinc mining	9
017	Iron gold silver and other metal ore mining	9
018	Stone mining and quarrying	10
019	Other nonmetallic mineral mining and quarrying	10
020	Drilling oil and gas wells	11
021	Other support activities for mining	11
022	Electric power generation transmission and distribution	12
023	Natural gas distribution	13
024	Water sewage and other systems	14
025	Maintenance and repair	15
026	Residential structures	15
027	Nonresidential structures	15
028	Dog and cat food manufacturing	16
029	Other animal food manufacturing	16
030	Flour milling and malt manufacturing	17
031	Wet corn milling	17
032	Fats and oils refining and blending	17
033	Soybean and other oilseed processing	17
034	Breakfast cereal manufacturing	17
035	Sugar and confectionery product manufacturing	18
036	Frozen food manufacturing	19
037	Fruit and vegetable canning pickling and drying	19

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
038	Cheese manufacturing	20
039	Dry condensed and evaporated dairy product manufacturing	20
040	Fluid milk and butter manufacturing	20
041	Ice cream and frozen dessert manufacturing	20
042	Poultry processing	21
043	Animal (except poultry) slaughtering rendering and processing	21
044	Seafood product preparation and packaging	22
045	Bread and bakery product manufacturing	23
046	Cookie, cracker, pasta, and tortilla manufacturing	23
047	Snack food manufacturing	24
048	Coffee and tea manufacturing	24
049	Flavoring syrup and concentrate manufacturing	24
050	Seasoning and dressing manufacturing	24
051	All other food manufacturing	24
052	Soft drink and ice manufacturing	25
053	Breweries	25
054	Wineries	25
055	Distilleries	25
056	Tobacco product manufacturing	26
057	Fiber yarn and thread mills	27
058	Fabric mills	27
059	Textile and fabric finishing and fabric coating mills	27
060	Carpet and rug mills	27
061	Curtain and linen mills	27
062	Other textile product mills	27
063	Apparel manufacturing	28
064	Leather and allied product manufacturing	29
065	Sawmills and wood preservation	30
066	Veneer plywood and engineered wood product manufacturing	31
067	Millwork	32
068	All other wood product manufacturing	32
069	Pulp mills	33
070	Paperboard mills and container manufacturing	33
071	Paperboard container manufacturing	34
072	Paper bag and coated and treated paper manufacturing	34
073	Stationery product manufacturing	34
074	Sanitary paper product manufacturing	34

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
075	All other converted paper product manufacturing	34
076	Printing	35
077	Support activities for printing	35
078	Petroleum refineries	36
079	Asphalt paving mixture and block manufacturing	36
080	Asphalt shingle and coating materials manufacturing	36
081	Other petroleum and coal products manufacturing	36
082	Petrochemical manufacturing	37
083	Industrial gas manufacturing	37
084	Synthetic dye and pigment manufacturing	37
085	Other basic inorganic chemical manufacturing	37
086	Other basic organic chemical manufacturing	37
087	Plastics material and resin manufacturing	38
088	Synthetic rubber and artificial and synthetic fibers and filaments manufacturing	38
089	Fertilizer manufacturing	39
090	Pesticide and other agricultural chemical manufacturing	39
091	Pharmaceutical and medicine manufacturing	40
092	Paint and coating manufacturing	41
093	Adhesive manufacturing	41
094	Soap and cleaning compound manufacturing	42
095	Toilet preparation manufacturing	42
096	Printing ink manufacturing	43
097	All other chemical product and preparation manufacturing	43
098	Plastics packaging materials and unlaminated film and sheet manufacturing	44
099	Plastics pipe, pipe fitting, and unlaminated profile shape manufacturing	44
100	Laminated plastics plate sheet (except packaging) and shape manufacturing	44
101	Plastics bottle manufacturing	44
102	Other plastics product manufacturing	44
103	Polystyrene urethane and other foam manufacturing	44
104	Tire manufacturing	45
105	Rubber and plastics, hoses, and belting manufacturing	45
106	Other rubber product manufacturing	45
107	Clay product and refractory manufacturing	46
108	Glass and glass product manufacturing	47
109	Cement manufacturing	48
110	Ready-mix concrete manufacturing	48

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
111	Concrete pipe brick and block manufacturing	48
112	Other concrete product manufacturing	48
113	Lime and gypsum product manufacturing	49
114	Abrasive product manufacturing	49
115	Cut stone and stone product manufacturing	49
116	Ground or treated mineral and earth manufacturing	49
117	Mineral wool manufacturing	49
118	Miscellaneous nonmetallic mineral products	49
119	Iron and steel mills and ferroalloy manufacturing	50
120	Steel product manufacturing from purchased steel	51
121	Alumina and aluminum production and processing	52
122	Primary smelting and refining of copper	53
123	Primary smelting and refining of nonferrous metal (except copper and aluminum)	53
124	Copper rolling, drawing, extruding, and alloying	53
125	Nonferrous metal (except copper and aluminum) rolling, drawing, extruding, and alloying	53
126	Ferrous metal foundries	54
127	Nonferrous metal foundries	54
128	Custom roll forming	55
129	All other forging, stamping, and sintering	55
130	Crown and closure manufacturing and metal stamping	55
131	Cutlery and handtool manufacturing	56
132	Plate work and fabricated structural product manufacturing	57
133	Ornamental and architectural metal products manufacturing	57
134	Power boiler and heat exchanger manufacturing	58
135	Metal tank (heavy gauge) manufacturing	58
136	Metal can, box, and other metal container (light gauge) manufacturing	58
137	Hardware manufacturing	59
138	Spring and wire product manufacturing	60
139	Machine shops	61
140	Turned product and screw nut and bolt manufacturing	61
141	Coating, engraving, heat treating, and allied activities	62
142	Fixture fitting valve and trim (plumbing and other) manufacturing	63
143	Ball and roller bearing manufacturing	63
144	Fabricated pipe and pipe fitting manufacturing	63
145	Ammunition arms ordnance and accessories manufacturing	63
146	Other fabricated metal manufacturing	63

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
147	Farm machinery and equipment manufacturing	64
148	Lawn and garden equipment manufacturing	64
149	Construction machinery manufacturing	64
150	Mining and oil and gas field machinery manufacturing	64
151	Plastics and rubber industry machinery manufacturing	65
152	Semiconductor machinery manufacturing	65
153	Other industrial machinery manufacturing	65
154	Optical instrument and lens manufacturing	66
155	Photographic and photocopying equipment manufacturing	66
156	Office vending, laundry, and other commercial service industry machinery manufacturing	66
157	Heating equipment (except warm air furnaces) manufacturing	67
158	Air conditioning refrigeration and warm air heating equipment manufacturing	67
159	Air purification and ventilation equipment manufacturing	67
160	Industrial mold manufacturing	68
161	Special tool die jig and fixture manufacturing	68
162	Metal cutting and forming machine tool and accessory rolling mill and other metal work machinery manufacturing	68
163	Turbine and turbine generator set units manufacturing	69
164	Other engine equipment manufacturing	69
165	Speed changer industrial high speed drive and gear plus power transmission equipment manufacturing	69
166	Pump and pumping equipment manufacturing	70
167	Air and gas compressor manufacturing	70
168	Material handling equipment manufacturing	70
169	Power driven handtool manufacturing	70
170	Packaging machinery manufacturing	70
171	Industrial process furnace and oven manufacturing	70
172	Other general purpose and fluid power process machinery manufacturing	70
173	Electronic computer manufacturing	71
174	Computer storage device manufacturing	71
175	Computer terminals and other computer peripheral equipment manufacturing	71
176	Telephone apparatus manufacturing	72
177	Broadcast and wireless communications equipment	72
178	Other communications equipment manufacturing	72
179	Audio and video equipment manufacturing	73
180	Semiconductor and related device manufacturing	74
181	Printed circuit assembly and other electronic component manufacturing	74

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
182	Electromedical and electrotherapeutic apparatus manufacturing	75
183	Search detection and navigation instruments manufacturing	75
184	Automatic environmental control manufacturing	75
185	Industrial process variable instruments manufacturing	75
186	Totalizing fluid meter and counting device manufacturing	75
187	Electricity and signal testing instruments manufacturing	75
188	Analytical laboratory instrument manufacturing	75
189	Irradiation apparatus manufacturing	75
190	Watch clock and other measuring and controlling device manufacturing	75
191	Manufacturing and reproducing magnetic and optical media	76
192	Electric lamp bulb and part manufacturing	77
193	Lighting fixture manufacturing	77
194	Small electrical appliance manufacturing	78
195	Household cooking appliance manufacturing	78
196	Household refrigerator and home freezer manufacturing	78
197	Household laundry equipment manufacturing	78
198	Other major household appliance manufacturing	78
199	Power distribution and specialty transformer manufacturing	79
200	Motor and generator manufacturing	79
201	Switchgear and switchboard apparatus manufacturing	79
202	Relay and industrial control manufacturing	79
203	Storage battery manufacturing	80
204	Primary battery manufacturing	80
205	Communication and energy wire and cable manufacturing	80
206	Wiring device manufacturing	80
207	Carbon and graphite product manufacturing	80
208	All other miscellaneous electrical equipment and component manufacturing	80
209	Automobile and light truck and utility vehicle manufacturing	81
210	Heavy duty truck manufacturing	81
211	Motor vehicle body manufacturing	82
212	Truck trailer manufacturing	82
213	Motor home manufacturing	82
214	Travel trailer and camper manufacturing	82
215	Motor vehicle parts manufacturing	83
216	Aircraft manufacturing	84
217	Aircraft engine and engine parts manufacturing	84
218	Other aircraft parts and auxiliary equipment manufacturing	84

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
219	Guided missile and space vehicle manufacturing	84
220	Propulsion units and parts for space vehicles and guided missiles	84
221	Railroad rolling stock manufacturing	85
222	Ship building and repairing	86
223	Boat building	86
224	Motorcycle bicycle and parts manufacturing	87
225	Military armored vehicle tank and tank component manufacturing	87
226	All other transportation equipment manufacturing	87
227	Wood kitchen cabinet and countertop manufacturing	88
228	Upholstered household furniture manufacturing	88
229	Nonupholstered wood household furniture manufacturing	88
230	Institutional furniture manufacturing	88
231	Other household nonupholstered furniture	88
232	Office furniture and custom architectural woodwork and millwork manufacturing	88
233	Showcase partition shelving and locker manufacturing	88
234	Other furniture related product manufacturing	90
235	Surgical and medical instrument manufacturing	91
236	Surgical appliance and supplies manufacturing	91
237	Dental equipment and supplies manufacturing	91
238	Ophthalmic goods manufacturing	91
239	Dental laboratories	91
240	Jewelry and silverware manufacturing	92
241	Sporting and athletic goods manufacturing	92
242	Doll toy and game manufacturing	92
243	Office supplies (except paper) manufacturing	92
244	Sign manufacturing	92
245	All other miscellaneous manufacturing	92
246	Wholesale trade	93
247	Air transportation	95
248	Rail transportation	96
249	Water transportation	97
250	Truck transportation	98
251	Transit and ground passenger transportation	99
252	Pipeline transportation	100
253	Scenic and sightseeing transportation and support activities for transportation	101
254	Postal service	170

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
255	Couriers and messengers	102
256	Warehousing and storage	103
257	Retail trade	94
258	Trade electric utilities	201
259	Trade natural gas utilities	202
260	Newspaper publishers	104
261	Periodical publishers	104
262	Book publishers	104
263	Directory mailing list and other publishers	104
264	Software publishers	105
265	Motion picture and video industries	106
266	Sound recording industries	106
267	Other information services	109
268	Radio and television broadcasting	107
269	Cable and other subscription programming	107
270	Telecommunications	108
271	Data processing hosting and related services	109
272	Nondepository credit intermediation and related activities	110
273	Securities commodity contracts and other financial investments	111
274	Insurance carriers	112
275	Insurance agencies brokerages and related activities	113
276	Funds trusts and other financial vehicles	114
277	Monetary authorities and depository credit intermediation	110
278	Real estate	115
279	Automotive equipment rental and leasing	116
280	Commercial and industrial machinery and equipment rental and leasing	118
281	Consumer goods and general rental centers	117
282	Lessors of nonfinancial intangible assets	119
283	Legal services	120
284	Accounting tax preparation bookkeeping and payroll services	121
285	Architectural engineering and related services	122
286	Specialized design services	123
287	Custom computer programming services	124
288	Computer systems design services	124
289	Other computer related services including facilities management	124
290	Management consulting services	125
291	Environmental and other technical consulting services	125

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
292	Scientific research and development services	126
293	Advertising public relations and related services	127
294	Photographic services	128
295	Veterinary services	128
296	Marketing research and all other miscellaneous professional scientific and technical services	128
297	Management of companies and enterprises	129
298	Office administrative services	130
299	Facilities support services	131
300	Employment services	132
301	Business support services	133
302	Travel arrangement and reservation services	134
303	Investigation and security services	135
304	Services to buildings and dwellings	136
305	Other support services	137
306	Waste management and remediation services	138
307	Elementary and secondary schools	139
308	Junior colleges colleges universities and professional schools	140
309	Other educational services	141
310	Home health care services	143
311	Physician dentist and other health practitioner offices	142
312	Outpatient care centers medical and diagnostic labratories	144
313	Hospitals	145
314	Nursing and residential care facilities	146
315	Child day care services	149
316	Social assistance	147
317	Performing arts companies	150
318	Spectator sports	151
319	Independent artists writers and performers	153
320	Promoters of performing arts and sports and agents for public figures	152
321	Museums historical sites zoos and parks	154
322	Amusement gambling and recreation industries	155
323	Accommodation	156
324	Food services and drinking places	157
325	Food services (service only)	200
326	Automotive repair and maintenance	158
327	Electronic and precision equipment repair and maintenance	159

Appendix Table A.2—FEDS Benchmark Commodities with concordances to FEDS Annual Commodities		
FEDS Commodity Benchmark Series Code	FEDS COMMODITY DESCRIPTION	FEDS Commodity Annual Series Code
328	Commercial and industrial machinery and equipment repair and maintenance	160
329	Personal and household goods repair and maintenance	161
330	Personal care services	162
331	Death care services	163
332	Dry cleaning and laundry services	164
333	Other personal services	165
334	Religious organizations	166
335	Grantmaking giving and social advocacy organizations	167
336	Civic social professional and similar organizations	168
337	Private households	169
338	Other federal government enterprises	172
339	Other state and local government enterprises	180
340	Miscellaneous special industries	171
341	Scrap used and secondhand goods	192
342	Federal general government (defense)	173
343	State and local general government	181
344	Owner occupied dwellings	190

Source: USDA, Economic Research Service

Appendix Table A.3—Cohorts defined by age and gender

Cohort	Age	Gender	n
1	2-5	Male	455
2	2-5	Female	377
3	6-11	Male	550
4	6-11	Female	571
5	12-17	Male	460
6	12-17	Female	426
7	18-24	Male	351
8	18-24	Female	345
9	25-44	Male	862
10	25-44	Female	893
11	45-54	Male	462
12	45-54	Female	461
13	55-64	Male	445
14	55-64	Female	474
15	65+	Male	688
16	65+	Female	708
Total			8528

Source: NHANES 2007-2008

Appendix B: Food Environment Data System (FEDS)

FEDS is a system of national environmental economic accounts which is organized into a food system life-cycle framework. To compile FEDS for the years 1993 to 2012, the starting point is the ERS Food Dollar accounts (Canning, 2011), which are compiled primarily from two main data sources: benchmark IO accounts published in 5-year intervals by the BEA, and annual IO tables (1993 to 2012) published by BLS. The ERS Food Dollar accounts reconfigure the IO accounting structure to better represent salient attributes of the U.S. food system, and incorporate other primary data sources into the estimation process. A detailed documentation of the first-edition Food Dollar accounts is reported in a separate ERS report (Canning, 2011), and updates and changes to these accounts are reported in the online documentation to the Food Dollar data product (www.ers.usda.gov/data-products/food-dollar-series.aspx).

In the 1993-2012 time-series Food Dollar accounts, industry outputs of goods and services are partitioned into 178 distinct commodity groups, and personal consumption expenditures on food are distinguished by 22 food-related expenditure categories. For the benchmark year accounts (1997, 2002, 2007), industry outputs of goods and services are partitioned into 344 distinct commodity groups, and personal consumption expenditures on food are distinguished by 84 food-related expenditure categories. Appendix tables A.1 and A.2 list the expenditures and commodity categories.

A concise statement of the FEDS accounts and all subsequent energy-flow analysis in this report is best facilitated with matrix/vector notation. Our notation convention and set definitions are summarized in appendix table B.1.

Appendix Table B.1—Matrix, vector and operation notation, subsets, and supersets*

*Bold uppercase letters represent matrices; bold lowercase letters represent column vectors; if preceded with a ***Q*** or ***q*** (annual only) the account is units in constant year 2005 prices; if preceded with a **P** or **p** the account is reported in annual unit prices; if preceded with an **H** or **h** (annual and benchmark) the account is in hybrid units (Btu per dollar); if preceded with an **R** or **r** (benchmark only) the account is multiregional (State or county); if italic then only represented in the annual accounts.

Symbol	Description
A, **HA**, **RA**	Direct requirement matrix for inter-industry transactions, including hybrid and regional
$\underline{\mathbf{HA}}$, $\underline{\mathbf{RHA}}$	Reduced dimension (ec0×sc0/er0×sc0) hybrid agri-food chain direct requirement matrix for inter-industry transactions, including regional hybrid
x, rx, *x*, *rx*	Gross industry output vector, including regional
C	Multiregional commodity trade matrix
Y, ***y***, **HY**, **ry, rhy**	Final demand matrix or vector for personal consumption expenditures, including hybrid, regional, and regional hybrid
V, *v*, *qv*, *pv*	Net industry unit output matrix (benchmark only) or vector (only total factor value added is measured annually), including price and quantity
T, **HT**, **RT, RHT**	Total requirement matrix of inter-industry transactions, including hybrid, regional, and regional hybrid
$\boldsymbol{\varepsilon}$, $\mathbf{r}\boldsymbol{\varepsilon}$, $\mathbf{p}\boldsymbol{\varepsilon}$	Energy consumption vector by commodity or primary fuel
Alpha-numeric superscript	Identifies specific supersets, where “superset” refers to the outer boundaries of a specially defined data subsystem (e.g., $\mathbf{x}^{sc1}$ is the set of gross industry outputs for stage 1 industries of a specially defined agri-food chain sub-system)
Alpha-numeric subscript	Identify specific subsets of rows and/or columns (e.g., $\mathbf{T}_{sc1,5}$ is the elements in column 5 located in the group of rows associated with subset sc1 of matrix **T**)
Numeric subscript	Identifies specific rows or columns of a matrix or vector (e.g., $\mathbf{T}_{10,5}$ is the element in row 10, column 5 of matrix **T**)

Symbol	Description
′	Prime symbol indicates the transpose of either a matrix or vector (e.g., convert each column to a row)
I	Identity matrix (e.g., a matrix with a “1” along the diagonal and zeros otherwise)
“0” subscript or superscript	Alone or within any alphanumeric, it denotes the set of all defined numerals (e.g., $\mathbf{T}_{10,0}$ is all column elements in row 10 of matrix **T**)
“#” subscript or superscript	Alone or within any alphanumeric, it denotes any one in the set of all defined numerals (e.g., $\mathbf{T}_{10,\#}$ is one of all possible column elements in row 10 of matrix **T**)
“-1”	In a superscript, “-1” indicates a matrix or vector inversion
i	Unit vector (“1” in all elements) that assumes the dimensions of vector it is paired with, or same number of elements as columns (rows if **i**′) of matrix with which it is paired—used to sum values in vector or columns (rows if **i**′) of a matrix
fd0	Set of all food-related final demand categories, fd1 to fd83 (fd22 if annual)
ec0	Set of all energy commodities, ec1 to ec6
ef0	Set of all electricity fossil fuel sources, ef1 to ef3
sc0	Set of all agri-food chain industry groups, sc1 to sc8
nc0	Set of all non-agri-food chain industries
fc0	Set of food commodity purchases as consumed, comprised of 83 commodity groups representing 4,067 food items

Source: USDA, Economic Research Service

For benchmark year accounts in dollar units, FEDS data are comprised of four primary sub-accounts: (i) an industry direct-requirement matrix (**A**), (ii) a final demand matrix (**Y**), (iii) a gross industry-output vector (**x**), and a net industry-unit output matrix (**V**), also called the per unit value-added matrix. In a benchmark year account, the direct requirement matrix (**A**) has 344 rows and columns representing industry groups (columns) and commodity groups (rows) that are the corresponding outputs of each industry.[1] The rows represent all intermediate sales, whereas columns represent all intermediate outlays by industry. The gross industry output vector has 344 rows that represent annual industry production valued in producer prices.[2] The final demand matrix has 344 rows that represent annual final-market sales and 84 columns that each represent 83 specific food-related expenditure categories (e.g., fresh fruits) plus 1 representing all other final demand. The net industry-output matrix has the same 344 rows as the gross industry-output vector and a column for each primary production factor plus imports.

Each annual or benchmark account must be in balance, which requires that for every commodity, gross output must equal the sum of final market sales ($\mathbf{y}=\mathbf{Y}\times\mathbf{i}$) and all intermediate sales ($\mathbf{A}\times\mathbf{x}$). This implies that any gross output that is not marketed as an intermediate product is sold in the final market:

B.1) $\mathbf{x} - (\mathbf{A}\times\mathbf{x}) = \mathbf{y} \Leftrightarrow (\mathbf{I} - \mathbf{A}) \times \mathbf{x} = \mathbf{y}$

Two important identities can be derived from (B.1). By multiplying both sides of the equation by $(\mathbf{I} - \mathbf{A})^{-1}$ and setting $\mathbf{T} = (\mathbf{I} - \mathbf{A})^{-1}$ we have:

B.2) $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1} \times \mathbf{y} \Leftrightarrow \mathbf{x} = \mathbf{T} \times \mathbf{y}$

Matrix **T** is a system of total requirement multipliers and is the basis for IO models. Whereas any element $\mathbf{A}_{j,k}$ in matrix **A** tells us the direct requirements of commodity "j" used per dollars' worth of industry output "k," element $\mathbf{T}_{j,k}$ in matrix **T** tells us the total requirements (direct and indirect) of commodity "j" necessary to accommodate the final market purchases of a dollars' worth of output "k". Multiplying $\mathbf{T}_{j,k}\times\mathbf{y}_k$ translates this final market purchase into the total

[1] All trade and transportation margin costs added to producer prices are recorded separately in the appropriate margin industry rows.
[2] The FEDS accounts treat commodity imports as an addition to gross industry output rather than a subtraction from Gross Domestic Product (see appendix equations A1-A4 in Canning, 2011).

required production (in dollars) of commodity “j”, for example electricity, to facilitate supply of $\mathbf{y}_k$, for example, fresh vegetables.

Returning to (B.1), given that each element in the vector resulting from the matrix-vector product on the left side of the equality is equal to its right-side counterpart, it must also be true that the sum value of all elements on both sides is also equal:

B.3) $\mathbf{i'} \times (\mathbf{I} - \mathbf{A}) \times \mathbf{x} = \mathbf{i'} \times \mathbf{y} \Leftrightarrow \mathbf{v'} \times \mathbf{x} = \mathbf{i'} \times \mathbf{y}$,

where $\mathbf{v'} = \mathbf{i'} \times \mathbf{V'}$.

Recalling that $\mathbf{V}$ is the net unit-output matrix such that multiplication of this matrix by the gross industry-output vector produces net industry output, (B.3) is a scalar identity that states net industry output (or industry value added) equals total final demand.

To understand the importance of the identities in (B.2) and (B.3) we need to consider the linear homogeneity property. Linear homogeneity is a property of IO models that implies any fraction of total final demand requires the same fraction of total industry output to supply this final demand; for example, $0.5 \times \mathbf{x} = \mathbf{T} \times (0.5 \times \mathbf{y})$.[3] But since this holds for any fraction, each element in any column from $\mathbf{Y}$ such as fd31 (personal expenditures on fresh vegetables) is some fraction of the values in the corresponding elements in $\mathbf{y}$. By this linear homogeneity property, the value of all electricity (row 22) used directly and indirectly to accommodate fresh vegetable expenditures is measured as:

$$\mathbf{x}_{22}^{fd31} = \mathbf{T}_{22,0} \times \mathbf{y}^{fd31}$$

The value of $\mathbf{x}_{22}^{fd31}$measures the amount of electricity purchased by farmers growing vegetables for the fresh market to run their irrigation equipment, as well as the electricity purchased by a great many other establishments directly or indirectly facilitating these fresh-market vegetable sales, from the fertilizer manufacturer that produces nitrogen fertilizers purchased by vegetable farmers to the grocery stores that sell fresh produce to packaging manufacturers that made the

[3] This property can be problematic when used for forecasting, but is widely applied and embraced when used to assess average historical relationships, as is the present purpose.

packages containing the fresh produce, to name just a few. More generally, let ec0 represent the set of all energy commodity rows in the FEDS accounts (coal, electricity, natural gas, refined petroleum, fuel ethanol, and other renewables).[4] Then, for any column in the final demand matrix, fd1 to fd83, the total output requirements (in dollars) of each energy commodity are measured as:

$$\mathbf{x}_{ec0}^{fd\#} = \mathbf{T}_{ec0,0} \times \mathbf{y}^{fd\#}$$

In the context of this study, there are two problems with these values. First, this study concerns the use of fossil fuels. This requires knowing the quantity of fossil fuels embodied in the electricity used by the food system, so the location of the electricity that was used must be known. A second problem with the IO model result is that it measures energy use in dollars, and this study seeks to measure the physical units of food-related energy flows, such as Btu, which can then be converted to CO_2 emissions.

Multiregional Input-Output Model

To address the question of fuel sources for electric power generation, a spatial dimension is added to the IO model in (B.2) and (B.3). The framework adopted is called the multiregional input-output model (Miller & Blair, 2009). The multiregional input-output system is comprised of the same subaccounts as the national IO system, plus an interregional commodity trade matrix. Just as in the national IO accounts, the multiregional IO accounts include the same primary components: (i) a final demand vector, $\mathbf{ry} = [\mathbf{y}^{r1} \ldots \mathbf{y}^{rs}]'$, comprised of stacked regional final demand vectors for regions 1 to s[5]; (ii) a gross industry-output vector, $\mathbf{rx} = [\mathbf{x}^{r1} \ldots \mathbf{x}^{rs}]'$, comprised of stacked regional gross industry-output vectors for regions 1 to s; (iii) a direct requirement matrix, $\mathbf{RA} = ([\mathbf{A}^{r1} \ldots \mathbf{A}^{rs}])''$, comprised of diagonal stacked regional direct-requirement matrices for regions 1 to s; (iv) a net industry unit-output vector , $\mathbf{rv} = [\mathbf{v}^{r1} \ldots \mathbf{v}^{rs}]'$, comprised of stacked regional net industry unit-output vectors for regions 1 to s; and (v) a

[4] Each energy commodity listed excludes its use in electric power generation, since such uses are reflected in the electricity commodity.

[5] Here we use “s” to denote the endpoint of the region index, which could represent counties or states, depending on the context.

multiregional commodity-trade matrix comprised of bilateral commodity trade coefficient matrices among regions 1 to s:

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_{11} & \cdots & \mathbf{C}_{1s} \\ \vdots & \ddots & \vdots \\ \mathbf{C}_{s1} & \cdots & \mathbf{C}_{ss} \end{bmatrix},$$

These subaccounts are related by the matrix algebra identities:

B.4) $\mathbf{rx} = \mathbf{RT} \times \mathbf{C} \times \mathbf{ry}$

Interpretation of the model in (B.4) is the same as that in (B.2), with the addition of a spatial dimension. A restatement of (B.3) for the regional accounts involves replacing **x**, **y,** and **v** with **rx**, **ry,** and **rv** but is otherwise not modified or reinterpreted under the newly defined regional subaccounts.

Not all transactions will need to be spatially allocated for the purpose of this study. To measure total electricity requirements by U.S. States, we compile only the necessary elements of a multiregional input-output account. Using the national direct-requirement matrix and a database of State-level employment or output for every industry group represented in the 2007 benchmark FEDS account,[6] our approach is as follows. The national direct-requirement reduced-dimension hybrid matrix, $\underline{\mathbf{HA}}$, is assumed to be representative of technologies in each State:

B.5) $\underline{\mathbf{HA}}_r = \underline{\mathbf{HA}}$ for r = 1,…,51 (50 States plus District of Columbia)

Equation B.5 implies that production inputs do not vary by State. This assumption is more credible for the benchmark year accounts because of the high degree of detail. For example, most commodity groups in the benchmark accounts represent 4-, 5-, or 6-digit North American Industry Classification System (NAICS) commodities (www.census.gov/eos/www/naics/).

We use the trade pool method (Leontief, 1953) of calibrating interregional trade coefficients:

[6] Data sources include 2007 Census of Agriculture (www.agcensus.usda.gov/Publications/2007/), Quarterly Census of Employment and Wages (www.bls.gov/cew/), American Association of Railways (www.aar.org/), 2007 Census of Government (www.census.gov/govs/), Internal Revenue Service Statistics on Income (www.irs.gov/uac/SOI-Tax-Stats-Historic-Table-2), and County Business Patterns (www.census.gov/econ/cbp/download/).

$$\text{B.6) } \mathbf{C}^{\#,s} = (\mathbf{x}^{\mathbf{r}\#})'' \times (\mathbf{x}'')^{-1} = \mathbf{C}^{\#}, \text{ for } s = 1,\ldots,51$$

Equation B.6 indicates that in meeting the demand for any commodity j in any region s, the share of that demand met by trade from any region # equals that region's gross output share of the national gross output for commodity j. This relationship holds for all commodities and for demands from all regions, s = 1 to 51. Because $\mathbf{C}^{\#,s}$ is the same for all destinations, the second superscript can be dropped such that $\mathbf{C}^{\#,s} = \mathbf{C}^{\#}$ for s = 1 to 51.

There are clear limitations to using the trade pool approach for regional studies. For example, for a study of the economic linkages between the dairy industries in adjacent U.S. East Coast States, it would be implausible to assume that each of these eastern States provides the same share of the dairy demand from its adjacent State as it does to U.S. States on the West Coast. However, for a national study such as the one presented in this report, it is far more realistic to assume that each U.S. State supplies a share of the national consumer demand for dairy equal to that State's share of total production.[7]

[7] Although not discussed, import share is also factored into the trade pool model estimation of regional trade coefficients.

Material Flow Accounting

Material flow accounts extend the IO accounting framework, and when the “materials” are linked to environmental accounting, these are known as environmentally extended accounts.[8] To proceed, we first note that all commodity rows in the **A** and **Y** matrix that represent marketed energy commodities—coal, natural gas, electricity, refined petroleum, ethanol for vehicle fuel blends—are converted from monetary units to physical units (Btu). Next, new rows are added to both matrices for self-supplied energy sources—other renewables (see appendix table B.2). The sole data source used in this part of the study for both national and State-level energy consumption data by fuel source and type of end user is the State Energy Data System (SEDS), an annually updated data product of the U.S. Energy Information Administration (EIA). Appendix table B.2 reports the complete national data summaries for all energy consumption and prices that will be assigned to the 2007 benchmark energy flow account. These data are available for all annual and benchmark years, 1993 to 2012, and are used to convert all benchmark and annual accounts to this hybrid form of Btu, rather than dollars.

[8] Here we focus on developing a primary energy flow subaccount, but the identical framework is expandable to other materials linked to environmental accounting.

Appendix Table B.2--Primary U.S. Energy Consumption and Price by Fuel and End-User, 2007						
	End User					
Fuel	Industrial	Electricity	Transportation	Commercial	Commercial & Residential	Residential
	Billion Btu and $ per Million Btu					
Coal	1,864,461	20,807,149		70,384		7,820
	$2.58	$1.78		$2.47		$3.50
Fuel Ethanol	9,675		557,550	1,373		
	$22.01		$22.01	$21.94		
Geothermal	4,700	144,674		14,400		22,000
	N/A	N/A		N/A		N/A
Hydroelectric	15,715	2,429,909		764		
	N/A	N/A		N/A		
Natural Gas	8,097,550	7,028,340	665,156	3,095,321		4,848,707
	$8.29	$7.11	$9.19	$10.99		$12.7
Nuclear Electric		8,458,589				
		$0.46				
Petroleum Products	9,460,713	657,128	28,335,182	651,436		1,253,649
	$15.88	$7.94	$20.61	$17.52		$21.11
Solar		6,047			69,610	
		N/A			N/A	
Wood	1,413,023	185,956		69,796		420,000
	$2.52	$3.22		$5.55		$8.80
Waste	144,783	237,492		30,960		
	$2.52	$3.22		$5.55		
Wind		340,503				
		N/A				
Source: U.S. Department of Energy, Energy Information Administration; State Energy Data System (www.eia.gov/state/seds/)						

To demonstrate the method of assigning energy use by fuel type to the IO accounts, consider the entry for natural gas consumption (commodity row 24) by industrial end users in table B.2. Industrial consumption, roughly 8.1 qBtu, represents end users from three industry groups: (i) Agriculture, Forestry, Fishing, and Hunting ($\mathbf{A}_{24,1}$ to $\mathbf{A}_{24,12}$); (ii) Mining ($\mathbf{A}_{24,13}$ to $\mathbf{A}_{24,21}$); and (iii) Manufacturing ($\mathbf{A}_{24,28}$ to $\mathbf{A}_{24,245}$). Altogether, these end users purchased $49.8 billion of natural gas in 2007, retrieved from the IO matrix. The biggest buyer was the "Paperboard mills and container manufacturing" industry (column 76), having a total outlay of $4.1 billion, or around 8.2 percent of total outlays from all industrial end users. To convert this outlay from dollars to Btu, 8.2 percent of the 8.1 qBtu from industrial end-use of natural gas (row 5 of column 1 in table B.2) is allocated to the paperboard mills and container industry, and after division by that industry's gross output ($\mathbf{x}_{76}$) converts the direct per-dollar requirement coefficient to a hybrid Btu per $ measure.

Applying this hybrid calculation to all fuels and end users reported in appendix table B.2 converts direct requirement and final demand matrices to their hybrid equivalent. Repeating the transformations outlined in (B.2) and (B.4) with the hybrid accounts produces the hybrid total requirement matrix (**HT**) and hybrid final demand matrix (**HY**) used for material flow analysis:

B.7) $\boldsymbol{\varepsilon} = (\mathbf{I} - \mathbf{HA})^{-1} \times (\mathbf{HY} \times \mathbf{i}) \Leftrightarrow \boldsymbol{\varepsilon} = \mathbf{HT} \times \mathbf{hy}$

B.8) $\mathbf{r}\boldsymbol{\varepsilon} = \mathbf{RHT} \times \mathbf{C} \times \mathbf{rhy}$

The use of industry outlays to allocate the SEDS energy consumption data to detailed industries assumes that each industry faces the same unit price for their energy purchases. The SEDS data do include prices paid by type of end user, but these data are reported at the same level of detail as the consumption data, and so the energy allocations by industry based on both outlays and prices paid would be the same as the method adopted. An alternative approach would be to use data from other sources that report the quantity of energy used by type of industry, such as the 2006 Manufacturing Energy Consumption Survey (www.eia.gov/consumption/manufacturing/data/2006/). For example, data from this source indicate about 303 trillion Btu of natural gas energy was used in 2006 by the nitrogen (NAICS 325311) and phosphatic (NAICS 325312) fertilizer manufacturing industries, whereas the 2007 hybrid IO in FEDS reports 371 trillion Btu of natural gas use in 2007. The higher FEDS estimate might be explained by the 2007 versus 2006 reference year, but since these industries produced about the same output in both years, it is uncertain if this is the only explanation for the different estimates. In addition, many of the industries covered in FEDS (appendix table A.2) do not have alternative sources of energy use. For these reasons, our determination is that the use of industry outlays data from FEDS to allocate SEDS energy use data by end user groups (see appendix table B.2) provides the most informed estimates.

Next, a reduced-dimension direct requirement hybrid matrix ($\underline{\mathbf{HA}}$) is compiled through a double-matrix inversion procedure (Leontief, 1967) to distinguish and measure all energy transactions along each stage of the agri-food chain for a more detailed analysis. This special partition consolidates all energy transactions into eight distinct stages that include farm and agribusiness (sc1), food processing (sc2), packaging (sc3), commercial transportation (sc4), retail and wholesale trade (sc5), commercial food service (sc6), household transportation (sc7), and household food service (sc8). Application of this matrix reduction procedure to the Food Dollar accounts is described in ERS report ERR-114 (see pp. 41-42 in Canning, 2011).

A complete accounting of all food-related energy transactions throughout the domestic economy, broken out by supply chain stage and energy commodity, is computed as:

B.9) $\boldsymbol{\varepsilon}^{fd\#(sc\#)} = \underline{\mathbf{HA}}_{ec0,sc\#} \times [\mathbf{HT}_{sc\#,0} \times \mathbf{hy}^{fd\#}]$,

where sc# = {sc1 to sc8} and represents the supply chain stages. The superscript fd# represents the set of food-related final demand categories and fd# = {fd1 to fd84} for benchmark years or fd# = {fd1 to fd22}, if annual.

As discussed above, an accounting of electricity use must be at the State level in order to accurately identify the fuel sources used for power generation. The expression in brackets on the right side of the equality in (B.9) represents total gross-output requirements (in dollars for non-energy commodities and Btu for all energy commodities) of all industries producing outputs to accommodate the food-related final demand, fd#. From equation (B.6) we can translate the bracketed term in (B.9) to an expression describing total output requirements of region # as $[\mathbf{C}^{\#}_{sc\#,sc\#} \times \mathbf{HT}_{sc\#,0} \times \mathbf{hy}^{fd\#}]$. Finally, from (B.5) we can relabel the national reduced dimension hybrid direct-requirement matrix as the region # reduced-dimension hybrid direct requirement expression, and isolate the electricity commodity row (denoted "*elec*"):

B.10) $\mathbf{r\varepsilon}^{\#}_{elec} = \underline{\mathbf{RHA}}^{\#}_{elec,sc\#} \times \mathbf{C}^{\#}_{\mathrm{sc\#,sc\#}} \times \mathbf{HT}_{\mathrm{sc\#},0} \times \mathbf{hy}^{\mathrm{fd\#}},$

for fd# = fd1 to fd83, $\mathbf{C}^{\#} = \mathbf{C}^{r1}$ to $\mathbf{C}^{r51}$, sc# = sc1 to sc8, and $\mathbf{r\varepsilon}^{\#} = \mathbf{r\varepsilon}^{r1}$ to $\mathbf{r\varepsilon}^{r51}$.

Indexing Annual Time-Series Data

For each final-demand/supply-chain combination, (B.9) is compiled for benchmark years (1997, 2002, 2007) and the 84 fd# results are aggregated up to 22 summary-level categories reported in the annual accounts. To reconcile benchmark year and annual estimates of energy transaction, $\boldsymbol{\varepsilon}^{\mathrm{fd\#,sc\#}}$, an indexing procedure is employed (see Kuchler & Burt, 1990). The index procedure is a geometric interpolation of inter-benchmark energy-flow estimates that maintains relative magnitudes of the annual estimates and distributes a constant annual percentage change to each inter-benchmark year. This constant term is expected to embody the unmeasured structural change in energy using technologies between benchmark years.[9] Because there is no information on how much of this unmeasured technical change occurs in each inter-benchmark year, percentage change is distributed equally in each period.

To demonstrate, recall that data from the annual accounts are represented in bold italics and benchmark year data in bold non-italics. For the period 2002 to 2007, annual estimates of embodied energy at agri-food chain stage sc# for consumer purchases of food commodity fd# are (suppressing superscripts) $\boldsymbol{\varepsilon}_{02}$ to $\boldsymbol{\varepsilon}_{07}$ respectively. We seek to produce a revised set of annual estimates $\underline{\boldsymbol{\varepsilon}}_{02}$ to $\underline{\boldsymbol{\varepsilon}}_{07}$, such that the endpoints of the revised series replicate the benchmark year figures and the annual percentage change for each revised annual estimate is adjusted by the same percentage:

B.11) $\frac{\underline{\varepsilon}_t}{\underline{\varepsilon}_{t-1}} = \frac{\varepsilon_t}{\varepsilon_{t-1}} \times \exp(c)$, for t = 02 to 07

where,

B.12) $\underline{\boldsymbol{\varepsilon}}_{02} = \boldsymbol{\varepsilon}_{02}$, $\underline{\boldsymbol{\varepsilon}}_{07} = \boldsymbol{\varepsilon}_{07}$ (endpoint constraints)

[9] All other determinants of change—population growth, changes in per capita total food availability, and changes in the product mix of purchased food commodities—are measured in the annual series, whereas technical change is imputed through a matrix-balancing procedure (see ch. 13 in the BLS Handbook of Methods: www.bls.gov/opub/hom/pdf/homch13.pdf).

The "c" exponent of the natural exponential function in (B.11) is a constant of proportionality that ensures year-to-year percentage changes to the revised series are the same proportion of percentage changes in the unrevised series for any period over the interval. Due to the endpoint conditions, the value for c in (B.12) can be solved empirically as (see p. 34 in Kuchler & Burt, 1990):

B.13) $c = 0.2 \times \left(\frac{\boldsymbol{\varepsilon}_{07}/\boldsymbol{\varepsilon}_{02}}{\boldsymbol{\mathit{\varepsilon}}_{07}/\boldsymbol{\mathit{\varepsilon}}_{02}}\right)$

In addition to the properties of the revised annual series based on (B.11) to (B.13) discussed above, there is another property of this revision method that is important to its application in this research. Revisions to the nominal monetary series to adjust values for inflation can be applied to the revised nominal series and produce the same result as those obtained when first adjusting the preliminary series for inflation and then applying the revision procedure. This is important when combining the revised energy transaction data with data on energy prices and the prices and quantities of net industry outputs, as is done in equations 1 to 4 of this report.

The same methods described in (B.11) to (B.13) are applied to the inter-census updates between the 1997 and 2002 benchmark accounts. To back-cast each 1997 benchmark calculation of equation (B.9) for the years 1993 to 1996, annual estimates in those years are adjusted based on the ratio of the corresponding 1997 benchmark to annual estimate for $\boldsymbol{\varepsilon}^{fd\#,sc\#}$. The same approach is employed to forecast 2007 benchmark calculations for the years 2008 to 2012 using the corresponding annual estimates for those years.

Appendix C: Diet Model

Mathematical Optimization

This study uses the newly compiled Food Environment Data System (FEDS) described in Appendix B. FEDS yields a complete accounting of all food-related energy market transactions throughout the domestic economy, broken out by supply chain stage and energy commodity. For the 2007 benchmark year considered in this study, there are 84 final demand categories (see the Appendix Table A.1). These final demand categories represent expenditures on food and beverage commodity groups, so $\mathbf{y}_c$ is a vector of annual expenditure totals across all agri-food stages where c is the set of all commodity groups[10] {1,…,84} and $\boldsymbol{\xi}_c$ represents the vector of embodied energy by each of these 84 commodities purchased.[11]

To carry out the diet analysis, we must translate what Americans are buying into what they are eating. We link the 84 final demand categories from the FEDS to the grams of foods and beverage items consumed through the matrix $\mathbf{Q}_{c,f}$ where f = food items = {1,…,4067}. Another way to describe the matrix $\mathbf{Q}_{c,f}$ is that it is the set of all food and beverage items as consumed, organized into the commodity groups as purchased. The number of columns equals the number of food and beverage products as consumed by all Americans ages 2 and above, and the number of rows equals the number of consumer food and beverage commodity groups as purchased. For example, whole milk (USDA food code 11111000) maps 100 percent to the fresh milk commodity, so it is a vector of all zeros except for the cell that intercepts the fresh milk commodity row (c=16). An example of a multi-ingredient food would be shrimp stir fry (USDA food code 27450400). In this case, 23 percent of the grams consumed maps to the shellfish commodity (15), 3 percent of the grams map to the oil commodity (24), and 75 percent of the grams map to the vegetables commodity (31) based on the proportions of these ingredients used in the meal.[12] For the diet analysis, we are only concerned with food items consumed, so we can

[10] The set of final demand categories, or commodity groups (c), was previously referred to as the superset fd0 in Appendix B. We switch the notation for clarity and to represent matrix or vector dimensions.
[11] There are 84 total, but 74 food commodity categories (see appendix table A.1)
[12] These percentages are rounded.

collapse the rows in the $\mathbf{Q}_{c,f}$ matrix: $\mathbf{q}_f^{\mathbf{0}} = \{q_f^0\} = (\mathbf{i}' \times \mathbf{Q}_{c,f})'$ = baseline diet column vector, indexed by food items.

Let $\mathbf{N}_{n,f}$ represent a matrix populated with conversion factors that transform grams as consumed for each food and beverage product into units corresponding to all specific dietary requirements in the DGA; n = food attributes = {1,…,49}. A list of these food attributes is provided in appendix table A.4. For example, the $\mathbf{N}_{n,f}$ matrix will transform grams of a fresh apple reported in the $\mathbf{q}_f^{\mathbf{0}}$ vector into calories,[13] cup equivalents of fruits, and many other nutrition metrics. Next, let $\mathbf{n}^G$ and $\mathbf{n}^L$ represent the goal and limit vectors, reporting the dietary goals and dietary limits (omitting age/gender cohort distinctions for notational clarity) across all metrics including calories, FP components, and nutrients. These are the complete set of dietary metrics we use in this research from the 2010 DGA, subsets of which only specify (i) goals (lower bound), (ii) limits (upper bound), or (iii) both goals and limits. Then for any diet outcome $\mathbf{q}_f^{\mathbf{1}}$ to be in alignment with the DGA, the following two conditions must hold: $(\mathbf{N}_{n,f} \times \mathbf{q}_f^1) \geq \mathbf{n}^G$ and $(\mathbf{N}_{n,f} \times \mathbf{q}_f^{\mathbf{1}}) \leq \mathbf{n}^L$. These two inequality expressions state that for each cohort's average observed diet represented in $\mathbf{q}_f^1$, the embodied dietary characteristics of all items consumed as measured by multiplying by $\mathbf{N}_{n,f}$ (conversion matrix) must at least meet all consumption goals ($\mathbf{n}^G$), but not exceed consumption limits ($\mathbf{n}^L$).

To get Btu per gram for each expenditure group, we rely on the grams consumed by expenditure group represented by $\mathbf{q}_c^0 = (\mathbf{Q}_{c,f} \times \mathbf{i})$ and divide each element in $\boldsymbol{\xi}_c$ by the corresponding element in $\mathbf{q}_c^0$. Then, we map this Btu per gram back to each food item using the proportions of commodities from $\mathbf{Q}_{c,f}$. This results in $\boldsymbol{\xi}_f$. In the same way, to get dollars per gram for each food item, we use the same process, but use $\mathbf{y}_c$ in place of $\boldsymbol{\xi}_c$ resulting in $\mathbf{y}_f$, which after dividing through by total grams consumed, produces the price vector $\mathbf{pq}_f$.

If $\{q_f^0\}$ represents annual average current diets (baseline) of all Americans ages 2 and above and distinguished by age/gender cohort groupings (see appendix table A.3), we seek a similar diet outcome, $\{q_f^1\}$, which is as close as possible to $\{q_f^0\}$ while also meeting the DGA. We run the model for all cohorts,[14] k = {1,...,16}. The basic model is stated as:

[13] In our work, 1 calorie refers to a kilocalorie, or food calorie, equivalent to 4,184 joules.
[14] This subscript is left out for clarity

C.1) $Min_{\Delta} = \sum_{f}\left\{\omega_{f}^{-1} \times \left(q_{f}^{1} - q_{f}^{0}\right)\right\}^{2}$

subject to

C.2)

a) $\mathbf{N}_{n,f} \times \mathbf{q}_{f}^{1} \geq \mathbf{n}^{G}$ (dietary goal constraints),

b) $\mathbf{N}_{n,f} \times \mathbf{q}_{f}^{1} \leq \mathbf{n}^{L}$ (dietary limit constraints),

c) $q_{f}^{0}, q_{f}^{1} \geq 0 \;\forall\; f \in F$ (non-negative consumption constraint),

d) $\mathbf{pq}_{f}\,' \times \mathbf{q}_{f}^{1} \leq \mathbf{pq}_{f}\,' \times \mathbf{q}_{f}^{0}$ (budget limit constraint)

where $\mathbf{q}_{f}^{1}$ is a quantity vector of food and beverage items in the estimated healthy diet and $\mathbf{pq}_{f}$ is the corresponding wholesale price vector that applies to both the baseline and healthy diets. The model specifies a weighted least square objective function (equation C.1) where the vector $\boldsymbol{\omega}_{f}$ represents weights applied as a penalty for each unit of deviation between $\mathbf{q}_{f}^{1}$ and $\mathbf{q}_{f}^{0}$. We are seeking to minimize the mean absolute percentage difference between healthy and baseline diets, so we set the weight vector equal to $\mathbf{q}_{f}^{0}$. The complete constraint sets are stated in equations C.2a-C.2d.

An extension of the basic model (equation C.1) changes the objective function for a new diet $\mathbf{q}_{f}^{2} = \{q_{f}^{2}\}$ that minimizes use of fossil fuels:

C.3) $Min_{\boldsymbol{\xi}} = \sum_{f}\{\boldsymbol{\xi}_{f} \times q_{f}^{2}\}$

where $\boldsymbol{\xi}_{f}$ represent embodied Btu per gram consumed of food item f.

Data

To compile the datasets for implementing the models defined in C.1 to C.3, we follow a methodology similar to the *Thrifty Food Plan, 2006* (Carlson et al., 2007). First, data from WWEIA, the dietary intake component of the 2007-2008 NHANES, characterize a baseline American diet ($\mathbf{q}_{f}^{0}$). NHANES is a nationally representative survey that is done in 2-year cycles.

The 2007-2008 data correspond with the 2007 BEA benchmark accounts, the most recent data that characterize the U.S. economy by detailed industry, used in FEDS.

We use only Day 1 of the NHANES data because of underreporting in Day 2 (Todd et al., 2010), different reporting modes, and possible survey fatigue, as Lin and Guthrie (2012) do in their research. We weight the NHANES data by the reported sample weights for Day 1 to represent the U.S. population's food consumption for 16 age-gender cohorts of our analysis, defined by the American Community Survey[15] (see appendix table A.3). The 2010 DGA contain only nutrition information for those 2 years old and above, so we restrict the sample size, which results in 8,528 participants.[16] In our sample, there are 4,067 unique food or beverage items consumed ($\mathbf{q}_{\mathrm{f}}^{0}$). The Baseline Diet is the grams of food or beverages consumed by each cohort as reported in NHANES, meaning there is a $\mathbf{q}_{\mathrm{f}}^{0}$ for each cohort. We confirm our baseline diets to the WWEIA and FPED data tables to ensure the weighting of the sample is correct[17] (U.S. Department of Agriculture, Agricultural Research Service, 2010a; U.S. Department of Agriculture, Agricultural Research Service, 2010b).

The $\mathbf{N}_{\mathrm{n,f}}$ matrix is comprised of calories, FP components, and nutrients. First, data on nutrient and caloric content of the food and beverage items are retrieved directly from NHANES.[18] The nutrients selected come from Appendix 5 of the 2010 DGA, and we convert the data to nutrient per 1 gram of each food item. Secondly, the USDA Food Patterns recommend daily consumption of food groups, or FP components. We use FPED, which converts the food and beverage items from NHANES to the 37 FP components per 100 grams. FP components are reported in either cup equivalents, ounce equivalents, teaspoons, grams, or number of alcohol drinks. "An equivalent is an amount considered nutritionally equal to 1 cup in the vegetable, fruit, or dairy components or 1 ounce in the grains or protein components" (National Collaboration for Childhood Obesity Research, n.d.). For example, 1 to 2 ounces of natural cheese and 245 grams of fluid milk are both equal to 1 cup equivalent (Bowman et al., 2013). With the normalized units, the FPED allows us to make nutritional comparisons across food items that are in different

[15] The American Community Survey is a public data source published by the U.S. Census Bureau and allows for estimation of age-gender population counts at the county level.
[16] One participant in the sample did not report eating anything, so this participant was excluded.
[17] Male and female cohorts of 2- to 5-year-olds are reported in these tables, which exactly match our cohorts 1 and 2. Also, we were able to compare and confirm the full sample means.
[18] Nutrient data on Day 1 consumption comes from the NHANES dr1iff_e file.

forms. This database also allows us to compare dietary intake data to the 2010 DGA. We use the FPED 2007-2008 corresponding to Day 1 of the 2007-2008 cycle of NHANES,[19] which converts all of the USDA food codes reported in our sample to FP components. Then, we convert these data to FP components per gram of food or beverage consumed by cohort. Together, the nutrient and caloric content from NHANES and the FP components from FPED form $\mathbf{N}_{n,f}$.

To model primary energy[20] embodied in diets, we harmonize what is purchased with what is consumed by linking the NHANES food items as-consumed to the commodity groups in FEDS ($\mathbf{Q}_{c,f}$). Similar mapping is done by Volpe et al. (2013) to link 2003-2004 NHANES data with the 52 Quarterly Food-at-Home Price Database groups to assess healthfulness of food purchases.

We begin with a manual matching process with a number of accuracy checks. First, we determined whether or not a food or beverage reported in NHANES was a one-ingredient food or a multi-ingredient food based on data from the FNDDS 4.1[21] corresponding with NHANES 2007-2008 data. The FNDDS disaggregates food items into ingredients such as a recipe might.

In cases where an item had only one ingredient, the item was mapped directly to an expenditure category or row in the $\mathbf{Q}_{c,f}$ matrix. An apple (USDA food code 63101000) is one example of a one-ingredient food. Another way to think of the one-ingredient foods is the foods that are consumed as they are purchased in the retail store, such as a frozen pizza (USDA food code 58106200). The USDA food code description, the Standard Reference (SR) Code description, and approximately 150 unique food categories from What We Eat in America (WWEIA) inform the classification of these one-ingredient foods in the NHANES foods and beverages by expenditure category.

In the multi-ingredient case, the item needs to be disaggregated before assigning an expenditure category. To provide an example, consider a grilled ham and cheese sandwich (USDA food code 27520350). The sandwich can be disaggregated into its ingredients: bread, ham, cheese, and margarine. After identifying the multi-ingredient foods, we assign a share to each ingredient based on its weight (in grams) relative to the total weight of the item from the FNDDS. These

[19] Food Patterns component data on Day 1 consumption comes from the FPED dr1iff file.
[20] Recall we consider both primary energy (Btu) and food energy (calories); we reference their respective units instead of energy to avoid confusion.
[21] We use the SR-Links file, which is based on the USDA National Nutrient Database, for Standard Reference 22.

ingredients are then individually mapped to one of the 74 expenditure categories. We assume that all of the multi-ingredient foods are homemade and made from purchasing the individual ingredients. To put it another way, multi-ingredient foods are not purchased in the way they are ultimately consumed; they are prepared from the purchased ingredients. After the initial mapping was done, some manual refinements were made by using Appendix B from the FNDDS 4.1, which outlines the USDA coding scheme.[22]

To resolve any uncertainty in the manual mapping process, the grams mapped to the initial 74 categories from FEDS are aggregated to 38 commodities. With grams and Btu both organized by expenditure category, we calculate 38 energy pathways with unique Btu per gram ratios. We map these Btu per gram ratios back out to the original food item by the proportion of ingredients in each particular food item. This mapping results in embodied Btu for each food or beverage item in our baseline diet from NHANES ($\boldsymbol{\xi}_f$). There are 1,672 unique Btu ratios associated with these food items. Just as we can trace Btu back to each food item, we can also do this with dollars. The cost is the weighted average based on the commodity makeup of the food or beverage $\mathbf{pq}_f$. This cost is not reflective of an item's price paid at a retail store, rather its wholesale price.[23]

Constraints

Finally, with the input data compiled, we shift our focus to the model constraints ($\mathbf{n}^G$ and $\mathbf{n}^L$). All of the constraints are weighted based on the age and gender demographics of NHANES Day 1 participants. First, we assume a moderately active activity level for caloric needs, which we allow to vary by 5 percent above or below the target to give the model flexibility (see Appendix 6 in U.S. Department of Agriculture & U.S. Health and Human Services, 2010).

Secondly, we include the 14 FP components as constraints; the subcomponents are selected for grains, vegetables, and protein foods[24] (see Appendix 7 in U.S. Department of Agriculture & U.S. Health and Human Services, 2010). Daily alcohol limits are also included and are set at zero

[22] For example, all of the multi-ingredient foods whose food code began with 281 were moved to the frozen foods expenditure category and assumed to be a one-ingredient item (purchased as-is). Some other items such as bagels, crackers, and some ice creams treats were also moved to the one-ingredient list, since these are products likely purchased as-is, rather than being homemade.

[23] Wholesale prices are used to avoid having the model tradeoff between lower price margins for food at home versus away from home. This approach assumes the share consumed home versus away do not change.

[24] Weekly recommended intakes are converted to daily intakes for consistency with the rest of the FP components. Beans and peas (legumes) are counted in the vegetables group as in the 2010 DGA, Appendix 7.

for those under the legal drinking age. The FP constraints account for palatability and diet variety, since food from all of the FP components must be chosen by the model. The FP constraints also require an omnivorous diet, meaning when the FP constraints are included in the model, the resulting healthy diet cannot be vegetarian.

Lastly, we impose 33 nutrient targets as constraints mostly from the Institute of Medicine (2016) that are listed in Appendix 5 of the 2010 DGA, supplemented by Tolerable Upper Intake Levels (UL) when necessary (Institute of Medicine, n.d.).[25] A UL is defined as "the highest level of daily nutrient intake that is likely to pose no risk of adverse health effects to almost all individuals in the general population." We calculate the (percentage of calories) constraints using a conversion factor of 4 calories per gram of protein, 4 calories per gram of carbohydrate, and 9 calories per gram of fat (University of Illinois at Urbana-Champaign, 2014).

The calories, FP components (including the limit on alcohol), and the nutrient targets make up the dietary constraints for the models. We use combinations of these constraints in the modeling and label them by numeric sets shown in appendix table C.1. Examining different constraint sets allows us to test a range of scenarios and definitions of a healthy diet. A complete list of constraints are included in appendix table C.2.

Appendix Table C.1—Constraint sets defined over dietary and cost constraints

	Constraint set					
	1	2	3	4	5	6
Calories	x	x	x	x	x	x
Food Patterns components	x		x	x		x
Nutrient targets		x	x		x	x
Cost				x	x	x

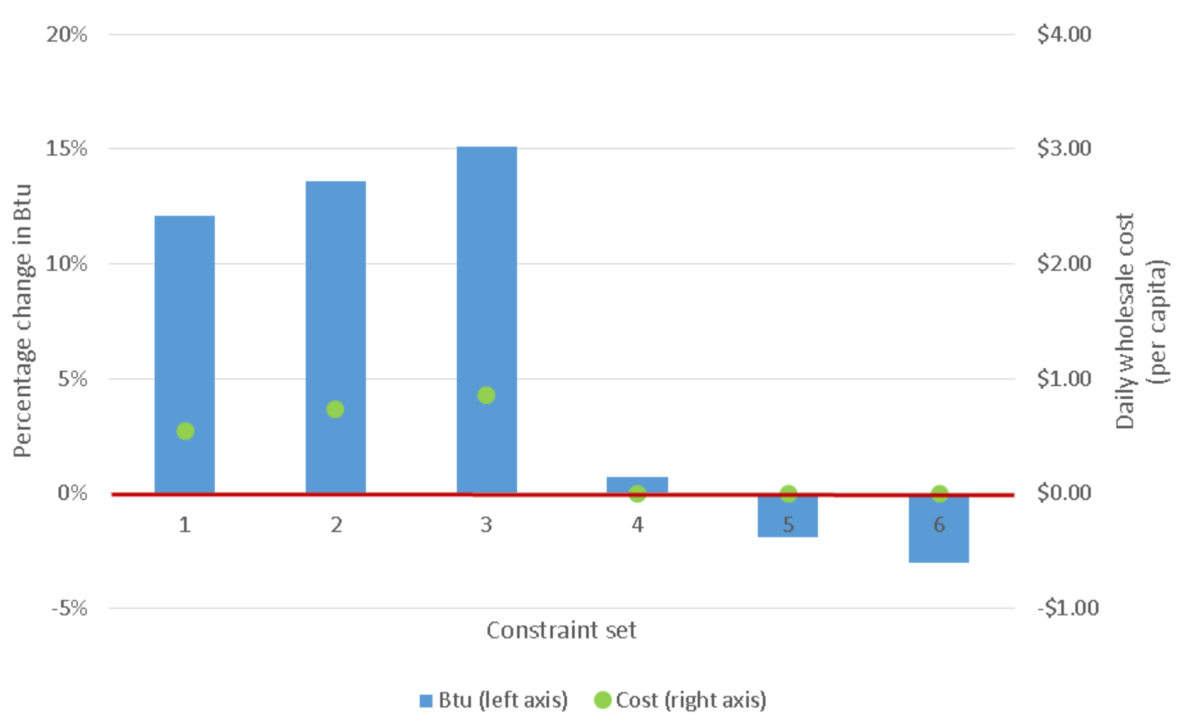
Source: USDA, Economic Research Service

[25] The tolerable upper intake levels for vitamin E, niacin, and folate apply to synthetic forms obtained from supplements, fortified foods, or a combination of the two. Vitamin E is the only variable of these three that breaks out the added vitamin E, and the model output mostly hits the lower bound. For niacin and folate, we have no other information about whether they are fortified or not, so we also apply the upper bounds here (see appendix table A.4).

Extended Model Results

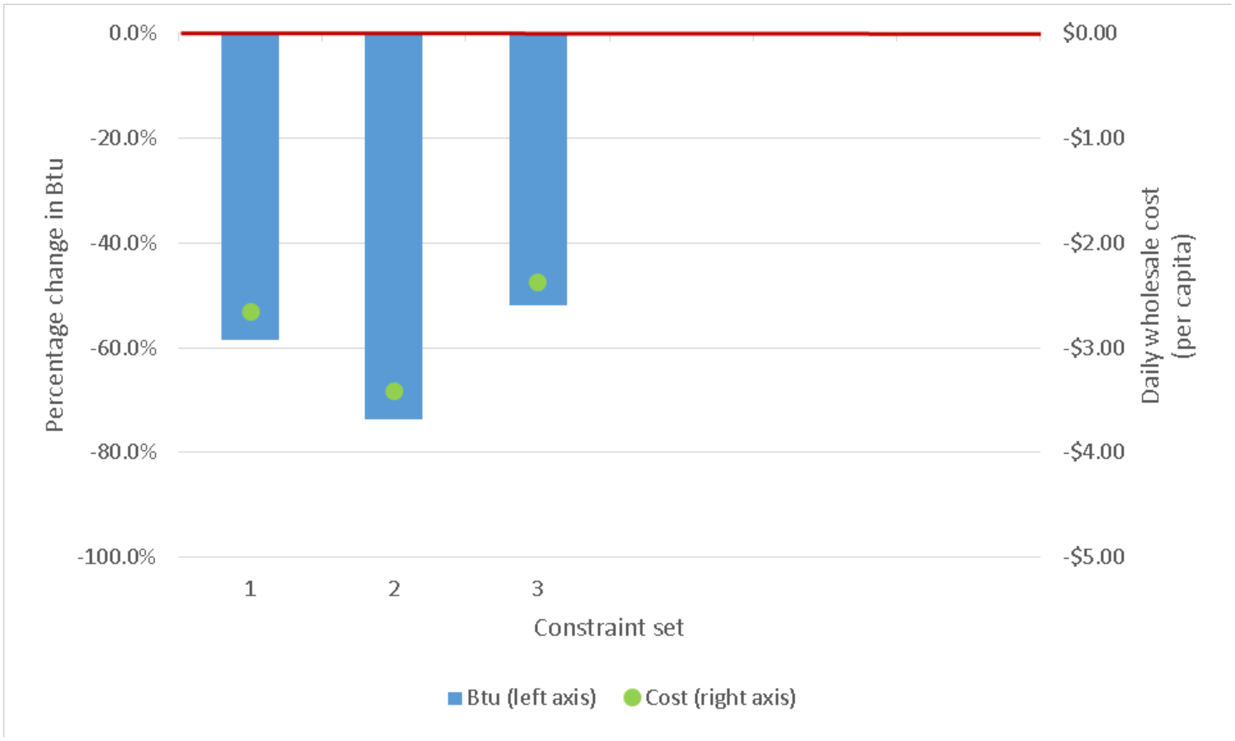
We use the General Algebraic Modeling System (GAMS) with the solver CONOPT3 since the objective functions are quadratic and the constraints are both linear and non-linear. The models are run for each cohort separately, and we obtain an optimal solution for each within the included constraints. Appendix figures C.1 and C.2 compare the results from both models for the total population using two metrics: Btu and cost. Each bar is an alternative diet.

Appendix Figure C.1—Minimum difference model results relative to Baseline Diet



Source: USDA, Economic Research Service

Appendix Figure C.2—Minimum Btu model results relative to Baseline Diet



Source: USDA, Economic Research Service

Appendix figure C.1 summarizes results for the minimum difference model under the six constraint sets. When only combinations of dietary constraints are considered, both Btu and cost increase from the baseline levels. Constraint Set 3 produces a substantial increase in both metrics; Btu increases 15 percent while wholesale cost increases 86 cents per capita per day. Therefore, making minimal shifts to eat healthy, without regard to cost, will require more Btu. Btu also increases with Constraint Set 4. Btu may be reduced when keeping dietary costs the same, but only when applying Constraint Sets 5 and 6.

The results show that nutrient targets are important constraints to consider in addition to the FP components. The FP are designed to meet nutritional requirements if the nutrient-dense forms of the food items are consumed (Britten et al., 2012). Nutrient density implies that a food item provides nutrients without extra calories from both naturally-occurring and added solid fats, added refined starches, and added sugars (U.S. Department of Agriculture and U.S. Department of Health and Human Services, 2010, p. 5). However, the most nutrient-dense forms of food are not the foods chosen by most Americans (Britten et al. 2012), which our data confirm. For example, in Constraint Set 1, with only the calorie and FP component constraints, we discover that the cohorts were not meeting nutrient goals or limits. For example, sodium is still being over-consumed by 1,536 mg, or 69 percent above the daily recommended maximum.

Appendix figure C.2 shows the results for the model that minimizes Btu embodied in diets. We do not test Constraint Sets 4-6, which include a cost constraint. A cost constraint would be redundant with the minimum Btu objective function since costs decrease when only considering dietary constraints. Wholesale costs decrease by $2.38 to $3.41 per person per day and Btu decreases from between 52 and 74 percent compared to the Baseline Diet. The minimum Btu model with Constraint Set 2 is the most efficient diet of all in terms of Btu, and also the lowest cost.

Appendix Table C.2—Model constraints with sources and units

	Lower bound source	Upper bound source	Unit
Calories			
Calories	2010 DGA, Appendix 6; authors' calculations	2010 DGA; authors' calculations	calories
Food Patterns components			
Alcohol	N/A	2010 DGA for adults of legal drinking age	number of drinks
Beans and peas (legumes)	2010 DGA, Appendix 7	N/A	cup equivalents
Dairy	2010 DGA, Appendix 7	N/A	cup equivalents
Dark-green vegetables	2010 DGA, Appendix 7	N/A	cup equivalents
Enriched grains	2010 DGA, Appendix 7	N/A	ounce equivalents
Fruits	2010 DGA, Appendix 7	N/A	cup equivalents
Meat, poultry, eggs	2010 DGA, Appendix 7	N/A	ounce equivalents
Nuts, seeds, soy products	2010 DGA, Appendix 7	N/A	ounce equivalents
Oils	2010 DGA, Appendix 7	N/A	grams
Other vegetables	2010 DGA, Appendix 7	N/A	cup equivalents
Red and orange vegetables	2010 DGA, Appendix 7	N/A	cup equivalents
Seafood	2010 DGA, Appendix 7	N/A	ounce equivalents
SoFAS (solid fats + added sugars)	N/A	2010 DGA, Appendix 7	calories
Starchy vegetables	2010 DGA, Appendix 7	N/A	cup equivalents
Whole grains	2010 DGA, Appendix 7	N/A	ounce equivalents
Nutrient targets			
alpha-Linolenic acid	2010 DGA, Appendix 5	N/A	grams
alpha-Linolenic acid (% of calories)	2010 DGA, Appendix 5; authors' calculations	2010 DGA, Appendix 5; authors' calculations	calories
Calcium	2010 DGA, Appendix 5	DRIs, UL	mg
Carbohydrate	2010 DGA, Appendix 5	N/A	grams
Carbohydrate (% of calories)	2010 DGA, Appendix 5; authors' calculations	2010 DGA, Appendix 5; authors' calculations	calories
Cholesterol	N/A	2010 DGA, Appendix 5	mg
Choline	2010 DGA, Appendix 5	DRIs, UL	mg
Copper	2010 DGA, Appendix 5	DRIs, UL	mcg
Folate	2010 DGA, Appendix 5	DRIs, UL	mcg_DFE
Iron	2010 DGA, Appendix 5	DRIs, UL	mg
Linoleic acid	2010 DGA, Appendix 5	N/A	grams
Linoleic acid (% of calories)	2010 DGA, Appendix 5; authors' calculations	2010 DGA, Appendix 5; authors' calculations	calories
Magnesium	2010 DGA, Appendix 5	N/A	mg
Niacin	2010 DGA, Appendix 5	DRIs, UL	mg
Phosphorus	2010 DGA, Appendix 5	DRIs, UL	mg

--continued

Appendix Table C.2—Model constraints with sources and units--continued

	Lower bound source	Upper bound source	Unit
Potassium	2010 DGA, Appendix 5	N/A	mg
Protein	2010 DGA, Appendix 5	N/A	grams
Protein (% of calories)	2010 DGA, Appendix 5; authors' calculations	2010 DGA, Appendix 5; authors' calculations	calories
Riboflavin	2010 DGA, Appendix 5	N/A	mg
Saturated fat (% of calories)	2010 DGA, Appendix 5; authors' calculations	2010 DGA, Appendix 5; authors' calculations	calories
Selenium	2010 DGA, Appendix 5	DRIs, UL	mcg
Sodium	N/A	2010 DGA, Appendix 5	mg
Thiamin	2010 DGA, Appendix 5	N/A	mg
Total fat (% of calories)	2010 DGA, Appendix 5; authors' calculations	2010 DGA, Appendix 5; authors' calculations	calories
Total fiber	2010 DGA, Appendix 5	N/A	grams
Vitamin A	2010 DGA, Appendix 5	DRIs, UL	mcg_RAE
Vitamin B12	2010 DGA, Appendix 5	N/A	mcg
Vitamin B6	2010 DGA, Appendix 5	DRIs, UL	mg
Vitamin C	2010 DGA, Appendix 5	DRIs, UL	mg
Vitamin D	2010 DGA, Appendix 5	DRIs, UL	mcg
Vitamin E	2010 DGA, Appendix 5	DRIs, UL	mg_AT
Vitamin K	2010 DGA, Appendix 5	N/A	mcg
Zinc	2010 DGA, Appendix 5	DRIs, UL	mg
Cost			
Cost	N/A	IO model	dollars

Note: 2010 DGA refers to the Dietary Guidelines for Americans (U.S. Department of Agriculture and U.S. Department of Health and Human Services, 2010). DRIs refers to the Dietary Reference Intakes and UL refers to the Tolerable Upper Intake Level (Institute of Medicine, n.d.).

Maximum-Likelihood Properties of the Realistic Healthy Diet Model

To support the assertion that the Realistic Healthy Diet is the most likely among many possible diets that Americans might adopt to align their food choices with the DGA, it would be useful to demonstrate that it is the most representative diet among Americans who are currently aligned with the DGA. Here we define the conditions necessary for this assertion to hold.

Recall from above that $\mathbf{q}_f^0$ represents the weighted average of all survey responses (ignoring cohort designations for clarity) that inform what the respondent's intake (in grams) of food item "f" amounted to over a 24-hour dietary recall period. The sample surveyed was weighted to be representative of the American population such that, together with a measure of variance, we can make inferences about the range and frequency of all responses. For any other food item "f#", it is reasonable to expect that individual decisions about consumption of "f" and "f#" are not always independent—French-fries and catsup is a case in point.

Denote $\mathbf{C}_{\mathrm{f,f}} = \left\{c^2_{\mathrm{f,f\#}}\right\}$ the covariance matrix describing the variance and covariance statistics across all food intake decisions, f ∈ F. With $\mathbf{q}^0_{\mathrm{f}} = \left\{q^0_{\mathrm{f}}\right\}$ describing the Baseline Diet and $\mathbf{q}^1_{\mathrm{f}} = \left\{q^1_{\mathrm{f}}\right\}$ describing some unobserved healthy diet whose values are bound by constraints C.2.a and C.2.b above, suppose we want to test the hypothesis that $\mathbf{q}^0_{\mathrm{f}} = \mathbf{q}^1_{\mathrm{f}}$? Weale (1985) demonstrates that a constrained least squares solution to problems like this, when survey data are normally distributed, is also maximum likelihood:

C.4) $$Z = (\mathbf{q}^1_{\mathrm{f}} - \mathbf{q}^0_{\mathrm{f}})' \times \mathbf{C}^{-1}_{\mathrm{f,f}} \times (\mathbf{q}^1_{\mathrm{f}} - \mathbf{q}^0_{\mathrm{f}})$$

Byron (1996) points out that the log ratio test can be used to evaluate the hypothesis that initial parameter values ($\mathbf{q}^0_{\mathrm{f}}$) are unbiased estimates of the maximum likelihood solution ($\mathbf{q}^1_{\mathrm{f}}$). This model is solved through minimization of C.4 subject to constraints C.2.a and C.2.b. The optimal solution, $\mathbf{q}^1_{\mathrm{f}}$, describes a set of food intake choices, $\left\{q^1_{\mathrm{f}}\right\}$, that meets the DGA constraints (C.2.a and C.2.b) and is statistically most similar (least different) to the greatest number of current diets among the population under study (all Americans ages 2 and above). In statistical terms, we know that among all possible solutions to C.4, $\mathbf{q}^1_{\mathrm{f}}$ has the lowest sum of squared differential from the food choices among the sample population.

The equivalence of equations C.1 and C.4 holds when $\boldsymbol{\omega}_{\mathrm{f}} = \mathbf{C}_{\mathrm{f,f}}$. Recalling that $\boldsymbol{\omega}_{\mathrm{f}} = (\mathbf{q}^0_{\mathrm{f}})''$, this equality holds under the following conditions:

i. *For all* $q^0_{\mathrm{f}} \in \mathbf{q}^0_{\mathrm{f}}$ *coefficients of variation,* $c_{\mathrm{f,f}}/q^0_{\mathrm{f}}$, *are equal to a constant,* α

ii. *All non-diagonal elements of the matrix,* $\mathbf{C}^{-1}_{\mathrm{f,f}}$, *are 0 (uncorrelated)*

Condition (*i*) is a reasonable assumption for the Realistic Healthy Diet model provided, by age/gender cohort; all mean statistics, $\left\{q^0_{\mathrm{f}}\right\}$, have uniformly small sample variance measures relative to their mean values. Note that for (*i*) to hold, $c_{\mathrm{f,f}} = \alpha \cdot q^0_{\mathrm{f}}$, so the difference between diagonal elements in $\boldsymbol{\omega}_{\mathrm{f}}$ and $\mathbf{C}_{\mathrm{f,f}}$ is the constant of proportionality, α, and this is the only difference in the two matricies when condition (ii) also holds. Introducing a constant of proportionality to a diagonal matrix when used in either C.1 or C.4 will not impact the optimal solution to the model.

Condition (ii) is not realistic and counterexamples are easy to imagine—again, French fries and catsup are a case in point. However, it is standard practice for users of the NHANES survey, and many other surveys, to implicitly accept condition (ii). For example, when using the What We Eat in America tables (http://www.ars.usda.gov/Services/docs.htm?docid=23429) developed from the NHANES data to summarize average American diets of different age/gender groups, comparisons of average diets by cohort are used to evaluate how well the population is doing in meeting the different DGA requirements, such as is done in figures 8 to 10 in this report. This practice assumes the average intake across all food items represents the average diet for each cohort. The sufficient condition for this assumption to hold is condition (ii), since the assumption only holds if choices are independent. By extending this practice to our interpretation of the model result in the Realistic Healthy Diet, we can make the assertion that it is the most representative diet among Americans who are currently aligned with the DGA.